CEO NETWORK IN FINANCE

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DECLARATION

I, **Emmanuel Joel Aikins ABAKAH** certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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I acknowledge the support I have received for my research through the provision of an **Australian Government Research Training Program Scholarship.**

Signed:

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‘’ But as for you, be strong and do not give up, for your work will be rewarded’’

2 Chronicles 15:7 (NIV)

ABSTRACT

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This thesis examines how information flow among CEOs with social and professional connections affects firms and the market environment. Using biographical information about CEOs of U.S. public companies supplied by BoardEx from 2000-2016, the thesis relies on CEOs' educational background, employment history and social activities (e.g., social clubs) to estimate the social and professional connections of CEOs as a measure of firms' network size. The thesis then examines how networks among CEOs facilitate commonality in liquidity and commonality in asset growth among connected firms.

The essay titled "CEO Connectedness and Commonality in Liquidity", examines the effects of CEOs' social and professional networks on stock liquidity commonality. We hypothesize that the stock liquidity of firms whose CEOs are connected will covary. In this essay, we uniquely construct our measure of commonality in stock liquidity among connected firms and provide strong evidence supporting the hypothesis. Outcomes reveal that the more connections firms share with each other, the more their stock liquidity comove. The essay further tests channels through which CEOs social and professional networks drive commonality in stock liquidity across connected firms. Results indicate that similarity in corporate finance policies and trading activities across connected firms are two channels through which CEOs' personal connections drive liquidity covariation. We address endogeneity concerns and provide results that demonstrate that the magnitude of stock liquidity covariation among connected firms reduces when a CEO dies.

The essay titled "CEO Peer Effects and Commonality in Asset Growth", sought to investigate whether educational, social and professional networks among CEOs affect managerial asset growth decisions. We hypothesize that the asset growth rate of firms whose CEOs are connected will comove because of group thinking and peer influence. Using biographical information regarding CEOs of U.S. public firms from 2000 – 2016, the results suggest that CEO connectedness facilitates asset growth covariation. We conclude that a CEO is more likely to increase assets if peers in the network have recently done so leading to asset growth covariation across connected firms. Next, we test for channels through which CEOs' connections may drive asset growth commonality across connected firms. The results reveal that commonality in asset growth decisions among connected firms stems from two possible channels: the adoption of related acquisition and research and development investment strategies. On the economic benefits of commonality in asset growth to shareholders, results show that commonality in asset growth across connected firms affects shareholders negatively. On endogeneity, tests indicate that the death of a CEO significantly reduces the extent of asset growth comovement between connected firms.

DEDICATION

To my lovely future wife and children with love and gratitude.

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"Trust in the Lord with all your heart; do not depend on your own understanding"

Proverbs 3:5

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TABLE OF CONTENTS

CHAPTER 1

GENERAL INTRODUCTION

1. Introduction and Research Objective

Recent empirical finance research suggests that CEOs' social and professional networks affect managerial decisions. These studies indicate that corporate decisions such as firms' financial policies, investment styles, corporate governance practices, acquisitions, and compensation decisions are influenced significantly by the CEOs' network ties through information diffusion across top executives social networks (Fich and Shivdasani, 2006; Schonlau and Singh, 2009; El-Khatib, Fogel, and Jandik, 2015; Kaustia and Rantala, 2015; Fracassi, 2016). This thesis adds to the literature by investigating how a CEO's network of social and professional contacts, a potentially valuable source of external information, impacts stock liquidity and asset growth decisions across connected firms.

The thesis specifically investigates the role of CEO networks as a determinant of commonality in liquidity and commonality in asset growth among connected firms for several reasons. First, CEO networks represent a pivotal channel through which firms disseminate information to make informed decisions. This channel is critical because CEOs' contributions are crucial in firm decisions coupled with the fact that CEOs possess specialized expertise that the board of directors may lack. In addition, social and professional connections of top executives provide better access to valuable information on product characteristics, regulatory change, industry trends and market dynamics (Granovetter, 1974; Ellison and Fudenberg, 1995a; Tsai, 2001; Inkpen and Tsang, 2005). This information advantage, according to Burt (1997) and Faleye, Kovacs, and Venkateswaran (2014), makes individuals more innovative in taking quality strategic decisions. Secondly, Asch and Guetzkow (1951) observe that the tendency of an individual to fall victim to group thinking increases among individuals with social and professional connections. This indicates that CEOs with connections are prone to group thinking because of constant pressure from peer CEOs. Arguably, peer practices and decisions driven by group thinking can convey information or effect changes in the market environment that can motivate firms and individuals to undertake similar actions. Fracassi (2016) confirms this view in indicating that top management with social and professional connections adopt similar corporate finance policies.

Though firms benefit enormously from social and professional networks of top executives, CEOs in a network are more susceptible to group thinking bias (Mizruchi, 1996). For instance, when wrong information permeates through CEOs' social and professional networks, it is more likely that the information would be reinforced and accepted without much consideration because of the trust among individuals within the network. Thus, analyzing the effects of group thinking among CEOs with social and professional networks, which may cause market conditions to change and cause individuals to adopt similar corporate policies and practices, is essential. This thesis contributes to the stream of research that examines the effects of CEOs' social and professional networks in finance (Kirchmaier and Stathopoulos, 2008; Engelberg, Goa, and Parsons, 2013; Liu, 2014; El-Khatib, Fogel, and Jandik, 2015; Khanna, Kim, and Lu, 2015).

This thesis addresses two key questions. The first question is whether stock liquidity across connected firms covaries. This question is distinguished from previous research on social networks in finance in that: it examines how CEOs' social and professional networks may facilitate commonality in stock liquidity. In the market microstructure literature, extensive research shows that commonality in stock liquidity is prevalent among stocks (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001); however, we know relatively little about the factors that fuel commonality in liquidity among stocks. Some key prior studies attribute liquidity commonality among stocks to [1]supply-side sources and [2]demand-side sources (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001; Coughenour and Saad, 2004; Hameed, Kang, and Viswanathan, 2010; Koch, Ruenzi, and Starks, 2016).

As explained above, the first question investigates whether CEOs' networks, which create firm connectedness, are a potential source of liquidity covariation among stocks. Thus, we propose that the stock liquidity of firms that are connected strongly covary. Specifically, we argue that the adoption of similar corporate policies among firm CEOs with network ties facilitates the transfer of similar information into security markets by connected firms. The release of similar information into security markets may cause changes in the market environment and influence the trading strategies of market participants and investors holding stocks that are connected to be related. This essay is the first to determine whether connectedness among firms influences liquidity commonality among stocks. We next test for possible channels through which CEOs' connectedness may drive commonality in liquidity. First, we investigate whether CEOs' networks impact commonality in liquidity through the adoption of similar corporate finance policies across connected firms. Second, we examine whether the trading activities of connected firms are related leading to stock liquidity covariation across connected stocks.

[1] **Supply-side explanation** for liquidity commonality argues that when there is uncertainty about the market or when there is a market drop, liquidity providers are forced to liquidate their positions across many assets to recover from losses, which leads to a decline in market liquidity creating an illiquidity spiral. This decrease in liquidity or increase in volatility fuels commonality in liquidity. The supply side-sources argue that commonality in liquidity is higher during high market volatility, higher interest rates in the economy and poor financial market conditions, which affect the availability of capital to financial intermediaries.

[2] **Demand-side explanation** for sources of liquidity commonality mainly lies in the intense trading by institutional investors, mutual fund institutions, banking firms and insurance companies

Our second question is whether asset growth decisions among connected firms are related. Specifically, we conjecture that through peer effects, CEOs are likely to mimic asset growth decisions of peers. Previous psychology studies demonstrate that social interactions lead to group thinking because of peer effects (Cowan and Todorovic, 2000). Peer effects are a subject of increasing attention in many areas of economics and finance. Empirical evidence comes from individual's investment choices (Duflo and Saez, 2002; Hong, Kubik, and Stein, 2004), labour markets (Topa, Bayer, and Ross, 2008), consumption decisions (Cai, Chen, and Fang, 2009) and the use of welfare benefits (Bertrand, Luttmer, and Mullainathan, 2000). Peer influence is interesting since it can generate social multiplier effects through which a small initial shock can lead to more substantial changes as the actions of peers directly influence individuals. Clearly, corporate activities are a potential domain for such peer effects since corporate managers pay close attention to the actions of their peers. For example, Bizjak, Lemmon, and Naveen (2008) note that 96% of firms report utilizing peer groups to set executive pay. Recently, Kaustia and Rantala (2015), examining social learning and corporate peer effects, discover that firms are more likely to split their stock if peer firms have recently done so. In line with the above intuition, we probe further to ascertain whether a CEO is more likely to grow assets after peer CEOs belonging to the same network have done so. We hypothesize that through peer influence, commonality in asset growth will exist across connected firms. The essay further tests for the economic benefits of peer firms imitating each other when it comes to asset growth decisions.

2. A Summary of the Major Findings

In this thesis, we test the hypotheses on a sample of U.S. firms listed on U.S. stock exchanges (NYSE/AMEX/NASDAQ) from 2000 to 2016. The first essay examines CEO networks as a potential determining factor of liquidity commonality among stocks in U.S. stock exchanges.

In line with Anton and Polk (2014) and Koch, Ruenzi, and Starks (2016), we construct our measure of stock liquidity commonality across connected firms. The results suggest that stock liquidity commonality exists among connected stocks. Additional tests demonstrate that the magnitude of stock liquidity commonality increases with firm network size. This implies that the larger the network of a firm, the greater the extent of comovement between the firm's stock liquidity and the stock liquidity of firms connected to the firm. To explain our findings, we argue that firms with a large network adopt or mimic the actions of a large number of firms; hence, their trading activities end up having related components with other firms. In effect, their stock liquidity covaries with the stock liquidity of several firms, hence the greater their liquidity commonality. From the work of Kamara, Lou, and Sadka (2008), we control for time and firm effects and find that the main results are not driven by time-invariant unobservable heterogeneity. Overall, our results show that the more connections firms share with each other, the more comovement their stock liquidity has.

Next, we conduct tests to examine the potential channels through which CEOs' networks may influence commonality in liquidity across connected firms. First, we test whether similarity in corporate finance policies among connected firms facilitates liquidity commonality across the firms. We conjecture that similarity in corporate finance policy decisions among connected firms facilitates the transfer of related information from these firms to the security markets, which affects market conditions. Hence, traders holding stocks of firms that are connected and, as a result, adopt similar actions may employ similar trading strategies when trading these stocks leading to a correlated trading pattern across the stocks. We provide evidence that similarity in corporate finance policy decisions, such as capital investment, as well as R&D, drive liquidity commonality across connected firms. As a second channel, we analyze the trading activities of connected firms to ascertain whether they have shared components. Using the number of trades as the measure of trading activity, the results indicate that the trading activities of connected firms have a common component that drives liquidity commonality in the stocks. The essay attributes the commonality in trading activities among connected stocks to activities of a group of investors trading in the stocks. We argue that if a group of investors trades in such stocks around the same time, then there will be a common component in their ‘buy’ and ‘sell’ orders leading to commonality in liquidity across connected stocks.

In the next set of analyses, we investigate whether CEOs’ networks influence asset growth rates of firms with CEOs having social and professional connections. We conjecture that, because of peer effects, asset growth rates across connected firms will covary. We test this claim using U.S. firms listed on NYSE/AMEX/NASDAQ. We discover that CEO connectedness significantly affects asset growth rate decisions. The results show that connected firms grow assets similarly leading to commonality in asset growth across the firms. We attribute the results to group thinking across the CEOs’ networks that influences individuals in the network to adopt similar actions. We conclude that a CEO is more likely to increase a firm’s assets if a colleague CEO in the network has done so. Thus, the asset growth rates of firms are influenced significantly by peer performance and peer effects.

With the above discoveries, we test the net economic significance of asset growth commonality on shareholder value. Cooper, Gulen, and Schil (2008) and Watanabe, Xu, Yao, and Yu (2103) suggest that asset growth negatively affects stock returns. Those studies demonstrate that firms with higher asset growth rates record lower stock returns. In a recent study, Hvide and Östberg (2015) find that stock market investment decisions of individuals are positively correlated with those of coworkers. As per the findings above, we hypothesize that asset growth commonality can negatively affect firms. This is because, through peer influence, a CEO may imitate a peer

CEO to increase assets even if the asset addition may not add value to the firm. With our earlier findings confirming that asset growth decisions of connected CEOs are related, it is essential we test for the relationship between commonality in asset growth and firm performance. It is likely that commonality in asset growth may not yield significant economic benefits to firms since a firm may increase assets at a specific time as a result of CEO peer effects that may not be strategic for the firm.

The results indicate a significant negative relationship between commonality in asset growth and firm performance. Thus, the similarity in asset growth across connected firms does not enhance shareholder value. Focusing on the channels that information flow through, CEOs' networks may drive asset growth commonality across connected firms; we find that similarity in M&A decisions among CEOs with personal connections significantly influences commonality in asset growth among these firms. Additional tests reveal that similarity in R&D investment decisions among connected firms drives commonality in asset growth. These outcomes confirm that CEOs' networks significantly influence several aspects of corporate decisions through peer effects (Grennan, 2019; Bouwan, 2011).

3. Contribution

This thesis contributes to several lines of research. First, the thesis contributes to studies on the determinants of commonality in liquidity across stocks in various stock markets by establishing that CEOs' networks drive commonality in stock liquidity across connected stocks (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001; Coughenour and Saad, 2004; Hameed, Kang, and Viswanathan, 2010; Koch, Ruenzi, and Starks, 2016). From the results, asset growth decisions of connected CEOs are closely related because of peer influence. The thesis also contributes to work on peer effects in corporate finance (Bouwan, 2011; Shue, 2013; Fracassi, 2016; Grennan, 2019).

This thesis complements studies examining the determinants of asset growth (Simon and Bonini, 1958; Eatwell, 1971; Lucas Jr, 1978; Sawyer, 1985; Evans, 1987b, Audretsch, Klomp, and Santarelli, 2004) and how asset growth affects firm performance (Cooper, Gulen, and Schil, 2008; Lipson, Morta, and Schill, 2011; Lam and Wei, 2012). In addition, this thesis contributes significantly to studies on social learning among individuals with personal connections and the effects on individuals within the network (Kaustia and Rantala, 2015)

The discoveries reported in this thesis is close to studies that analyze the influence of peer actions of firm executives in security markets. Cohen, Frazzini, and Malloy (2008) infer that through social networks, information is transferred to security markets, which influences the decisions of mutual fund managers. Kaustia and Knupfer (2012) find that social influence affects an individual's stock market entry especially when better opportunities exist for the individual to gain knowledge through social learning. We provide evidence to suggest that convergence in corporate behavior among connected firms facilitates the transfer of similar information to stock markets which causes changes in the market environment that influence investors' trading strategies leading to commonality in liquidity.

4. Thesis Structure

The remainder of this thesis is structured as follows. Chapter 2 investigates the role of CEOs' networks on stock liquidity commonality. Chapter 3 explores the effects of CEOs' personal connections on a firm's asset growth decisions. Chapter 4 concludes the thesis.

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CHAPTER 2

CEO CONNECTEDNESS AND COMMONALITY IN LIQUIDITY

1. Introduction

Several studies report the significant role of stock liquidity in asset pricing, market efficiency, and corporate finance. Lam and Tam (2011), for example, indicate that liquidity is an essential factor for pricing returns after taking well-documented asset pricing factors into consideration. Similarly, Amihud (2002) demonstrates that there exists a significant relationship between liquidity and expected returns. Chordia, Roll, and Subrahmanyam (2008) suggest that liquidity stimulates arbitrage activity, which, in turn, enhances market efficiency. In the context of stock liquidity and corporate investment decisions, Beeker-Blease and Paul (2006) find a positive relationship between changes in capital expenditure and changes in stock liquidity, indicating that stock liquidity influences corporate investment decisions. On the other hand, substantial literature provides evidence that stock liquidity covary across stocks using single and multiple market datasets, i.e., there is commonality in liquidity among stocks (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Coughenour and Saad, 2004; Kamara, Lou, and Sadka, 2008; Hameed Kang, and Viswanathan, 2010; Chordia, Roll, and Subrahmanyam, 2011; Karolyi, Lee, and van Dijk, 2012; Koch, Ruenzi, and Starks, 2016).

These studies on the determinants of liquidity covariation across stocks offer several hypotheses on why stock liquidity covary. Some of these studies hypothesize that stock liquidity covariation is influenced by noise trading effects (Huberman and Halka, 2001), liquidity demand heterogeneity (Fernando, 2003), macroeconomic announcements (Brockman, Chung, and Pérignon, 2009), market volatility (Hameed, Kang, and Viswanathan, 2010), institutional stock ownership (Kamara, Lou, and Sadka, 2008; Koch, Ruenzi, and Starks, 2016), and country level supply-side and demand-side factors (Karolyi, Lee, and van Dijk, 2012). All these studies primarily focus on financial market-level determinants but ignore firm-specific determinants such as the personal traits and characteristics of corporate decision makers. Although extensive research suggests commonality in liquidity is prevalent among stocks, , the current literature on factors causing commonality in liquidity is limited to the asset pricing and market microstructure literature, hence, this current study aims to be the first to establish a link between the corporate finance literature and liquidity commonality.

Interestingly, although available research suggests that CEO networks impact corporate policies, earlier studies on the sources of commonality in liquidity do not consider the crucial role of social and professional networks of top executives (e.g. CEOs) who direct corporate behavior and implement policies that can cause changes in stock markets to influence individual stock liquidity and stock liquidity covariation among stocks. To the extent that a growing number of studies in empirical finance infer that CEOs' social and professional networks significantly influence firms' corporate policies such as capital investment (Fracassi, 2016), earnings management (Chiu, Teoh, and Tian, 2013), acquisition activities (El-Khatib, Fogel, and Jandik, 2015; Shue, 2013), and board monitoring (Fracassi and Tate, 2012), this factor is crucial and noteworthy for consideration as a potential source of stock liquidity covariation. In addition, a number of studies have long acknowledged the existence of social interaction effects among individual investors (Hong, Kubik, and Stein, 2004; Shiller, 1984; Shiller and Pound, 1989), which further indicates the need for an investigation into the relationship between CEOs' networks and commonality in stock liquidity.

This essay investigates whether the presence of social, educational and professional connections among CEOs of U.S. public companies drives liquidity commonality among connected firms. The essay focuses on social networks because, in the sociology literature, Coleman (1988), for instance, finds that social interactions greatly influence economic behavior. In another study, Ellison and Fudenberg (1995a) indicate that economic agents often rely on whatever information they have obtained via casual word-of-mouth communication in making decisions leading to similarity in corporate behavior. In effect, we hypothesize that the stock liquidity of connected firms will comove. Specifically, the essay seeks to address the following research questions: Does stock liquidity of firms that are connected through CEOs' social and professional networks covary? If so, through which channel(s) does liquidity covariation manifest itself through CEOs' networks?

The intuition for our hypothesis is as follows: From the social network literature, Banerjee (1992), Park and Sabourian (2011), and Welch (1992), using information based models, explain that social network and information structures, which play significant roles in information diffusion, often fuel similarity in behavior among individuals with personal connections because of peer effects. In finance, Fracassi (2016) shows that information flow through the social and professional networks of directors and top executives influence corporate decisions across firms leading to convergence in corporate policies. Fracassi (2016) reveals that connected firms have similar corporate finance policies such as capital investment. Similarly, Bouwman (2011) finds that networks among firm executives cause corporate governance practices to converge. These studies demonstrate the effects of social interaction that creates peer effects among firm top executives and directions in corporations.

In this essay, we argue that the convergence of corporate policies and practices among connected firms can convey information to market participants or cause changes in the stock market that can motivate individual investors to trade in the same direction or adopt similar trading strategies to cause commonality in liquidity. In line with the intuition outlined in this stream of research, this essay argues that, if connected public companies take similar corporate finance policies and corporate governance practices around the same time, then similar signals will be transmitted to the broader market because of the similarity in corporate behaviour. We, therefore, conjecture that this can influence and induce decisions by economic agents' trading strategies in connected stocks. If stocks of connected firms are held by a large group of investors who tend to trade in the same direction and at the same time, then these connected stocks would be characterized by strong comovements in their liquidity. We argue that similarity in corporate behavior among connected firms could influence investors' decisions to trade in the same direction causing their stock liquidity to comove.

To answer the baseline question, we construct a measure of liquidity commonality across connected stocks and then estimate its relationship with the stock's network size measured by the CEO's connectedness degree. Specifically, we use Amihud (2002) and CRSP Bid-Ask Spread as proxies for daily stock liquidity. In line with the approach of Koch, Ruenzi, and Starks (2016), we construct our measure of liquidity covariation among connected firms by first estimating the relationship between the stock's own liquidity and the liquidity of a portfolio of stocks connected to the individual stock (excluding the individual stock from the portfolio). We label the regression coefficient of an individual stock's liquidity on the liquidity of a portfolio of stocks connected to the individual stock, the *Social Network Liquidity Beta.*

As anticipated in our hypotheses, our results reveal a significant positive relationship between individual stock liquidity and the liquidity of a portfolio of stocks connected to the individual stock. Our results thus establish that the stock liquidity of firms that are connected comoves. We further extend our investigation in two directions. First, we carry out an additional test to determine whether indeed liquidity commonality is prevalent across connected stocks. Focusing on the extent of a firm's total network size, we study the relationship between the social network liquidity beta coefficient for each stock and the network size of each firm measured by the firm's CEO's network size. Consistent with our baseline hypotheses, we find a significant positive relationship between the social network liquidity beta and a CEO's network size.

Following the results above, we investigate the channels through which information flows across CEOs' social network ties could drive liquidity commonality across connected stocks. First, we examine whether commonality in stock liquidity across connected stocks could be driven by commonality in corporate outcomes that can affect stock liquidity. To address that, we examine the relationship between social network liquidity beta and our measure of corporate policy similarity for each stock. Consistent with our hypothesis, we observe a significant relationship between social network liquidity beta and the similarity of corporate finance policies.

To explain our results, let us assume that different mutual fund managers hold different portfolios of stocks with stocks in each portfolio that are socially connected. If these socially connected firms end up taking similar corporate finance policy decisions, we argue that voluntary trading is likely to correlate across funds because similar information is transmitted to the market through similar corporate finance policy decisions. The reason is that fund managers react to the same kind of public information, rely on many of the same information sources and follow similar investment styles with similar catalysts because of the similarity in corporate finance policies across connected firms that induces liquidity comovement. If voluntary trading is correlated across funds, we anticipate that firms with large network size will have a particularly high commonality in liquidity. We provide evidence to support this argument. We further argue that, through similarity in corporate behavior, spontaneous trading will be observed when stocks experience liquidity shocks leading to buying and selling pressure (Coval and Stafford, 2007; Khan, Kogan, and Serafeim, 2012). If this buying and selling pressure is correlated across connected stocks, it will result in liquidity commonality.

Secondly, we investigate whether commonality in trading activities of connected firms induces liquidity comovement. Karolyi, Lee, and van Dijk (2012) note that there exist time series patterns in commonality in stock returns, liquidity and trading activity across individual stocks in developed and emerging economies. The time-series tests show that commonality in liquidity is high during periods of high market volatility and high market-wide trading activity. This essay argues that the trading activity of connected firms' will have common components, which can give rise to liquidity commonality among connected stocks. This essay proposes that the more connected two firms are, the more similar their trading activities are because of the similarity in trading strategies of market participants. Using the number of trades as our measure of trading activity, we examine the relationship between social network liquidity beta and commonality in trading activities across connected firms. We find strong evidence that commonality in trading activity across connected stocks is an essential driver of the relationship between liquidity commonality and CEOs' social networks. This evidence aligns with our hypothesis that liquidity comovement across connected stocks could be induced by similarity in trading activity among connected stocks.

The essay contributes to various threads of research. First, the investigation contributes to the literature on the impact of social networks in finance. Several studies have shown that social and professional interaction across firms affects corporate behaviour (Renneboog and Zhao, 2011; Engelberg, Gao, and Parsons, 2013; Renneboog and Zhao, 2014; Khanna, Kim, and Lu, 2015) and corporate financial policies (Davis, 1991; Cohen, Frazzini, and Malloy, 2008; Bizjak, Lemmon, and Whitby, 2009; Cohen, Frazzini, and Malloy, 2010; Larcker, So, and Wang, 2013; Shue, 2013; Fracassi, 2016). We add to the literature on CEOs' social networks with evidence that CEOs' social and professional network ties drive liquidity commonality across connected stocks through two channels. Precisely, we establish the role of CEOs' social network's in explaining commonality in liquidity.

Secondly, we contribute to research on information sources of traders and market participants. Akbas, Meschke, and Wintoki (2016) observe that, through director connectedness, information spreads either directly or inadvertently to sophisticated traders such as short sellers, options traders and institutional investors. Cohen, Frazzini, and Malloy (2010) infer that sell-side equity analysts and mutual fund managers, through their educational networks, obtain superior information. Generally, we contribute immensely to the emerging literature regarding how the corporate policies of firms affect the information environment. We demonstrate that the imitation of corporate policies gives information to traders through a signal effect that influences their trading behavior leading to liquidity comovement across connected firms.

The essay proceeds as follows. Section 2 is the literature review and hypothesis development. Section 3 describes the data and sample selection. Section 4 presents the empirical findings and Section 5 documents the conclusion and recommendation.

2. Literature Review and Hypothesis Development

2.1 CEO Networks and Corporate Policies

In developing the hypotheses for this essay, we combine two strands of literature. We first rely on the social science literature to define a CEO's social and professional network as the number of ties the CEO has with other CEOs through shared educational, work experience and social activities. From the literature, CEOs who are well connected have two essential qualities: (i) they have better access to relevant information both internal and external to the firm and (ii) they have higher status and greater economic and political power (Brass and Burkhardt, 1992; Haunschild, 1993a; Mizruchi, 1996; Mizruchi and Potts, 1998; Granovetter, 2005). Through strategic alignment, CEOs and firms both benefit from these traits through advantages in the product, labor, and corporate control markets. For example, Glaeser, Kallal, Scheinkman, and Shleifer, (1992) and Jaffe, Trajtenberg, and Henderson (1993) find that members in a network rely on shared information obtained from other members in the network to improve, advocate and institute acceptable and beneficial practices. The essay argues that CEOs rely on the accomplishments of other CEOs in the networks to implement policies and develop strategies for actions that tend to influence firms' stock liquidity levels.

The application of the networks of top executives to business matters is well established in the management literature (Powell, Koput, and Smith-Doerr, 1996; Tsai, 2001); however, recently studies in the finance literature examine the effect of social and professional networks of CEOs in corporate decisions. Hochberg, Ljungqvist, and Lu (2010), for example, examine whether strong networks among incumbent venture capitalists in local markets help restrict entry by outside venture capitalists, thus improving the incumbent's bargaining power over entrepreneurs. Additionally, El-Khatib, Fogel, and Jandik (2015) investigate whether CEOs' networks influence mergers and acquisitions and Khanna, Kim, and Lu (2015) examine whether CEO connectedness enhances corporate fraud. Likewise, Ahern and Harford (2014) examine whether industry connectedness leads to a higher incidence of cross-industry mergers. These studies focus on CEOs because of the significant "soft" influence CEOs have aside from the legal authority to direct corporate behavior and dictate board decisions. In this essay, we build on this line of research to study the impacts of CEOs' networks on commonality in stock liquidity. We argue that CEOs, through their social and professional interactions, obtain vital, sensitive information shared across the networks that they rely on to influence decisions in the firm that can cause changes to the firm's stock liquidity. Through information diffusion, managers belonging to the same network end up having similar preferences regarding corporate financial decisions because of the actions of their social peers. Consistent with Coughenour and Saad (2004), we argue that commonality in corporate decisions across connected firms could generate commonality in stock liquidity. Arguably, this essay is the first in the empirical finance literature to consider establishing a relationship between commonality in liquidity and similarity in corporate policies.

We focus on social and professional networks as a potential source of commonality in stock liquidity because activities across social ties by individuals within the networks can significantly influence firm level decision-making that can affect the decisions of market participants and investors. For instance, top executives' networks facilitate information diffusion and transmission within the group (Holzer, 1987; Granovetter, 1995; Calvo-Armengol and Jackson, 2004), which causes managers to often rely on their social and professional networks to obtain valuable experience, gather vital market information, exchange resources, and identify business opportunities (Engelberg, Gao, and Parsons, 2013). Ellision and Fundenberg (1995) and Watts (2003) reveal that, in situations where individuals do not have all the required information, they often depend on whatever information they receive from an individual within their network due to peer effect.

There is now a growing literature on the effects of CEOs' social and professional networks in finance. Key studies have explored the role and the effects of CEO networks in corporate finance policy decisions of firms: compensation (Coles, Daniel, and Naveen, 2008; Hwang and Kim, 2009; Engelberg, Gao, and Parsons, 2013), executive employment options in the labour market (Liu, 2014), stock options backdating (Bizjak, Lemmon, and Whitby, 2009), corporate innovation (Faleye, Kovacs, and Venkateswaran , 2014), board monitoring (Fracassi and Tate, 2012), acquisition activity (Haunschild, 1993b; Cai and Sevilir, 2011; Ishii and Xuan 2014; Renneboog and Zhao, 2014;), tax rates (Brown and Drake, 2013), private equity transactions (Stuart and Yim, 2010), IPOs (Cooney, Madureira, and Singh, 2015), earnings management (Chiu, Teoh, and Tian, 2013), and future performance (Horton, Millo, and Serafeim, 2012; Larcker, So, and Wayng, 2013). However, none of these studies examined the relationship between CEOs network size and stock liquidity commonality. Primarily, these studies do not consider whether the strength and the size of top management's social and professional networks can affect stock liquidity covariation among connected firms.

2.2 Overview of Commonality in Liquidity

The second strand of literature centres on stock liquidity and sources of liquidity commonality. Liquidity, defined as the ease with which investors trade assets in a timely manner at a low cost, plays a significant role in the price formation process of individual stocks. Hence, a stock's liquidity and how it changes over time are important to market participants. Earlier studies document that liquidity goes beyond individual securities (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and

Seppi, 2001; Huberman and Halka, 2001; Amihud, 2002; Brockman and Chung 2002; Domowitz, Hansch, and Wang, 2005; Brockman, Chung, and Pérignon, 2009). These studies specify that stock liquidity comove with other securities, which makes liquidity more than just a feature of individual securities. In the past two decades, a number of studies confirmed this phenomenon (Chordia, Roll and Subrahmanyam, 2000; Brockman and Chung, 2002; Brockman and Chung, 2008; Brockman, Chung, and, Pérignon, 2009; Karolyi, Lee, and van Dijk, 2012; Koch, Ruenzi, and Starks, 2016). Understanding liquidity comovement across stocks and its determinants are relevant to market participants for several reasons. For example, some studies discovered liquidity covariation across stocks can influence expected returns (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005). Chordia, Roll, and Subrahmanyam (2000, 2011) note the determinants and pricing of stock liquidity commonality have vital implications for international asset pricing. Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) show that a stock's exposure to systematic liquidity is most likely a price source of risk.

Most studies on liquidity commonality attribute the fundamental sources of liquidity comovement in stock markets to two sources: asymmetric information and market conditions. Asymmetric information can occur at the market and/or industry level. For instance, during transactions, market participants who have no private information about firms are likely to lose by transacting business with an informed trader whose knowledge regarding the stock may be superior. Similarly, when new information that affects all stocks in the market hits the market, liquidity covariation across stocks tends to occur. Huberman and Halka (2001) specify that for quote driven markets, the trading frequency of individual stocks positively affects liquidity proxies. Brockman and Chung (2002) suggest that since trading volume contains relevant information regarding informed trading, traders end up splitting their orders into small and medium size trades to hide their existence; this process of tactfully breaking up orders results in having market-wide and industry-wide trading frequencies with related components that contribute to liquidity commonality.

Market conditions sources of liquidity commonality are classified into supply-side and demand-side sources. Prior studies suggest that supply-side sources of comovement in liquidity include funding constraints of financial intermediaries (Coughenour and Saad, 2004; Brunnermeier, 2009; Hameed, Kang, and Viswanathan, 2010; Karolyi, Lee, and van Dijk, 2012). A cross-section of prior studies provides evidence that demand-side sources of commonality in liquidity include investor sentiment (Huberman and Halka, 2001), ownership level of institutions (Kamara, Lou, and Sadka, 2008; Koch, Ruenzi, and Starks, 2016) and correlated trading patterns among investors (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001). Brockman, Chung, and Pérignon, (2009) show that, in addition to the demand-side and supply-side sources of liquidity commonality, both country-specific (domestic) and U.S. macroeconomic announcements drive stock liquidity comovement.

2.3 Hypothesis Development

An important factor motivating this essay is that the actions of people in a network can influence individual preferences and decisions as a result of shared information through interactions; this influences corporate outcomes. This is highlighted by Nguyen, Hagendorff, and Eshraghi (2016) and Hvide and Östberg (2015) who show that personal connections facilitate the exchange of vital, sensitive information, ideas and knowledge that significantly influences the decision making of individuals. Ellison and Fudenberg (1995b) and DeMarzo, Kaniel, and Kremer (2008) comprehensively evaluate the impact of word-of-mouth effects among connected individuals. In the financial context, Cohen, Frazzini, and Malloy (2008) use social networks to identify the transfer of information in security markets. They find social networks to be an essential mechanism for information flow into asset prices since portfolio managers perform significantly better by holding stocks that are connected than holding stocks that are not connected. This essay conjectures that liquidity commonality across stocks may arise from the transfer of similar information from connected firms to security markets, which can influence the trading strategies of market participants leading to liquidity commonality.

As outlined above, network ties provide better access to information and enhance decision making at the firm level. As prior studies point out (Chiu, Teoh, and Tian, 2013; Shue, 2013; Leary and Roberts, 2014; Kaustia and Rantala, 2015), directors use information obtained through their networks to direct corporate behavior. This essay extends the impact of director network ties to market microstructure by focusing on how similarity in corporate decisions across connected firms taken at the firm level drive liquidity commonality. We argue that the transfer of information into the security market by connected stocks might influence the decisions of liquidity demanders trading strategies across these connected stocks to be correlated. The novelty of this essay rests on the application of social network measures to ascertain how they influence stock liquidity comovement across stocks.

The essay hypothesizes that social and professional network ties among corporate executives influence the trading pattern of investors. This assertion is driven by the fact that the more two companies are connected with each other, the more similar their corporate decisions are. Thus, similar decisions will send similar signals from the two companies to the stock market, which will affect the trading choices and strategies of analysts and investors. We argue that similar signals sent to markets by the two connected companies causes investors to trade in a correlated pattern contributing to commonality in liquidity. Accordingly, we predict that the liquidity of firms that are connected would comove. The first hypothesis is:

Hypothesis 1 (H1): Stock liquidity of connected firms will strongly comove.

Next, we examine whether the relationship in hypothesis 1 vary for differences in network size. The connection to an executive director facilitates information sharing since executive directors have better, excellent, direct knowledge regarding their company and have the power to influence corporate decisions. Since information sharing in the network benefits both the CEO and the firms, we expect that the relationship in hypothesis 1 will strengthen for firms with a larger network. We employ the CEO's number of connections to other CEOs as the proxy for a firm's network size. Following the above, we expect the extent and magnitude of liquidity comovement for firms with a larger network to be greater. Consequently, we predict a positive relationship between liquidity commonality and CEOs' networks size. The second hypothesis is:

Hypothesis 2 (H2): Liquidity commonality increases with the CEO's network size.

Conceptually, empirical evidence implies that liquidity covariation can arise from supply-side and demand-side sources (Hasbrouck and Seppi, 2001; Coughenour and Saad, 2004; Kamara, Lou, and Sadka, 2008; Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes, 2010; Koch, Ruenzi, and Starks, 2016). However, for factors influencing commonality in liquidity among stocks, some studies suggest that different investor types drive liquidity commonality (Karolyi, Lee, and van Dijk, 2012). Other studies attribute liquidity comovements to market design with evidence of the existence of commonality in liquidity in quote driven (Chordia, Roll, and Subrahmayam, 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001) and order driven markets (Brockman and Chung, 2002). However, Coughenour and Saad (2004) find that liquidity commonality arises from the fact that each NYSE specialist firm provides liquidity to many stocks because of shared capital and information among specialist firms. Thus, stock liquidity comoves with the liquidity of other stocks handled by the same specialist firm. We argue that firm interconnections that lead to similarity in corporate behavior could give rise to liquidity comovement across connected firms since similarity in corporate behavior could cause changes in stock markets and influence market participants' decisions.

Chiu, Teoh, and Tian (2013) specify that directors who serve on different boards are information carriers who 'infect' other susceptible firms on whose board they sit with information. Hence, firms with shared directors are likely to make similar corporate decisions such as earnings management, around the same time. Likewise, Fracassi (2016) uses the social and professional networks of key executives and directors to explain how social networks affect the corporate finance policy decisions of connected firms. He argues that managers are influenced by their social peers when making corporate policy decisions because of information flow through the social and professional networks. A natural implication of this theory is that one firm can transmit its shocks or decisions to another firm through information flow irrespective of the industry affiliation of the firm. From Fracassi's work, the information flow enables companies in the network to invest in a less idiosyncratic way and exhibit better economic performance. We expand on this argument by applying it to stock liquidity commonality. The third hypothesis is:

***Hypothesis 3: Similarity in corporate finance policies across firms is a channel through which CEO connectedness contributes to liquidity commonality*.**

We conduct tests to examine whether commonality in trading activity across connected firms drives liquidity commonality. We argue that daily movement in liquidity and trading activity of firms can be influenced by shared information across CEOs' social and professional networks since market participants rely on information from the security markets to adopt trading strategies. Hence, the stock liquidity of connected firms adopting similar corporate decisions is likely to experience similar trading activity. We conjecture that the number of daily transactions and volume of trade across firms whose CEOs are connected could have common components because of similar corporate behavior that can fuel liquidity covariation across the firms. The fourth hypothesis is:

Hypothesis 4: Correlated trading activity across connected firms is a channel through which CEO connectedness contributes to liquidity commonality.

3. Data and Sample Selection

We begin with the BoardEx database, which provides biographical information on firms' senior executives and board members. For each director or executive, BoardEx compiles a full historical profile containing employment history, current employment, board memberships, educational background, and social activities such as memberships in social and charitable organizations. For this essay, we focus only on U.S. firms in BoardEx with a sample period from 1 January 2000 to 31 December 2016.BoardEx reports generated in December 2016 provide a summary of board composition and/or senior executives by year for 18,314 firms in North America including 13,688 U.S. firms.

We proceed to extract firm-level financial and accounting information from Standard & Poor's Compustat North American Database and merge the BoardEx data with Compustat by linking the BoardEx firm identifier (Company ID) to the Compustat Identifier (GVKEY). BoardEx provides the ISIN for firms with stock quotes. We extract CUSIP from ISIN and match it to Compustat header CUSIP. Of the 13,688 U.S. firms in BoardEx, we are able to find the GVKEY for 7,527. For BoardEx firms without an ISIN, we use a Levenshtein algorithm to aid approximate name matching and verify the matched pairs manually. We are able to find the GVKEY for an additional 3,563 U.S. firms in BoardEx under this procedure. In total, we found 11,090 out of 13,688 (81%) U.S. firms covered by BoardEx for 1 January 2000 to 31 December 2016.

Next, we identify CEOs from the 11,090 U.S. firms obtained from BoardEx. In BoardEx, individual's employment role is recorded regardless of whether the individual's role continues or has ended. Hence, we identify CEOs as individuals with the role name *CEO, CEO/President, CEO/Chairman, Chairman/President/CEO and CEO/CFO*. Next, we select individuals with those employment roles and find 13,980 CEOs for 8,736 out of 11,090 U.S. firms. We use the biographical information of the CEOs to define four social networks representing different social interactions among pairs of individuals in the final data sample.

We obtain stock price information from CRSP. Using the link history table of the CRSP/Compustat dataset, we merge BoardEx and Compustat fundamentals data with CRSP stock liquidity data. To identify a unique CRSP security identifier (PERMNO) for each firm-year observation, we ensure the fiscal year end date is within the effective link dates.

3.1 Variable Construction

3.1.1. CEO Network Size Measure

We start by aggregating all types of CEOs' social and professional ties (hereafter, CEO network size) into a single index and test whether it explains liquidity commonality. A CEO's network size is calculated by counting the number of other CEOs with whom the CEO has connections each year. A CEO network connection at year *t* is defined as one established between a CEO and another CEO if they link on one or more of employment, education or other social activities (e.g., social club) during or the prior to year *t* (Fracassi. 2016).

From earlier studies, such as Engelberg, Goa, and Parsons (2013), Liu (2014) and Fracassi (2016), this essay defines CEO professional and social networks as follows: two CEOs are connected in a professional network through their previous employment if CEO 1 of company 'A' was a board member or top management member of company 'B' headed by CEO 2. In situations where CEO 1 and CEO 2 sat on the board of directors of a third company, the essay classify the two CEOs as professionally connected through their past employment. For this essay, we focus on past employment connections in the last 5 years because past employment connections that go beyond 5 years are weak connections. Two CEOs are connected in a professional network through their current employment if CEO 1 of company 'A' is a board member or top management member of company 'B' headed by CEO 2. Where CEO 1 and CEO 2 sit on the board of directors of a third company, the essay classify the two CEOs as professionally connected through their employment network.

Two CEOs are connected in a social network through their past education if they graduated within one year of each other from the same school and have the same degree type. We identify educational overlaps based on BoardEx's education file. We clean the BoardEx education file in two ways following Cohen, Frazzini, and Malloy (2008). First, for universities that have multiple institute IDs, we aggregate them into single institute ID. For instance, BoardEx assigns "Stanford University" ID# 743905436, "Stanford University School of Law" ID# 9164011235, "Stanford University Graduate School of Business" ID# 8034910975 and "Stanford Medical School" ID# 5881139024. We merge all of these into the "Stanford University" ID. BoardEx does not list a unique ID for degree type, only a description of the executive's qualification. We map each degree description on one of six types: (1) undergraduate, (2) masters, (3) MBA, (4) PhD, (5) law, and (6) other. We ignore professional certificates such as CFA or CPA because we focus only on university qualifications as in earlier studies (Engelberg, Gao, and Parsons, 2011). Following Engelberg, Gao, and Parsons (2013), two CEOs are connected socially if they belong or share membership in a social club or professional/non-professional association and are both active.

Our measure of CEO network size for a firm CEO is the sum of the direct professional and social connections for each year as follows:

$$CEO\_Total\_Network\_Size_{i,t} = \sum Network\_Employment_{i,t} + \sum Network\_Education_{i,t} + \sum Network\_Other\_Social\_Activities_{i,t} \quad (1)$$

where network employment sums a CEO's current and past employment connections, network education sums a CEO's education connections, and network other activities sums a CEO's other social activity connections.

3.1.2. Liquidity Measures

a. Amihud Illiquidity Measure

We calculate the daily change in stock illiquidity for all stocks in our sample. Our sample of stocks includes ordinary common shares (share codes 10 and 11) listed on NYSE and AMEX. We exclude NASDAQ stock from our main analysis because the NASDAQ trading volume is inflated relative to NYSE/AMEX trading volumes because of different trading mechanisms (Koch, Ruenzi, and Startks, 2016). We obtain data on stock price, return, trading volume, the number of transactions, bid and ask from the CRSP daily file and construct daily Amihud and CRSP-Spread measures from 1 January 2000 to 31 December 2016. Following Amihud, (2002) and Koch, Ruenzi, and Startks (2016), we calculate the daily change in stock illiquidity for all common stocks on NYSE and AMEX that trade above $5 per share and have at least 10 trades a month. To prevent outliers from affecting our analysis, we eliminate the top and bottom 1% of observations of the measure. From the filtering process, we obtain a sample of 8,048 ordinary stocks listed on NYSE/AMEX.

Following Amihud (2002), Karolyi, Lee, and van Dijk (2012), Koch, Ruenzi, and Starks, (2016) and Fong, Holden, and Trzcinka (2017), we estimate stock liquidity using the Amihud (2002) measure of daily stock illiquidity, which equals the absolute value of stock *i's* return for day *d* divided by the dollar volume of stock *i's* trading on day d. The Amihud measure is ideal for the purposes of the study because it is based on widely available data and can be calculated for a large number of stocks at a daily frequency. Evidence also supports the use of the Amihud measure as a reliable proxy for a stock's liquidity with strong correlations between it and alternative liquidity measures based on intraday microstructure measures (Hasbrouck and Seppi, 2001; Korajczyk and Sadka, 2008). In addition, Goyenko and Ukhov (2009) show that the Amihud measure is a good proxy for price effect. We then calculate the daily change in Amihud Illiquidity for all stocks in our sample by taking the difference of the logs of Amihud's Illiqudity measure (Kamara, Lou, and Sadka, 2008; Koch, Ruenzi, and Starks, 2016). This is done to reduce the effects of non-stationarity.

$$\Delta illiq_{i,d} = \ln\left[\frac{\Delta illiq_{i,d}}{\Delta illiq_{i,d-1}}\right] = \frac{\left[\dfrac{r_{i,d}}{dvol_{i,d}}\right]}{\left[\dfrac{r_{i,d-1}}{dvol_{i,d-1}}\right]} \qquad 2$$

Where ***r*** ***i,d*** is the return on stock *I* for day d and $dvol_{i,d-1}$ is the dollar volume for stock *i* on day d .

b. The CRSP Bid-Ask Spread

Following Chung and Zhang (2014) we calculate the CRSP bid-ask spread for stock *i* for day *d* using the following formula.

$$CRSP\_Spread_{i,t} = (Ask_{i,t} - Bid_{i,t}) / M_{i,t}, \qquad 3$$

where $Ask_{i,t}$ is the ask price of stock *i* on day t from the CRSP daily data, $Bid_{i,t}$ is the bid price of stock *i* on day *t* from the CRSP daily data, and $M_{i,t}$ is the mean of $Ask_{i,t}$ and $Bid_{i,t}$. To reduce the effect of data errors and outliers, we exclude all $CRSP\_Spread_{i,t}$ that are greater than 50% of the quote midpoint. We delete CRSP observations if both ask and bid are zero (Chung and Zhang, 2014) for each stock. The daily values of $CRSP\_Spread_{i,t}$ are calculated from 2000 to 2016. From the filtering process, we obtain a sample of 7,431 ordinary stocks listed on NYSE/AMEX.

3.1.3 Corporate Finance Variables

Based on Bertrand and Schoar (2003) and Fracassi (2016), we obtain corporate variables of interest from Compustat for 2000-2016. We focus on three different sets of corporate decisions, investment policy, financial policy and organisational strategy. For investment policy, we consider capital investment whereas for financing policy decisions we consider: financial leverage, cash reserve ratio/cash holdings, interest coverage and dividend payout. Finally, for organizational strategy, we focus on research and development expenditure.

3.2 Summary Statistics

Panel A, Table 1, summarises the statistics for the two main liquidity variables used in the essay with a mean value of 0.307 for Amihud Illiquidity and 0.006 for the CRSP-Spread, which is consistent with prior studies such as Goyenko and Ukhov (2009) and Chung and Zhang (2014). For the liquidity measures, it can be observed that the median for Amihud Illiquidity is not close to the mean. Amihud illiquidity recorded a mean of 0.307 with a median of 0.003. Thus, Amihud Illiquidity shows right skewness since the sample mean is larger than the median. This is consistent with previous studies such as by Chordia, Roll, and Subrahmayam (2000) and Fabre and Frino (2004). Panel B, Table 2, reports the statistics of the daily changes in stock liquidity for the two liquidity measures. The results indicate that variability in daily changes in Amihud Illiquidity is more than the CRSP-Spread.

Table 1 also reports the statistics for aggregate liquidity across connected firms. Panels C and D, Table 1 show the statistics of daily liquidity changes for the portfolio of stocks constructed to investigate the study objectives. In Panel C, summary statistics of the daily changes in liquidity for the portfolio of stocks that are connected to individual stock irrespective of the industry of connection are presented. Since each stock in the sample is connected to a number of stocks, we estimate the statistics of the portfolio of stocks connected to each firm first without taking into consideration the industry of connection. However, in Panel D, we estimate the statistics for the portfolio of connected stocks that share the same industry with the individual stock to which they are connected. Using the standard deviation to measure variability, from Panels C and D, we discover that the Amihud Illiquidity is more variable for all cases than the CRSP-spread.

Panel E, Table 1, summarises the statistics of CEOs Network Size measured as the sum of Network-Employment, Network-Education and Network-Other Social Activities. The panel presents the mean value of CEO Network Size with aggregate statistics for the full sample where we ignore the industry of the firms connected to the individual stock. The table further details descriptive statistics of CEO Network Size where we consider the industry of firms with which the individual stock is connected. Thus, we tally the number of CEOs on a CEO network with reference to the industry of interconnections. For the full sample, we find the median number of total network contacts is 10. However, we recorded a median of the total contacts to be 9 and 2 for CEO total connections in a different industry and same industry, respectively. From the above, we find CEO network total to be positively skewed for all categories. For instance, the results show that the mean number of total contacts for a CEO in the sample irrespective of industry affiliation of the other CEOs is 23.526. For CEOs who are connected but belong to different industries, we find the mean number of contacts to be 17.242 whereas the mean number contacts for CEOs who are connected and belong to the same industry is 4.19. This shows that CEOs tend to have more connections with other CEOs working in all industries.

Comparing the means with the full sample, on average, there is 73.2% chance that two firms that are connected will belong to different industries and there is 17.8% chance that two connected firms will belong to the same industry.

INSERT TABLE 1

4. Empirical Results

4.1 Estimating Liquidity Commonality across Connected Stocks

Prior research on commonality in liquidity estimates liquidity comovement using different approaches. For example, Chordia, Roll, and Subrahmayam (2000), Coughenour and Saad (2004) and Kamara, Lou, and Sadka (2008) applied a market model that measures the sensitivity of stocks own liquidity to variation in broader market liquidity to estimate liquidity commonality. Hameed, Kang and Viswanathan (2010), Karolyi, Lee, and van Dijk (2012) define commonality in liquidity as the R^2 (Roll, 1988) of a regression of the stock's daily liquidity measured by the price impact proxy of Amihud (2002) on daily market liquidity.

For this essay, we adopt the approach of Anton and Polk (2014) and Koch, Ruenzi, and Starks (2016) to estimate the measure of liquidity commonality across connected firms. For each firm, we estimate the covariance between the daily changes in individual stock liquidity and changes in the liquidity of portfolio of stocks having connections with the individual stock. We control for value-weighted market liquidity documented by Chordia, Roll, and Subrahmayam, (2000). For each firm, we estimate regressions of daily changes in individual stock liquidity $\Delta liq_{i,t}$, on changes in the liquidity of portfolio of stocks connected to individual stock $\Delta liq_{j,t}$, and on changes in the market-wide stock liquidity $\Delta liq_{mkt,t}$. Our focus is on the extent of liquidity covariation across connected firms; however, to proxy for market effects, we include market liquidity in the model. The market liquidity was computed as changes in the value-weighted liquidity of two portfolios; a market portfolio containing all stocks and a portfolio comprising only stocks connected to the individual stock of interest. To cater for industry effects, we add changes in the liquidity of a portfolio of stocks connected to the individual stock and in the same industry $\Delta liq_{k,t}$ to the model. We add $\Delta liq_{k,t}$ to the regression as industry factors that influence stock liquidity levels**.** Specifically, we separately estimate the following regression for each stock across trading days.

$$\Delta liq_{i,t} = \alpha + \beta_{CI} \Delta liq_{j,t} + \beta_{mkt} \Delta liq_{mkt,t} + \delta controls + \varepsilon_{i,t} \tag{4}$$

$$\Delta liq_{i,t} = \alpha + \beta_{CI} \Delta liq_{j,t} + \beta_{mkt} \Delta liq_{mkt,t} + \beta_{ind} \Delta liq_{k,t} + \delta controls + \varepsilon_{i,t} \tag{5}$$

The regression coefficient of a stock's own liquidity on the liquidity of the portfolio of stocks connected to the individual stock is labelled the *Social Network Liquidity Beta,* β_{CI} . In this essay, we use changes in logs for the liquidity measure. The use of log-differences helps solve potential econometric problems that may arise as a result of potential non-stationarity of the liquidity measures (Kamara, Lou, and Sadka, 2008). For each regression, we remove the individual stock that is the firm of interest from the market portfolio. In the regression model, the following controls are included: contemporaneous market returns and contemporaneous firm return squared to control for possible correlations between returns and the liquidity measure; and lead and lag changes in the illiquidity measures to cater for lagged adjustments in liquidity (Chordia, Roll, and Subrahmayam, 2000; Koch, Ruenzi, and Starks, 2016). The squared returns is included to cater for any volatility effect that may be linked to liquidity.

If there is commonality in liquidity, then changes in daily individual stock's liquidity will be significantly related to changes in the liquidity of the portfolio of stocks connected to the individual stock. Based on Koch, Ruenzi, and Starks (2016), we are interested in the significance of the mean coefficient of liquidity betas to look for evidence of liquidity in commonality. As the hypothesis predicts, we anticipate the coefficient of social network liquidity beta in equation (3) and equation (4) above to be $\beta_{CI} > 0$ and statistically significant. The positive significance of the estimated social network liquidity beta implies that firm's interconnections bring about convergence of each firm's liquidity with the variation in the liquidity of the portfolio of stocks with which the individual firm has connections. As per Kamara, Lou, and Sadka (2008), we define β_{CI} as the sensitivity of changes in an individual stock's own liquidity to changes in aggregate liquidity of the portfolio of firms connected to the individual stock.

Table 2 summarizes the time series regression output using equation 4 above and reports strong evidence of liquidity commonality across connected stocks irrespective of industry. We find β_{CI}, our measure of liquidity commonality across connected stocks, to be positive and statistically significant at 1% for both Amihud Illiquidity and CRSP-Spread. The mean of β_{CI} is 0.222 at 1% significance level for Amihud illiquidity. This magnitude establishes significant evidence for the existence of stock liquidity convergence across connected firms. This result confirms that firm-level factors such as CEOs' social and professional networks influence stock liquidity comovement and not only market-level determinants as described in prior studies (Huberman and Halka, 2001; Fernando, 2003; Kamara, Lou, and Sadka, 2008; Hameed, Kang, and Viswnathan, 2010; Karolyi, Lee, and van Dijk, 2012; Koch, Ruenzi, and Starks, 2016).

We replicate the regressions using CRSP-Spread and report the results in Table 2, model 2. From Table 2, for a stock's own social network liquidity beta β_{CI}, we obtain results similar to those employing the Amihud illiquidity measure. However, comparing the average means of social network liquidity beta for both Amihud and CRSP-Spread, indicates that the mean of β_{CI} for Amihud Illiquidity, 0.222, is greater than the overall mean of β_{CI} for CRSP-Spread, 0.112. Thus, liquidity commonality across connected firms using the Amihud Illiquidity measure is approximately twice the magnitude using the CRSP-Spread. The variability in the Amihud measure recorded in the results agrees with Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) who find the Amihud measure as a reliable proxy for a stock's liquidity, and with Goyenko and Ukhov (2009) who show that the Amihud measure is a good proxy for price effect. The positive statistically significant coefficient of the market liquidity beta, β_{mkt} for Amihud and CRSP-Spread measures reveals that individual stock liquidity on average comoves positively with market liquidity (Chordia, Roll, and Subrahmayam, 2000; Koch, Ruenzi, and Starks, 2016).

From the baseline regression results in Table 2, we provide evidence to support the hypothesis that a stock's liquidity comoves with the liquidity of the portfolio of stocks connected to the individual stock irrespective of the industry to which the connected firms belong. It is noteworthy to mention that for both Amihud and CRSP Spread, the results show liquidity covaries strongly across stocks that are connected than with the market liquidity, i.e., liquidity commonality is stronger among connected firms.

INSERT TABLE 2

4.2 Estimating Liquidity Commonality across Connected Stocks in Same Industry

According to Chordia, Roll, and Subrahmayam (2000) and Brockman and Chung (2002), it is possible that in systematic liquidity, there are both industry and market components. Hence, we investigate the possibility that individual stock liquidity comoves with the liquidity of stocks that are connected to the individual stock and belong to the same industry. We classify stocks into industries using the 2-digit SIC code and extract the number of firms an individual firm is connected to that belong to the same industry. We include the industry liquidity variable $\Delta liq_{k,t}$ in equation 5. We estimate this regression because, aside from market level factors such as macroeconomic indicators, interest rate, market return, volatility and seasonality, which according to Chordia, Roll and Subrahmanyan (2001) significantly affects stock liquidity, specific industry factors can also affect stock market liquidity. Table 3 reports the results based on equation 5. We find evidence of the existence of liquidity commonality across firms that are connected and belong to the same industry confirming the view that individual stock liquidity is influenced significantly by industry wide common factors consistent with Chordia, Roll, and Subrahmayam (2000). This result indicates that industry wide connectedness is an example of industry wide common factors that drive stock liquidity commonality

Following the findings reported in Table 3, we conduct additional analysis to compare the magnitude of the social network liquidity beta coefficients using equation 5. We include in equation 5, lead and lag variables for the two liquidity measures: portfolio of stocks connected to the individual stock irrespective of industry of affiliation and portfolio of stocks connected to the individual and belonging to the same industry. In Table 4, we find that for all the liquidity measures, the cross-sectional mean of social network liquidity beta (β_{CI}) irrespective of industry of connectedness is generally larger than the industry social network liquidity beta (β_{ind}) across U.S. public firms for both Amihud and CRSP-Spread. This result is consistent with Chordia, Roll, and Subrahmayam (2000) and Brockman and Chung (2002). It implies that, on the NYSE and AMEX stock exchanges, industry-wide liquidity is relatively less important in explaining individual stock liquidity commonality.

INSERT TABLE 3 & INSERT TABLE 4

4.3 Effect of Network Size (Large vs Small) on Stock Liquidity Betas

To examine the potential effect of network size on systematic liquidity, we divide the sample into five quintiles based on firms' network size and estimate the cross-sectional means of social network liquidity beta for each quintile. We investigate whether firms with a large network have a larger social network liquidity beta (β_{CI}) than firms with small network as hypothesized. From Table 5, we summarize averages of the social network stock liquidity betas for both Amihud and CRSP-Spread across the five quintiles using equation 3. We use CEO network size since it is regarded as a proxy for the relative importance of connections in the social network literature (Fracassi, 2016). The first quintile contains the bottom fifth of the firms on network size (i.e., the 20% of the total firms with the lowest network size), the second quintile represents the second fifth (from 21% to 40%) and the fifth quintile represents the 20% of the firms with the largest networks. For the social network stock liquidity beta, β_{CI} , results show that the sorted averages using firm network size is not monotonic. The average β_{CI} varies with network size as hypothesised. For instance, using Amihud Illiquidity, we find the β_{CI} average for a firm in quintile 1 is 0.065; for quintile 3 and 5 the β_{CI} averages 0.022 and 0.264, respectively.

Comparing the averages of β_{CI} for quintiles 1 and 5, we find the magnitude of liquidity covariation is about four times larger than the magnitude of liquidity co-movement for firms in quintile 1. The results confirm the hypothesis that the magnitude of sensitivity of liquidity covariation is stronger for firms with large network size than their counterparts with small network size for both Amihud and CRSP-Spread. Comparing the magnitude of β_{CI} for both liquidity measures across the five quintiles, the results shows that the magnitude for Amihud is much larger than for CRSP-Spread. We report in Table 5b test of difference between quintile 1 and quintile 5 using liquidity betas.

INSERT TABLE 5a & 5b

4.3.1 Association between CEO Network Size and Liquidity Commonality

We further estimate a time series regression to test the second hypothesis that liquidity commonality increases with CEOs' network size. We regress the measure of liquidity commonality β_{CI} on Network Total Size for each firm and control for firm size and average liquidity. The variable of interest, Network Total Size, is the sum of the CEO's employment, education, and other activity connections. We control for scale effects by adding firm size since the size of a firm can influence the CEO's network size. In the main specification, we include time-fixed effects and cluster the standard errors at the firm and time-dimensional levels to account for cross sectional dependence. The specification is:

$$\beta_{CI\,i,t} = \alpha + \beta_1 (Network\_Total\_Size)_{i,t} + \beta_3 liq(ave)_{i,t} + \beta_4 \ln(size)_{i,t} + time\_effects + \varepsilon_{i,t} \tag{6}$$

The results of this regression model using Amihud and CRSP-Spread are presented in Table 6 and 7, respectively. Column 1, Table 6 presents results for the full sample. Consistent with hypothesis 2, we find that liquidity of stocks that are connected exhibit comovement evidenced by the statistically significant positive coefficient of 0.112 for the effect of network size. In column 2, we include controls for the stock size and average liquidity. Again, the coefficient of social network index in column 2 is positive and statistically significant as estimated in column 1.

Columns 3 – 10, Table 6, include fixed firm effects to subsume the effect of any time-invariant firm-level characteristics that CEOs/top management may have stable preferences for and might have an effect on commonality. We also include a time-fixed effect and cluster standard errors at the firm level. The coefficient estimate of social network liquidity beta β_{CI} is somewhat reduced to 0.086 even though it is still positive and statistically significant at 1%. This shows that time-invariant unobservable heterogeneity is not driving the main findings, which is consistent with the findings of Kamara, Lou, and Sadka (2008). As CEOs' Network Size increases, the magnitude of liquidity covariation also increases. Of the controls in the regressions in columns 3-10, the significant contributor is firm size. Thus, firm size significantly influences the extent to which firms' liquidity comoves with the liquidity of firms belonging to the same network. For CRSP-Spread, we find a similar association between liquidity commonality and a CEO's network size as presented in Table 7. Overall, we find that stock liquidity covariation across firms is influenced by the extent of a firm's social and professional connectivity.

INSERT TABLE 6 & TABLE 7

4.4. Liquidity Commonality and Similarity in Corporate Finance Policies

We next investigate the possible channels through which CEOs social and professional networks drive liquidity commonality across connected firms. We test hypothesis 3 that examines whether similarity in corporate finance policy decisions across connected firms is a channel through which CEO connectedness drive liquidity commonality among connected firms.

To investigate hypothesis 3, we adopt the approach of Fracassi (2016) to obtain similarity in corporate finance policies across connected firms. We consider eight corporate finance policies: investment ratio, R&D ratio, SG&A ratio, cash reserve ratio, leverage, interest coverage ratio, dividend over earnings, and advertising expense. In a recent study, Moshirian et al. (2017) show that liquidity commonality is driven by both market level determinants and firm-level determinant factors. On the firm-specific factors, they argue that the sensitivity of an individual's stock's liquidity to market liquidity can be firm specific. Thus, the transparency and information asymmetry of an individual firm can affect its stock liquidity. This is because more firm-specific information can invite more individual trading in the stock. We focus on the above policies because the information set of investors on firms can be expanded through the policies to influence their trading. Gelos and Wei (2005) conclude that a higher level of financial transparency reduces information asymmetry and increase stock price informativeness. We further argue that the above corporate policies will increase the stock price informativeness of individual firms which can affect the stock liquidity. First, we test whether firms that are connected take similar corporate policy decisions using a pair model. Using the model, we account for as much of a firm's policy as possible by regressing on each policy, specific control variables that determine the policy. The residual (or excess) policy of connected firms is obtained and used to define a measure of corporate finance similarity across connected firms. In the second step, we test whether similarity in corporate policy across connected firms drives liquidity commonality among the connected firms.

As explained above, first, we regress each firm's corporate finance policy decisions on a set of control variables that relate to each specific policy using equation 7 after which we obtain the residual of the policy. In the specification model reported in equation 7, $Policy_{i,t}$ and $X_{pi,t}$ represents the set of corporate finance policies and control variables, respectively.

$$Policy_{i,t} = a_o + a_1 X_{pi,t} + \varepsilon_{i,t} \qquad 7$$

For all regressions presented in Table 8, we control for year fixed effects. For the investment policy regression in column 1, following Chava and Roberts (2008), we use log (total assets) to control for size, Tobin's Q to control for investment opportunities and cash flow. In the R&D regression, we follow Brown, Fazzari, and Peterseen (2009) and use sales (log) and cash flow as control variables. In the selling, general and administrative (SG&A) and cash reserves regressions, following Harford, Mansi, and Maxwell (2008), we control for size (log Total Assets), investment opportunities (Tobin's Q), cash flow, investment and R&D expenditure. For the regressions using leverage and interest coverage, we follow Lemmon, Roberts, and Zender (2008) and use sales (log), investment opportunities (Tobin's Q), asset tangibility, and cash flow. For estimate using dividends over earnings and advertising, we follow Fracassi (2016) and control for variables that determine each policy. In Appendix B, we present the correlation matrix of the corporate finance variables and controls; the results are in Table 8. The coefficients of the main control variables are consistent with the ones documented in prior literature.

Next, we estimate the similarity in corporate policy across connected firms using the residual from equation (7), which represents the excess, or idiosyncratic, component of each policy for each firm relative to the expected policy according to the standard model. We define policy dissimilarity across connected firms using equation 8 as the absolute value of the difference in the residuals of each firm's corporate finance policy, $\varepsilon_{i,t}$ and average of the residuals of corporate finance policies of the portfolio of firms ($\varepsilon_{i,j}$) that are connected to the individual firm.

$$PolicyDissimilarity = \left|\Delta\varepsilon_{i,j,t}\right| = abs(\varepsilon_{i,t} - \varepsilon_{i,j}). \qquad 8$$

The variable is a proxy for the difference in the corporate finance policy decisions among the connected firms. The smaller the variable, the more similar are the policies of the connected firms (Fracassi, 2016).

Finally, we regress social network liquidity beta β_{CI}, on our measure of dissimilarity in corporate finance policy $(Policy - Dissimilarity)$ for each firm as shown in equation (9), controlling for size, average liquidity, and time effects. In estimating equation (9), we cater for serial correlation by allowing clustering of the error term at the firm level for both each firm and the portfolio of firms connected to the individual firm (Petersen, 2009).

$$\begin{aligned} \beta_{CI\,i,t} &= \alpha + \beta_1 (PolicyDissimilarity)_{i,t} + \beta_2 liq(ave)_{i,t} \\ &+ \beta_3 \ln(size)_{i,t} + time\_effects + \varepsilon_{i,t} \end{aligned} \qquad 9$$

Using equation (9), we test whether social and professional ties between CEOs influence liquidity comovements through similarity in corporate finance policy decisions. We argue that, as the deviation of our measure of policy dissimilarity increases, then the corporate finance policies of connected firms deviate from each other so there will be no convergence in corporate policy decisions across connected firms. A negative coefficient for β_1 in equation (9) implies that, as corporate policy dissimilarity becomes more negative or as policy dissimilarity decreases, the corporate policy decisions among connected firms become more similar leading to transfer of related information from connected firms to the broader market. Hence, we predict that the stock liquidity of these connected firms adopting similar corporate finance policies will strongly comove.

Tables 9 and 10 show the results of the regressions using the strength of the aggregate policy dissimilarity as the main variable of interest as shown in equation 9. In Table 9, we consider the Amihud illiquidity measure and, for capital investment policy, we find a significant negative effect of the strength of capital investment dissimilarity among connected firms on liquidity comovement across the connected firms, supporting our hypothesis that social ties drive liquidity comovement across connected firms via similarity in investment decisions. This shows that capital investment is one corporate policy through which connected firms impact stock liquidity. Given that the sample mean for capital investment is 0.364 and the coefficient of corporate investment dissimilarity is 0.088, we find the economic impact, 24.2%, to be significant. From Table 9, we also find that stock liquidity covariation among connected stocks is also driven by similarity in R&D, and leverage decisions across connected stocks. We find insignificant results for similarity in the cash reserves ratio, SG &A interest coverage ratio, advertising expense and dividend policy since these policies do not drive liquidity co-variation across connected stocks. We replicate the above results using CRSP Spread social network liquidity beta and present results in Table 10 with similar findings.

This result may explain the findings of Coughenour and Saad (2004) who show that because of information sharing among specialists within a firm, stock liquidity comoves with the liquidity of other stocks handled by the same specialist firm. Thus, when connected firms adopt similar corporate finance policy decisions, specialists will obtain similar information transferred to security markets after announcements, which eventually induces their trading strategies as they transfer such information to their colleagues leading to liquidity covariation across connected firms.

INSERT TABLE 8, TABLE 9 & TABLE 10

4.5 Liquidity Commonality and Commonality in Trading Activity

We test hypothesis 4 that states that trading activities of connected firms are a channel through which CEO networks drive liquidity commonality across connected firms. To do this, we regress a stock's own *social network liquidity beta,* $\beta_{CI_{i,t}}$ for each stock on $\Delta Trade_{j,t}$ which is defined as the daily changes in the number of trades of portfolio of stocks connected to each firm controlling for size, average liquidity, price, trade volume, and time effects. We argue that trading activities of connected stocks will be related leading to stock liquidity covariation through correlated trading. When related information among connected firms is conveyed to security markets, the trading activities of investors and market participants are likely to be related; they rely on the same public information to develop their trading strategies, which, in effect, drives commonality in liquidity across stocks that are connected.

Our argument is based on the premise that if a group of market participants swho hold a portfolio of stocks that are connected, then the transfer of related information across connected firms to the broader market can influence their decisions to trade in the same direction with similar timing since investors rely on information and signals from the market environment to decide on their trading strategies. In effect, these stocks are likely to experience large trade, buy and sell orders, at the same time to cause liquidity comovement across connected stocks. We also argue that this may arise from different investors holding stocks that are connected and take similar corporate decisions and face similar liquidity shocks. For instance, market participants holding connected stocks will have to adjust to the related liquidity shocks that might be affecting the firms with similar trading strategies. That eventually leads to correlated trading and commonality in liquidity. Consequently, we test hypothesis 4 using equation 10 and expect to find a significant positive relationship between our measure of liquidity commonality and changes in the trading activity of portfolio of stocks that are connected to an individual stock. The specification model is:

$$B_{CI\,i,t} = \alpha + \beta_{TRD}\Delta Trade_{j,t} + \beta_2 liq(ave)_{i,t} + \beta_3 \ln(size)_{i,t} + \beta_4 Volume_{i,t} + \beta_5 \Pr ice_{i,t} + time\_effects + \varepsilon_{i,t} \quad 10$$

Table 11 presents the results using the Amihud (2002) measure of stock liquidity commonality and measures of stock trading activities using changes in the number of trades. We find a statistically significant positive relationship in Table 11 confirming the hypothesis that trading activities of connected stocks are correlated and, as a result, drive liquidity covariation across these connected stocks. In model 1, Table 11, without controlling for time and firm fixed effect, we find the coefficient of β_{TRD} 0.025 to be statistically significant at 1%. This suggests that trading activities of investors across connected stocks are positively correlated. In model 2, Table 11, we control for time fixed effects and find the coefficient of β_{TRD} is positive and statistically significant at 1%, even though its magnitude reduces to 0.022. The significant relationship is also documented in models 3 to 6 where we control for time and firm fixed effects. Using CRSP-Spread, we find similar results (see Table 12). The results imply that trading activities in stocks that are connected through CEO connectedness will have a related component in their buy and sell orders, which facilitates stock liquidity covariation. As explained earlier, this effect could arise from trading activities of institutional investors who make a prime example of an investor group that generally holds a large, well-diversified portfolio of stocks and are regularly faced with similar information that drives liquidity across e stocks.

INSERT TABLE 11 & 12

4.6 Controlling for Endogeneity and Reverse Causality

4.6.1 Instrumental Variable Approach

So far, we have established that the stock liquidity of firms that are connected with each other comoves. This could prompt a CEO to build stronger networks to maximize the benefits associated with liquidity comovement. Moreover, firms experience shocks in their stock liquidity levels and dynamically adjust their policies and strategies over time. El-Khatib, Fogel, and Jandik (2015) show that firms in such situations could hire a CEO with specific social and professional connections to improve accounting and reporting quality as well as the quality of policies and decisions that could influence the firm's stock liquidity levels and broader market outlook in the eyes of market participants. For instance, a firm in financial distress is likely to hire a CEO with specific education, skills, or employment to turn things around. Arguably, the causality might as well run in the opposite direction since successful companies with high investment levels and high return on assets might lead to an expansion of the social networks of their CEOs. Interestingly, many factors determine a CEO's network size, only some of which are influenced by the CEO's choices. For example, a CEO can choose to become a member of a social organization or serve as an outside board member of a public company. On the other hand, CEOs have little control over whether other graduates from their alma mater become executive officers. In the same way, the board may consider the CEO's network in appointing the CEO, but it is unclear whether this is a first-order effect. A CEO's network is likely to change over time for reasons over which the board has no control.

The possibility that the CEO's network reflects choices creates the potential for endogeneity and potential bias from correlated omitted variables. To check for the effects of endogeneity, we use a two-stage instrumental variable approach, where, at the first stage, we use equation 11 to estimate a regression with the CEO's network size as the dependent variable and use the industry average network size for the other firms in the sample in the same industry of a firm in year t as the instrument. We follow prior studies and use industry average network size as the instrumental variable because it relates positively to CEO network size, which is the underlying explanatory variable but unrelated to the residuals in the second stage equation, which is *Social Network Stock Liquidity Beta* $\beta_{CI\,i,t}$ (Faleye, Kovacs, and Venkateswaran, 2014).. In constructing the instrumental variable, we follow the approach of prior studies and estimate the average industry network size as the average network size of all firms in a particular industry. We classify the industry a firm belongs to using the two-digit SIC code. In addition, the choice of instrument is based on the theory that firms follow an industry norm, and interlocking practices between CEOs would give more opportunity to build networks within the industry if CEOs, in general , have broader networks.

The first stage regression is:

$$(Network\_Total\_Size)_{i,t} = \alpha + \beta_1 (Industry\_Network\_Total)_{i,t} + \beta_3 liq(ave)_{i,t-1} + \beta_4 \ln(size)_{i,t-1} + time\_effects + \varepsilon_{i,t} \quad 11$$

The second stage regression is:

$$\beta_{CI\,i,t} = \alpha + \beta_1 (Instrumented\_Network\_Total\_Size)_{i,t} + \beta_3 liq(ave)_{i,t} + \beta_4 \ln(size)_{i,t} + time\_effects + \varepsilon_{i,t} \quad 12$$

Table 13 presents the two-stage regressions using the Amihud Illiquidity measure. Estimates of equation 11 indicate that *Industry Network Total* $_{i,\,t}$ is positive and statistically significant at 1% in determining network size. The Cragg-Donald Wald F statistic is 5641.73, which exceeds the 10% (25%) critical values of 16.38 (5.53) suggesting that the instrument, Industry Network Total, is unlikely to be a weak instrument (Stock and Yogo 2005; Larcker and Rusticus, 2010).

The second stage includes the predicted CEO Network Total Size as the regressor from the first-stage equation. Because the test variable is determined solely by the variables identified in the first stage, it is less likely to reflect unobservable factors that are correlated with our measure of liquidity commonality. The results show a positive significant coefficient ($p<0.001$) for CEO Network Size, like the main result reported in Table 5. Overall, the results suggest that the instrument passes the weak instrument test by explaining a significant amount of the CEO's network size. Table 14 shows the results for CRSP Spread liquidity measure that documents similar findings.

INSERT TABLE 13 & 14

4.6.2 Difference-in-Difference Approach

The results obtained so far could be biased because of the presence of an omitted variable that could drive both social network size and the stock liquidity level of firms. Hence, an exogenous shock to the social network ties is needed to test the direction of causality between social connections and liquidity co-movement. We thus use individuals' deaths as an exogenous shock to a firm's social and professional connectivity. We obtain information on CEO death from BoardEx for the period of January 2000 to December 2016. In the sample period, there are 680 CEO deaths. When an individual dies, his/her social ties with other individuals in the network cease, altering exogenously the social connections between companies. Simultaneously, the death of a CEO is an event that can deeply influence corporations and can lead to large changes in corporate policies and hence liquidity comovement.

The choice of CEO death as an exogenous shock to CEO Network Size is based on prior studies. Several studies investigate the effect of CEO and senior executive deaths as exogenous shocks to the composition of the board of directors (Bennedsen, Perez-Gonzalez and Wolfenzon, 2006;

Salas, 2010). Fracassi and Tate (2012) use death as an exogenous shock to social ties to test governance implications of firms with CEOs having social ties with directors. In a recent study, Fracassi (2016) used the death of a director or top executive to test for its implications on the firm's corporate finance policy. In view of the above, I use the death of a CEO in the group of connected firms to test its effect on liquidity commonality across connected firms. The intuition is that the death of a CEO will break information flow across the connected firms, which, we argue, will weaken liquidity comovement across connected firms. Tables 15 and 16 show the difference in difference approach for Amihud and CRSP Spread, respectively.

In this test, we group all companies in the sample into two groups. Panel A is our treatment group and covers all firms that recorded the death of a CEO. Panel B report estimates from the control group and reports all individual firms that did not record the death of a CEO but rather a CEO of firms in the network connected to the individual firm died. We then compare the measure of liquidity commonality between firms for both Panels A and B. For each regression, the variable of interest is the interaction between Death Dummy and CEO Network Total Size. For the Death Dummy, a dummy variable of one is created for a firm if a CEO within the number of firms connected to the individual firm died. We argue that the death of a CEO within the group will weaken the strength of liquidity comovement. More specifically, we predict that stock liquidity commonality for firms in Panel A will be weakened more than firms in Panel B because the effect of a breakdown in information flow will decline more for firms in Panel A. This is because individual firms in Panel A recorded CEO's death coupled with the fact that a CEO within the network of firms connected to the individual firm also died.

$$\begin{aligned}\beta_{CI\,i,t} &= \alpha + \beta_1 (Death\_Dummy)_{i,t} + \beta_2((Death\_Dummy)_{i,t} * (Network\_Total)_{i,t})) + \\ &\beta_3 liq(ave)_{i,t} + \beta_4 \ln(size)_{i,t} + \varepsilon_{i,t}\end{aligned} \qquad 13$$

The results using equation 13 shows that the coefficient of Death Dummy is negative and significant for both Panels A and B using the Amihud illiquidity measure (see Table 15). This result suggests the death of a CEO within the group affects the magnitude of stock liquidity co-movement across connected firms in all specifications. The interaction coefficient between Death Dummy and CEO Network Size is positive and statistically significant in all specifications. These results further suggest that a CEO's death within the group of connected CEOs makes the comovement of stock liquidity across the connected firms more dissimilar because the magnitude of comovement is weakened. The results of the difference in difference regression suggest that a break in the flow of information in social and professional connections has a causal effect on changes in comovement of liquidity. Table 16 reports the results using CRSP-Spread.

In the difference in difference approach reported above, we argue that the death of a CEO will alter the extent of connectivity between two firms, its noteworthy to mention that, our findings could be driven by characteristics of an incoming CEO. This is a because an incoming CEO with strong network ties will definitely influence the information environment of the firm and stock liquidity.

INSERT TABLE 15 & TABLE 16

5. Conclusion

This essay is the first in empirical finance literature to investigate whether CEOs' social and professional network ties, which drive firm-level connectedness, facilitate liquidity comovement across the connected firms. The essay theorizes that the transfer of similar information to security markets by connected firms because of the similarity in corporate decisions across connected firms could play a key role in liquidity covariation across stocks.

Using the biographical information of CEOs, we create a social index of network ties for each CEO from current employment, past employment, education, and other activities. We show that social connections influence stock liquidity covariation across NYSE and AMEX stocks that are connected. Specifically, we find evidence that stock liquidity covary strongly across connected firms. Next, we examine the link between CEOs' network size and our measure of liquidity commonality across connected firms. We find evidence supporting the link between social and professional connectivity between connected firms and commonality in liquidity with the results not driven by common time trends in commonality in liquidity (Kamara, Lou, and Sadka, 2008).

Subsequently, we test possible channels through which CEOs social and professional network ties could drive liquidity commonality across connected stocks. We hypothesize that similarity in corporate finance policies across connected firms is a possible channel that drives liquidity covariation. Using a multi-stage process, we find evidence supporting our hypothesis that similarity in corporate decisions across connected firms drives liquidity commonality. We also test whether trading activities of connected firms using the number of trades is a possible channel that drives comovement across connected firms. We find a significant positive relationship confirming our hypothesis that trading activities of connected firms drive commonality in liquidity. We address concerns for endogeneity problems and direction of causality.

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Appendix A: Variable Definitions

Key Variable Name		Definition	Source
Amihud-Illiquidity Measure	=	The absolute value of stock i's return on day d divided by the dollar volume of stock i's trading on day d	CRSP
CRSP Spread	=	Difference between the ask price and the bid price of stock i on day t from the CRSP daily data divided by the mean of the ask price and bid price.	CRSP
Network Education	=	Sum of the CEO's educational ties. An educational tie occurs if the CEO went to the same university at the same time as another CEO	BoardEx
Network Employment	=	Sum of the CEO's employment ties. An employment tie occurs if the CEO currently or historically overlapped with another CEO	BoardEx
Network Other Social Activity	=	Sum of the CEO's other activity ties. Another activity tie occurs if the CEO participated in the same organization (e.g., a charity or recreational club) at the same time as another CEO.	BoardEx
CEO Network Total	=	Log(Sum of Network Employment, Network Education, and Network Other Social Activity) for connected CEO irrespective of Industry	BoardEx
CEO Network Total (Same Industry)	=	Log (Sum of Network Employment, Network Education, and Network Other Social Activity) for CEOs who are connected and in the same industry.	BoardEx
CEO Network Total (Different Industry)	=	Log (Sum of Network Employment, Network Education, and Network Other Social Activity) for CEOs who are connected but in a different industry.	BoardEx
Corporate Finance Variables			
Dividend Over Earnings	=	Dividends over earnings are the ratio of the sum of common dividends (COMPUSTAT item 21) and preferred dividends (COMPUSTAT item 19) over earnings before depreciation, interest, and tax (COMPUSTAT item 13)	Compustat
Cash Reserves Ratio	=	Cash Reserves Ratio is the ratio cash and short-term investments (che)/total assets, winsorized at the [1,99] quantile.	Compustat
Interest Coverage	=	Interest Coverage is the ratio between operating income before depreciation and amortization (oibdp) and the interest expenses (xint), winsorized at the [1,99] quantile.	Compustat
Investment Ratio	=	Investment Ratio is the ratio between capital expenditure (capx) and lagged PP&E (ppe), winsorized at the [1,99] quantile.	Compustat
Leverage	=	Leverage is the ratio (debt in current liabilities (dlc) C long-term debt (dltt))/(debt in current liabilities (dlc) C long-term debt (dltt)) + common shares outstanding (csho)_ price close at the end of fiscal (prcc_f)	Compustat
R&D	=	R&D Ratio is the ratio R&D expense (xrd)/lagged sales (sale), trimmed at the [1,99] quantile.	Compustat
SG&A	=	SG&A Ratio is the ratio selling, general and administrative expense (xsga)/sales (sale).	Compustat
Advertising Expense	=	Advertising is the ratio of advertising expenditures (COMPUSTAT item 45) over lagged total assets (COMPUSTAT item 6)	Compustat
Firm Characteristics			
Number of Employees	=	No. of Employees is the total number of employees in the firm (emp).	Compustat
Cash flow	=	Cash Flow is the ratio (income before extraordinary items (ib) + depreciation and amortization (dp))/lagged property, plants, and equipment (ppent), winsorized at the [1,99] quantile.	Compustat
Return on Assets	=	Return on Assets is the ratio income before extraordinary items (ib)/lagged total assets (at), trimmed at the [1,99]quantile.	Compustat
Sale	=	Sales are the net sales turnover (sale).	Compustat
Stock Return	=	Stock Return is the annual total stock return during the fiscal year.	Compustat
Stock Return Volatility	=	Stock Return Volatility is the 12-month rolling volatility of monthly stock returns	Compustat
Tangibility	=	Tangibility is the ratio (net property, plant and equipment (ppent)/total assets (at)	Compustat
Tobin's Q	=	Tobin's Q is the ratio (total assets (at) . stockholders' equity (seq) C common shares outstanding (csho) _ price close at the end of fiscal (prcc_f))/total assets (at), trimmed at the [1,99] quantile.	Compustat
Total Assets	=	Total Assets is the total assets of the company (at).	Compustat
Number of Trades	=	Daily number of trade transactions	CRSP

Most of the definitions for the financial variables follow the measures used in (Fama & French 2002) and considered standard in the literature. Data are available from Compustat and CRSP databases over the period from 2000-2016. The Compustat data refer to the end of the fiscal year. The item in parenthesis refers to the corresponding item in the Fundamentals Annual Compustat North America database.

APPENDIX B:
Descriptive Statistics of Corporate Finance Variables and Controls

Corporate Finance Variables & Controls

Variable	Mean	Std Dev	P25	P50	P75	No. of Obs.
Corporate Finance Variables						
Advertising	0.026	0.074	0.001	0.006	0.024	37,471
Cash Reserve Ratio	0.196	0.233	0.032	0.096	0.275	94,084
Dividend Payout	0.096	3.798	-	-	0.122	90,525
Interest Coverage	55.723	1,759.590	1.563	5.718	16.743	67,741
Investment Ratio	0.364	12.103	0.111	0.203	0.355	85,419
Leverage	0.257	0.258	0.018	0.184	0.424	93,542
SG&A Ratio	0.996	23.752	0.140	0.260	0.419	76,769
R & D	0.107	0.276	0.003	0.036	0.121	48,100
Controls						
Cash Flow	- 4.744	145.737	- 0.018	0.280	0.823	87,634
Total Asset ($)	12,070.240	95,636.980	120.473	570.300	2,567.220	94,097
Log(Total Asset ($))	6.389	2.282	4.792	6.346	7.851	94,087
Sale($)	3,500.540	16,049.900	52.740	270.100	1,375.960	93,971
Ln (Sale($))	5.665	2.403	4.076	5.664	7.270	91,952
Return on Asset(RoA)	- 0.055	1.895	- 0.034	0.015	0.059	93,959
Sales growth	- 0.392	22.143	- 0.047	0.058	0.164	80,594
Stock Return Volatility	1.252	3.259	0.435	0.908	1.390	89,476
Stock Return Annual	0.963	0.570	0.658	0.953	1.179	89,476
Tangibility	0.226	0.248	0.031	0.124	0.344	91,003
Tobins Q	26.128	790.302	3.450	8.562	18.311	93,925
Number of Employees	10.270	44.257	0.180	0.900	5.000	91,483

Notes: This table shows the summary statistics for all the corporate finance variables used in the paper. Appendix A defines all the variables

APPENDIX C:
Correlation Matrix of Corporate Finance Policies and Controls

Appendix C reports the correlation between the corporate policy measures adopted for this study and other stock characteristics

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1																	
2	-0.028	1																
3	0.001	-0.479	1															
4	-0.029	-0.067	0.108	1														
5	0.000	0.004	-0.005	-0.012	1													
6	-0.012	0.011	-0.011	-0.114	0.014	1												
7	-0.084	0.078	-0.032	-0.184	0.040	0.392	1											
8	-0.008	0.020	-0.001	0.060	0.004	-0.011	0.015	1										
9	0.024	-0.366	0.620	0.075	-0.004	-0.022	-0.061	-0.001	1									
10	-0.034	0.007	-0.027	-0.396	0.006	0.056	0.151	-0.070	-0.056	1								
11	-0.006	0.096	-0.051	-0.283	0.046	0.410	0.951	0.023	-0.072	0.154	1							
12	-0.005	-0.019	0.005	0.052	-0.002	-0.007	-0.034	-0.012	0.004	-0.020	-0.082	1						
13	-0.001	0.052	-0.002	-0.008	0.005	0.006	0.054	0.015	0.001	-0.053	0.099	-0.210	1					
14	0.001	-0.022	0.005	0.050	-0.002	-0.008	-0.044	-0.012	0.004	-0.020	-0.095	0.950	-0.228	1				
15	0.018	0.016	0.000	0.045	0.005	-0.010	-0.007	0.009	-0.004	-0.049	-0.002	-0.005	0.027	-0.006	1			
16	-0.009	0.051	-0.005	0.039	0.017	0.015	0.094	0.029	-0.014	-0.159	0.105	-0.018	0.079	-0.021	0.746	1		
17	0.033	0.036	-0.052	-0.374	0.009	0.166	0.121	-0.011	-0.094	0.273	0.180	-0.010	0.015	-0.017	-0.004	-0.005	1	
18	0.003	0.025	-0.015	-0.075	0.023	0.179	0.413	-0.005	0.010	-0.033	0.410	-0.010	0.041	-0.011	0.035	0.137	0.054	1

Advertising	Cash Flow	Cash Holding	Cash Reserve Ratio	Dividend Payout	Number Of Employees	Firm Size	Interest Coverage	Investment Ratio	Leverage
1	2	3	4	5	6	7	8	9	10
Ln(sale)	R&D	Sales growth	SG&A Ratio	Stock Return Volatility	Stock Return_ Annual	Tangibility	Tobin's Q		
11	12	13	14	15	16	17	18		

Table 1: Describing Liquidity Measures and CEO Network Measures

Panels A and B show descriptive statistics for the U.S. liquidity measures. The U.S. sample covers from 2000 through 2016. The liquidity measures examined are the Amihud (2002) illiquidity ratio (ILR) and CRSP-Spread consistent with Chung and Zhang (2014). The liquidity measures are calculated for each available stock for each day. We then calculate the daily change in Δ Amihud Illiquidity for all stocks in our sample by taking the difference of the logs of Amihud's illiquidity measure; we follow Koch, Ruenzi and Starks (2016) and Kamara, Lou, and Sadka (2008). This is replicated for CRSP-Spread. Panel A shows the mean, standard deviation and median of the liquidity measures, the number of securities used. Panel B shows the summary statistics of daily changes in liquidity measures. Panels C and Panel D show corresponding statistics for control variables. Appendix A defines all the variables.

Panel E presents summary Statistics of CEOs Network Size/Total for full sample data and sub-sample data where we take into consideration industry type. Appendix A defines all the variables

	Mean	Std Dev	P25	Median	P75	Observations
Panel A :Liquidity Measure, $(liq_{i,t})$						
Amihud-illiquidity	0.307	8.256	0.001	0.003	0.022	12,416,664
CRSP-Spread	0.006	0.094	0.001	0.006	0.045	14,662,384
Panel B: Daily Changes in Liquidity Measure, $(\Delta liq_{i,t})$						
Δ Amihud- Illiquidity	-0.008	1.461	-0.892	-0.006	0.887	12,410,486
Δ CRSP- Spread	-0.009	0.900	-0.419	0.0000	0.418	13,645,903
Panel C: Daily Changes in Liquidity of portfolio of stocks that are connected to stock (i) - (Full Sample), $(\Delta liq_{j,t})$						
Δ Amihud- Illiquidity	0.126	0.918	-0.377	0.057	0.565	11,158,603
Δ CRSP- Spread	0.023	0.459	-0.149	0.016	0.262	12,719080
Panel D: Daily Changes in Liquidity of portfolio of stocks that are connected to stock (i) (Same Industry), $(\Delta liq_{k,t})$						
Δ Amihud- Illiquidity	0.032	1.154	-0.637	0.017	0.714	5,395,249
Δ CRSP- Spread	0.007	0.688	-0.269	0.000	0.289	6,004,536
Panel E: Descriptive of Annual Network Size of CEOs						
CEOs Network Total - Full Sample	23.526	35.366	2.000	10.000	29.000	7,453
CEOs Network Total -Different Industry	17.242	20.199	2.00	9.000	24.000	6,128
CEOs Network Total -Same Industry	4.193	5.707	1.000	2.000	5.000	2,851

Table 2: Commonality in Liquidity Across Connected Firms [Full Sample]

For each firm (i) in a year (t), we run the time series regression $\Delta liq_{i,t} = \alpha + \beta_{CI}\Delta liq_{j,t} + \beta_{mkt}\Delta liq_{mkt,t} + \delta controls + \varepsilon_{i,t}$, where $\Delta liq_{i,t}$ the daily change in the stock is own liquidity, $\Delta liq_{j,t}$ measures the liquidity of portfolio of stocks that are connected to stock (i), $\Delta liq_{mkt,t}$ represents daily changes in market liquidity. $\Delta liq_{mkt,t}$ is computed as changes in the value-weighted liquidity of two portfolios; a market portfolio containing all stocks and a portfolio comprised of stock connected to stock (i). The regression coefficient β_{CI} measures the sensitivity of changes in firm (i's) liquidity to changes in aggregate liquidity of firms connected to the firm (i's) while β_{mkt} which measures the sensitivity of changes in firm (i's) liquidity to changes in aggregate market liquidity. Following, Koch et al. (2016), we are interested in the significance of the mean coefficient of liquidity betas to look for evidence of liquidity in commonality. Thus we expect liquidity betas to be $\beta_{CI} > 0$ & $\beta_{mkt} > 0$ and significant. Our sample includes daily data for NYSE/AMEX –listed firms with the beginning of day price greater than $5 from January 2000 to December 2016.

Independent variables	**Mean Estimated coefficient Amihud Illiquidity (t-stat)**	**Mean Estimated coefficient CRSP-Spread (t-stat)**
	(1)	(2)
B_{CI} (Stock Liquidity Beta)	0.222***	0.112***
	(51.93)	(32.54)
B_{MKT} (Market Liquidity Beta)	0.002*	0.001**
	(1.95)	(2.32)
Price	0.008***	-0.002
	(18.01)	(-1.51)
Returns	-0.212***	0.022
	(-4.93)	(1.32)
Stock Return Volatility	123.6***	0.815***
	(44.11)	(2.38)
Volume (000's)	-0.075 ***	0.062
	(-15.18)	(0.50)
Market Returns	-2.074***	-0.094**
	(-32.12)	(-2.49)
Lag Market Returns	0.762***	0.047
	(12.72)	(1.25)
Lead Market Returns	-0.113**	0.032
	(-2.00)	(0.91)
Market Volatility	44.193***	2.601***
	(11.92)	(1.34)
Number of regressions	5,136	5,225
Average Adjusted R-square	0.18	0.10

*All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables*

Table 3: Commonality in Liquidity Across Connected Firms [Same Industry Connections]

For each firm (i) in a year (t), we run the time series regression $\Delta liq_{i,t} = \alpha + \beta_{CI}\Delta liq_{j,t} + \beta_{mkt}\Delta liq_{mkt,t} + \beta_{ind}\Delta liq_{k,t} + \delta controls + \varepsilon_{i,t}$, where $\Delta liq_{i,t}$ the daily change in the stock is own liquidity, $\Delta liq_{j,t}$ measures the liquidity of portfolio of stocks that are connected to stock (i), $\Delta liq_{mkt,t}$ represents daily changes in market liquidity. $\Delta liq_{mkt,t}$ is computed as changes in the value-weighted liquidity of two portfolios; a market portfolio containing all stocks and a portfolio comprised of stock connected to stock (i). The regression coefficient β_{CI} measures the sensitivity of changes in firm (i's) liquidity to changes in aggregate liquidity of firms connected to the firm (i's) while β_{mkt} which measures the sensitivity of changes in firm (i's) liquidity to changes in aggregate market liquidity. $\Delta liq_{k,t}$ measures the liquidity of the portfolio of stocks that are connected to stock (i) and are in the same industry. Following, Koch et al. (2016), we are interested in the significance of the mean coefficient of liquidity betas to look for evidence of liquidity in commonality. Thus we expect liquidity betas to be $\beta_{CI} > 0$ & and $\beta_{ind} > 0$ significant. Our sample includes daily data for NYSE/AMEX –listed firms with the beginning of day price greater than $5 for the period of January 2000 to December, 2016.

Independent variable	Mean Estimated coefficient (t-stat)	Mean Estimated coefficient (t-stat)
	Amihud Illiquidity	**CRSP-SPREAD**
B_{CI} (Stock Liquidity Beta)	0.302***	0.159***
	(50.05)	(29.61)
B_{MKT} (Market Liquidity Beta)	-0.002	0.003
	(-0.77)	(0.92)
B_{IND} (Same Industry Stock Liq. Beta)	0.087***	0.052***
	(20.25)	(10.26)
Price	0.006***	-0.003
	(8.43)	(-0.21)
Returns	-0.012	0.002
	(-0.23)	(0.09)
Stock Return Volatility	122.700***	0.067
	(35.92)	(0.21)
Volume (000's)	-0.059 ***	-0.066
	(-6.60)	(-0.56)
Market Returns	-1.913***	-0.054
	(-20.17)	(-0.96)
Lag Market Returns	0.684***	0.004
	(7.67)	(-0.08)
Lead Market Returns	-0.143**	0.021
	(-1.78)	(0.43)
Market Volatility	31.106***	3.622
	(5.18)	(1.44)
Number of regressions	2,230	2,180
Average Adjusted R-square	0.095	0.022

All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 4: Market and Industry Commonality in Liquidity

Daily changes in an individual stock's liquidity measure are regressed in time series on daily changes in the liquidity of a portfolio of stock connected to the individual stock irrespective of the industry of affiliation and daily changes in the liquidity of a portfolio of stocks connected to the individual stock and belong to the same industry. Cross sectional averages of time series slope coefficients are reported with t-statistics in parenthesis. Coefficients for other control variables are not reported. ***All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables***

	Amihud illiquidity measure		**CRSP- Spread**	
Social Network Liquidity Beta	**Connections Across Industries**	**Connections Within Same Industry**	**Connections Across Industries**	**Connections Within Same Industry**
Concurrent	0.247***	0.092***	0.679	-0.031
	(8.23)	(5.97)	(1.34)	(-0.05)
Lag	-0.050*	-0.047*	0.035	0.315
	(-1.87)	(-1.82)	(0.60)	(144)
Lead	0.034	0.001	-0.069*	-0.259
	(1.04)	(0.06)	(-1.74)	(-0.87)
Adjusted R-Square	0.029		0.002	
Observations	24,617		26,536	

Table 5a: Effect of Network Size on Stock Liquidity Commonality (Liquidity Betas)

Table 5 presents stock own liquidity beta and market liquidity beta sorted by firms network size. Stock own liquidity and market liquidity betas are sorted into 5 Quintiles according to network size of individual firms. This table presents descriptive of liquidity betas for firms that are connected irrespective of the industry. We present these results to investigate whether the magnitude of liquidity co-movement as the evidence above increases with reference to network size of firms or to the number of firms connected to a specific firm.

	Amihud- Illiquidity **PANEL A**	**CRSP-Spread** **PANEL B**
	β_{CI} Mean, (Std Dev), Median,	β_{CI} Mean, (Std Dev), Median,
Network Size Quintile 1	0.065 (2.087) 0.003	0.004 (0.064) 0.002
Network Size Quintile 2	0.007 (0.242) 0.001	0.023 (0.114) 0.012
Network Size Quintile 3	0.022 (0.181) 0.008	0.055 (0.143) 0.044
Network Size Quintile 4	0.0623 (0.319) 0.030	0.136 (0.233) 0.102
Network Size Quintile 5	0.264 (0.521) 0.154	0.342 (0.377) 0.269

5b Test of Beta Significance between Q1 and Q5

AMIHUD	Observations	Mean	Std.Dev	Test of Means [t-test]
Q1	1410	0.065	2.087	-3.33***
Q5	1283	0.265	0.521	
CRSP-SPREAD				
Q1	929	0.004	0.002	-26.96***
Q5	1053	0.342	0.012	

*All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables.*

Table 6: Liquidity Commonality Measure (B_{CI}) on CEO Total Network Size and controls

Table 6 reports result from pooled OLS (1-10) specifications of the following regression:

$$\beta_{CIi,t} = \alpha + \beta_1 (Network\_Total)_{i,j,t-1} + \beta_3 liq(ave)_{i,t-1} + \beta_4 \ln(firm\_size)_{i,t-1} + time\_effects + \varepsilon_{i,t}$$

Where β_{CI} is estimated from equation (1), $(Network\_Total)$ and $\ln(firm\_size)$ are measured at the end of each year. $liq(ave)$ is the firms' average daily illiquidity measure measured at the end of each year.

AMIHUD ILLIQUIDITY MEASURE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total Network Size	0.112***	0.086***	0.085***	0.086***	0.086***	0.085***	0.086***	0.085***	0.084***	0.112***
	(6.31)	(4.50)	(4.38)	(4.08)	(3.56)	(3.42)	(3.62)	(3.48)	(3.43)	(6.27)
Ln(firm size)		0.056***	0.055***	0.056***	0.056***	0.055***	0.056***	0.055***	0.054***	
		(4.17)	(4.10)	(3.21)	(3.23)	(3.18)	(3.32)	(3.23)	(3.20)	
liquidity (avg)		-0.432*	-0.416	-0.432	-0.432	-0.416	-0.432	-0.416	-0.412	
		(-1.69)	(-1.63)	(-0.29)	(-0.33)	(-0.32)	(-0.33)	(-0.32)	(-0.30)	
Time effects		No	Yes	No	No	Yes	No	Yes	No	No
Firm effects		No	No	No	No	No	No	No	Yes	No
Time Clusters		No	No	Yes	No	No	Yes	Yes	Yes	Yes
Firm Clusters		No	No	No	Yes	Yes	Yes	Yes	No	Yes
Observations	21,232	20,932	20,932	20,932	20,932	20,932	20,932	20,932	20,932	21,232
Adjusted R-square	0.002	0.003	0.004	0.003	0.003	0.004	0.003	0.003	0.004	0.002

*All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables.*
NB: We observe that the number of observation drop when we include additional control variables.

Table 7: Liquidity Commonality Measure (B_{CI}) on CEO Network Size and controls

Table 7 reports result from pooled OLS (1-10) specifications of the following regression:

$\beta_{CIi,t} = \alpha + \beta_1 (Network\_Total)_{i,j,t-1} + \beta_3 liq(ave)_{i,t-1} + \beta_4 \ln(firm\_size)_{i,t-1} + time\_effects + \varepsilon_{i,t}$. Where β_{CI} is estimated from equation (1), $(Network\_Total)$ and $\ln(firm\_size)$ are measured at the end of each year. $liq(ave)$ is the firms' average daily illiquidity measure measured at the end of each year.

CRSP-SPREAD MEASURE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total Network Size	0.119***	0.105***	0.104***	0.105***	0.105***	0.104***	0.105***	0.104***	0.012*	0.119***
	(4.87)	(4.12)	(4.05)	(3.65)	(3.29)	(3.05)	(3.72)	(3.45)	(0.23)	(3.49)
Ln(firm size)		0.027*	0.025*	0.026	0.026	0.025	0.026	0.025	-0.008	
		(1.93)	(1.91)	(3.21)	(1.28)	(1.22)	(1.35)	(1.28)	(-0.13)	
liquidity (avg)		-2.248***	-2.243***	-2.248	-2.249	-2.243	-2.249	-2.243	-2.626	
		(-5.23)	(-5.21)	(-0.85)	(-0.88)	(-0.88)	(-0.90)	(-0.89)	(-1.03)	
Time effects		No	Yes	No	No	Yes	No	Yes	No	No
Firm effects		No	No	No	No	No	No	No	Yes	No
Time Clusters		No	No	Yes	No	No	Yes	Yes	Yes	Yes
Firm Clusters		No	No	No	Yes	Yes	Yes	Yes	No	Yes
Observations	18,817	18,503	18,503	18,503	18,503	18,503	18,503	18,503	18,503	18,817
Adjusted R-square	0.001	0.003	0.004	0.003	0.004	0.004	0.003	0.004	0.020	0.001

*All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables*
NB: We observe that the number of observation drop when we include additional control variables.

Table 8: Determinants of Corporate Policies Regressions.

This table shows the results of equation 7 where for each corporate policy, we regress a number of factors that determine the specific corporate policy following the literature. We then obtain the residual for each policy to measure policy dissimilarity. Refer to the text for the definition of the models

	Investment Ratio	**R & D Ratio**	**SG&A Ratio**	**Cash Reserve Ratio**	**Leverage Ratio**	**Interest Coverage Ratio**	**Dividend Over Earnings**	**Advertising**
Tobin's Q	-2.200	0.126**	0.010***	-0.002***	-0.001***	-0.002	-0.002	0.007**
	(-0.02)	(2.54)	(2.96)	(-4.23)	(-13.22)	(-0.13)	(-0.28)	(3.14)
Cash Flow	-0.003***	0.013*	-0.003***	-0.001***	-0.001**	0.291***	0.001	-0.001***
	(-41.49)	(1.87)	(-3.26)	(9.77)	(-3.24)	(4.30)	(-0.44)	(-3.69)
Sales(log)		-34.723***			0.020***		0.036**	0.022****
		(41.99)			(44.82)		(2..49)	(30.06)
Tangibility		31.121***			0.309***	-6.436	-0.072	
		(6.33)			(57.64)	(-0.20)	(-0.87)	
Investment Ratio			0.032	0.009***	-0.006**		-0.001	0.001**
			(0.39)	(2.63)	(-2.23)		(-0.15)	(2.18)
R & D Ratio			1.773***	0.001***			0.0003	0.002****
			(42.05)	(8.62)			(0.39)	(4.49)
Sales Growth			0.211***	-0.002***				
			(58.21)	(-3.87)				
Total Asset (log)	-0.025***	33.106***	-0.239***	-0.039***				
	(-4.14)	(34.42)	(-7.03)	(-59.67)				
No. of Employees(log)	0.002	0.032*	0.002	-0.001	-0.002***	-0.108	0.001	-0.007
	(0.41)	(1.86)	(1.43)	(-0.88)	(-3.63)	(-0.69)	(0.11)	(-0.96)
Stock Return Annual	-0.067**	3.054	-0.040	-0.006*	-0.068***	89.010***	0.006	-0.005***
	(-2.08)	(1.39)	(-0.26)	(-1.93)	(-28.50)	(4.21)	(0.17)	(-3.80)
Stock Return Volatility	0.007	-0.363	0.005	0.002***	0.006***	-9.404**	-0.001	0.009***
	(1.34)	(-1.09)	(0.21)	(3.45)	(17.82)	(-2.74)	(-0.17)	(4.32)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Square	0.026	0.047	0.855	0.139	0.194	0.002	0.001	0.062
No. of obs.	71,564	37,336	33,816	37,132	37,060	55,412	37,052	16,960

*Notes: All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables*

Table 9: Liquidity Commonality and Similarity in Corporate Policy Across Connected Stocks

Table 9 reports regression estimates for the relation between liquidity commonality and similarity in corporate policy using equation 9. Refer to the text for the definition of the models.

Dependent Variable Stock Liquidity Beta (Amihud Iliquidity)	Investment Ratio	R & D Ratio	SG&A Ratio	Cash Reserve Ratio	Leverage	Interest Coverage Ratio	Dividend Over Earnings	Advertising Expense
Dissimilarity in Policy	-0.088***	-0.155***	-0.009	-0.239	-0.387***	0.022***	-0.003	-0.009
	(-3.92)	(-3.41)	(-1.35)	(-0.622)	(-8.62)	(8.45)	(-0.42)	(-0.45)
Ln(firm size)	0.067***	0.072***	0.073***	0.070***	0.073***	0.071***	0.074***	0.073***
	(26.74)	(26.96)	(27.83)	(26.01)	(28.46)	(28.44)	(28.57)	(28.56)
liquidity (avg)	4.761***	5.510***	5.583***	5.418***	5.831***	4.957**	5.698**	5.702**
	(4.51)	(4.73)	(4.71)	(4.61)	(5.04)	(4.71)	(4.91)	(4.91)
Firm Clusters	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,198	4,468	4,422	4,465	4,505	5,210	4,504	4,504
Adjusted R-square	0.187	0.219	0.219	0.222	0.228	0.195	0.217	0.218

All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 10: Liquidity Commonality and Similarity in Corporate Policy Across Connected Stocks

Table 10 reports regression estimates for the relation between liquidity commonality and similarity in corporate policy using equation 9. Refer to the text for the definition of the models.

Dependent Variable Stock Liquidity Beta (CRSP-Spread)	Investment Ratio	R & D Ratio	SG&A Ratio	Cash Reserve Ratio	Leverage	Interest Coverage Ratio	Dividend Over Earnings	Advertising Expense
Dissimilarity in Policy	-0.048**	-0.071**	-0.006**	-0.143***	-0.218***	0.010***	-0.035***	-0.009***
	(-2.32)	(-2.42)	(-1.35)	(-4.51.)	(-5.39)	(5.19)	(-2.72)	(-2.84)
Ln(firm size)	0.032***	0.035***	0.036***	0.033***	0.036***	0.035***	0.036***	0.035***
	(14.50)	(14.42)	(14.86)	(14.08)	(15.08)	(15.30)	(15.06)	(15.06)
liquidity (avg)	-0.287	-0.072	-0.056	-0.132	0.107	-0.179	5.702**	0.061
	(-0.26)	(-0.06)	(-0.05)	(-0.11)	(0.09)	(-0.17)	(0.07)	(0.005)
Firm Clusters	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,193	4,467	4,421	4,465	4,504	5,205	4,503	4,503
Adjusted R-square	0.068	0.076	0.076	0.078	0.081	0.071	0.076	0.076

All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 11: Liquidity Commonality and Trading Activity Across Connected Firms

Table 11 reports from pooled OLS (1-6) specifications of the following regression:

$B_{CI\,i,t} = \alpha + \beta_{TRD}\Delta Trade_{j,t} + \beta_2 liq(ave)_{i,t-1} + \beta_3 \ln(size)_{i,t-1} + \beta_4 Vol_{i,t-1} + \beta_5 \Pr_{i,t-1} + time\_effects + \varepsilon_{i,t}$ Where β_{CI} is estimated from equation (1), $\beta_{TRD}\Delta Trade_{j,t}$ is defined as the portfolio of the number of trades of firms that are connected $(Network\_Total)$ and , $\ln(firm\_size)$, $Vol_{i,t-1}$ and $\Pr_{i,t-1}$ are measured at the end of each year. $liq(ave)$ is the firms' average daily illiquidity measure measured at the end of each year.

Dependent Variable : Stock Liquidity Beta (Amihud Illiquidity)	(1)	(2)	(3)	(4)	(4)	(5)	(6)
$\beta_{TRD}\Delta Trade_{j,t}$	0.025***	0.022***	0.017***	0.005**	0.025***	0.254***	0.255***
	(21.92)	(14.55)	(9.67)	(2.29)	(5.48)	(5.28)	(8.59)
Ln(firm size)	0.014***	0.013***	0.021***	0.011***	0.014***	0.014**	0.014**
	(11.09)	(13.78)	(8.70)	(4.07)	(3.34)	(2.59)	(3.09)
liquidity (avg)	0.077	0.075***	0.061***	0.062***	0.076	0.077	0.077
	(2.10)	(4.98)	(4.32)	(4.43)	(0.85)	(0.83)	(0.83)
Price	0.001***	0.001***	0.000	0.002**	0.001***	0.001***	0.001***
	(8.06)	(11.36)	(0.14)	(2.31)	(6.33)	(2.59)	(4.53)
Market Returns	-0.435	-0.437**	-0.467**	-0.494	-0.436	-0.435	-0.436
	(-0.66)	(-2.12)	(-2.42)	(-2.54)	(0.85)	(-0.62)	(-0.62)
Time Fixed Effects	No	Yes	No	Yes	No	No	No
Firm Fixed Effects	No	No	Yes	Yes	No	No	No
Time Clusters	No	No	No	No	Yes	No	Yes
Firm Clusters	No	No	No	No	No	Yes	Yes
Observations	34,834	34,465	34,465	34,465	34,834	34,834	34,834
Adjusted R-square	0.032	0.038	0.367	0.373	0.032	0.003	0.003

All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 12: Liquidity Commonality and Trading Activity Across Connected Firms

Table 12 reports from pooled OLS (1-6) specifications of the following regression:

$B_{CI\,i,t} = \alpha + \beta_{TRD}\Delta Trade_{j,t} + \beta_2 liq(ave)_{i,t-1} + \beta_3 \ln(size)_{i,t-1} + \beta_4 Vol_{i,t-1} + \beta_5 \Pr_{i,t-1} + time\_effects + \varepsilon_{i,t}$ Where β_{CI} is estimated from equation (1), $\beta_{TRD}\Delta Trade_{j,t}$ is defined as the portfolio of number of trades of firms that are connected $(Network\_Total)$ and , $\ln(firm\_size)$, $Vol_{i,t-1}$ and $\Pr_{i,t-1}$ are measured at the end of each year. $liq(ave)$ is the firms' average daily illiquidity measure measured at the end of each year.

Dependent Variable : Stock Liquidity Beta (CRSP-Spread)	(1)	(2)	(3)	(4)	(4)	(5)	(6)
$\beta_{TRD}\Delta Trade_{j,t}$	0.013***	0.007***	0.012***	0.002	0.013***	0.013***	0.013***
	(12.08)	(4.93)	(7.02)	(0.75)	(3.14)	(3.64)	(5.02)
Ln(firm size)	0.002**	0.013***	0.007***	-0.002	0.002	0.002**	0.002**
	(2.25)	(13.78)	(2.75)	(-0.57)	(0.90)	(0.67)	(0.98)
liquidity (avg)	0.001	0.075***	0.002	0.004	0.001	0.001	0.001
	(0.06)	(4.98)	(0.15)	(0.32)	(0.06)	(0.05)	(0.05)
Price	0.001***	0.001***	0.003***	0.001***	0.001**	0.001***	0.001***
	(5.01)	(9.59)	(4.25)	(6.03)	(2.91)	(2.63)	(3.24)
Market Returns	-0.057	0.033	-0.467	0.090	-0.056	-0.056	-0.057
	(-1.37)	(0.38)	(-2.42)	(1.09)	(-0.84)	(-0.69)	(-0.70)
Time Fixed Effects	No	Yes	No	Yes	No	No	No
Firm Fixed Effects	No	No	Yes	Yes	No	No	No
Time Clusters	No	No	No	No	Yes	No	Yes
Firm Clusters	No	No	No	No	No	Yes	Yes
Observations	34,712	34,712	34,712	34,712	34,712	34,712	34,712
Adjusted R-square	0.007	0.018	0.269	0.276	0.008	0.007	0.008

All t-statistics are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 13: 2 Stage Regressions Using Instrumental Variables

	1st stage Dep= CEO Total Network Size	2nd Stage Dep = Social Network Stock Liquidity Beta (Amihud)
CEO Total Network Size	-	0.0056***
		(3.54)
Industry Network Total	0.8316***	-
	(75.11)	
liquidity (avg)	1.5336	-0.3736
	(0.74)	(-1.41)
Ln(firm size)	4.1667***	0.0445***
	(38.64)	(2.62)
Year Effects	Yes	Yes
Industry Effects	No	Yes
Observations	20,118	20,118
Adjusted R- Square	32%	6.7%
Partial F-Statistics	3.29 (p-value <0.0001)	
Weak Identification Test	Cragg-Donald Wald F = 5641.728	
	Stock-Yogo C.V: 10% Max IV 16.38	
	Stock-Yogo C.V: 25% Max IV 5.53	

NB: Industry Network Total is the average network size in specific industry using 2-digit SIC code.

Table 14: 2 Stage Regressions Using Instrumental Variables

	1^{st} stage Dep= CEO Total Network Size	2^{nd} Stage Dep = Social Network Stock Liquidity Beta (CRSP-Spread)
CEO Total Network Size	-	0.0031***
		(3.94)
Industry Network Total	0.8092***	-
	(65.88)	
liquidity (avg)	5.7717	-2.0498***
	(0.50)	(-3.41)
Ln(firm size)	4.0084***	0.0074
	(31.31)	(0.92)
Year Effects	Yes	Yes
Industry Effects	No	Yes
Observations	17,652	17,652
Adjusted R- Square	30.7%	7.5%
Partial F-Statistics	3.74 (p-value <0.0001)	
Weak Identification Test	Cragg-Donald Wald F = 4339.915	
	Stock-Yogo C.V: 10% Max IV 16.38	
	Stock-Yogo C.V: 25% Max IV 5.53	

NB: Industry Network Total is the average network size in specific industry using 2-digit SIC code.

Table 15: Endogeneity: Difference-in-Difference using a CEO's Death				
Dependent Variable: Social Network Liquidity Beta (Amihud)	**PANEL A**		**PANEL B**	
Death Dummy	-0.0762**	-0.0587**	-0.0687***	-0.0484***
	(-2.64)	(-1.64)	(-8.08)	(-5.94)
Death Dummy *CEO Network Size	0.0041***	0.0031***	0.0045***	0.0036***
	(8.71)	(6.33)	(26.51)	(21.28)
liquidity (avg)		0.6487		2.7044***
		(0.18)		(3.16)
Ln(firm size)		0.0700***		0.0574***
		(12.75)		(30.15)
Adjusted R-Square	0.165	0.331	0.167	0.289
Observation	680	680	4,456	4,456

In Panel A we consider firms that actually recorded CEO death within the sample period.
In Panel B we consider firms that did not recorded CEO death but a CEO in the network of firms connected to the individual firm died.

Table 16: Endogeneity: Difference-in-Difference using a CEO's Death				
Dependent Variable: Social Network Liquidity Beta (CRSP-Spread)	**PANEL A**		**PANEL B**	
Death Dummy	-0.0967***	-0.0862***	-0.0832***	-0.0747***
	(-3.85)	(-3.50)	(-10.68)	(-9.69)
Death Dummy *CEO Network Size	0.0037***	0.0031***	0.0034***	0.0030***
	(7.97)	(6.56)	(20.34)	(18.17)
liquidity (avg)		8.9186**		-0.6711
		(2.05)		(-0.57)
Ln(firm size)		0.0356***		0.0253***
		(6.45)		(14.88)
Adjusted R-Square	0.176	0.241	0.128	0.172
Observation	680	680	4,454	4,545

In Panel A we consider firms that actually recorded CEO death within the sample period.
In Panel B we consider firms that did not recorded CEO death but a CEO in the network of firms connected to the individual firm died.

CHAPTER 3

CEO PEER EFFECTS AND COMMONALITY IN ASSET GROWTH

1. Introduction

The impact of social and professional ties among top executives and directors in corporations is a central issue in corporate finance. It is well established that information flow among connected executives significantly affects corporate policies and governance practices. Fracassi (2016) shows that managers are influenced by their social peers in making corporate policy decisions. Fracassi (2016) notes that the more connections two companies share, the more similar are their capital investments. Investigating the implications of social networks among corporate executives has become a growing body of research in finance. These studies support the idea that social and professional network interactions that facilitate peer influence, motivate connected firms to adopt similar actions leading to commonality in corporate behaviour. In the context of stop split, Kaustia and Rantala (2015) find that through peer effects, firms are more likely to split their stocks if their peers have recently done the same. Bouwan (2011) notes that peer effects and peer influence facilitate corporate governance practices to spread from one firm to another leading to convergence in governance practices. Similarly, Grennan (2019) shows that dividend policies have peer effects. He finds that payment of dividends by firms increases by 16% in response to peer firms' changes and speeds up the time taken to make a dividend change by about 1.5 quarters.

Some recent social network studies in finance reveal that CEO networks significantly influence several aspects of corporate decisions and corporate behavior. El-Khatib, Fogel, and Jandik (2015) show that high network centrality can allow CEOs to efficiently gather and control private information, which facilitates value-creating acquisitions. Brown, Gao and

Stathopoulos (2012) and Engelberg, Gao, and Parson (2013) find that CEOs with large networks earn more than those with small networks. Faleye, Kovacs, and Venkateswaran (2014) present evidence that firms with better-connected CEOs invest more in research and development and receive more, higher quality patents. On earnings management, Chiu, Teoh, and Tian (2013) find that a firm is more likely to manage earnings when it shares a common director with a firm that is currently managing earnings and is less likely to manage earnings when it shares a common director with a non-manipulator. In line with these studies, this essay contributes to the literature by examining the influence of peer effects across CEO networks on asset growth decisions (Bertrand and Schoar 2003; Bennedsen, Perez-Gonzalex, and Wolfenzon, 2006; Cronqvist ,Makhija, and Yonker, 2012; Graham, Harvey, and Puri, 2013; Jenter and Lewellen, 2015).

Specifically, this essay examines whether social and professional connections among CEOs influence asset growth decisions of firms leading to e commonality in asset growth across connected firms. Our quest to investigate the above relationship to establish whether CEO networks fuels asset growth commonality rest on the fact that, studies such as Cooper , Gulen, and Schil (2008) and Watanabe, Xu, Yao, and Yu (2013) find that asset growth affect stock returns. On the contrary, McConnel and Muscarells (1985) find that announcements of capital investments affect stock prices favourably. In addition, recent research in empirical corporate finance show that social network of firm executives greatly influence corporate decision outcome focusing on several corporate outcome such as compensation structure, stock split, dividend policies, mergers and acquisition among other. Interestingly, even though the corporate finance literature provide evidence on the impact of executives network on firms, the literature is yet to consider the link between social network of firm executives and asset growth decisions of firms. Since asset growth decisions of firms can be influenced by management, its prudent a study is a carried to ascertain the linkage between asset growth decisions of connected CEOs. Gupta, Guha, and Krishnaswami (2013) define asset growth as an increase in certain attributes such as sales, employment and profit of a firm between two times. According to Nelson and Winter (1982), asset growth is determined by the combination of firm-specific resources, capabilities and routines. Zhou and de Wit (2009) find that asset growth at the firm level is driven by individual, organizational and environmental determinants. Focusing on the individual determinants of asset growth, prior studies show that asset growth, to a large extent, is driven by the decisions and preferences of top management. These studies suggest that personality traits, growth motivation, individual competencies and the personal background of top management are the most important factors that determine a firm's asset growth rate (Delmar, 1996; Baum , Locke and Smith, 2001; Shane, Locke, and Collins, 2003). Renneboog and Zhao (2014) and El-Khatib, Fogel, and Jandik (2015), in examining the role of CEO networks in finance, classify CEOs' network size as personality traits and soft skills of the CEO. This is because social and professional networks of CEOs affect CEOs' personal decisions as well as corporate behaviour. Indeed, top executives draw upon these networks to derive valuable information that will be beneficial to their firms (Coleman, 1988; Granovetter, 2005; McDonald, Khanna, and Westphal, 2008). Larcker, So, and Wang (2013) show that social networks among firm executives serve as channels for interpersonal and inter-organizational support, influence, and information flow. Thus, social interactions among firm executives can be beneficial for companies because they facilitate information exchange, allowing diffusion of ideas, knowledge and private information. In addition, social and professional connections can serve as channels whereby top executives obtain business opportunities and learn key market information that enhances the quality of their decisions (Granovetter, 2005).

From the above discussion, we realise that asset growth decisions at the firm level can be influenced greatly by top managements, hence, we conjecture in this essay that connected CEOs, belonging to the same network, through peer effects are likely to imitate each other's asset growth strategies if the CEO believes that the information obtained from peer CEOs is valuable. We hypothesise that the asset growth of firms that are connected will comove. This is because social connections increase a CEO's access to relevant network information, which may encourage asset growth and innovation since, through social networks, a CEO obtains non-public information that helps them identify, evaluate, and exploit innovative ideas and good projects. Specifically, the study addresses the following research questions: Does the asset growth of connected firms covary, and, if so, through which channel(s)? What are the implications of commonality in asset growth on shareholders wealth?

The intuition for our hypotheses is as follows: A substantial body of literature examines the empirical relationship between asset growth and stock returns. Xing (2007) finds a negative relationship between investment and stock returns. Cooper, Gulen, and Schill (2008), using total asset variations, confirm the results of Xing (2007). Likewise, Lam and Wei (2011) find a negative, significant relationship between stock returns and asset growth in U.S. firms. From the above, understanding factors that drive asset growth is important because it affects expected returns (Titman, Wei, and Xie, 2004; Cooper, Gulen, and Schill, 2008). A fundamental question is: given the well-known asset growth effect, do connected CEOs imitate asset growth strategies of peer CEOs to increase assets? Following, Kaustia and Knüpfer (2012), who find that peer performance can influence the adoption of financial innovations and investment styles, Davis (1991) and Davis and Greve (1997), who show that connections among firm executives lead to the adoption of similar poison pill and golden parachute strategies, and Bouwman (2011), who finds a link between board interlocks and the convergence of governance practices, we argue that, through peer performance, CEOs with personal connections imitate each other and grow their firm's asset just like their peers even if the addition of more assets is detrimental to shareholders' value. We argue that connected CEOs in a network in their quest to run big empires may want to grow their firms to a level close to their network peers since that will subsequently enhance their prospects in the labour market. Our proposition stems from the findings of Delmar and Wiklund (2008) who conclude that motivated managers can effectively utilise resources and select appropriate strategies to improve growth. Thus, connected CEOs, through peer effects, can motivate each other to embark on related asset growth strategies.

Accordingly, we argue that CEOs with personal connections through the peer effect may adopt similar asset growth strategies around the same time, which, in effect, may lead to similarity in asset growth rates among connected firms leading to commonality in asset growth. We evaluate the impact of peers on firms' asset growth decisions and test whether commonality in asset growth impacts shareholders' value.

To test the hypothesis, we rely on biographical information about CEOs of U.S. public companies supplied by BoardEx from 2000-2016 to establish connections among firms through CEOs' social networks. Next, we follow Cooper, Gulen, and Schill (2008) and use annual total asset variations as a measure of annual asset growth rate. We construct a measure of commonality in asset growth among connected firms by adopting an approach similar to that of Anton and Polk (2014) and Koch, Ruenzi, and Starks (2016). To obtain the measure for commonality in asset growth across connected firms, we estimate the relationship between a firm's own asset growth rate and the asset growth rate of a portfolio of firms that are connected to that firm. We label the regression coefficient of individual firms' asset growth on the average asset growth of a portfolio of firms connected to the individual firm our measure of commonality in asset growth among connected firms, as *Asset Growth Beta*. Following Kamara, Lou, and Sadka (2008), we define *Asset Growth Beta* as the sensitivity of each firm's asset growth change to the variation in asset growth rate of portfolio of firms connected to the firm.

Consistent with our hypothesis, we find a significant positive relationship between individual firm asset growth and the asset growth of a portfolio of firms connected to the firm. The results suggest that asset growth across connected firms strongly comove. Thus, through personal connections among firm executives, connected firms imitate each other in asset additions by observing the actions of peers. We next test the empirical relationship between commonality in asset growth, *Asset Growth Beta* and CEO network size. We regress the *Asset Growth Beta* coefficient for each stock on the network size of each firm. Again, as predicted, we find a significant positive relationship between asset growth beta and the CEO's network size. This evidence further confirms our earlier assertion that asset growth among connected firms comoves.

We further examine the economic benefits of asset growth commonality. We argue that connected firms growing their assets similarly may not be economically beneficial to shareholders. This is because a CEO may be influenced by peers in the social network to embark on asset expansion, even if the expansion is not needed, since the CEO's personal characteristics and preferences impact corporate policies. This, we argue, will not add significant economic benefit to the firm. Moreover, misleading and incorrect information may spread through the CEO network, resulting in value decreasing strategies and investments as a result of peer influence. We hypothesise that commonality in asset growth across connected firms will negatively affect firm performance. To test this claim, we regress, return on assets (RoA) and stock returns on *Asset Growth Beta,* our measure of commonality in asset growth among connected firms for each firm, while controlling for factors that can determine RoA and stock returns. Consistent with our hypothesis, we find evidence that asset growth commonality significantly reduces shareholders' wealth.

Next, we evaluate potential channels through which CEO connections facilitate commonality in asset growth across connected firms. First, we test whether connected CEOs adopt similar M&A decisions by investigating acquisitions of connected CEOs. Evidently, several factors determine investment decision similarity across firms. For instance, firms in different industries are less likely to invest in similar assets than firms in the same industry. We use multiple regressions to test whether the findings obtained could be driven by similarity in acquisition decisions across connected firms. In the first regression, using data from SDC, we compute the acquisition growth rate for each individual firm and the acquisition growth rate of firms connected to that firm. We then regress each individual firm's acquisition growth rate on the average acquisition growth rate of portfolio of firms connected to that firm. Consistent with our hypothesis, we find a significant positive relationship between the acquisition growth rate of individual firms and the acquisition growth rate of a portfolio of firms connected to that firm.

Following Bliss and Rosen (2001), we further investigate whether connected firms grow their assets similarly through non-merger and acquisition strategies. We estimate the non-merger growth rate for each firm by finding the difference between each firm's annual total assets and the total value of acquisitions. We then regress the non-merger growth rate for each firm on the non-merger asset growth of a portfolio of firms connected to that firm. We find evidence suggesting connected firms grow their assets similarly through non-mergers and acquisitions.

Secondly, we investigate whether commonality in asset growth across connected firms may be attributed to similarity in research and development investment (hereafter, R&D). Following Pan, Wang, and Weisbach (2016), we compute the annual R&D growth rate for each firm and the average R&D growth rate of a portfolio of firms connected to that firm. We hypothesise that connected CEOs belonging to the same network influence each other to embark on similar R&D investments in their quest to grow assets to similar levels and at a similar rate. We find a significant positive relationship between each individual firm's R&D growth rate and the R&D growth rate of a portfolio of firms connected to the firm.

Subsequent to our results that show that CEO network size influences asset growth strategies, one issue with our results is that a CEO may build stronger networks to maximize the net benefits associated with asset growth, at least in the short term. We use a two stage instrumental variable (IV) approach to check for endogeniety. We argue that the positive relationship between CEO network size and commonality in asset growth is susceptible to reverse causality. This is because a firm can grow assets through the firm's own efforts, resources, and capabilities without relying on information obtained by the CEO from peer CEOs in the CEO networks. If the above scenario happens, then eventually the chances of the CEOs' network size increasing surges to successfully increase the firms' assets even though the growth might not come from the CEO's efforts. On the other hand, a firm with less access to quality non-market information may rely on the information obtained by the CEO from peer CEOs to increase assets. We find that the positive effect of CEO network on similarity in asset growth among connected firms is robust to the IV approach. Another possible reverse-causality could be that when firms want to change corporate finance policies, they hire people with the appropriate skills and social connections to implement the desired strategies, hence we use a CEO's death as an exogeneous shock to a firm's social and professional connectivity to test the direction of causality between a CEO's social connections and commonality in asset growth since, when a CEO dies, his/her social ties with other individuals in the network ceases, exogeneously altering the social connections between companies. We find that a CEO's death significantly reduces the extent of asset growth comovement of connected firms.

The study contributes to two distinct literatures. First, we contribute to the strand to literature on the determinants of asset growth. Some key early studies on this topic in economics and finance (Simon and Bonini,1958; Eatwell,1971; Lucas Jr ,1978; Sawyer, 1985; Evans ,1987 ; Audretsch, Klomp, and Santarelli, 2004) focus on the role of firm characteristics such as firm size and firm age as determinants of asset growth. Other studies on the topic concentrate on the relationship between environment, business strategy and firm growth (McDougall, Robinson, and DeNisi, 1992).We extend the literature and consider the effects of network ties among top management who direct corporate behaviour to ascertain whether social ties facilitate asset growth at the firm level through peer effects. We use personal connections among firm CEOs and show that access to network information plays a significant role in explaining the determinants of asset growth in U.S. public firms.

Secondly, we contribute to empirical research on the impact of CEO connections on firm value. Advances in this research area show that top executive connections affect firm decisions and behaviour. Hwang and Kim (2009) find that personal connections between CEOs and directors aid higher pay levels, lower turnover profitability and low pay performance sensitivity. Ishii and Xuan (2014) find negative effects from relationships between an acquirer and targets, and the audit committee and the firm's auditor (He, Pittman, and Wu, 2014). Kramarz and Thesmar (2013) observe that CEO and board connections lead to a decline in turnover performance sensitivity. Our results show that CEO personal connections that facilitate asset growth commonality across connected firms can have a positive effect on corporate investment decisions. Thus, through personal connections, CEOs are well positioned to make the right investment choices because of valuable information that flows across the network. However, additional tests to investigate the economic benefits of asset growth commonality suggest that co-variation in asset growth across connected firms significantly affects firm performance.

Overall, we find that larger CEO connections are associated with higher asset growth commonality across connected firms, which confirms the view that network contacts fuel the diffusion of economic information from external sources that enables CEOs to obtain more accurate, quality information relating to asset growth. The significant positive relationship between commonality in asset growth and CEO network size, suggests that the more connections a CEO has, the more is the tendency that the CEO will grow assets more because of peer influences from a large number of individuals in the network even if increasing assets may not be beneficial to the firm. Our result confirms that commonality in asset growth negatively affect firms. Finally, we find evidence that similarity in M&A decisions and R&D investment are two channels that drive commonality in asset growth among connected firms.

The study proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes data and sample selection. Section 4 presents empirical findings and Section 5 documents the conclusion.

2. Literature Review

2.1 CEO Personal Connections

First, we rely on the comprehensive literature in organisation psychology, economics and finance that provides evidence of the potential benefits and costs of being well-connected through social and professional network ties. The benefits of having a well-connected top executive such as a CEO take several forms. First, CEOs are carriers of a wealth of information that relates to industry dynamics, market trends, regulatory changes and key market data, which may flow across the CEO network. This implies that a well-connected CEO has better access to information that may aid in making decisions that may be beneficial to the firm (Larcker, So, and Wang, 2013). Second, when designing contracts, personal connections among firm CEOs allow firms to leverage on social relationships to reduce information asymmetry since both factors can help in developing the terms of contract agreements between firms (Engelberg, Goa, and Parsons, 2013). Third, through CEO connectedness, CEOs can obtain important business contacts that can be sources of useful business relationships or sources of other economic benefits and resource exchanges. Lastly, personal connections among CEOs can be a channel of information diffusion through which value-improving business strategies and innovations may spread. Thus through information flow across the network, CEOs can obtain useful information such as efficient corporate governance and compensation practices (Hvide and Östberg, 2015; Nguyen, Hagendorff, and Eshraghi, 2016).

In empirical finance literature, numerous studies on the effect of social networks in corporations acknowledge the significant impact of personal connections among firm top executives on corporate decisions and behaviour, resource allocation in capital markets (Hirshleifer and Teoh, 2009), option backdating (Bizjak, Lemmon, and Whitby, 2009), information transfer in security marekts (Cohen, Frazzini, and Malloy, 2008), acquisiton activity (Cai and Sevilir, 2011; El-

Khatib, Renneboog and Zhao, 2011; Ishii and Xuan, 2014; Fogel and Jandik, 2015), compensation practices (Renneboog and Zhao, 2011), board monitoring (Fraccasi and Tate, 2012), earnings management (Shu, Yeh, and Yang, 2015), IPO outcomes (Cooney, Madureira, Singh and Yang, 2015), corporate fraud (Chidambaran, Kedia and Prabhala, 2011; Khanna, Kim and Lu, 2015) and innovation (Faleye, Kovacs and Venkateswaran, 2014).

A number of these studies conclude that personal connections among top executives positively influence firm behaviour. For example, Khanna, Kim, and Lu (2015) show that a CEO's close connections with directors and other top management help detect fraud. Thus, a CEO's closeness with top directors and executives may possibly assist the CEO to discover early signals of any negative activity. Renneboog and Zhao (2014) examined the impact of corporate network ties on takeovers. Their results show that when the respective executives and directors of the bidder and target are connected, the propensity for the takeover to be successful increases and the duration of the takeover transaction shortens. Likewise, Burt (2004) and McDonald, Khanna, and Westphal (2008) provide evidence that CEOs personal connections positions the CEO to have alternative points of view that enhance the quality of strategic decisions in unfamiliar settings. Schonlau and Singh (2009) find that well-connected CEOs can improve their ability to identify and exploit innovation opportunities because of vital information that permeates through their networks.

An existing literature strand concludes that personal connections among firm top executives adversely affects firm behaviour and performance. This is attributed to misleading information that may flow through the network, resulting in individuals within the network adopting strategies that can decrease firm value and jeopardize firm behaviour. For example, Armstrong and Larcker (2009) and Bizjak, Lemmon, and Whitby (2009) show that personal connections among firm executives facilitate the spread of option backdating. Fracassi and Tate (2012) show that network ties among CEOs and directors destroy corporate value and weaken board monitoring. On the effectiveness of boards comprising highly connected directors, Fich and Shivdasani (2006) find board members are unable to keep a watchful eye on management thus negatively affecting corporate activities. Khanna, Kim, and Lu (2015) find that through appointment, CEOs develop networks with directors and executives that directly fuel the likelihood of fraud in the firm. Similarly, Chidambaran, Kedia and Prabhala (2011) show that connections between CEOs and directors significantly increase the probability of fraud; CEOs close connections with top executives and directors provide the support required to engage in fraudulent activities. A number of studies show that firms with CEOs who are connected to board of directors receive higher compensation, demonstrate lower pay-performance sensitivity and are unlikely to be fired for under-performance (Hallock, 1997; Hwang and Kim, 2009; Kramarz and Thesmar, 2013).

The arguments and conclusions from the literature on the effects of personal connections among firm executives on firm behaviour highlight the ambiguity regarding the net economic impact of top executives' network ties. In this essay, we examine the relationship between CEO connectedness and commonality in asset growth and its ripple effect on shareholders.

2.2 Firms Asset Growth Strategies

Prior evidence suggests that asset growth strategies and choices adopted by firms are not static (Cyert and March, 1963; Nelson and Winter, 1982; Penrose and Penrose, 2009). Thus, firms grow in many different ways, and the growth patterns can vary across firms (Delmar and Wiklund, 2008). As a multidimensional construct, firm growth primarily involves expansion of organisation size measured by assets and employees; increase in volume of sales and profit levels as well as the generation of new economic functions or more product or service lines

(Starbuck, 1965; Greiner, 1972; Kimberly, Kimberly and Miles, 1980; Chandler, 1990; Eisenhardt and Schoonhoven, 1990; Penrose and Penrose, 2009). Although the traditional strategy for growth has been either through generic expansion or mergers and acquisitions (Yip, 1982; Peng and Heath, 1996; Penrose and Penrose, 2009), a strand of literature advances that firms have become increasingly interested in relying on trust-based network relationships to achieve growth (Contractor and Lorange, 1988; Williamson, 1991; Powell, 2003). These network-based relationships assume various forms, such as strategic alliances, joint ventures, hybrid organisations, partnerships, corporate groups and research consortia (Thorelli, 1986; Johanson and Mattsson, 1987; Jarillo, 1988; Borys and Jemison, 1989; Ring and Van de Ven, 1994; Tallman and Shenkar, 1994; Browning, Beyer, and Shelter, 1995).

Research has classified the drivers of firm growth into three dimensions: individual, organisational and environmental (Zhou and de Wit, 2009). Empirical studies attribute the following as organizational determinants of firm growth: firm attributes, firm strategies such as market orientation, firm specific resources including human capital and financial resources, organizational structure and dynamic stability. Prior studies classify firm age and size as attributes that influence firm growth. The relationship between firm size/age and firm growth has its roots in Gibrat's law which states that the rate of growth in a firm is independent of its initial size (Audretsch, Klopm and Santarelli, 2004). Becchetti and Trovato (2002) find that firm growth is affected by firm size and firm age. Other studies show that the growth rate of younger firms is higher than firms that existed for many years. The negative effects of firm age on firm growth are well established in a long history of literature that examines the relationship between firm age and firm growth (Glancey, 1998; Liu, Tsou and Hammitt, 1999; Robson and Bennett, 2000; Geroski and Gugler, 2004; Reichstein and Dahl, 2004; Yasuda, 2005). Studies on the stylized fact of firm size and firm growth have yielded mixed findings. For example, Yasuda (2005) finds a negative effect whereas Audretsch, Klopm, and Santarelli (2004) record a positive effect.

Firm growth is also attributed to how successful companies sell services and products to customers thus making market orientation a key determinant of firm growth. This is because firms with market orientation are able to track and respond swiftly to customers' preferences which positions the firm to develop market intelligence and coordinate internal processes to respond quickly to stakeholders. Prior studies show that market orientation facilitates better satisfaction of stakeholders and customers, which eventually aids a firm's growth (Narver and Slater, 1990; Hult, Snow, and Kandemir, 2003). Furthermore, Jaworski and Kohli (1993) find that market orientation significantly affects firm performance.

Firm specific resources such as financial and human capital are important determinants of firm growth (Wiklund, Patzelt, and Shepherd, 2009). It has been argued that securing financial resources significantly promote firm growth (Sexton and Bowman-Upton, 1991; Bamford, Dean, and McDougal, 1997). This is because financial resources can be converted to other types of resource (Dollinger, 1999). With sufficient funds, firms can carry out R&D to experiment with new things which not only improve firm innovation but also position the firm to venture into new growth opportunities (Zahra, 1991; Castrogiovanni ,1996). Cooper, Gimeno-Gascon, and Woo (1994) show that access to financial resources significantly drives firm growth. The financial performance of a firm is a secondary input to financial resources for firms; past profit can be reinvested into the firm. By this means, a firm not only relies on external funding, but also uses internal funds to finance investments. Human capital resources include knowledge, skills and experience. Birley and Westhead (1990) and Chandler (1990) show that the human capital in managers contributes significantly to firm growth. Thus personal the characteristics and experience of managers play a determined role in firm growth.

A general finding in the literature is that environmental determinants such as dynamism, heterogeneity, munificence, and hostility largely influence firm growth (Dess and Beard, 1984; Covin and Slevin, 1991; Pelham and Wilson, 1995). A dynamic environment, which relates to market dynamics or technology dynamics, is measured by the level of environmental predictability (Houston, 1986). Wiklund, Patzelt, and Shepherd (2009) conclude that changes in society, politics, markets and technology offer firms more growth opportunities. Aldrich and Wiedenmayer (1993) conclude that munificence represents an environment's support for firm growth. It is argued that a firm in such an environment with better access to required resources has higher chances to grow. Baum, Locke and Smith, (2001) find a significant direct effect of munificence on firm growth. A hostile environment serves as a threat to firms through intensive competition because intensive competition reduces the growth prospects of small firms (Houston, 1986). Heterogeneity indicates the complexity of the environment regarding the concentration or dispersion of organizations in it. It is argued that small firms that serve niche markets can find growth opportunities with relatively more ease in a heterogeneous market than in a homogeneous one (Wiklund, Patzelt, and Shepherd, 2009).

Firm growth is hugely determined by individuals at the helm of affairs; their personality traits, personal background, competencies and growth motivation significantly influence the growth choice and strategies adopted. Baum, Locke and Smith (2001) find that specific competencies of managers such as technical and industrial skills affect a firm's growth significantly. The personal background of managers includes age, education, personal experience and gender. Studies show that experienced managers have a positive impact on firm performance. Orser, Hogarth-Scott and Riding (2000) find a positive relationship between related industry experience and willingness to pursue growth opportunities. Likewise, Delmar and Shane (2006) find that experience matters in venture success. It is also observed that the education level of managers significantly impacts firm performance in terms of growth (Sexton and Bowman-Upton 1991; Storey, 2016). However, the nexus between firm growth and higher education remains mixed. Kolvereid (1992) find a positive effect but Welter (2001) notes a negative effect.

Recently, a growing amount of literature on the effects of social networks of top executives in corporate finance concludes that the personal connections of top executives affects several corporate practices such as compensation, corporate innovation, board monitoring, investment styles and firm performance (Haunschild, 1993; Hwang and Kim, 2009; Fracassi and Tate, 2012; Engelberg, Gao, and Parsons, 2013; Larcker, So, and Wang, 2013; Fracassi, 2016). Most of these studies attribute their results to peer effects and peer influence from individuals having personal connections. We build on this growing body of literature that examines the impacts of peer effects on firms' and managers' decisions by examining the impact of peer effects and group thinking on asset growth decisions among CEOs with personal connections. Larcker, So, and Wang (2013) find that social connections can enhance firm value. We argue that social structure can impact on asset growth, which, to some extent, may lead to commonality in asset growth among connected firms.

There exists a substantial number of factors that may have a relationship with firm growth. We argue the social and professional connections of top executives such as CEOs which facilitates the transfer of ideas, knowledge and resources can influence firm growth.

2.3 Asset Growth and Firm Performance

The literature on asset growth and firm performance is relatively new. Existing studies show that firm asset and investment growth affects stock returns. Cooper, Gulen, and Schil (2008) observe that asset growth rates are strong predictors of stock returns. They conclude that a firm's annual asset growth rates significantly predict stock returns. Cooper, Gulen, and Schil (2009) find a strong negative relationship between the growth of total firm assets and subsequent stock returns. Fu (2011) finds that firms that shrink their assets or investments subsequently earn higher returns than firms that expand their assets or investments. Lipson, Mortal, and Schill (2011) show that the asset growth effect is pervasive in stock markets. Lam and Wei (2012) testing the prominent rational and behavioural explanations for the negative relationships between corporate asset growth or investments and subsequent stock returns find that returns on low growth firms with low subsequent growth are not higher than those on high growth firms with high subsequent growth. Watanabe, Xu, Yao, and Yu (2013) find that firms with higher asset growth rates subsequently experience lower stock returns. Following this literature on asset growth effect on stock returns, we predict that asset growth commonality among connected firms will negatively affect firm performance. Our argument rests on the fact that a CEO can suffer from group thinking bias because of trust among individuals within a network to adopt certain asset growth policies through the peer effect that may not add value to the firm.

2.4 Hypothesis Development

Considerable evidence indicates that social networks facilitate innovation and information diffusion (Goyal and Moraga-Gonzalez, 2001). Gomes-Casseres, Hagedoorn, and Jaffe (2006) show through firm interconnections, a firm's ability to learn is increased and it is able to adapt quickly to new technology and innovation. Rodan and Galunic (2004) examine a manager's social networks and find that access to heterogeneous knowledge through social contacts is useful in generating and implementing new ideas. Oldham and Cummings (1996) attribute managerial innovation to information obtained from the heterogeneous social network of managers. Engelberg, Goa, and Parsons (2011), in examining CEOs' social networks, find that social networks provide an informal medium for managers to share each other's valuable experiences, gather key market information, exchange resources and identify business opportunities. From social network theory, social network ties provide access to diverse groups so that one can gain superior information and resources beyond one's own group (Burt, 2004). Kaustia and Knüpfer (2012) show that peer performance can influence the adoption of similar financial innovations and investment styles. Consequently, network members with similar personal characteristics can lead to group thinking.

Following these arguments, we argue that access to heterogeneous social networks offers CEOs a broader knowledge base, adds information richness, and provides alternative problem-solving insights. Hence, diverse social ties are beneficial for managerial decision-making in terms of selecting value-enhancing investments. Thus, we argue that through group thinking, CEOs with personal connections may grow their firms' assets leading to asset growth commonality across connected firms. Following the literature that shows a significant positive relationship between managerial social networks and corporate finance decisions, we hypothesize that:

Hypothesis 1: The asset growth of firms with CEOs having personal connections will strongly covary.

To empirically test for the channels through which personal connections among CEOs can drive asset growth commonality, we first examine an external channel of asset growth by focusing on the M&A of connected firms by studying whether connected CEOs through peer influence increase assets through acquisition. We examine M&A because it is considered a major type of corporate investment and asset addition. Theoretically, M&A should create economic synergies among merging firms and increase the value of the acquirers. Since M&A transactions require manager capability in selecting the right strategies, we argue that social networks help CEOs make better decisions through information diffusion across the networks. Hence, CEOs with personal connections may grow their firm's assets through acquisitions by adopting similar strategies leading to asset growth commonality. We argue that peer performance can give rise to CEOs with personal connections imitating each other in asset addition. This leads to our second hypothesis; CEOs with personal connections make similar M&A decisions.

Hypothesis 2: Similarity in M&A decisions among firms with CEOs with personal connection is a channel through which CEO connectedness drives asset growth commonality.

In addition to M&A decisions, we also examine the R&D investment performance of connected firms which is classified as internal growth opportunity. Our motivation to examine R&D investment is inspired by a number of studies. Faleye, Kovacs, and Venkateswaran (2014) provide evidence that better connected CEOs invest more in R&D and often receive higher quality patents. This shows that CEO connections drive investments that lead to corporate innovation. Also, Goyal and Moraga-Gonzalez (2001) find that benefits arise from knowledge sharing among connected firms, which enhances R&D investment. Following, Bertrand and Schoar (2003), who find that individual managers affect corporate behaviour and performance by focusing on several corporate policies, we argue that CEOs with personal connections through information sharing may adopt similar investments in their quest to grow their firm's assets since they direct corporate behaviour. This leads to our third hypothesis; CEOs with personal connections make related R&D investment decisions.

Hypothesis 3: Similarity in R&D decisions among firms with CEOs with personal connection is a channel through which CEO connectedness drive asset growth commonality.

We next examine the relationship between commonality in asset growth and firm performance. Some studies in corporate finance provide evidence supporting the darker side of social networks among firm top executives. For example, Ishii and Xuan (2014) examine the level of social connections between managers and boards of directors of acquirer and target firms. The results show that social network negatively affects acquirer returns. They attribute the result to flawed decision-making and a lack of due-diligence because of familiarity between the two connected firms. Asch and Guetzkow (1951) find that members in a group with similar personal characteristics and attitudes may lead to group thinking and flawed decisions because of a lack of challenging views and ignorance.

Other studies provide strong evidence of an asset growth effect. These studies show that asset growth negatively affects stock returns (Cooper, Gulen, and Schil, 2009; Fu, 2011; Lam and Wei, 2012; Watanabe, Xu, Yao, and Yu, 2013). The question is, if asset growth affects stock returns and firm performance, why do firms grow assets? We argue that CEO connections, which create peer effects, may be a reason firms grow assets.

Ellison and Fudenberg (1995) and Watts (2004) show word-of-mouth communication aggregates the information of individual agents and that the structure of the communication determines whether all agents end up making identical choices. In particular, it is argued that economic agents do not know all the information and alternative choices when making decisions. Hence, agents are more likely to rely on whatever information they can acquire via word-of-mouth communication. They may also change preferences and beliefs because of the actions of their social peers. In finance, Hong, Kubik, and Stein (2005) display the word-of-mouth effects between mutual fund managers by showing that trades of mutual funds located in the same city are correlated. Fracassi (2016) finds that CEOs who are well connected in the corporate elite network make financial decisions that are like those of their social peers. Social network theories also examine issues related to the mutual trust and exchange of social support (McPherson, Smith-Lovin, and Coo, 2001; Powell, 2003). The enhanced trust between socially connected individuals leads them to interpret the behaviour of one another favourably, and thus assume that each will take actions that are predictable and mutually acceptable (Uzzi, 1996; 1999).

In line with the arguments above, we argue that trust among CEOs with social and professional connections can cause a CEO to accept and rely on whatever information permeates through the network to carry out investments or overinvest in a project without due diligence. We conjecture that, in situations where the information obtained from the network is flawed, then decisions taken by the CEO based on the flawed information to overinvest in a project may negatively affect firm performance Following Titman, Wei, and Xie (2004), who find a negative relationship between overinvestment and future stock returns, we argue that firms with CEOs who follow whatever information is obtained from their peers to increase or overinvest in an asset may reduce the wealth of shareholders and firm performance. This is because a CEO, using information obtained from his/her social peers, can influence the board of directors to accept increasing the firm's assets or overinvestment in a specific project.

Consequently, we infer that commonality in asset growth strategies of connected firms can affect wealth of shareholders because, as Titman, Wei and Xie (2004) show, a market normally underreacts to negative implications of overinvestment, but because of limits to arbitrage, mispricing is not quickly arbitraged away. In another study, *McConnel and Muscarells (1985) show that firms when firms announce major capital investments, stock prices tend to respond favourably*. Our fourth hypothesis is:

Hypothesis 4: Asset growth commonality among connected firms can affect the wealth of shareholders.

3. Data and Sample Selection

We obtain data from three sources. Data on CEO characteristics and personal connections is sourced from BoardEx database, which provides biographical information on directors and top executives. Our data from BoardEx goes from 2000 to 2016. We obtain accounting data from Compustat and M&A transactions data from SDC. Our final sample includes all firms in the intersection of these three databases, 8,736 U.S. firms for 13,980 CEOs.

3.1 Variable Definitions

1. Measures of CEO Network Size

From BoardEx, we measure CEO personal connections by counting the number of individuals with whom the CEO shares a common educational, employment, or social history. Two CEOs are connected through employment history in a particular year if they were employed at or served on the board of the same company before or during that year. Two CEOs are connected through education if the two attended the same institution, graduated within one year of each other and obtained a same type of degree (Cohen, Frazzini and Malloy, 2010). Two CEOs are connected through social connections if they have established connections through social activities such as clubs, charities, sporting or other not-for-profit organisations.

$$CEO\_Network\_Total_{i,t} = \sum Network\_Emp_{i,t} + \sum Network\_Edu_{i,t} + \sum Network\_Other\_Act_{i,t} \qquad 1$$

where ***Network Emp**$_{i.t}$* sums a CEO's current and past employment connections, ***Network Edu**$_{i,t}$* sums a CEO's education connections, and ***Network Other Act**$_{i,t}$* sums a CEO's other social activity connections.

2. The Measure of Asset Growth

We calculate the annual change in total assets for all stocks in the sample. The sample includes ordinary common shares listed on NYSE/AMEX/NASDAQ. We obtain annual data from 2000 to 2016 from Compustat to construct the main variable of interest, the annual firm asset growth rate (ASSETGRWTH). Following Cooper, Gulen, and Schill (2008), we calculate the annual firm asset growth using the year-on-year percentage change in total assets. We filter the data by removing all firms with zero or negative total assets. The firm asset growth rate for year t is estimated as the percentage change in total assets from fiscal year ending in calendar year $t-1$ to fiscal year ending in calendar year t, as below:

$$ASSETGRWT(t) = \frac{\left[(Total\_Asset_{(t)}) - (Total\_Asset_{(t-1)})\right]}{\left|(Total\_Asset_{(t-1)})\right|} \qquad 2$$

3. Measures of Corporate Investment

We consider two major forms of corporate investment to investigate the channels through which firms increase assets: acquisitions and R&D investments. We define *Acquisitions rate* as the value of acquisitions scaled by the total book assets at the beginning of the year. For acquisitions, we follow Pan, Wang, and Weisbach (2016) to include only completed deals covered by the SDC database, either the acquisition of assets or equity interest. For each sample firm, we include domestic and international acquisitions with disclosed transaction values above $1 million over the period[3]. Similarly, *Investment Rate* is defined as the sum of acquisition value and capital expenditure scaled by lag of total book assets (Pan, Wang, and Weisbach, 2016). We define *R&D investment rate* following Faleye, Kovacs, and Venkateswaran (2014) as the ratio of R&D expenditure to total assets.

3.1 Control Variables

We control for several firm factors (e.g., firm size, cash flow, return on assets) that can potentially affect corporate investments. Appendix A defines all variables.

3.2 Descriptive Statistics

Table 1 reports the descriptive statistics for the described variables. The table shows that firms in our sample are large with average sales of $2.6 billion and total assets of $7.1 billion. Focusing on the main variable of interest, the average (median) asset growth rate is 8.9% (2.4%) and the standard deviation of asset growth is 33%. Table 1 also shows that the average *Acquisition rate* is 1.4% (median 0%), the average *R&D investment rate* is 10.3%, the *average non-merger growth rate,* i.e., growth not attributed to mergers and acquisitions, is 98.3%. The table also reports firm characteristics. It shows that the *acquisition ratio*, defined as the ratio between acquisition expenditure and total assets, averages 3.1% (median 0%), the average *Capx rate* is 3.8% (median 1.8%), the average *investment ratio* is 5.4%, the average *cash ratio* 19.4% and the average leverage is 25.4% (median 18.2%).

[3] We exclude leveraged buyouts, exchange offers, repurchases, spin-offs, minority stake purchases, recapitalizations, self-tenders and privatizations.

We also report summary statistics of CEO network size in Table 1. The results show that, without taking into consideration industry connections, on average, a CEO is connected to approximately 24 individual CEOs. Focusing on connections among CEOs belonging to the same industry, the results reveal that, on average, a CEO has four connections with other CEOs in the same industry. This shows that CEOs in the sample have more connections with CEOs working in different industries.

INSERT TABLE 1

In the Appendix, we report the additional summary statistics of our main variable of interest on a year by year basis from 2000 – 2016. We find the average annual asset growth rates for the period to be monotonic with 2000 and 2004 recording the least and highest average asset growth rates, respectively. The yearly average standard deviation of growth is 32.1% over the entire period. We group all firms in our sample into 10 deciles. The average annual asset growth rate for decile 10 firms is substantially high at 82.7 %, which is similar to the results in Cooper, Gulen and Schill (2008). The average annual asset growth rate for decile 1 firms, which are low growth firms, is -31.8%. The average annual asset growth rate of decile 6 is 4.2% per year, and decile 7 is 8.2%.

4. Empirical Analysis and Results

4.1 Estimating Commonality in Asset Growth Across Connected Firms

Our first hypothesis (H1) predicts that asset growth among firms with CEOs having personal connections covary strongly with each other, i.e., we hypothesized a positive relationship between asset growth comovement and CEOs' personal connections.

To construct a measure of commonality in asset growth across connected firms, we adopt the approach of Anton and Polk (2014) and Koch, Ruenzi and Starks (2016). Following this approach, we obtain a measure of commonality in asset growth among connected firms by estimating the covariance between annual asset growth of an individual firm and the average annual asset growth of a portfolio of firms connected to the individual firm. The portfolio of stocks constructed for each firm is a representative of all stocks connected to an individual firm. For instance, if a firm is connected to 10 firms, then the portfolio of stocks will comprise of the 10 firms having connections with the individual firm. The coefficient obtained is a measure of asset growth comovement across connected firms. To begin, we estimate regressions of changes in annual asset growth, for each individual firm, which we denote as $\Delta AssetGrowth_{i,t}$ on changes in the annual asset growth of a portfolio of firms connected to the individual firm denoted as $\Delta AssetGrowth_{j,t}$. We follow the literature and include a number of control variables that can influence firm level asset growth in estimating our baseline regression model presented in equation 3 (Fracassi, 2016; Pan, Wang, and Weisbach, 2016). In Appendix B, w**e** report the summary statistics of the value-weighted portfolio average of annual asset growth rate of the portfolio of firms connected to each individual firm, $\Delta AssetGrowth_{j,t}$.We find $\Delta AssetGrowth_{j,t}$ to be monotonic.

We use equation 3 to test the first hypothesis. We conduct additional tests for robustness by adding a new variable, $\Delta AssetGrowthInd_{k,t}$ to cater for the industry influence as shown in equation 4 in testing my first hypothesis since industry factors can influence the asset growth decisions of firms. The new variable, $\Delta AssetGrowthInd_{k,t}$ is defined as the average asset growth rate of a portfolio of firms that are connected to the firm belonging to the same industry.

$$\Delta AssetGrowth_{i,t} = \beta_0 + \beta_{AG}\Delta AssetGrowth_{j,t} + \delta X_{i,t} + \varepsilon_{i,t} \qquad 3$$

$$\Delta AssetGrowth_{i,t} = \beta_0 + \beta_{AG}\Delta AssetGrowth_{j,t} + \beta_{AGI}\Delta AssetGrowthInd_{k,t} + \delta X_{i,t} + \varepsilon_{i,t} \qquad 4$$

If there is asset growth commonality across connected firms, then the annual asset growth of the individual firm and the average annual asset growth of a portfolio of firms connected to the individual firm will have a statistically significant positive relationship. Following the primary hypothesis, significance of asset growth betas will be evidence of asset growth covariation across connected firms (Koch, Ruenzi, and Starks, 2016). Hence, we anticipate the coefficients of asset growth betas $\beta_{AG} > 0$ in equation 3 and $\beta_{AGI} > 0$ in equation 4 to be positive and statistically significant. Obtaining statistically significant asset growth betas signifies that personal connections among CEOs, which facilitate firm connectedness, leads to the convergence of asset growth across connected firms.

Table 2 reports the regression results of equation 3[4]. We find that *Asset Growth Beta*, β_{AG}, which measures asset growth commonality across connected firms, is statistically significant at 1% level. We define the coefficient, asset growth beta, as the sensitivity of the individual firm asset growth to the variation in asset growth of firms connected to the firm (Kamara, Lou and Sadka, 2008). Table 2 results show that *Asset Growth Beta*, β_{AG}, without any control variables is 0.204 at 1% level of significance (see column 1). This value provides strong evidence of asset growth covariation across connected firms.

[4] For all regression results reported in this study, we include the constant term in the estimations but don't report the constant in the tables.

This results shows that not only firm level factors such as financial performance influence asset growth decisions, but the personal network of firms' top executives greatly influence asset growth. We attribute this phenomenon to CEO peer effects driven by CEO personal connections. We make this conclusion because one key objective of CEOs is to maximise their career outcomes in which their ability to grow a firm's assets and expand their corporations plays a key role. Hence, we argue that a CEO, in a network consisting of colleague CEOs who may have added assets in the current or previous year at their firm, is more likely to be influenced to follow the same trend by also increasing assets because of the strong effect of group thinking among individuals in a group with personal connections. Also, the quality of information flowing through a network can influence CEOs in the network to increase asset, relatedly. For instance, if private information flows through the network about potential projects, CEOs with access to such information may take advantage of it, which, we argue, may cause them to adopt similar actions in asset growth policies. We conclude that a CEO is more likely to increase assets if his peers have recently done so leading to asset growth comovement across connected firms. Thus, CEO connectedness can influence the adoption of related asset growth styles across connected firms. This conclusion confirms the findings of some earlier studies that examined the influence of peer effects across social networks and provided evidence that peers in a network imitate each other's actions (Kaustia and Rantala, 2015; Kaustia and Knüpfer, 2012).

In column 2, we include several control variables without including fixed effects. Again, we find asset growth beta, β_{AG}, is positive and highly significant at 1% level though its size is smaller (0.087) than that obtained in the absence of controls (0.204). In column 3, we include time fixed effects, which include the effect of any time-invariant firm level characteristics that may affect asset growth commonality. We find that although the coefficient estimate β_{AG} is somewhat reduced (to 0.024), it is still positive and highly significant at the 1% level. This shows the earlier results are not driven by time-invariant unobservable heterogeneity. From columns 4 - 7, we find β_{AG} to be positive and highly significant at 1%, which provides further evidence supporting earlier findings. For instance, in column 7 where we control for time fixed effects, firm fixed effects, industry fixed effects and several firm level characteristics, we still find β_{AG} to be positively significant at 1% level. These results confirm that CEO connectedness facilitates asset growth commonality across connected firms.

INSERT TABLE 2

Table 3 reports the regression output of equation 4 where we add a new variable to cater for industry effects. We estimate this regression because industry level factors also have a tendency to affect asset growth. We argue that though the peer effect directly influences the decisions of individuals, industry events may not permit CEOs to grow assets even if their peers have done so recently. From Table 3, we find both β_{AG} (0.175) and β_{AGI} (0.101) to be positive and statistically significant at 1% level in the absence of control variables, which supports earlier findings. We include several controls and fixed effects from columns 2 - 7 and get results similar to those in Table 2. These results confirm that the personal connections of a CEO are a strong determinant of asset growth among connected firms irrespective of the dictates of the industry.

INSERT TABLE 3

4.2 CEO Network Size and Commonality in Asset Growth

In section 4.1, we show that commonality in asset growth is prevalent among connected firms. For this section, we investigate the association between *Asset Growth Beta*, which is a measure of commonality in asset growth across connected firms, and CEO network size. We conjecture that, if connected firms grow assets similarly, then there must be a significant positive relationship between a firm's *Asset Growth Beta* and the firm's network size. This is because the magnitude of *Asset Growth Beta* depends on the total connections of the firm. Following the above argument, we examine whether firms with a large network have a larger *Asset Growth Beta*, β_{AG} than firms with a small network. As a test, we divide the sample into five quintiles on the basis of total CEO connections and estimate the cross-sectional means of asset growth beta for each quintile. We use CEO network size since it's regarded as a proxy for the relative importance of connections in the social network literature (Fracassi, 2016).

In Table 4, the mean asset growth beta decreased from 12.5% in the first quintile to 10.2% in the second quintile. However, it increased to 29.3% in quintile 3, 66.2% in quintile 4 before declining marginally to 62.6% in quintile 5. Comparing the averages of asset growth beta for the five groups, I observe that commonality in asset growth increases with network size even though the pattern is not monotonic. Comparing quintiles 1 and 5, the average *Asset Growth Beta* for quintile 5 is 80% (0.501) more than the average mean *Asset Growth Beta* for quintile 1 (0.125). Univariate analysis suggests that a larger network is associated with a larger *Asset Growth Beta*.

INSERT TABLE 4

Next, we estimate regressions of commonality in asset growth on total CEO network size to test the hypothesis that the magnitude of commonality in asset growth increases with size of CEO connections using equation 5 below. The dependent variable in equation 5 is the measure of commonality in asset growth across connected firms, *Asset Growth Beta* β_{AG} obtained for each firm using equation 3.Obtaining a positive and statistically significant coefficient value for CEO network size, the variable of interest in equation 5, implies that CEO network size is a determinant of commonality in asset growth. In the regression, we include industry-fixed effects and cluster the standard errors at the firm level to account for cross sectional dependence. The specification is:

$$\ln(\beta_{AGi,t}) = \alpha + \beta_1 \ln(CEO\_Network\_Total)_{i,t} + \delta X_{i,t} + \varepsilon_{i,t} \qquad 5$$

The results of this regression model are summarized in Table 5. In Column 1, Table 5, the coefficient of CEO total network size is 0.091, which is statistically significant at 1% level. This indicates that a CEO's network size influences asset growth decisions taken by the CEO. Given that the sample mean of CEO network size is 23.526 and CEO network size increases commonality in asset growth among connected firms by 0.091, we find the economic impact of 0.39% (0.091/23.526) is significant. In column 2, we include control variables and obtain similar results as recorded in column 1. Again, we find the coefficient of the CEO's network size to be statistically significant at 1% level with it increasing to 0.146. From columns 3 - 5, we find the main variable of interest, the CEO network, to be statistically significant at 1% in all specifications. Following the results presented in Table 5, we conclude that CEOs with a large network are likely to increase assets if their peers have recently done so. According to Décaire, Gilje, and Taillard (2019), firms learn by observing investment decisions of other firms. Hence, we attribute our findings to the CEO peers' influence.

INSERT TABLE 5

We estimate additional regressions to support earlier findings that there is a positive significant relationship between Asset Growth Beta and CEO network size as reported in Table 5. First, we estimate the relationship between annual asset growth rate and annual CEO network size for each firm using the specification model in equation 6[5]. From equation 6, we define $\Delta AnnaulAssetGrowth_{j,t}$ as the annual average asset growth rate of a portfolio of firms connected to the individual firm per year and define $Annaul\_CEO\_Network\_Total_{i,t}$ as the annual CEO network size as a measure of the individual firm's annual network size. We estimate these variables for each firm for each year. We predict a significant positive relationship between the two key variables of interest in equation 6. We construct the dependent variable in equation 6, $\Delta AnnaulAssetGrowth_{j,t}$, by creating a portfolio of firms connected to each individual firm in a particular year based on the network size of the individual firm for that year then we estimate the average asset growth rate.

$$\ln(\Delta AnnaulAssetGrowth_{j,t}) = \alpha + \beta_1 \ln(Annaul\_CEO\_Network\_Total)_{i,t} + \delta X_{i,t} + \varepsilon_{i,t} \qquad 6$$

We further investigate the significant positive association between CEO network and commonality in asset growth using equation 7. In this regression, we calculate the overall average annual asset growth rate of a portfolio of firms connected to the firm for 2000-2016

[5] The results are . Consistent with the hypothesis and earlier results, we find that the coefficient of annual CEO network size is 0.010, which is statistically significant at 1% level. In column 2, we include controls in the model and obtain similar results. In columns 3 - 5, we add year effects, firm effects and industry effects to cater for any unobserved heterogeneity and correlations. Again, we find a statistically significant coefficient of annual CEO network size at 1% level, even though the magnitude is reduced for regressions in columns 3 - 5. This additional test confirms that asset growth decisions by CEOs are influenced by their peers.

and label it $\Delta TotalAssetGrowth_{j,t}$. Succinctly, we obtain the dependent variable in equation 7 by finding the overall average of annual asset growth rate for each firm. We then regress each firm's $\Delta TotalAssetGrowth_{j,t}$ on total the CEO network size for the period to examine whether we obtain similar results to those from equations 5 and 6:

$$\ln(\Delta Total\_Asset\_Growth_{j,t}) = \alpha + \beta_1 \ln(CEO\_Network\_Total)_{i,t} + \delta X_{i,t} + \varepsilon_{i,t} \qquad 7$$

As predicted, we find from columns 1 – 5, Table 7, that the coefficient of CEO network size to be statistically significant at 1% level for all models. From the regressions, we find that the more connections CEOs share with each other, the more that the CEOs may adopt similar asset growth strategies.

In summary, asset growth increases with the size of the CEO's personal network suggesting that social and professional interactions among CEOs affects firms' asset growth strategies.

INSERT TABLE 7

There are multiple reasons why CEO networks influence the asset growth strategies of connected CEOs leading to commonality in asset growth among connected firms. A CEO has access to internal information through the firm's internal information system and information from personal outside contacts. Prior literature shows social and professional ties as an efficient conduit for information transfer in many business settings (Hochberg, Ljungqvist and Lu, 2007; Cohen, Frazzini, and Malloy, 2008, 2010; Engelberg, Reed, and Ringgendberg, 2012). One mechanism through which CEO networks impact on asset growth is that the social and professional ties among CEOs can help improve the quality of CEOs' asset growth strategies by providing information regarding future industry or macro level trends. When a CEO decides to increase assets, we argue that his/her network contacts will be more useful than the firm's internal information. To illustrate this intuition, suppose three CEOs in a network want to increase assets in the coming year. CEO A has a high reputation and ranking whereas CEOs B and C are upcoming CEOs hoping to maximise their career outcomes through empire building. Let's say CEO A, who is highly respected, releases information relating to new investment opportunities, CEOs B and C, who are socially connected to CEO A, may accept the information for implementation in their firms because of the expectation that it will produce better outcomes following the background and experience of CEO A. This information may be classified as quality information by CEOs B and C.

We argue that CEO networks impact on asset growth choices of CEOs since they reduce the search costs associated with finding the right investment opportunities. Podolny (1994) argues that managerial decisions are often based on personal experience because of cognitive constraints and information search costs. That is, because of the cost of searching for the right investment, CEOs may first choose from within a subset of potential partners with whom they are familiar. For example, from the earlier example of three CEOs, CEOs B and C may easily rely on the information obtained from CEO A because of the huge costs associated with finding the right investment, which leads to all CEOs adopting similar asset growth strategies creating asset growth commonality among them. Similarly, let's assume CEO A announces to the members of the group about a potential investment opportunity in his firm, then CEOs B and C, following Podolny's (1994) argument, may first consider the investment opportunity offered by CEO A since CEO A is within their network and it will reduce their search costs for investment opportunities. Additionally, following Cai and Sevilir (2012), we argue that CEOs B and C will consider the investment opportunity offered by CEO A because prior studies show that in an investment transactions, social ties among CEOs increases each firm's knowledge and understanding of the other firm's operation, which leads to better transactions because of enhanced knowledge and information advantage.

Our findings agree with some key earlier studies. For example, theory and research in both social psychology and sociology show that people who share social ties tend to hold similar points of view on relevant issues, which leads to similarity in actions (Lazerfeld and Merton, 1954; Byrne, 1971). These studies show that frequent interactions among individuals with social ties results in their opinions becoming even more similar (Hackman, 1983; Marsden and Friedkin, 1993; Rogers and Kincaid, 1981; Tichy, 1981). Other studies suggest that managers with a similar functional background with personal connections are often associated with similarity in points of view and often develop similar mental models and diagnose strategic issues in similar ways (Beyer, Chattapadhyay, George, Glick, Ogilvie and Pugliese, 1997; Dearborn and Simon, 1958; Finkelstein and Hambrick, 1996). Thus, in general, people with social ties tend to offer similar points of view.

We argue that our findings can be attributed to bonds that exist among CEOs having personal connections; McDonald and Westphal (2003) show that managers prefer to interact with individuals who are similar to themselves or with whom they share strong social bonds. Thus, a CEO with a social bond with other CEOs through social and professional interactions can mimic their asset growth decisions as explained earlier because of similar points of view leading to commonality in asset growth among these CEOs. We conclude that CEOs in a network with similar beliefs and aspirations are more likely to grow assets similarly. Additionally, we conjecture that social and professional ties among CEOs make them potential information sources for a firm's asset growth decisions. Thus, to a large extent, CEOs exploit information relating to asset growth that permeates through the network making CEO network size a potential determinant of firm asset growth strategies and the ability to identify new investment opportunities.

4.3 Potential Channels for facilitating Commonality in Asset Growth among connected firms.

In this section, we explore the underlying channels that lead to the positive correlation between CEOs personal connections and commonality in asset growth. We consider two potential channels: M&A decisions and R&D investment decisions. We discuss and evaluate each in turn.

4.3.1 Commonality in Asset Growth and Similarity in M&A Decisions

We test the hypothesis that similarity in M&A decisions by connected firms is a channel through which CEO connectedness drives asset growth commonality. Findings in the finance literature propose a number of corporate polices, such as the allocation of capital through M&A activities and the design of compensation schemes by a firm, are influenced significantly by the discretionary power of executives (Bertrand and Schoar, 2003; Frank and Goyal, 2007; Graham, Li and Qiu, 2012). In addition, a large finance literature body shows that executives' personal characteristics such as risk aversion, optimism and ability, influence corporate outcomes (Malmeidier and Tate, 2008; Graham, Campbell and Puri, 2012; Kaplan, Klebanov and Sorensen, 2012). However, firm executives are extremely networked social agents. Even though executives tend to be guided by their own inherent preferences and beliefs when taking corporate decisions, they are also likely to be influenced by their peers (Kaustia and Rantala 2015). Renneboog and Zhao (2013) and Cai and Sevilir (2011) reveal that M&A transactions are affected by director networks. Shue (2013), in examining the relationship between executive peer networks and managerial decisions, concludes that firm acquisiton outcomes are significantly more similar among executives who were students in the same MBA section.

In line with the above, we argue that a firm's asset growth outcomes, faciliated by the adoption of inoganic growth strategies such as M&A and takovers, can be affected by the social and professional connections of executives since it is well established that social ties among executives significantly affect several aspects of corporate behaviour. This is because valuable information on a dizzying number of new opportunities and investment projects can flow through executive networks on which a CEO through peer influence may act to the mean group behaviour, follow group leaders, or adopt the group norm to increase assets. In such a situation, we argue that, regardless of how peer influence occurs, section-based interactions will lead connected CEOs to increase assets like everyone in the group is doing because CEOs have discretionary power when it comes to allociation of capital for investment and can convince the board of directors to adopt projects being adopted by colleague CEOs. Following that argument, we predict that such behavior will lead to commonality in asset growth among CEOs with personal connections. We use the regression model, equation 8, to test the conjecture.

To test this hypothesis, we compute the annual acquisition rate of each individual firm as the dependent variable in equation 8. The annual acquisition rate, $Acquisition\_Rate_{i,t}$, in equation 8 is defined as the value of acquisitions during the year scaled by the total assets at the beginning of the year. We then calculate the annual average acquisition rate of a portfolio of firms connected to specific the firm and label that $Network\_Acquisition\_Rate_{i,t}$. We then estimate regressions of the individual firm acquisition rate on the average acquisition rate of the portfolio of firms connected to the firm as indicated in equation 8.

$$\ln(Acquisition\_Rate_{i,t}) = \beta_0 + \beta_1 \ln(Network\_Acquisition\_Rate_{i,t}) + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \qquad 8$$

The results in Table 8 are consistent with our hypothesis. In column 1, in the absence of controls, we find the coefficient of $Network\_Acquisition\_Rate$ is 14.8% and statistically significant at 1% level. In column 2, we include control variables that are likely to influence acquisitions and again we obtain significant results similar to those in column 1. We also include year fixed effects, firm fixed effects and industry fixed effects to control for common fluctuations in M&A activities across connected firms over time and industry differences in the level of M&A activities. We get significant results in columns 3 - 6 with the magnitude of coefficient being statistically significant at 1% level. Overall, the evidence indicates that CEOs with personal networks grow assets similarly in M&A decisions as observed by Shue (2013).

INSERT TABLE 8

We conduct further tests using a different approach to check whether the conclusions from Table 8 results change. First, we use equation 9 below to obtain the residual (or excess) of acquisition policy rate for each firm by finding the absolute difference between each firm's annual acquisition rate and the average annual acquisition rate of firms connected to the individual firm as reported from equation 9.The outcome variable, which we denote as $Firm\_Own\_Acquisition\_Growth_{i,t}$, in equation 9 is proxy for the difference in the acquisition policy decisions between the individual firm and the firms connected to the that firm. We define the output obtained from equation 9 as acquisition policy decisions that can be attributed to the effort of the individual firm excluding influence from firms connected to that firm. The smaller the variable, then the more the individual firm is influenced by firms connected to it when it comes to acquisition policy decisions and vice versa.

$$Firm\_Own\_Acquisition\_Growth_{i,t} = \left|\varepsilon_{i,t}\right| = abs(Acquisition\_Rate_{i,t} - Network\_Acquisition\_Rate_{i,t}) \quad 9$$

In the second step, we regress $Firm\_Own\_Acquisition\_Growth_{i,t}$ obtained from equation 9 for each individual firm on $Network\_Acquisition\_Rate_{i,t}$, which is the average acquisition rate of the portfolio of firms connected to the firm to test whether the acquisition policy attributed to the individual firm relates to the average acquisition rates of the portfolio of firms connected to the firm using equation 10. From equation 10, a significant negative relationship between the two main variables shows that the individual firm is able to make its own acquisitions without peer influence from firms connected to it. However, following El-Khatib, Fogel, and Jandik (2015) and Fracassi (2016), we expect a significant positive relationship between the two main variables in equation 10 because of the strong effect of group influence and peers. We argue that a CEO in all situations observes the activities and actions of his/her peers and makes decisions, hence, in all instances, a CEO's decisions will have some component that can be attributed to influence from personal connections.

$$\begin{aligned} &\ln(Firm\_Own\_Acquisition\_Growth_{i,t}) = \beta_0 + \beta_1 \ln(Network\_Acquisition\_Rate_{i,t})_{i,t} + \\ &\beta_2 Controls_{i,t} + \varepsilon_{i,t} \end{aligned} \quad 10$$

The results from equation 10 are summarized in Table 9. As predicted, we find the coefficient of $Network\_Acquisition\_Rate$ is 0.972, which is statistically significant at 1% level in the absence of controls. In models 2-6, Table 9, we include several control variables and control for time, industry and firm effects. Again, we find the coefficient of acquisition rates of firms connected to the individual firm to be positive and statistically significant at 1% level in all specifications. This explains the earlier conclusion that the asset growth of firms that are connected comoves. The results from Tables 8 and 9 point to the fact that the acquisition policy of firms in all situations is influenced by the acquisition policies connected firms.

INSERT TABLE 9

Faleye, Kovacs, and Venkateswaran (2014) find that CEO connections help CEOs to be more innovative. Hence, we argue that CEOs in a network may obtain information relating to new opportunities and investments that may not relate to M&A decisions, but they can also lead to increased asset growth. We conjecture that CEO connections can facilitate asset growth commonality from sources other than M&A decisions. Following Bliss and Rosen (2001), we calculate non-merger growth for each firm and test whether non-merger growth among connected firms is similar. We test whether asset growth commonality among connected firms may also be fuelled by non-merger growth strategies. We use equation 11 below to test the claim by estimating the regression of annual non-merger growth of each individual firm, which we denote as $Non\_Merger\_Growth\_Rate_{i,t}$, on the average of annual non-merger growth of a portfolio of firms connected to the firm, $Network\_Non\_Merger\_Growth\_Rate_{j,t}$.

$$\ln(Non\_Merger\_Growth\_Rate_{i,t}) = \beta_0 + \beta_1 \ln(Network\_Non\_Merger\_Growth\_Rate_{j,t}) + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \quad (11)$$

We estimate equation 11 above and present results in Table 10. We find the regression coefficient of $Network\_Non\_Merger\_Growth\_Rate_{j,t}$ is statistically significant at 1% level for all specifications reported in columns 1- 5, Table 10, which suggests that the non-merger growth rate of connected firms is related confirming the strong effect of executives' networks in corporate outcomes

INSERT TABLE 10

To further substantiate the findings obtained regarding non-merger growth among connected firms reported in Table 10, we conduct additional tests as using equations 12 and 13 below. Like the earlier analysis, we obtain the absolute difference between the non-merger growth of each firm, $Non\_Merger\_Growth\_Rate_{i,t}$, and non-merger growth of firms connected to the the firm, $Network\_Non\_Merger\_Growth\_Rate_{j,t}$, using equation 12. We then regress the outcome from equation 12, which we define as non-merger growth policies attributed to the individual firm without influence from firms connected to it on the average non-merger growth rate of firms connected to the firm, $Network\_Non\_Merger\_Growth\_Rate_{j,t}$, as shown in equation 13.

The results in Table 11 are consistent with our prediction in all specifications. This result confirms that social ties among CEOs enhances innovativeness since aside from growing assets through similar M&A decisions, they also adopt similar non-merger decisions.

$$\begin{aligned}&Firm\_Own\_Non\_Merger\_Growth_{i,t} = \left|\varepsilon_{i,t}\right| = abs(Non\_Merger\_Growth\_Rate_{i,t} - \\ &Network\_Non\_Merger\_Growth\_Rate_{j,t})\end{aligned} \qquad 12$$

$$\begin{aligned}&\ln(Firm\_Own\_Non\_Merger\_Growth\_Growth_{i,t}) = \beta_0 + \beta_1 \ln(Non\_Merger\_Growth\_Rate_{j,t}) \\ &+\beta_2 Controls_{i,t} + \varepsilon_{i,t}\end{aligned} \qquad 13$$

INSERT TABLE 11

4.3.2 Commonality in Asset Growth and Similarity in R&D Investment Rates

Faleye, Kovacs and Venkateswaran (2014) show that social and professional interactions among firms' top executives enable better connected CEOs to invest more in R&D and often receive higher quality patents. Malmendier and Tate (2008) and Shue (2013) indicate that executives can meaningfully affect firm policies. Based on those findings, we argue that a CEO can influence R&D investment decisions at the firm level by relying on information relating to R&D investments obtained from peer CEOs. In effect, if other CEOs in the network react to the same information to invest in the same R&D projects, then asset growth commonality is likely to prevail among the connected firms.

Hypothesis 3 states that the similarity in R&D decisions among firms with CEOs with personal connections is a channel through which CEO connectedness drives asset growth commonality. To do this, we test whether the R&D policies of connected firms are similar using a pair model.

$$R\&D\_Policy_{i,t} = a_o + a_1 X_{pi,t} + \varepsilon_{i,t} \qquad 14$$

First, we account for as much of a firm's R&D policy as possible by regressing the R&D policy for each firm, $R\&D\_Policy_{i,t}$, specific control variables, $X_{pi,t}$, that determine R&D policy as shown in equation 14. As described, first, we estimate the regressions of the individual firm's R&D policy, $R\&D\_Policy_{i,t}$, on a number of control variables, $X_{pi,t}$, that mostly determine R&D policy decisions. The residual, $\varepsilon_{i,t}$, in equation 14 denotes residual (or excess) of R&D policy of the individual firm at time (t). We present results from equation 14 in Table 12. We find the significance of the regression coefficients of the main control variables to be consistent with prior studies.

INSERT TABLE 12

$$PolicyDissimilarity = \left|\Delta\varepsilon_{i,j,t}\right| = abs(\varepsilon_{i,t} - \varepsilon_{i,j}). \quad 15$$

Next, we estimate the dissimilarity in R&D policies across connected firms using the residual from equation (14), which represents the excess, or idiosyncratic, component of the policy for the individual firm at time t relative to the expected policy according to the standard model. We define R&D policy dissimilarity across connected firms using equation 15 as the absolute value of the difference in the residuals of the individual firm R&D policy, $\varepsilon_{i,t}$, and the average of the residuals of R&D of the portfolio of firms, $\varepsilon_{i,j}$, that are connected to the firm, $\varepsilon_{i,t}$. The results from equation 15 measure the difference in R&D policy decisions among firms that have connections with each other. Following Fracassi (2016), the smaller the variable, the more similar the R&D policies of connected firms and vice versa.

$$\ln(\beta_{AGi,t}) = \alpha + \beta_1 \ln(\left|\Delta\varepsilon_{i,j,t}\right|) + \delta_{controls_{i.t}} + \varepsilon_{i,t} \quad 16$$

In the third and final step, we regress *Asset Growth Beta* from equation 3 on R&D policy dissimilarity from equation 15 using equation 16. Using equation 16, we test whether similarity in R & D policy decisions among connected firms facilitates asset growth commonality. The definition of R&D policy dissimilarity, which is the key independent variable of interest in equation 16, indicates that R&D policy investment decisions of firms that are connected will not be similar if coefficient β_1 increases positively. Thus, R&D policy decisions of connected firms will deviate from each other. The above proposition in equation 15 implies that there will be no similarity in R&D investment among connected firms to facilitate commonality in asset growth as predicted. In effect, we expect a negative coefficient β_1 for equation (16). This implies that, as R&D investment policy dissimilarity becomes more negative, then R&D investment decisions among connected firms become more similar leading to commonality in asset growth. The results from equation 16 are in Table 13 with strong evidence supporting my hypothesis. In column 1, Table 13, the coefficient of R&D investment dissimilarity is -0.108, which is statistically significant at 1% in the absence of controls. This result implies that holding all other factors constant a unit decrease in dissimilarity in R& D policy increases commonality in asset growth. We obtain similar results in columns 2 - 5 where we add control variables and cluster the standard error at the firm level. These findings confirm earlier studies that CEO connections facilitate similarity in corporate finance policies and investment strategies (Kaustia and Rantala 2015; Fracassi 2016). We show that CEO peer networks meaningfully affect the asset growth decisions of connected firms making them similar through the adoption of similar R&D investment.

INSERT TABLE 13

To provide further evidence supporting our findings related to similarity in R&D policy decisions and asset growth commonality among connected firms, we estimate additional regressions to test hypothesis 3.

$$Firm\_Own\_R\&D\_Growth_{i,t} = \left|\varepsilon_{i,t}\right| = abs(R\&D\_Rate_{i,t} - Network\_R\&D\_Rate_{j,t}) \qquad 17$$

First, we obtain the absolute difference between R&D policy rates of the individual firm at time t, $R\&D\_Rate_{i,t}$ and average the R&D policy rates of the portfolio of firms connected to that firm at time t, $Network\_R\&D\_Rate_{j,t}$ using equation 17. We define the residual outcome from equation 17, $Firm\_Own\_R\&D\_Growth_{i,t}$, as R&D policy decisions that can be attributed to the individual firm exclusive of influence from firms connected to the firm. The smaller the variable, the more the individual firm is influenced by peer firms in R&D policy decisions and vice versa.

$$\ln(Firm\_Own\_R\&D\_Growth_{i,t}) = \beta_0 + \beta_1 \ln(Network\_R\&D\_Rate_{i,t}) + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \quad 18$$

We next test for the relationship between R&D policy decisions attributed to the individual firm without influence from peers and the R&D policy decisions of firms connected to the firm. We regress the outcome of equation 17 on the average R&D policy of portfolio of firms connected to the individual firm, $Network\_R\&D\_Rate_{i,t}$ as shown in equation 18. A positive significant result for the coefficient $Network\_R\&D\_Rate_{i,t}$ implies that, when it comes to R&D investment decisions, a CEO will, at all costs rely on decisions of peer CEOs to arrive at a decision. We report results from equation 18 in Table 14 with strong evidence supporting the earlier conclusion that connected firms observe the R&D decisions of peers. In column 1, we find the coefficient of β_1 in equation 18 to be 0.551, statistically significant at 1% level. This indicates the strong influence of social ties among firm executives in corporations since we find evidence of a positive, statistically significant relationship between an individual firm's own efforts in R&D investment decisions and the R&D decisions of firms connected to the firm. We conduct additional test using investment rate.[6]

[6] Additional Analysis on Potential Channels using investment rates. Following, Pan, Wang, and Weisbach, (2016) we test for additional channels using investment rate defined as the sum of value of acquisition and capital expenditure lagged by total assets. Similar to the above analysis, we estimate investment rate for each firm for the

INSERT TABLE 14

4.4 Commonality in Asset Growth and Firm Performance

Following the comprehensive evidence indicating that asset growth rates of firms with connections covary, we test its economic benefit by investigating the relationship between asset growth commonality and firm performance. Shue (2013), in examining the relationship between executive peer networks and several corporate policies, reveals that peer influence can operate in ways that do not contribute to firm productivity. We test hypothesis 4 which state that: commonality in asset growth affect firms negatively

In this essay, we base our analysis of firm performance on both accounting performance and stock market performance. To test the claim, we focus on year-to-year changes in a firm's return on asset (RoA) and annual stock returns as a measure of firm performance (Titman, Wei, and Xie, 2004; Cooper, Gulen, and Schil, 2009; Larcker, So and Wang ,2013).

$$(ROA_{i,t}) = \alpha + \beta_1 \ln(\beta_{AGi,t}) + \delta_{controls_{i.t}} + \varepsilon_{i,t} \qquad 19$$

Next, we regress Asset *Growth Beta*, $\beta_{AG,i,t}$ for each firm obtained from equation 3, our measure of commonality in asset growth among connected firms, on $ROA_{i,t}$ return on assets as shown in equation 19.

period under review and run regressions to ascertain whether investment rate across connected firms is a channel that drives asset growth commonality across connected firms. We argue that investment rate across connected firms will be similar as a result of information propagation across the network through different nodes. We obtain similar findings recorded earlier using acquisition rates and R&D investment rates and reports results in the Appendix C

The results from equation 19 are summarized in Table 15. We find the regression coefficient of Asset *Growth Beta* is negative and statistically significant at 1% level. This results shows that asset growth commonality affects shareholders negatively. One possible explanation for this outcome can be attributed to strong peer influence and trust that comes from the personal connections of CEOs as well as group thinking (Asch and Guetzkow, 1951). For example, Uzzi (1996, 1999) finds that enhanced trust that exists among individuals with social connections most often leads individuals with personal connections to take actions that are mutually acceptable and predictable, which leads to group thinking. Additionally, we argue access to same information flowing through the firm executives network is likely to influence connected individuals to think similarly leading to group thinking since individuals may depend on whatever information is obtained through the network to take strategic decisions at the firm level. As a result, we conclude that group thinking, which is a potential driver of asset growth commonality among connected firms, has no economic benefits for firms.

INSERT TABLE 15

$$(Annual\_Stock\_\mathrm{Re}turns_{i,t}) = \alpha + \beta_1 \ln(\beta_{AGi,t}) + \delta_{controls_{i,t}} + \varepsilon_{i,t} \qquad 20$$

We further test using annual stock returns as shown in equation 20 and obtain similar results. The negative, statistically significant results obtained for the relationship between asset growth commonality and firm performance confirms earlier studies that examine the dark side of network ties among top management on firm (eg., Ishii and Xuan 2014).

INSERT TABLE 16

The results from Tables 15 and 16 are important, since they raise further questions whether CEO networks add value to a firm. We find that commonality in asset growth among CEO's with personal connections does not seem to have any beneficial impact on a firm's performance, which challenges the significance of CEOs' social and professional networks to firms (Larcker, So and Wang, 2013; Renneboog and Zhao, 2013). Clearly, imitation of asset growth strategies among peer CEOs having personal connections does not improve firm performance. One possible explanation is that CEO connections influence CEOs to pursue additional unprofitable projects. This result supports the managerial power approach observed by Bebchuk, Fried, and Walker (2002). We argue that through managerial power and influence a CEO may grow a firm's assets even if not necessarily leading to no value addition to the firm.

Is the commonality in asset growth economically significant? Recent papers have debated on the negative correlation between asset growth and subsequent returns and conclude that the asset growth effect is not economically material, as it exist only among small cap stocks. We add to the literature by providing evidence that asset growth commonality is pervasive across connected firms through firm executives social network ties. The implications of our findings on the link between commonality in asset growth and firm performance is that, social network of CEOs is at least powerful in explaining asset growth effects and that the asset growth effect is economically material from our results because the effect exist for both large and small cap stocks in our sample.

4.5 Controlling for Endogeneity and Concerns

The main question that we consider in the essay is whether personal connections among CEOs lead to commonality in asset growth across connected firms. We argue that firms with CEOs having personal connections are more likely to adopt similar asset growth strategies leading to asset growth commonality among connected firms. Our hypothesis was tested in a regression framework in which we provide evidence of asset growth commonality among connected firms.

Interestingly, although prior literature shows the impact of peer effects among firm executives in corporations (Leary and Robert, 2014; Grennan, 2019), clear identification of the factors that fuel the causal relationship remains a challenge (Manski, 1993). This is because peer effects among CEOs with personal connections cannot be observed directly and this raises concerns about omitted variables since they are distinct from industry and location factors. These endogeneity issues call into question the proper interpretation of the OLS regression results in Table 5. We address endogeneity issues in this essay using instrumental variables and a difference in difference approach.

4.5.1 Instrumental Variable Regression

We have shown that CEO personal connections are determinants of a firm's asset growth strategies. The knowledge that CEOs obtain valuable information from their peers through social interactions that enhances the quality of decisions they take and investments opportunities that they make could prompt CEOs to build stronger networks to maximise the benefits relating to asset growth strategies. Also, a CEO hired by a firm to improve the quality of asset growth may lead to an increased network of the CEO should the CEO succeed in increasing the firm's profitability and growth. However, the CEO's network size is influenced by several factors, only some of which are influenced by the CEO's choices. Burt (1992) and Granovetter (1995) note that the strength and structure of a CEO's overall connectedness represents his or her social capital and outside employment opportunities. Hence, firms are compelled to consider a CEO's network size before appointing them; what remains uncertain is whether this is a first-order effect. The probability that CEOs' personal connections enhances the choice of CEO creates a potential endogeneity and bias from correlated omitted variables since CEO's network size changes over time. To address potential endogeneity concerns arising from unobservable heterogeneity, we estimate instrumental variables by two-stage least squares (2SLS) regressions to check the effects of endogeneity on the results.

Following, Faleye, Kovacs, and Venkateswaran (2014), we chose the industry average CEO network size as the instrumental variable since it relates positively to the underlying explanatory variable, the CEO total network size, but is unrelated to the residuals in the second stage equation, *Asset Growth Beta.* We adopt this instrument because firms follow industry practices and norms of which interlocking practices among CEOs with personal connections would pave way for individuals to build networks within their industry. The basic requirement for the validity of the selected instrument is that it must have no effect on the dependent variable other than through the effect on the suspected endogenous independent variable.

The structural equation estimated in earlier analysis to test the influence of CEO networks on commonality in asset growth is:

$$\ln(\beta_{AGi,t}) = \alpha + \beta_1 \ln(CEO\_Network\_Total)_{i,t} + \delta_{controls} X_{i,t} + \varepsilon_{i,t} \qquad 21$$

The dependent variable is Asset Growth Beta, β_{AG}, the measure of commonality in asset growth.

In the first stage of the two-stage instrumental regressions adopted to address the endogeneity issue, we fit *CEO network size total* unto the instrumental variable *Industry Average CEO Network Size* as in equation 22 and then use the fitted value of this variable in the second-stage-regression. The first-stage-regression is:

$$\ln(CEO\_Network\_Size\_Total)_{i,,t} = \alpha + \beta_1 \ln(Industry\ Average\ CEO\ Network\ Size)_{i,,t} + \delta_{controls} X_{i,t} + \varepsilon_{i,t} \quad 22$$

In the second stage regression, we replace *CEO Network Size Total* with its fitted value from equation 22 and thus estimate equation 23:

$$\ln(\beta_{AGi,t}) = \alpha + \beta_1 (Instrumented\_CEO\_Network\_Size\_Total)_{i,t} + \delta_{controls} X_{i,t} + \varepsilon_{i,t} \quad 23$$

Table 17 reports the estimates of the IV-2SLS. The results from the first stage regressions indicate that the selected instrument that is the coefficient of *Industry Network Size* is positive and statistically significant at 1%. The Cragg-Donald Wald F statistic suggests that *Industry Average CEO Network Size* is unlikely to be a weak instrument. The first stage regression thus indicates that *Industry Average CEO Network Size* is a strong predictor of network size among connected firms. Table 17 also reports the estimates of the second stage regression using equation 23. The results show that the coefficient of the instrumented CEO Network Size is positive and statistically significant at 1% like the earlier findings in Table 5. The results provide additional evidence that CEO network size has a positive impact on asset growth.

INSERT TABLE 17

4.5.2 Difference-In-Difference

When firms want to change their corporate strategies and policies, they often appoint individuals (CEOs) with specific skills and appropriate social and professional connections to carry out such strategic changes (Fracassi, 2016). When that individual dies, his/her social ties with other individuals in the network end. We argue that this will lead to a breakdown of information flow between the firm that recorded the death of a CEO and firms that are connected to the firm that recorded CEO's death. Hence, we further test for potential endogeneity issues using the death of a CEO as an exogenous shock to network size to test the direction of causality between CEO personal connections and commonality in asset growth. We examine whether the death of a CEO of a company affects the extent of asset growth similarity among connected firms. We obtain information on CEO death from BoardEx for the period of January 2000 to December 2016. In all we record 680 CEO deaths.

$$\beta_{AGi,t} = \alpha + \beta_1 (Death\_Dummy)_{i,t} + \beta_2 ((Network\_Total)_{i,t}) + \beta_3 ((Death\_Dummy)_{i,t} * (CEO\_Network\_Size\_Total)_{i,t}) + \delta controls_{i,t} + \varepsilon_{i,t} \quad 24$$

Using equation 24 above, we estimate the difference in difference regressions. Table 18 shows the difference in difference approach when we restrict the sample to all firms that actually recorded CEO death in columns 1 – 2 with firms that recorded no CEO death in columns 3-4. We then compare our measure of commonality in asset growth between firms that recorded a CEO death and those that did not record a CEO death. In all specifications, we investigate whether the death a CEO in the network weakens the extent of commonality in asset growth for firms that actually recorded a CEO death and for firms that did not record CEO death. The variable of interest is the interaction between *Death Dummy* and *CEO Network Size*. For the *Death Dummy*, a dummy variable of one is created if a CEO died within the group of connected firms irrespective of whether the individual firm recorded CEO death. We argue that the death of a CEO within the group weakens the strength of asset growth covariation among connected firms.

The estimates from equation 24 are reported in Table 18. For both Panels A and B, Table 18, the results show that the coefficient of *Death Dummy* is negative and statistically significant for all regression specifications with the exception of column 3, Panel B. This result suggests that the death of a CEO within the group of CEOs with personal connections affects the magnitude of asset growth comovement across connected firms irrespective of whether a firm recorded the CEO death since there will be a break in information flow. Thus, asset growth opportunities that came from the CEO who died will cease slowing the magnitude of asset growth commonality. Following the coefficient estimate of *Death Dummy* in both Panel A and Panel B, we find that the coefficient of *Death Dummy* is negative and significant at 1% level for firms in Panel A for models 1 and 2. This result confirms that the extent and magnitude of commonality in asset growth is reduced by the death of a CEO. In Panel B, the coefficient of *Death Dummy* is positive and statistically significant at 1% level, which does not agree with our prediction. However, when we include control variables, we find the *Death Dummy* coefficient is negative and statistically significant at 1% confirming our claim that the death of a CEO breaks contacts and, as a result, reduces the extent of commonality in asset growth across connected firms. Furthermore, we find the interaction coefficient between *Death Dummy* and *CEO Network Size* is positive and statistically significant in all specifications. This indicates that the death of a CEO within a network of CEOs reduces the magnitude of commonality in asset growth among connected firms. Overall, the results of the difference in difference regressions suggest that a break in the flow of information in social and professional connections has a causal effect on changes in commonality in asset growth rates. In the difference in difference approach reported above, we argue that the death of a CEO will alter the extent of connectivity between two firms, its noteworthy to mention that, our findings could be driven by characteristics of an incoming CEO. This is a because an incoming CEO with strong network ties will definitely influence the information environment of the firm and stock liquidity.

INSERT TABLE 18

5. Conclusion

This study examines the relationship between CEO networks and asset growth for several reasons. First, the CEO is regarded as the principal change agent and, as a result, sets the tone for both quality asset growth rate strategies, decisions and policies. Additionally, a CEO faces several personal consequences should the adopted asset growth strategies fail to yield the expected outcomes. For instance, a CEO could be fired for failure to increase firm growth or become open to public ridicule for failure to add value for shareholders. We focus on the personal connections that exist among firm CEOs because prior evidence suggests individuals can access non-public information from their social and professional connections which enables them to identify and evaluate innovative projects that eventually reduce the risk of failure. Prior studies show that social and professional networks lead to group thinking as a result of peer influence and performance, hence, we hypothesize in this study that asset growth rates of firms that are connected through CEO connectedness will comove. We test this hypothesis on a sample of 13,980 CEOs in 8,736 firms during 2000-2016.

This essay provides evidence that the asset growth rate of firms that are connected through CEOs personal connections strongly comove. Tests suggest that asset growth commonality increases with the size of a CEO's personal connections. This finding suggests that better connected CEOs receive more information that drives the increase in asset growth rate with the pool of firms connected to the individual firm leading to greater asset growth covariation. This raises an important question of whether asset growth covariation among connected firms is value enhancing. Using return on assets (RoA) and annual stock returns as a measure of performance, we find in both cases that comovement in asset growth rates among connected firms affects shareholders negatively. Thus, commonality in asset growth reduces the wealth of shareholders. We believe that peer influence, trust and lack of due diligence among CEOs with connections can lead to wasteful overinvestment or asset growth that might not bring any benefit. Another possible explanation is that a CEO is more likely to increase his/her assets if his/her peers in the network have recently done so.We conclude that asset growth commonality reduces shareholders' wealth.

Next, we test for the channels through which personal connections among CEO drive asset growth commonality. First, we find that similarity in M&A decisions among connected firms positively drives asset growth commonality. Secondly, we find that similarity in R&D investment rate decisions is a channel through which CEOs' personal connections fuel asset growth commonality. We address potential endogeneity problems and find that the death of a CEO significantly affects the extent of asset growth rate similarity among connected firms.

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APPENDIX A: VARIABLE DEFINITIONS

Key Variable Name		Definition	Source
CEO Connection Measures			
Network Education	=	Sum of the CEO’s educational ties. An educational tie occurs if the CEO went to the same university at the same time with another CEO	*BoardEx*
Network Employment	=	Sum of the CEO's employment ties. An employment tie occurs if the CEO currently or historically overlapped with another CEO	*BoardEx*
Network Other Social Activity	=	Sum of the CEO’s other activity ties. Another activity tie occurs if the CEO participated in a same organization (e.g., charity or recreational club) at the same time as another CEO.	*BoardEx*
CEO Network Total	=	(Sum of Network Employment, Network Education, and Network Other Social Activity) for connected CEO irrespective of Industry	*BoardEx*
CEO Network Total (Same Industry)	=	(Sum of Network Employment, Network Education, and Network Other Social Activity) for CEOs who are connected and in same industry.	*BoardEx*

CEO Network Total (Different Industry)	=	(Sum of Network Employment, Network Education, and Network Other Social Activity) for CEOs who are connected but in different industry.	*BoardEx*
Corporate Investment Variables			
Asset Growth Rate	=	Total asset in the fiscal year – total assets last fiscal year/total asset in last fiscal year	*Compustat*
Acquisition Rate	=	Value of acquisitions/lagged total assets. Acquisitions include completed deals covered in SDC with the deal form of "Acquisitions of Assets" "Acquisitions of certain Assets" "Acq. Maj. Int." "Acq. Part. Int." "Acq. Rem. Int" "Acquisition" or "Merger" (as the acquirer".	*SDC& Compustat*
Non-Merger Rate	=	(Value of acquisitions-Total Asset)/lagged total assets	*SDC & Compustat*
Investment Rate	=	(Value of Acquisitions + Capital Expenditure/lagged total assets)	*SDC& Compustat*
R&D Rate	=	R&D Rate is the ratio R&D expense (xrd)/lagged sales (sale), trimmed at the [1,99] quantile.	*Compustat*
Firm Performance Measures			
ROA	=	Return on Assets is the ratio income before extraordinary items (ib)/lagged total assets (at), trimmed at the [1,99]quantile.	*Compustat*
Tobin's Q	=	Tobin's Q is the ratio (total assets (at) . stockholders' equity (seq) C common shares outstanding (csho) _ price close at the end of fiscal (prcc_f))/total assets (at), trimmed at the [1,99] quantile.	*Compustat*
Firm Characteristics			
Acquisition Ratio	=	Acquisition Ratio is the ration between the acquisition expenditure (aqc) and the total sales(sale)	*Compustat*
Capital Expenditure Rate	=	Capital Expenditure/lagged total book assets, with missing or negative Capx set to zero	*Compustat*
Cash flow	=	Cash Flow is the ratio (income before extraordinary items (ib) + depreciation and amortization (dp))/lagged property, plants, and equipment (ppent), winsorized at the [1,99] quantile.	*Compustat*
Cash Ratio	=	Cash and short term investment divided by total assets	*Compustat*
Cash Changes	=	Cash and short-term investments in the fiscal year – Cash and short-term investments last fiscal year/ Cash and short-term investments in last fiscal year	*Compustat*
Employment Growth	=	Total employment in fiscal year – Total employment in last fiscal year/ Total employment in last fiscal year	*Compustat*
EP		EP is earnings to price ratio [EPS/Price)	*Compustat*
Internal Finance **(∆RE)**	=	Retained Earnings in fiscal year – retained earnings in last fiscal year/total asset in last fiscal year	*Compustat*
Investment Rate	=		
Leverage	=	Leverage is the ratio (debt in current liabilities (dlc) C long-term debt (dltt))/(debt in current liabilities (dlc) C long-term debt (dltt)) + common shares outstanding (csho)_ price close at the end of fiscal (prcc_f)	*Compustat*
M/B	=	Market value of equity (closing price at the fiscal year end times shares outstanding) divided by book value of equity	*Compustat*
Number of CEOs	=	No. of CEO is the total number of CEOs employed in the firm	*BoardEx*
Number of Employees	=	No. of Employees is the total number of employees in the firm (emp).	*Compustat*
Sale	=	Sales is the net sales turnover (sale).	*Compustat*
Stock Return	=	Stock Return is the annual total stock return during the fiscal year.	*Compustat*
Size	=	Logarithm of the total book asset	*Compustat*
Tangibility	=	Tangibility is the ratio (net property, plant and equipment (ppent)/total assets (at)	*Compustat*
Total Assets	=	Total Assets is the total assets of the company (at).	*Compustat*

APPENDIX B:
ADDITIONAL SUMMARY STATISTICS OF KEY VARIABLES

SUMMARY STATISTICS OF ANNUAL ASSET GROWTH RATE FOR EACH FIRM (FULL SAMPLE)

YEAR	MEAN	STD. DEV	P1	P25	P50	P75	P99	N
2000	0.000	0.041	0.000	0.000	0.000	0.000	0.000	5543
2001	0.051	0.369	-0.582	-0.105	0.007	0.127	2.050	5141
2002	0.040	0.321	-0.582	-0.093	0.014	0.123	1.452	4883
2003	0.120	0.342	-0.490	-0.020	0.060	0.176	1.938	4729
2004	0.164	0.374	-0.470	0.000	0.078	0.210	2.050	4762

2005	0.136	0.346	-0.478	-0.009	0.063	0.183	1.830	4735
2006	0.149	0.353	-0.475	0.000	0.071	0.201	2.050	4659
2007	0.138	0.379	-0.498	-0.010	0.058	0.183	2.050	4542
2008	0.019	0.312	-0.582	-0.113	0.002	0.102	1.428	4283
2009	0.031	0.283	-0.555	-0.079	0.005	0.087	1.351	4058
2010	0.103	0.320	-0.457	-0.025	0.038	0.142	2.034	3929
2011	0.104	0.318	-0.456	-0.021	0.043	0.148	1.811	3860
2012	0.094	0.317	-0.522	-0.025	0.039	0.129	1.757	3830
2013	0.108	0.334	-0.459	-0.020	0.034	0.137	2.034	3901
2014	0.124	0.362	-0.499	-0.016	0.039	0.149	2.050	4059
2015	0.087	0.372	-0.582	-0.052	0.017	0.124	2.050	4041
2016	0.062	0.310	-0.582	-0.049	0.024	0.115	1.578	3918
Total	**0.089**							**74,783**

SUMMARY STATISTICS OF ANNUAL ASSET GROWTH RATE FOR EACH FIRM IN DECILES (FULL SAMPLE)

DECILES	MEAN	STD. DEV	P1	P25	P50	P75	P99	N
1	-0.318	0.132	-0.582	-0.404	-0.279	-0.207	-0.161	7488
2	-0.098	0.030	-0.157	-0.122	-0.094	-0.072	-0.055	7487
3	-0.029	0.014	-0.054	-0.040	-0.028	-0.017	-0.007	7487
4	0.000	0.001	-0.006	0.000	0.000	0.000	0.000	10065
5	0.012	0.007	0.000	0.006	0.012	0.018	0.024	4910
6	0.042	0.011	0.025	0.033	0.042	0.051	0.060	7487
7	0.081	0.013	0.061	0.070	0.081	0.093	0.104	7488

8	0.136	0.020	0.105	0.119	0.135	0.153	0.174	7487
9	0.241	0.046	0.176	0.201	0.234	0.276	0.336	7487
10	0.827	0.527	0.343	0.436	0.604	1.022	2.050	7487
Total	**0.089**							**74,873**

SUMMARY STATISTICS OF VALUE- WEIGHTED PORTFOLIO AVERAGE ANNUAL ASSET GROWTH RATE [FULL SAMPLE]

YEAR	MEAN	STD. DEV	P1	P25	P50	P75	P99	N
2000	0.000	0.028	0.000	0.000	0.000	0.000	0.000	5543
2001	0.042	0.130	-0.239	0.000	0.000	0.079	0.446	5141
2002	0.030	0.118	-0.263	0.000	0.000	0.062	0.399	4883
2003	0.074	0.097	-0.082	0.000	0.055	0.125	0.407	4729
2004	0.187	0.127	0.000	0.104	0.170	0.312	0.555	4762
2005	0.151	0.112	-0.030	0.070	0.136	0.271	0.451	4735
2006	0.147	0.105	-0.030	0.082	0.150	0.199	0.496	4659
2007	0.105	0.104	-0.084	0.049	0.098	0.132	0.491	4542

2008	-0.080	0.135	-0.289	-0.167	-0.045	0.001	0.220	4283
2009	-0.059	0.128	-0.255	-0.137	-0.022	0.015	0.275	4058
2010	0.065	0.122	-0.163	0.000	0.036	0.111	0.456	3929
2011	0.059	0.116	-0.136	0.000	0.030	0.098	0.450	3860
2012	0.053	0.123	-0.154	0.000	0.014	0.080	0.537	3830
2013	0.057	0.115	-0.170	0.000	0.016	0.092	0.521	3901
2014	0.062	0.146	-0.161	0.000	0.000	0.092	0.590	4059
2015	0.029	0.128	-0.207	0.000	0.000	0.038	0.501	4041
2016	0.025	0.104	-0.199	0.000	0.000	0.040	0.411	3918
Total	**0.057**							**74,873**

SUMMARY STATISTICS OF VALUE- WEIGHTED PORTFOLIO AVERAGE ANNUAL ASSET GROWTH RATE IN DECILES [FULL SAMPLE]

DECILES	MEAN	STD. DEV	P1	P25	P50	P75	P99	N
1	-0.144	0.098	-0.404	-0.255	-0.106	-0.062	-0.035	7,488.00
2	-0.002	0.007	-0.031	0.000	0.000	0.000	0.000	27,117.00
5	0.009	0.005	0.000	0.005	0.010	0.014	0.018	2,832.00
6	0.038	0.011	0.018	0.029	0.039	0.048	0.057	7,487.00
7	0.076	0.011	0.058	0.067	0.076	0.086	0.095	7,488.00
8	0.113	0.012	0.096	0.101	0.112	0.124	0.136	7,487.00
9	0.169	0.021	0.137	0.151	0.167	0.188	0.201	7,487.00

10	0.322	0.166	0.203	0.239	0.271	0.320	1.048	7,487.00
Total	**0.057**							**74873**

APPENDIX C:
ADDITIONAL CHANNELS DRIVING SIMILARITY IN ASSET GROWTH USING INVESTMENT RATE

Similarity in Investment Rate across connected firms						
We regress similarity in investment rate of stock (i) on average investment rate of firms connected to stock i						
Dependent Variable: Annual Investment Rate of stock (i)						
	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Average Annual investment Rate	**0.173*** (0.000)**	**0.134*** (0.000)**	**0.070*** (0.000)**	**0.106*** (0.000)**	**0.050*** (0.000)**	**0.049*** (0.000)**

	(1)	(2)	(3)	(4)	(5)	(6)
Size. Log(sale)		-0.002*** (0.000)	-0.001*** (0.001)	-0.002*** (0.000)	-0.001** (0.026)	-0.001** (0.026)
ROA		0.043*** (0.000)	0.037*** (0.000)	0.048*** (0.000)	0.041*** (0.000)	0.041*** (0.000)
EP		0.005*** (0.001)	0.003 (0.112)	0.012*** (0.000)	0.010*** (0.000)	0.010*** (0.000)
Tangibility		0.174*** (0.000)	0.176*** (0.000)	0.118*** (0.000)	0.122*** (0.000)	0.122*** (0.000)
Cash-Flow		-0.001*** (0.000)	-0.003*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Leverage		-0.036*** (0.000)	-0.033*** (0.000)	-0.001 (0.877)	-0.005 (0.375)	-0.005 (0.375)
Tobin’s Q		0.004*** (0.000)	0.004*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Annual Stock Returns		-0.006*** (0.001)	0.001 (0.413)	-0.002 (0.228)	0.005** (0.013)	0.005** (0.013)
No of Observations	74,873	67,393	67,393	53,194	53,194	53,194
Year Fixed Effects	No	No	Yes	No	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	No	Yes
Adjusted R-Square	0.002	0.044	0.053	0.062	0.072	0.017

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

APPENDIX C (Continued):

Similarity in Investment Rate across connected firms leading the similarity in asset growth rate

We regress investment rate residual of stock (i) on average investment rate of firms connected to stock (i) to further test whether connected firms grow asset related. The dependent variable is the absolute difference between investment rate of stock (i) and average investment rate of portfolio of firms connected for stock (i). We refer to the difference as stock (i) own investment rate without the influence of firms connected to firm (i)

Dependent Variable: Residual Annual Investment Rate of stock (i)

	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Average Annual investment Rate	**0.818*** (0.000)**	**0.803*** (0.000)**	**0.771*** (0.000)**	**0.841*** (0.000)**	**0.816*** (0.000)**	**0.816*** (0.000)**

Size. Log(sale)		-0.006***	-0.006***	- 0.006***	-0.005***	-0.005***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ROA		0.030***	0.028***	0.031***	0.027***	0.027***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EP		0.004**	0.002	0.008***	0.007***	0.007***
		(0.016)	(0.196)	(0.000)	(0.000)	(0.000)
Tangibility		0.104***	0.106***	0.038***	0.040***	0.040***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash-Flow		-0.002**	-0.001*	- 0.000***	-0.000***	-0.000***
		(0.006)	(0.075)	(0.000)	(0.002)	(0.002)
Leverage		-0.009**	-0.007**	0.019***	-0.021**	-0.021**
		(0.013)	(0.038)	(0.000)	(0.000)	(0.000)
Tobin's Q		0.002***	0.002***	0.002***	0.001	0.001
		(0.000)	(0.000)	(0.000)	(0.489)	(0.489)
Annual Stock Returns		-0.000***	-0.004**	0.003**	0.008***	0.008***
		(0.886)	(0.009)	(0.047)	(0.000)	(0.000)
No of Observations	74,873	67,393	67,393	53,194	53,194	53,194
Year Fixed Effects	No	No	Yes	No	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	No	No	Yes
Adjusted R-Square	0.047	0.096	0.053	0.128	0.131	0.111

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 1
Descriptive Statistics of Key Variables and Controls

Corporate Finance Variables & Controls						
Variable	**Mean**	**Std. Dev**	**P25**	**P50**	**P75**	**Obs.**
Key Variable of Interest						
Annual Asset Growth Rate	0.089	0.332	-0.028	0.024	0.135	74,873
Corporate Investment Variables						
Acquisition Rate	0.014	0.067	0.000	0.000	0.000	74,873
Non-Merger Growth Rate	0.983	1.653	0.875	1.018	1.121	74,873

R&D Rate	0.103	0.721	-0.171	-0.010	0.168	22,427
Investment Rate	0.061	0.276	0.001	0.019	0.056	74,873
Acquisition Ratio	0.031	0.112	0.000	0.000	0.005	74,873
Firm Performance Measure						
ROA	0.030	0.235	0.015	0.077	0.142	72,122
Firm Characteristics						
CapX rate	0.038	0.061	0.001	0.018	0.046	74,873
Cash Ratio	0.194	0.234	0.029	0.091	0.274	74,866
EP	-0.123	0.591	-0.049	0.035	0.065	74,708
Investment Ratio	0.539	1.948	0.067	0.171	0.356	74,873
Leverage	0.254	0.254	0.017	0.182	0.421	74,493
M/B	2.730	4.493	1.085	1.794	3.162	74,771
No of CEOs per firm	1.875	1.054	1.000	2.000	2.000	8,736
No of Employees	8.554	42.579	0.179	0.826	4.290	74,377
Sale($billion)	2,662.70	12,592.38	53.55	253.45	1,166.97	74,772
Stock Return (Annual)	-0.014	0.532	-0.199	0.000	0.236	74,873
Tangibility	0.210	0.237	0.029	0.113	0.310	72,106
Total Assets ($billion)	7,178.439	60,034.290	120.208	537.728	2,176.265	74,873
CEO Network Size						
CEO Network Total	23.526	35.366	2.000	10.000	29.000	7,453
CEO Network Total (Same Industry)	4.193	5.707	1.000	2.000	5.000	2,851

Notes: This table shows the summary statistics for all the corporate finance variables used in the paper. Appendix A defines all the variables

Table 2: Commonality in Asset Growth across connected firms [Full Sample]						**Independent Variable: Annual Asset Growth**	

From (1)-(7): For each firm (i) in year (t), we run the time series regression $\Delta AssetGrowth_{i,t} = \beta_0 + \beta_{AG}\Delta AssetGrowth_{j,t} + \delta X_{i,t} + \varepsilon_{i,t}$, where $AssetG$ is defined as the percentage change in total asset from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar $t-1$, $AssetG - Connected$ measures the percentage change in total asset from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar $t-1$ of firms that are connected to firm (i) while X represent control variables that influence total assets. The regression coefficient β_1 thus asset growth betas measures the asset growth rate in firm (i's) to asset growth rate of firms connected to firm (i's). Thus we investigate whether firms in same network grow asset similarly. Thus we expect asset growth betas to be $\beta_1 > 0$ and significant. Our sample includes annual data for NYSE/NASDAQ/AMEX –listed firms for the period of January 2000 to December, 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Commonality in Asset Growth (B_{AG})	**0.204*** (0.000)**	**0.087*** (0.000)**	**0.024** (0.011)**	**0.083*** (0.000)**	**0.023** (0.016)**	**0.090*** (0.000)**	**0.027** (0.006)**
Cash Ratio		0.086***	0.089***	0.068***	0.071***	0.098***	0.193***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Investment Ratio		0.008****	0.007***	0.009***	0.008***	0.008***	0.009***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CapX Rate		2.039***	2.012***	2.316***	2.299***	2.164***	2.534***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition Ratio		0.795***	0.790***	0.846***	0.842***	0.799***	0.845***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage		0.126***	0.129***	0.120***	0.125***	0.139***	0.214***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Sales)		0.003***	0.004***	0.002	0.004**	0.003**	0.014***
		(0.003)	(0.001)	(0.333)	(0.022)	(0.013)	(0.000)
EPS		0.082***	0.078***	0.081***	0.085***	0.082***	0.085***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M/B		0.003***	0.003***	0.003***	0.003***	0.002***	0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility		-0.349***	-0.343***	-0.462***	-0.457***	-0.379***	-0.799***
		(0.000)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(No of Employees)		-0.007***	-0.006***	-0.004**	-0.006***	-0.005***	0.039***
		(0.000)	(0.00)	(0.017)	(0.003)	(0.000)	(0.000)
Annual Stock Returns		0.107***	0.116***	0.099***	0.107***	0.106***	0.104***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year effects	No	No	Yes	No	Yes	No	Yes
Firm effects	No	No	No	No	No	Yes	Yes
Industry Effects	No	No	No	Yes	Yes	No	Yes
Adjusted R-Square	0.007	0.258	0.262	0.279	0.284	0.257	0.292
Observations	74,873	67,975	67,975	53,440	53,440	67,975	53,440

*All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables*

Table 3: Commonality in Asset Growth across connected firms in same industry [Sub Sample] **Independent Variable: Annual Asset Growth**

For (1)-(7): For each firm (i) in year (t), we run the time series regression $\Delta AssetGrowth_{i,t} = \beta_0 + \beta_{AG}\Delta AssetGrowth_{j,t} + \beta_{AGS}\Delta AssetGrowth_{k,t} + \beta_3 X_{i,t} + \varepsilon_{i,t}$, where $AssetG$ is defined as the percentage change in total asset from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar $t-1$, $AssetG-Connected-SameInd$ measures the percentage change in total asset from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar $t-1$ of firms that are connected to firm (i) an in same industry while X represent control variables that influence total assets. The regression coefficient β_1 thus asset growth betas measures the asset growth rate in firm (i's) to asset growth rate of firms connected to firm (i's) but in same industry. Thus we investigate whether firms in same network grow asset similarly. Thus we expect asset growth betas to be $\beta_1 > 0$ and significant. Our sample includes annual data for NYSE/NASDAQ/AMEX –listed firms for the period of January 2000 to December, 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Commonality in Asset Growth	**0.175*****	**0.075*****	**0.013**	**0.074*****	**0.024**	**0.078*****	**0.017***
(B_{AG})	**(0.000)**	**(0.000)**	**(0.165)**	**(0.000)**	**(0.274)**	**(0.000)**	**(0.086)**
Commonality in Asset Growth	**0.101****	**0.043*****	**0.040*****	**0.036*****	**0.033*****	**0.042*****	**0.034*****
in Same Industry (B_{AGS})	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Cash Ratio		0.084***	0.088***	0.067***	0.068***	0.096***	0.090***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Investment Ratio		0.008**	0.008***	0.009***	0.009***	0.009***	0.009***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CapX Rate		2.036****	2.010***	2.313***	2.462***	2.161***	2.404***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition Ratio		0.793***	0.789***	0.845***	0.829***	0.799***	0.845 ***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage		0.126***	0.129***	0.120***	0.094***	0.139***	0.150***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Sales)		0.003**	0.004**	0.001	0.005**	0.003**	0.003
		(0.005)	(0.002)	(0.383)	(0.048)	(0.019)	(0.100)
EPS		0.082***	0.078***	0.081***	0.076***	0.082***	0.080***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M/B		0.003***	0.003***	0.003***	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility		-0.349***	-0.342***	-0.461***	-0.519***	-0.379***	-0.516***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(No of Employees)		-0.006***	-0.006***	0.004***	0.008**	-0.005***	-0.002
		(0.000)	(0.000)	(0.043)	(0.009)	(0.000)	(0.345)
Annual Stock Returns		0.106***	0.116***	0.099***	-0.113***	0.018***	0.111***
		(0.000)	(0.000)	(0.00)	(0.00)	(0.00)	(0.000)
Year effects	No	No	Yes	No	Yes	No	Yes
Firm effects	No	No	No	No	No	Yes	Yes
Industry Effects	No	No	No	Yes	Yes	No	Yes
Adjusted R-Square	0.009	0.261	0.263	0.280	0.280	0.268	0.282
Observations	74,873	67,975	67,975	53,440	53,440	67,975	53,440

*All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables*

Table 4: Effect of Network Size on Asset Grwoth Commonality (Asset Growth Beta) [Full Sample]

Table 4 presents Asset Growth Beta sorted by firms network size.This table presents descriptive of Asset Growth Betas for firms that are connected irrespective of the industry. We present this results to investigate whether the magnitude of Asset Growth co-movement as evidence above increases with reference to network size of firms or to the number of firms connected to a specific firm.

	MEAN	**P50**	**STD DEV**	**P1**	**P25**	**P75**	**P99**	**NO OF OBS.**
Network Size Quintile 1	**0.125**	0.000	1.014	-2.940	0.000	0.321	2.614	1,534
Network Size Quintile 2	**0.102**	0.028	21.567	-10.258	-0.135	0.421	5.290	1,280
Network Size Quintile 3	**0.293**	0.077	10.785	-10.406	-0.197	0.606	6.316	1,297
Network Size Quintile 4	**0.662**	0.203	12.568	-7.868	-0.201	0.794	11.722	1,380
Network Size Quintile 5	**0.626**	0.361	6.449	-6.696	-0.119	1.090	15.444	1,347
Total								**6,838**

Table 5: Association between Commonality in Asset Growth and CEO Network Size [Full Sample]

Dependent Variable: Asset Growth Beta	**(1)**	**(2)**	**(3)**	**(4)**	**(3)**
Total Network Size	**0.091*** (0.000)**	**0.146*** (0.000)**	**0.143*** (0.000)**	**0.145*** (0.000)**	**0.143*** (0.000)**
Size. Log(sale)		0.020 (0.216)	0.034 (0.127)	0.021 (0.225)	0.034 (0.127)
Log (No. of Employees)		-0.064*** (0.000)	-0.089*** (0.000)	-0.064*** (0.000)	-0.089*** (0.000)
Log (No. of CEOs)		-0.192*** (0.000)	-0.182*** (0.000)	-0.1930** (0.000)	-0.182*** (0.000)
Cash Ratio		0.231** (0.003)	-0.117 (0.263)	0.230*** (0.003)	-0.117 (0.263)
Annual Stock Returns		-0.384*** (0.000)	-0.337*** (0.000)	-0.383*** (0.000)	-0.337*** (0.000)
ROA		-0.602 *** (0.000)	-0.623*** (0.000)	-0.602*** (0.000)	-0.623*** (0.000)
CapX Rate		1.493*** (0.000)	0.676*** (0.000)	1.493*** (0.000)	0.676*** (0.000)
No of Observations	6,838	6,261	6,261	6,261	6,261
Firm Cluster	No	No	No	Yes	Yes
Industry Effects	No	No	Yes	No	Yes
Adjusted R-Square	0.015	0.078	0.097	0.079	0.158

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 6: Association between Commonality in Asset Growth and CEO Network Size [Full Sample]

Dependent Variable: Total Value- Weighted Portfolio Average Asset Growth Rate

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Total Network Size	**0.033****	**0.065*****	**0.050*****	**0.066*****	**0.049*****
	(0.006)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Size. Log(sale)		0.020	-0.004***	0.020	-0.004
		(0.345)	(0.878)	(0.339)	(0.878)
Log (No. of Employees)		-0.045**	-0.064**	-0.045**	-0.064**
		(0.029)	(0.022)	(0.025)	(0.023)
Log (No. of CEOs)		-0.295***	-0.275***	-0.295***	-0.275***
		(0.00)	(0.000)	(0.00)	(0.00)
Cash Ratio		0.388***	-0.216*	0.388***	-0.216*
		(0.000)	(0.092)	(0.000)	(0.092)
Annual Stock Returns		-0.996***	-0.764***	-0.995***	-0.764***
		(0.000)	(0.000)	(0.000)	(0.000)
ROA		-0.794 ***	-0.811***	-0.795 ***	-0.811***
		(0.000)	(0.000)	(0.000)	(0.000)
CapX Rate		-0.586	-3.299***	-0.586*	-3.299***
		(0.143)	(0.000)	(0.074)	(0.000)
No of Observations	6,327	5,983	5,983	5,984	5,984
Firm Cluster	No	No	No	No	Yes
Industry Effects	No	No	Yes	Yes	Yes
Adjusted R-Square	0.001	0.084	0.210	0.086	0.210

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 7: Similarity in Acquisition Growth Rate across connected firms

We regress annual acquisition growth rate of stock (i) on average acquisition rate of firms connected to stock (i) to test whether acquisition rate across connected firms is related.

Dependent Variable: Annual Acquisition Rate of stock (i)

	(1)	(2)	(3)	(4)	(5)
Portfolio Average Annual Acquisition Rate	**0.148***** **(0.000)**	**0.120***** **(0.000)**	**0.040***** **(0.000)**	**0.078***** **(0.000)**	**0.859***** **(0.000)**
Size. Log(sale)		-0.003 (0.217)	0.005* (0.085)	-0.002 (0.570)	0.001** (0.041)
ROA		0.004*** (0.002)	-0.001 (0.464)	0.004** (0.022)	0.001 (0.714)
Acquisition Ratio		0.205*** (0.000)	0.206*** (0.000)	0.233*** (0.000)	0.234*** (0.000)
Investment Ratio		-0.006 (0.000)	-0.002 (0.189)	-0.001*** (0.000)	-0.001 (0.367)
CapX		0.074*** (0.000)	0.062*** (0.000)	0.116*** (0.000)	0.097*** (0.000)
Cash-Ratio		-0.001 (0.673)	-0.001 (0.543)	-0.017*** (0.000)	-0.018*** (0.000)
Log(No of Employees)		0.003 (0.174)	-0.000 (0.844)	-0.000 (0.990)	-0.001 (0.000)
Tobin's Q		0.002 (0.300)	0.003* (0.063)	-0.001* (0.058)	-0.003 (0.129)
Annual Stock Returns		0.006 (0.639)	0.001** (0.006)	0.001** (0.017)	0.003 (0.424)
No of Observations	74,873	68,510	68,510	53,901	53,901
Year Fixed Effects	No	No	Yes	No	Yes
Industry Fixed Effects	No	No	No	Yes	Yes
Firm Fixed Effects	No	Yes	No	No	No
Adjusted R-Square	0.003	0.120	0.132	0.150	0.160

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table8 : Similarity in Acquisition Growth Rate across connected firms

We regress acquisition growth rate residual of stock (i) on average acquisition rate of firms connected to stock (i) to further test whether connected firms grow asset related. The dependent variable is the absolute difference between acquisition rate of stock (i) and average acquisition rate of portfolio of firms connected for stock (i). We refer to the difference as stock (i) own acquisitions without the influence of firms connected to firm (i)

Dependent Variable: Residual Annual Acquisition Rate of stock (i)

	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Average Annual Acquisition Rate	**0.972*** (0.000)**	**0.949*** (0.000)**	**0.883*** (0.000)**	**0.860*** (0.000)**	**0.015*** (0.000)**	**0.862*** (0.000)**
Size. Log(sale)		-0.003 (0.134)	-0.003 (0.293)	-0.000 (0.336)	-0.001 (0.263)	-0.002* (0.056)
ROA		0.003** (0.011)	0.001 (0.686)	0.003** (0.070)	0.004* (0.803)	0.006** (0.017)
Acquisition Ratio		0.182*** (0.000)	0.184*** (0.000)	0.206*** (0.000)	0.206*** (0.000)	0.212*** (0.000)
Investment Ratio		-0.004*** (0.000)	-0.000 (0.452)	- 0.004*** (0.001)	-0.000 (0.716)	-0.000 (0.752)
CapX		0.067*** (0.000)	0.056*** (0.000)	0.101*** (0.000)	0.083*** (0.000)	0118*** (0.000)
Cash-Ratio		-0.001 (0.461)	-0.001 (0.308)	- 0.061*** (0.000)	-0.167*** (0.000)	-0.030*** (0.000)
Log(No of Employees)		0.002 (0.516)	0.000 (0.512)	-0.003 (0.417)	0.001 (0.111)	0.003*** (0.000)
Tobin's Q		0.001 (0.530)	0.003 (0.130)	-0.001** (0.029)	-0.000* (0.093)	-0.001*** (0.001)
Annual Stock Returns		0.006 (0.277)	0.002** (0.001)	0.002*** (0.003)	0.003*** (0.000)	0.002*** (0.000)
No of Observations	74,873	68,510	68,510	53,901	53,901	53,901
Year Fixed Effects	No	No	Yes	No	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	No	No	Yes
Adjusted R-Square	0.120	0.214	0.1223	0.237	0.244	0.235

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 9: Similarity in Non-Merger Asset Growth Rate across connected firms

We regress non-merger asset growth rate of stock (i) on average non-merger asset growth rate of firms connected to stock (i) to test whether asset growth commonality across connected firms is linked to other sources aside acquisitions.

Dependent Variable: Annual Non-Merger Asset Growth rate of stock (i)

	(1)	(2)	(3)	(4)	(5)
Portfolio Average Annual Non –Merger Growth Rate	**0.007***** **(0.000)**	**0.009***** **(0.000)**	**0.001***** **(0.002)**	**0.006***** **(0.000)**	**0.007***** **(0.000)**
Log(sale)		0.016*** (0.000)	0.007*** (0.000)	0.016*** (0.000)	0.044*** (0.000)
Investment Rate		-0.842*** (0.000)	-0.843*** (0.000)	-0.810*** (0.000)	-0.849*** (0.000)
ROA		-0.071*** (0.000)	-0.044*** (0.000)	-0.099*** (0.000)	-0.199*** (0.000)
Leverage		-0.004 (0.433)	0.008** (0.033)	0.006 (0.392)	0.005 (0.488)
M/B		-0.020 (0.231)	-0.001** (0.016)	-0.001** (0.044)	-0.001* (0.069)
CapX		2.898*** (0.000)	1.813*** (0.000)	2.982*** (0.000)	3.491*** (0.000)
Cash-Ratio		0.018 (0.801)	-0.026*** (0.000)	0.011 (0.165)	0.041*** (0.000)
Tangibility		-0.318*** (0.000)	-0.136*** (0.000)	-0.305*** (0.000)	-0.395*** (0.000)
Tobin's Q		-0.020*** (0.000)	-0.011*** (0.000)	-0.026*** (0.000)	-0.029*** (0.000)
Annual Stock Returns		0.009*** (0.000)	0.009*** (0.000)	0.012*** (0.000)	0.014*** (0.000)
No of Observations	74,873	69,904	69,904	54,591	69,904
Year Fixed Effects	No	No	Yes	No	No
Industry Fixed Effects	No	No	No	Yes	No
Firm Fixed Effects	No	No	No	No	Yes
Adjusted R-Square	0.002	0.264	0.682	0.688	0.311

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 10: Similarity in Non-Merger Asset Growth Rate across connected firms

We regress non-acquisition growth rate residual of stock (i) on average non-acquisition rate of firms connected to stock (i) to further test whether connected firms grow asset related. The dependent variable is the absolute difference between non-acquisition rate of stock (i) and average non-acquisition rate of portfolio of firms connected for stock (i). We refer to the difference as stock (i) own non-acquisitions without the influence of firms connected to firm (i)

Dependent Variable: Residual Annual Non-Merger Asset Growth rate of stock (i)

	(1)	(2)	(3)	(4)	(5)
Portfolio Average Annual Non –Merger Growth Rate	**0.925*** (0.000)**	**0.918*** (0.000)**	**0.929*** (0.000)**	**0.974*** (0.000)**	**0.965*** (0.000)**
Log(sale)		-0.088*** (0.000)	-0.093*** (0.000)	-0.058*** (0.000)	-0.057*** (0.000)
Investment Rate		0.615*** (0.000)	0.662*** (0.000)	0.741*** (0.000)	0.685*** (0.000)
ROA		0.228*** (0.000)	0.303*** (0.000)	0.178*** (0.000)	0.053*** (0.001)
Leverage		0.213*** (0.000)	0.185*** (0.000)	0.093*** (0.000)	0.121*** (0.000)
M/B		0.001 (0.157)	0.001 (0.326)	-0.000 (0.326)	-0.001 (0.299)
CapX		-1.506*** (0.000)	-1.029*** (0.000)	-2.638*** (0.000)	-2.088*** (0.000)
Cash-Ratio		-0.170*** (0.801)	-0.173*** (0.000)	-0.065*** (0.000)	-0.055*** (0.003)
Tangibility		0.132*** (0.000)	0.030* (0.051)	0.338*** (0.000)	0.258*** (0.000)
Tobin's Q		0.006** (0.027)	0.004 (0.113)	0.014*** (0.000)	0.006*** (0.003)
Annual Stock Returns		0.041*** (0.000)	0.020*** (0.000)	0.006*** (0.000)	0.027*** (0.000)
No of Observations	74,873	69,904	69,904	54,591	69,904
Year Fixed Effects	No	No	Yes	No	No
Industry Fixed Effects	No	No	No	Yes	No
Firm Fixed Effects	No	No	No	No	Yes
Adjusted R-Square	0.863	0.861	0.682	0.953	0.943

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 11: Determinants of R&D Investment Rate Regressions

This table shows results where we regress a number of factors that determine the R&D investment decisions following the literature. We then obtain the residual for the R&D policy to measure R&D dissimilarity.

Dependent Variable: Annual Acquisition Rate

	(1)	(2)	(3)	(4)	(5)
Size. Log(Total Assets)	-0.124***	-0.157***	-0.130***	-0.164***	-0.273***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.028	0.074**	-0.012	0.056	-0.189***
	(0.345)	(0.029)	(0.684)	(0.103)	(0.000)
MB	0.001	-0.001	0.001	0.001	0.001
	(0.214)	(0.456)	(0.279)	(0.589)	(0.666)
Cash Flow	-0.006***	-0.004***	-0.006***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TobinsQ	-0.002	-0.004	-0.004	-0.006*	-0.003
	(0.476)	(0.265)	(0.204)	(0.097)	(0.595)
Tangibility	-0.070*	-0.182***	-0.061*	-0.156***	-0.342***
	(0.054)	(0.000)	(0.098)	(0.002)	(0.001)
Log(Employees)	0.115***	-0.153***	-0.119***	-0.157***	-0.236***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No of Observations	22,026	18,743	22,026	18,743	18,743
Year Fixed Effects	No	No	Yes	Yes	Yes
Industry Fixed Effects	No	Yes	No	Yes	Yes
Firm Fixed Effects	No	No	No	No	Yes
Adjusted R-Square	0.040	0.044	0.046	0.050	0.074

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 12: Similarity in R&D Growth Rate and Commonality in Asset Growth.					
Dependent Variable: Asset Growth Beta					
	(1)	(2)	(3)	(4)	(5)
R&D Policy Dissimilarity	**-0.108***** **(0.000)**	**-0.134***** **(0.000)**	**-0.124***** **(0.000)**	**-0.133***** **(0.000)**	**-0.123***** **(0.000)**
Size. Log(sale)		0.016 (0.239)	0.012 (0.458)	-0.016 (00.262)	0.012 (0.497)
Log (No. of CEOs)		-0.025 (0.600)	-0.044 (0.379)	-0.024 (0.603)	-0.043 (0.392)
Cash Ratio		0.815*** (0.000)	0.255 (0.158)	-0.814*** (0.000)	0.255 (0.171)
Annual Stock Returns		-0.680*** (0.000)	-0.616*** (0.000)	-0.680*** (0.000)	-0.615*** (0.000)
ROA		-1.262*** (0.000)	-1.345*** (0.000)	-1.263 *** (0.000)	-1.349*** (0.000)
CapX Rate		3.961*** (0.000)	2.978*** (0.000)	3.961*** (0.000)	2.978*** (0.000)
No of Observations	3,912	3,772	3,772	3,772	3,772
Industry Fixed Effects	No	No	Yes	No	Yes
Firm Clusters	No	No	No	Yes	Yes
Adjusted R-Square	0.004	0.092	0.122	0.094	0.213

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
Appendix A defines all the variables

Table 13: Similarity in R & D Growth Rate across connected firms

We regress R & D rate residual of stock (i) on average R & D rate of firms connected to stock (i) to further test whether connected firms grow asset related. The dependent variable is the absolute difference between R & D rate of stock (i) and average R & D rate of portfolio of firms connected for stock (i). We refer to the difference as stock (i) own R & D investments without the influence of firms connected to firm (i).

Dependent Variable: Residual R & D Growth Rate of stock (i)

	(1)	(2)	(3)	(4)	(5)	(6)
Portfolio Average Annual R&D Growth Rate	**0.551*** (0.000)**	**0.548*** (0.000)**	**0.551*** (0.000)**	**0.534*** (0.000)**	**0.540*** (0.000)**	**0.524*** (0.000)**
Size. Log(sale)		- 0.120*** (0.000)	-0.119*** (0.000)	- 0.147*** (0.000)	-0.145*** (0.000)	-0.183*** (0.000)
Log (No of Employees)		0.062*** (0.000)	0.061*** (0.000)	0.094*** (0.000)	0.092*** (0.000)	0.086*** (0.000)
Investment Ratio		0.036*** (0.000)	0.035*** (0.000)	0.035*** (0.000)	0.035*** (0.000)	0.029*** (0.000)
Leverage		0.200*** (0.000)	0.202*** (0.000)	0.142*** (0.000)	0.143*** (0.000)	-0.030 (0488)
M/B		0.001 (0.842)	0.000 (0.803)	-0.001 (0.269)	-0.001 (0.312)	0.000 (0.932)
CapX		0.265** (0.029)	0.264** (0.030)	0.569*** (0.000)	0.581*** (0.000)	0.544*** (0.001)
Cash Flow		- 0.006*** (0.000)	-0.006*** (0.000)	- 0.003*** (0.000)	-0.003*** (0.000)	-0.002*** (0.003)
Tangibility		-0.094** (0.013)	-0.094** (0.013)	- 0.320*** (0.013)	-0.327*** (0.000)	-0.387*** (0.000)
Tobin's Q		0.004 (0.194)	0.004 (0.166)	-0.007** (0.033)	-0.007** (0.033)	-0.012** (0.008)
Annual Stock Returns		-0.003 (0.664)	-0.005 (0.546)	0.001 (0.861)	-0.002 (0.846)	0.003 (0.715)
No of Observations	22,427	22,026	22,026	22,026	22,026	18,743
Year Fixed Effects	No	No	Yes	No	Yes	Yes
Industry Fixed Effects	No	No	No	Yes	Yes	Yes
Firm Fixed Effects	No	Yes	No	No	No	Yes
Adjusted R-Square	0.054	0.161	0.161	0.197	0.197	0.271

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 14: Commonality in Asset Growth and Firm Performance

We regress Asset Growth Beta of stock (i) on firm performance of stock (i) measured here by RoA to investigate whether asset growth commonality affects firm performance.

Dependent Variable: Return on Asset (ROA) [Full Sample]

	(1)	(2)	(3)
Asset Growth Beta	**-0.035***** **(0.000)**	**-0.012***** **(0.000)**	**-0.012***** **(0.000)**
Log(Sale)		0.042*** (0.000)	0.042*** (0.000)
Leverage		-0.049 (0.000)	-0.049 (0.001)
Tangibility		0.040* (0.082)	0.040 (0.126)
Acquisition Ratio		0.191*** (0.000)	0.191*** (0.000)
Cash Flow		0.008*** (0.000)	0.008*** (0.000)
Investment Ratio		-0.010*** (0.000)	-0.010*** (0.001)
CapX		0.573*** (0.000)	0.573*** (0.000)
No of Observations	3,727	3,630	3,630
Industry Fixed Effects	No	Yes	Yes
Firm Cluster	No	No	Yes
Adjusted R-Square	0.060	0.635	0.675

Table 15: Commonality in Asset Growth and Firm Performance

We regress Asset Growth Beta of stock (i) on firm performance of stock (i) measured by Stock Returns to investigate whether asset growth commonality affects firm performance.

Dependent Variable: Annual Stock Returns [Full Sample]

	(1)	(2)	(3)
Asset Growth Beta	**-0.023***** **(0.000)**	**-0.014***** **(0.000)**	**-0.014***** **(0.000)**
Log(Sale)		0.020*** (0.000)	0.020*** (0.000)
Tangibility		-0.164*** (0.000)	-0.165*** (0.000)
Acquisition Ratio		0.011 (0.842)	0.011 (0.876)
Cash Flow		-0.003*** (0.000)	-0.003*** (0.000)
Investment Ratio		-0.022*** (0.000)	-0.022*** (0.000)
CapX		1.011*** (0.000)	1.012*** (0.000)
No of Observations	3,803	3,632	3,632
Industry Fixed Effects	No	Yes	Yes
Firm Cluster	No	No	Yes
Adjusted R-Square	0.030	0.159	0.250

Table 16: 2 Stage Regressions Using Instrumental Variables

	1st stage Dep= CEO Total Network Size	2nd Stage Dep =Asset Growth Beta
CEO Total Network Size	-	0.252***
		(0.000)
Industry Network Total	0.726***	-
	(0.000)	
Log(Sale)	0.196***	-0.002
	(0.000)	(0.938)
Log(No of Employees)	0.001	-0.172***
	(0.944)	(0.000)
Log (No of CEOs)	0.825***	-0.273***
	(0.000)	(0.000)
Cash Flow	-0.006***	-0.004*
	(0.003)	(0.052)
Annual Stock Returns	-0.207**	-0.339***
	(0.018)	(0.000)
ROA	-0.923 ***	-0.490***
	(0.000)	(0.000)
CapX	-1.040**	-1.815***
	(0.006)	(0.000)
Observations	5,915	5,915
Adjusted R- Square	4.8%	18.7%
Partial F-Statistics	44.52 (p-value <0.0001)	
Weak Identification Test	Cragg-Donald Wald F = 553.664	
	Stock-Yogo C.V : 10% Max IV 16.38	
	Stock-Yogo C.V : 25% Max IV 5.53	

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively. Appendix A defines all the variables

Table 17 :Endogeneity: Difference-in-Difference using CEOs' Death

Dependent Variable Asset Growth Beta	**Panel A**	**Panel B**		
	1	**2**	**3**	**4**
Death Dummy	-1.563**	-1.249*	0.359**	-0.512***
	(0.036)	(0.095)	(0.006)	(0.000)
CEO Network Size	-0.001	-0.092	0.191***	0.213***
	(0.993)	(0.384)	(0.000)	(0.000)
Death Dummy *CEO Network Size	0.422**	0.350*	0.099**	0.145***
	(0.032)	(0.068)	(0.009)	(0.000)
Log(Sale)		0.581***		0.061**
		(0.001)		(0.009)
Log(No of Employees)		-0.518***		-0.146***
		(0.002)		(0.000)
Cash Flow		-0.099***		-.0005
		(0.001)		(0.136)
Annual Stock Returns		-0.199		-0.708***
		(0.908)		(0.000)
ROA		0.557		-1.072***
		(0.716)		(0.000)
CapX		1.676		3.183***
		(0.611)		(0.000)
Observations	715	715	5,247	5,247
Adjusted R- Square	0.006	0.032	0.041	0.137

All p-values are in brackets. *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.
Appendix A defines all the variables
In Panel A we consider firms that actually recorded CEO death within the sample period.
In Panel B we consider firms that did not recorded CEO death but a CEO in the network of firms connected to the individual firm died.

CHAPTER 4

CONCLUSION

1. Summary of Findings

Social networks have attracted much attention from researchers in finance in recent years. Numerous studies examine the impact of social connections on firm outcomes. However, it remains an open question the extent to which CEO networks affect firms. In this thesis, we explore the effects of CEO networks on corporations by focusing on two important dimensions that have been largely ignored in published studies. Specifically, this study examines the role of social and professional interactions among firm executives in corporations focusing on the link between CEO connectedness and commonality in liquidity and the association between CEO peer effects and asset growth across connected firms. In the first part, we investigate whether commonality in stock liquidity can be driven by CEO connectedness. We hypothesize that stock liquidity of connected firms will comove because of convergence in corporate activities among connected firms. In the second part, we argue that through peer effects, connected CEOs are likely to adopt similar asset growth strategies leading to commonality in asset growth.

Although a number of studies provide evidence of liquidity commonality among stocks, most of these studies primarily focus on market-level determinants leading to the conclusion that liquidity commonality is driven by supply-side and demand-side sources. In the first part, we focus on firm level determinants by focusing on CEO networks that create connectedness among firms as a potential source of liquidity commonality. In the light of the above argument, we analyse, for the first time in the literature, whether CEO networks that facilitate similarity in corporate behaviour drive commonality in liquidity. Using stocks listed on NYSE and AMEX for 2000-2016, we examine whether the stock liquidity of connected firms covary. We find strong evidence that suggests that stock liquidity of connected firms covary. We also show that the magnitude of liquidity covariation among connected stocks increases with network size. This suggests that the larger the network of a firm, the larger the liquidity covariation.

We further investigate the potential channels through which CEOs network ties drive liquidity commonality across connected stocks. We find evidence that indicates that similarity in corporate decisions across connected firms drives liquidity commonality. We also find that there are similarities in the trading activities of connected firms that drive commonality in liquidity. We address concerns for endogeneity and find that the death of a CEO in a firm reduces the extent and magnitude of liquidity covariation.

In essay two, we investigate the relationship between CEO networks and asset growth decisions. The extant literature on determinants of asset growth suggests that firm age and size are key factors that determine asset growth rates. However, following the significant influence of CEO networks on corporations, we investigate for the first time in empirical corporate finance literature, the linkages between asset growth rates of firms with CEOs having personal connections. We conjecture that through peer effects, CEOs with personal connections will grow assets similarly leading to commonality in asset growth among connected firms. Specifically, we hypothesize that the asset growth rates of firms that are connected through CEO connectedness will comove. We test this hypothesis on a sample of 13,980 CEOs in 8,736 firms listed on NYSE/AMEX/NASDAQ over 2000-2016. We find that the asset growth rates of firms that are connected through CEOs personal connection comove strongly. We next test whether commonality in asset growth among connected firms is beneficial to shareholders. We provide evidence that indicates that commonality in asset growth reduces the wealth of shareholders.

In the light of these results, we analyse whether similarity in M&A decisions and R&D investment rates among connected firms positively drives asset growth commonality. We provide evidence that suggests that CEOs with personal connections mimic the asset growth strategies of their peers through social learning leading to commonality in asset growth among firms with CEOs having personal connections. We address potential endogeneity problems and find that the death of a CEO significantly affects the magnitude of commonality in asset growth among connected firms.