CEO Networks and Bank Risk Taking

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We investigate the impact of CEO networks on bank risk during the recent financial crisis and test whether CEO networks have a bearing on CEO insider trading at the onset of the crisis. We construct a unique dataset of CEO networks based on 97 bank CEOs' social ties, which allows us to assign a Social Network (SN) score to each CEO. Our results provide evidence that CEO networks in 2006, the year prior to the financial crisis, are related to bank risk-taking ex post during the financial crisis. We also find that after controlling for bank and other CEO characteristics, a higher SN score is associated with lower bank risk. In addition, the CEO social network effect is magnified with CEO power, indicating that a well-connected bank CEO uses his internal dominance to influence corporate risk choices, and hence undertake less risk during the financial crisis. Furthermore, CEO social networks have a significantly positive impact in reducing CEOs' personal wealth loss in the wake of the financial crisis. Overall, our results suggest that CEO social networks provide an efficient information channel to bank CEOs.

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1. Introduction

Most of the existing literature that examines how CEOs' characteristics can be used to explain bank risk taking have been cast in a framework where CEOs make decisions in individualistic terms (see e.g., Victoravich et al. 2011). The influence of social networks on CEOs in shaping risk propensity has been largely unexplored. However, a prevailing view in social network theory indicates that individuals are not isolated entities but rather a component of social networks. These networks jointly provide culture norms, information flows, business opportunities, and social sanctions (Topa, 2001), and in turn affect an individual's preferences and decisions (Charness and Rabin, 2002). As such, CEOs' social networks will inevitably imprint a mark on their banks' risk propensity in the sense that a CEO is the key decision maker in a firm.

This study is timely and relevant given that excessive bank risk taking has been widely identified as a primary contributory factor in the recent financial crisis. For example, in May 2008, PricewaterhouseCoopers and the Economist Intelligence Unit conducted a global survey of financial industry executives and commentators about which factors were responsible for the credit/banking crisis. Interestingly, a striking seventy-three percent put the blame on "culture and excessive risk-taking" (PricewaterhouseCoopers survey, 2008).

To measure a bank CEO's social network, we first construct a unique social network database for CEOs of 97 U.S. banks based on biographical information including current and past employment experience, education background, as well as other roles in social organizations. We then use social-networking software called *Pajek* to gauge a CEO's social centrality. Specifically, we use three measures to accomplish this task. These measures include: (1) degree, which indicates how active a CEO is in social networks, (2) closeness, which measures the capability of a CEO to quickly interact with other peer CEOs in the network, (3) betweenness, which measures a CEO's ability to act as an intermediary in networks. Since it is not theoretically clear which measure is more important or less important, we form an aggregate social network measure (*SN*) based on the equal-weighted average of the three measures. We then compile a ranking of low-medium-high SN to reduce the influence of extreme values and ease results interpretation. In the end, the highest centrality is assigned a value of two and the lowest centrality is assigned a value of zero.

For the baseline regression, we use the KMV-Merton model, a probability of default forecasting model based on Merton's (1974) bond pricing model. The resulting expected default frequency (*EDF*) captures the probability that the market value of assets is worth less than the face value of liabilities at maturity.

To capture different perspectives of bank risk, we also use three bank risk measures derived from daily stock returns, namely total risk (*TR*), idiosyncratic risk (*IDIOR*), and systematic risk (*SYSR*). Following Anderson and Fraser (2000), *TR* of a bank is computed as the standard deviation of its daily stock returns for each fiscal year. *TR* captures the overall variability in bank stock returns. Bank regulators and bank management are most concerned with total risk, which reflects the market's perceptions about the risks inherent in the bank's assets, liabilities, and off-balance-sheet positions. *IDIOR* and *SYSR* are calculated using the two-index market model as in Chen et al. (2006) and Anderson and Fraser (2000). Diversified investors are more concerned with *SYSR* in order to build efficient portfolios.

The empirical evidence reveals a negative association between CEO networks and bank risk, as measured by *EDF*, *TR*, *IDIOR*, and *SYSR*. It appears that banks with well-connected CEOs take on less risk and, as a result, are more stable during the financial crisis. To further confirm that the results are associated with the information advantage from the CEO social network, we examine the probability of bank CEOs to reduce their personal equity holding prior to the crisis. Bank CEOs who have better access to information and anticipate the onset of the financial crisis should reduce their personal equity holding to minimize wealth losses. We find that bank CEOs with the highest *SN* score are indeed more likely to reduce equity holdings in 2008 than do CEOs with the lowest *SN* score.

Our results indicate that CEO networks have an impact on bank risk taking. A relevant question is whether CEO networks have a differential role in banks with different levels of CEO power and CEO ownership. Further analysis reports some evidence that the impact of CEO networks on bank risk taking is more evident in firms with powerful CEOs, as measured by a high fraction of the aggregate top-five total compensation paid to the CEOs. We find no evidence that the CEO network effect varies in banks with different percentage of shares outstanding held by a CEO (*%CEO_OWN*). These findings provide further evidence that the CEO network effect is more pronounced in banks where CEOs have the capability to make independent decisions. However, CEO network effect is not related to whether CEOs have strong incentives to make value-improving decisions.

This study contributes to the existing literature in several ways. First, we document the social networks of bank CEOs in the year leading up to the crisis. This is important to consider as it provides a snapshot of how bank CEOs link with each other at the onset of the worst financial crisis in decades and therefore provides a unique insight into the causes and remedies of financial crisis. Second, this paper moves beyond the traditional bank risk research setting by explicitly adding a new dimension, CEO networks, to the research. We contribute to the literature in this area by providing evidence that CEO network does indeed have an impact on bank risk taking. Third, this paper enriches the literature that investigates the effect of CEO power and CEO ownership on firms as we find some evidence of interactive effects of CEO networks with CEO power on banks.

The remainder of the paper is organized as follows; Section 2 discusses related literature and hypotheses and Section 3 describes the data and explains the methodology used. Section 4 provides the empirical results and Section 5 provides conclusions.

2. Literature Review and Hypotheses Development

There is an abundance of evidence suggesting that CEOs' social networks may contribute to efficient risk taking, and thus benefit their respective banks. First, social networks foster an enhanced information flow. Burt (1997) indicates that information benefits resulting from social networks include not only information access and information timing, but also information referral. Centrally positioned CEOs can acquire information faster and more accurately. This information channel is unique and important in the sense that CEOs are the most informed agents in the banking industry—in this way, each component of social networks may improve the quality and depth of the exchanged information.

Second, a better position in social networks facilitates knowledge sharing including the development, understanding, diffusion, and adoption of value-improving innovation (Coleman et al. 1966). In this regard, Uzzi (1996) establishes that social networks improve feedback among members, and facilitates recognition of shared interests, therefore alleviating the free-rider problem embedded in innovation processes. This free-rider problem is particularly severe in the banking sector due to the difficulty of obtaining a patent for a financial innovation. As a result, well-connected CEOs are more likely to understand the intrinsic nature of new financial products, leading to more efficient risk-taking behavior. Taken together, banks with well-connected CEOs are less likely to be exposed to excessive risk during the recent credit crisis and more likely to reduce equity holdings prior to the crisis to minimize wealth losses. Therefore, we test the following hypotheses as follows:

Hypothesis 1 : *Banks with well-connected CEOs are more likely to have low bank risk during the credit crisis.*

Hypothesis 2 : *Well-connected CEOs are more likely to reduce their equity holdings at the onset of the credit crisis.*

However, there are contrary arguments implying that CEOs' social networks may have an adverse effect on bank risk taking ex post. First, bad practices and value-destroying innovations may spread among social networks. For example, Snyder et al. (2009) report that the illegal innovation such as backdating of options is spread through interlock directors.

Second, social networks may promote group thinking or herding, thereby subjecting banks to more risk. Prior research provides evidence of strategic conformity resulting from social ties. For example, using a sample of food and computer industries, Geletkanycz and Hambrick (1997) show that executives' intra-industry ties result in a higher degree of strategic conformity. Therefore, when a perception of bank risk, albeit mistaken, takes hold in a CEO social network, it would be likely to be reinforced and accepted uncritically among members, with inconsistent information being suppressed.

In addition, prior research reports mixed results on the impact of CEO equity holding on corporate risk taking. Some research suggests that a higher percentage of equity holding incentivizes CEOs to align their interests with shareholders, thereby taking on more risk (Agrawal and Mandelker, 1987). On the contrary, a CEO with higher equity ownership is a less diversified investor, and thus may be more risk averse. For example, Gray and Cannella (1997) and Bloom and Milkovich (1998) find that systematic risk is associated with higher levels of equity holdings. To clarify this issue, we examine whether CEO ownership has an interactive effect with CEO networks on bank risk taking. We derive such an interactive effect by examining the following jointed hypothesis:

Hypothesis 3 : *There is a statistically significant interactive effect of CEO networks and CEO ownership on bank risk during the credit crisis.*

Similarly, we consider the interactive effect of CEO power and CEO networks on bank risk. The role of CEO power on bank risk taking has only recently been considered in bank risk-taking literature. However, results are mixed. For example, Adams et al. (2005) find positive association between CEO power and variance in stock returns. They suggest that the board of directors is less likely to monitor powerful CEOs thus leading to riskier corporate behavior.

On the other hand, Pathan (2009) reports that CEO power negatively affects bank risk taking based on a sample of 212 large US bank holding companies during 1997 to 2004. Her research suggests that risk-averse entrenched CEOs tend to take on less risk. This finding is surprising given the argument that the CEO power in banks is an important contributory factor in several bank failures, including Wachovia and Washington Mutual.

We therefore focus on the possibility that CEO power creates an interactive effect with CEO networks. The simplest way to derive such an interactive effect is to test the following jointed hypothesis:

Hypothesis 4 :_*There is a statistically significant interactive effect of CEO networks and CEO power on bank risk during the credit crisis.*

3. Data and Research Design

3.1 Data

We follow Beltratti and Stulz (2009) and Fahlenbrach and Stulz (2011) in the selection of banks. This study requires data on CEOs in 2006, the last complete year prior to the financial crisis, and financial data for 2007 and 2008. To this end, we first researched firms with Industry Classification (SIC) codes between 6000 and 6300 in the fiscal year 2006 and obtained a list of 132 firms from this effort. We then excluded firms with SIC code 6282, investment advice, since they are not in the lending business. Following the practice in Fahlenbrach and Stulz (2011), I excluded pure brokerage houses and also American Express, which is not a traditional bank. This step results in an original sample of 98 banks, which is consistent with the sample selection results in Fahlenbrach and Stulz (2011).

In the next step, we hand-collect all social network data for the 98 bank CEOs from the Boardex database. Boardex does not contain information on one CEO, resulting in the final 97 CEO sample size. Specifically, using biographical information of bank CEOs collected from the Boardex database, we defined five social networks that represent the ties among the individuals in this paper.

First, current employment network (*CE*): Two bank CEOs are defined as connected to each other through *CE* if one of them sits on another firm's board or both of them sit on the board of a third firm at the same time, which is called "interlocking board members" in finance literature.

Second, previous employment network (*PE*): Two bank CEOs are defined as tied to each other through PE if they have had overlapping working experience in the past. This paper only considers CEOs during their tenure as executives or board members, and does not take into account employment overlap as junior executives or employees. This approach seeks to maximize the likelihood of two CEOs' mutual acquaintance through *PE*.

Third, education network (*ED*): We defined two CEOs as connected to each other through *ED* if they graduated from the same school within one year of each other with the same professional or doctoral degree. This method does not include bachelor degrees and master degrees, and therefore maximizes the probability that two bank CEO know each other through shared education in the past.

Fourth, other activities network (*OA*): We defined two bank CEOs as connected to each other through other activities if they attend the same charities, sports clubs, or other organizations. To ensure that two bank CEOs have actually met, we do not include occurrences when the CEO's position in an organization is just as a member, e.g., a member of the American Financial Association.

Fifth, social network (*SN*): We defined two bank CEOs as connected to each other if they share at least one of the above networks. We concede that there are other social networks. For example, bank CEOs could get acquainted through mutual business providers, suppliers, and customers. There are also additional personal relationships such as family links and neighbors. However, the above four networks are arguably the most related social networks in terms of a CEO's business decisions. Figure 1 shows all the connections between the 97 bank CEOs resulting from either education, prior or current employment, or active role in other activities.

In this paper, we adopt three widely used centrality measures: degree, closeness, and betweenness to measure the relative centrality of a CEO in a network. Each measure captures a different dimension of a social network.

The first and simplest centrality measure is *degree*, which is defined as the number of arcs that a node has. It was first introduced by Proctor and Loomis (1951) to determine which node has more ties relative to other nodes. The degree centrality for node *i* is given as:

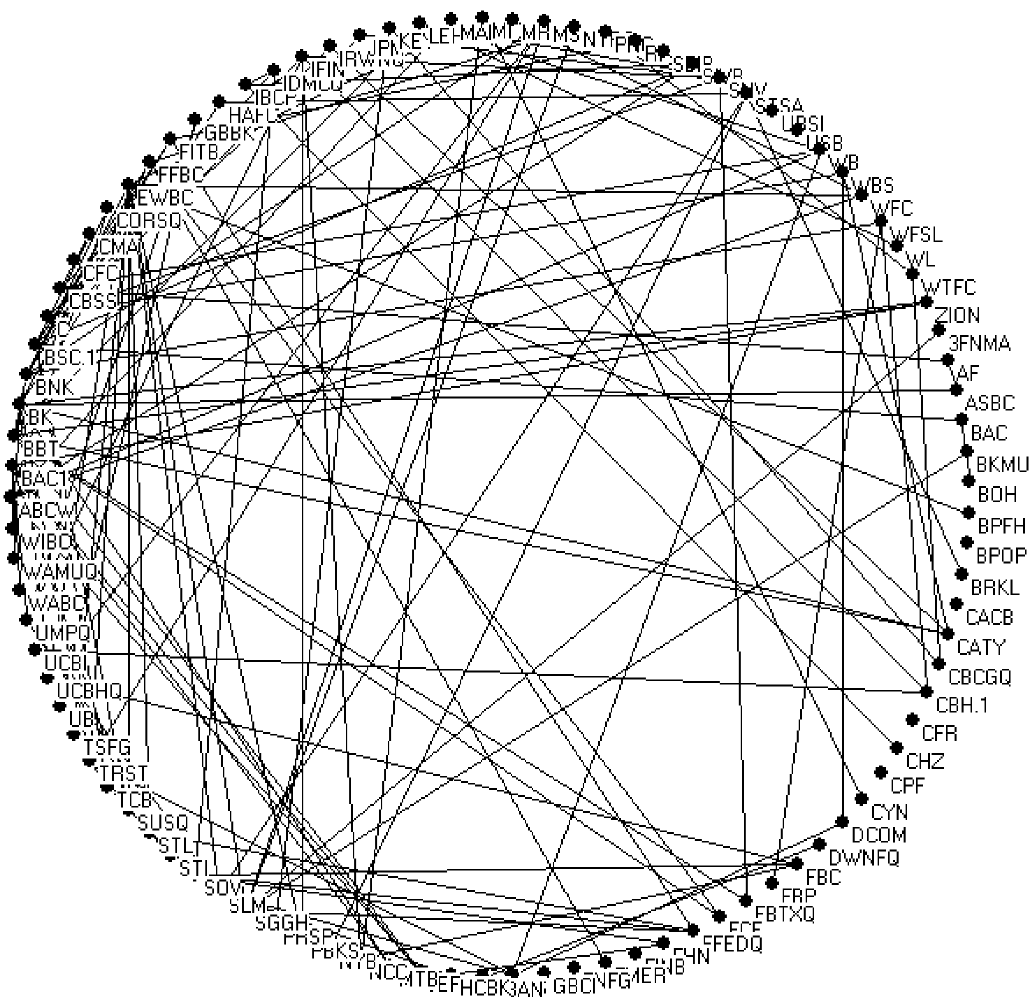
$$C_D(n_i) = d_i(n_i) \tag{1}$$

In order to make networks of different sizes (*g*) comparable between groups, we normalize the degree centrality. That is, we divide equation (1) by the maximum possible indegree nodes (= *g*-1) if everyone is directly connected to *i*, and express the result as a percentage. As such, a higher value of degree indicates that a particular CEO has more social ties with other CEOs.

$$C'_D(n_i) = d_i(n_i)/(g-1) \tag{2}$$

Figure 1: Bank CEO Networks in 2006

The figure below was drawn with the Pajek software. We used a Circular algorithm with random starting positions to draw the network .The network shows all the connections between 97 bank CEOs from either education, prior or current employment or active sole in other activities. For illustration purpose, we use the ticker code of bank to represent corresponding CEO.



The second measure, *closeness,* proposed by Sabidussi (1966), takes into account both direct and indirect links (arcs and edges) between nodes, and measures how easily one node connects to another. Closeness is defined as:

$$\mathbf{C_C(n_i)} = \left[\sum_{\mathbf{j=1}}^{\mathbf{g}} \mathbf{d(n_i, n_j)}\right]^{-1} \quad (3)$$

Where $d(x,y)$ is the short distance between nodes i and j.

The third measure, *betweenness*, first suggested by Freeman (1977), refers to the capability of a node to connect to other nodes. A node has a high betweenness if it lies on several shortest paths connecting other pairs of nodes. Intuitively, such a node is important in the sense that it has an informational advantage and possesses the ability to control the information and relationship.

$$\mathbf{C_B(n_i)} = \sum_{\mathbf{j<k}} \frac{\mathbf{g_{jk}(n_i)}}{\mathbf{g_{jk}}} \quad (4)$$

Where for all pairs of nodes j and k, node i is involved in a pair's geodesic(s).

We then create an aggregate measure in order to fairly capture all the different aspects of centrality of a network. Since it is not theoretically clear which measure is more important or less important, we use an equal-weighted average to form this aggregate measure,

$$C(n_i) = (C'_D(n_i) + C_C(n_i) + C_B(n_i))/3 \quad (5)$$

In the next step, we rank $C(n_i)$ to three social network (*SN*) scores: low (*SN*=0), medium (*SN*=1), and high (*SN*=2). The use of SN scores reduces the influence of extreme values and makes interpretation easy.

In addition to data on bank CEOs, we retrieved stock return data between 2007 and 2008 from the Center for Research in Security Prices (CRSP), accounting data for banks from Compustat, and compensation and insider-trading information via the website of the Securities and Exchange Commission (SEC).[1] Following Chesney et al. (2010), we identify firms as too big to fail (*TBTF*) if they either had to submit to the April 2009 stress test conducted by the Federal Reserve Board [2] or belonged to other national financial institutions in the largest market capitalization decile as of 2006. [3]

Table 1 provides descriptive statistics for the sample and detailed variable descriptions. Panel A reports descriptive statistics of various measures of risks, including *EDF*, *TR*, *IDIOR*, and *SYSR*. The means of *EDF*, *TR*, *IDIOR*, and *SYSR* are 0.49, 4.02%, 1.3%, and 2.78%, respectively. Panel B reports descriptive statistics regarding CEO networks, power, and ownership. SN represents an equally divided three groups: high SN (SN=2), medium SN (*SN*=1), and low SN (*SN*=0).The average ratio of CEO total compensation to the sum of all top five executives' total compensation is 36%, ranging from near 0% to about 76%. The average percentage of shares outstanding held by a CEO is 2%. Panel C documents descriptive information on other control variables. The average value of the natural log of total assets of banks in this sample is $9.80 billion at fiscal year-end of 2006. The average charter value of a bank is $1.22 billion, with a minimum value of $1.05 billion and a maximum value of $1.45 billion. The mean value of bank capital is $0.50 billion. It is not surprising that this study covers large-size and well capitalized banks since ExecuComp is biased toward large firms.

Table 2 also reports that CEO power is negatively correlated to *DIVER*, indicating CEO power dilutes in diversified activities. Surprisingly, CEO ownership is not associated with any other regression variables, which is inconsistent with other results from banking research in other time periods (e.g., see Houston and James, 1995). Further examination of the correlation matrix in Table 2 illustrates that bank chart value and bank capital are significantly and negatively correlated with risk taking, indicating well capitalized banks tend to be stable banks in the financial crisis. Finally, Table 2 shows that the *TBTF* dummy is positively related to bank risk, supporting the notion that *TBTF* status

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[1] Available at http://idea.sec.gov

[2] The stress test covered 19 institutions. The complete bank stress test list is available at: http://blogs.wsj.com/economics/2009/04/24/list-of-19-banks-undergoing-stress-tests/

[3] This adds four banks, Fannie Mae, Lehman Brothers, Merrill Lynch, and Wachovia, to the list of TBTF in this study.

provides a safety net to banks, and in turn, serve as an incentive for banks to take on more risk. There is no significant coefficient exceeding 0.5, implying that multicollinearity should not be a problem in the model specifications.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel A: Dependent variables (*RISK*)					
1. Expected Default Frequency (*EDF*)	0.49	0.34	0	1	78
2. Total risk (*TR*)	4.02%	1.56%	0.12%	10.38%	85
3. Idiosyncratic risk (*IDIOR*)	1.30%	0.35%	-2.56%	2.17%	85
4. Systematic risk (*SYSR*)	2.78%	1.06%	0.12%	6.69%	85
Panel B: CEO variables					
Social network (*SN*)	0.68	0.83	0	2	97
CEO power (*POWER*)	0.36	0.11	0	0.76	90
CEO ownership (*%CEO_OWN*)	0.02	0.03	0	0.15	66
Panel C: Other control variables					
Bank size (*LNTA*) (bill.)	9.80	1.51	7.54	14.19	83
Charter value (*CV*) (bill.)	1.22	0.08	1.05	1.45	83
Bank capital (*CAPITAL*) (bill.)	0.50	0.20	0	1.13	83
Diversification index (*DIVER*)	0.37	0.12	0.02	0.50	83
Previous M&A (*MERGER*) (bill.)	0.20	0.40	0	1	97
Too-big-to-fail (*TBTF*)	0.18	0.39	0	1	97

Notes: This table contains descriptive statistics for the sample firms used in the study. Expected Default Frequency *(EDF)* is calculated from the KMV-Merton model, where a bank's probability of default is equivalent to the likelihood that the option will expire unexercised and the firm's shareholders will default. Total risk *(TR)* is the standard deviation of the daily bank stock returns in each year. Idiosyncratic risk *(IDIOR)* is the standard deviation of the error terms in Eq. (12). Systematic risk *(SYSR)* is the coefficient of *Rmt* (i.e. $\beta 1$) in Eq. (13). *TR*, *IDIOR*, and *SYSR* are all averaged over years 2007-2008. Social network *(SN)* is the equal-weighted average of a CEO's social centrality: degree, closeness, and betweenness. CEO power *(POWER)* is the ratio of CEO total compensation to the sum of all top five executives' total compensation. CEO ownership *(%CEO_OWN)* is the percentage of shares outstanding held by a CEO. Bank size *(LNTA)* is the natural log of total assets at the end of 2006 fiscal year. *Charter value (CV)* is calculated as the sum of the market value of equity plus the book value of liabilities divided by the book value of total assets. Bank capital *(CAPITAL)* is computed as the book value of bank equity as a percentage of total assets. Bank revenue diversification index *(DIVER)* is calculated as one minus the sum of the squared fraction of operating income from interest and the squared fraction of net operating income from non-interest sources. Previous M&A *(MERGER)*, a dummy variable for M&A, equals one for a bank that involves with any take-over activities in a year, otherwise zero. Too-big-to-fail *(TBTF)* is a dummy variable that takes a value of one if a bank either has to submit to April 2009 stress test conducted by the Federal Reserve Board or belongs to other national financial institutions in the largest market capitalization decile as of 2006.

Table 2 : Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13
EDF	1												
TR	0.68***	1											
SYSR	0.61***	0.86***	1										
IDIOR	0.63***	0.96***	0.75***	1									
SN	-0.07**	0.03**	0.09**	0.03**	1								
Power	0.02	0.10	-0.31	0.20	0.04	1							
OWN	-0.11	-0.05	-0.11	0.09	-0.17	0.05							
LNTA	0.33***	0.27**	0.25**	0.11	0.23**	-0.05	-0.04	1					
CV	-0.53***	-0.33**	-0.29**	-0.35**	0.09	0.12	-0.18	-0.22**	1				
CAPITAL	-0.32**	-0.26**	-0.33**	-0.27**	0.07	0.00	0.02	-0.10	0.52***	1			
DIVER	0.16	0.19*	0.12	0.15	0.10	-0.24**	-0.17	0.43***	-0.03	-0.22**	1		
MERGER	0.03	0.14	0.06	0.07	0.14	-0.05	0.07	0.43***	-0.01	0.21*	0.11	1	
TBTF	0.25**	0.27**	0.35**	0.10	0.32**	-0.03	-0.06	0.71***	0.02	0.00	0.33**	0.24**	1

Notes: Pearson associations between the regression values. SN is positively associated with bank size, implying that CEOs of big banks tend to have more social connections. Similarly, SN is positively associated with the *TBTF* dummy, suggesting that CEOs of banks with *TBTF* status are more socially connected with other CEOs. In addition, *SN* is statistically significantly and positively correlated with *TR*, *SYSR*, and *IDIOR*, suggesting that banks with well-connected CEOs are related to risk taking. It is not surprising that the *EDF* is positively associated with *TR*, *SYSR*, and *IDIOR*, given that those risk measures are all market value based. The table shows Pearson Pairs-wise correlation matrix. All variables are defined the same as in Table 1. P values are reported in the parenthesis. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

3.2 Measures of Bank Risk

Merton (1974) provides a model that facilitates the estimation of probability of default. The basic insight underlying this approach is that a bank's equity can be viewed as a call option on the bank's assets with an exercise price equal to the maturity value of the bank's debt. However, if the market value of the firm's assets is less than the value of its debt, then the call option is left unexercised at maturity. Hence, a bank's probability of default is equivalent to the likelihood that the option will expire unexercised and the firm's shareholders will default.

Following Bharath and Shumway (2008), we stipulate the KMV-Merton model in the following ways: First, the total value of a bank is assumed to follow a geometric Brownian motion.

$$dV = \mu V dt + \sigma_V V dW \tag{6}$$

Where

μ is the expected continuously compounded return on V,

σ_V is the asset volatility

dW is a standard Brownian motion.

Second, the KMV-Merton model assumes that a bank has issued only one zero coupon bond maturing in time T. For the purpose of this paper, we assume T as 1. In particular, the equity value of a bank is given as,

$$E = V\Phi\left(\frac{\log\left(\frac{V}{D}\right)+\left(r+\frac{\sigma_V{}^2}{2}\right)T}{\sigma_V\sqrt{T}}\right) - e^{-rT}D\Phi\left(\frac{\log\left(\frac{V}{D}\right)+\left(r-\frac{\sigma_V{}^2}{2}\right)T}{\sigma_V\sqrt{T}}\right) \tag{7}$$

where

Φ is the cumulative standard normal distribution

E is the equity value, which is an option on a firm's asset value (V) with exercise price as the face value of the debt (D)

σ_V is the asset volatility

From Ito's lemma, the standard deviation of the process is given as,

$$\sigma_E = \left(\frac{V}{E}\right)\Phi\left(\frac{\log\left(\frac{V}{D}\right)+\left(r+\frac{\sigma_V{}^2}{2}\right)T}{\sigma_V\sqrt{T}}\right)\sigma_V \tag{8}$$

Hence, we can numerically solve for V and σ from equations (7) and (8). These estimates form inputs for the distance to default (Z) given as;

$$Z = \frac{\log\left(\frac{V}{D}\right)+\left(r-\frac{\sigma_V{}^2}{2}\right)T}{\sigma_V\sqrt{T}} \tag{9}$$

Therefore, the correspondent default probability using cumulative standard normal distribution, Φ, which is also commonly called Expected Default Frequency (EDF), is given as;

$$EDF = \Phi\left(-\frac{\log\left(\frac{V}{D}\right)+\left(r-\frac{\sigma_V{}^2}{2}\right)T}{\sigma_V\sqrt{T}}\right) = \Phi(-Z) \tag{10}$$

However, Bharath and Shumway (2008) point out that EDF can be improved further by taking into account financial constraints. This task is accomplished by a moral hazard model as given,

$$\frac{\partial Z}{\partial V} = \frac{1}{V\sigma_V\sqrt{T}} > 0, \frac{\partial Z}{\partial \sigma_V} = -\frac{\sqrt{T}}{2} < 0,$$

$$\frac{\partial EDF}{\partial V} = \frac{\partial EDF}{\partial Z}\frac{\partial Z}{\partial V} = -\frac{e^{\frac{Z^2}{2}}}{V\sigma_V\sqrt{2\pi T}} < 0, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\frac{\partial EDF}{\partial \sigma_V} = \frac{\partial EDF}{\partial Z}\frac{\partial Z}{\partial \sigma_V} = \frac{\partial \Phi(-Z)}{\partial Z}\left(-\frac{\sqrt{T}}{2}\right) = \frac{e^{\frac{Z^2}{2}}}{2}\sqrt{\frac{T}{2\pi}} > 0 \ldots\ldots\ldots \tag{11}$$

Empirically, the above computation requires the following inputs: the volatility of stock returns ($\sigma(E)$), the face value of debt (D), and the risk free rate (r). $\sigma(E)$ is calculated as the quarterized percent standard deviation of returns, which is estimated from the prior quarter's stock return data. For risk free rate, we use the 3-Month Treasury bill rate obtained from the Board of Governors of the Federal

Reserve System. The market value of each firm's equity is calculated as the product of share price and shares outstanding at the end of each quarter. [4]

Following Pathan (2009), we also measure bank risk-taking using total risk (*TR*), idiosyncratic risk (*IDIOR*), and systematic risk (*SYSR*). The *TR* of a bank is calculated as the standard deviation of its daily stock returns (*Rit*) for each fiscal year. *TR* represents the overall variability in bank stock returns. *SYSR* and *IDIOR* are calculated in a two-index market model as follows:

$$R_{it} = a_i + \beta 1_i Rmt + \beta 2_i INTEREST + \varepsilon_{it} \qquad (12)$$

Where

$\beta 1_i$ is the *SYSR* of bank *I;*

Ri is the bank's equity return;

Rm is the return on the S&P 500 market index;

INTEREST is the yield on the three-month Treasury-bill yield;

a is the intercept term and ε is the residuals;

IDIOR is calculated as the standard deviation of residuals of Eq. (12) for each year.

3.3 Measure of Other Variables

Following Bebchuk et al., (2007), we use the CEO's pay slice (*POWER*), defined as the fraction of the aggregate top-five total compensation paid to the CEO, as a proxy for CEO power. Bebchuk et al., (2007) argue that *POWER* reflects the relative importance of the CEO among the top executives and therefore can be used as a proxy for CEO internal dominance in the decision-making process. In addition, *%CEO_OWN* represents the percentage of shares outstanding held by a CEO. Prior research show that a high *%CEO_OWN* will align executives' risk-taking behavior with the shareholders (e.g., Lefebvre and Vieider, 2010), and hence have an impact on corporate risk taking.

As suggested by Pathan and Skully (2010), we control for bank size effect and bank diversification effect on bank risk-taking. Bank size (*LNTA*) is the natural log of total assets at the end of the 2006 fiscal year. Our bank revenue diversification index (*DIVER*) is calculated as one minus the sum of the squared fraction of operating income from interest and the squared fraction of net operating income from non-interest sources. Pathan and Skully (2010) argue that this measure is appropriate in banking since it captures the complexity deriving from various income sources.

Charter value (*CV*) is calculated as the sum of the market value of equity plus the book value of liabilities divided by the book value of total assets. Jonghe and Rudi (2008) argue that shareholders in a high *CV* bank have more to lose in case of insolvency, and thus reduce moral hazard problems in a bank.

The bank capital ratio (*CAPITAL*) is calculated as bank total equity as a percentage of the bank's total assets. Pathan and Skully (2010) point out that a bank with high *CAPITAL* tend to undertake more risk, resulting from the absence of monitoring mechanism from debt holders.

MERGER, a dummy variable for previous mergers and acquisitions, equals one for a bank that is involved with any take-over activities in a given year and zero otherwise.. This *MERGER* dummy is included to control for any bank board structure and the resulting bank risk appetite change. Finally, a too-big-to-fail (*TBTF*) dummy is included in the model. This dummy variable takes a value of one if a bank either has to submit to an April 2009 stress test conducted by the Federal Reserve Board or is in the largest market capitalization decile as of 2006. Prior research shows that banks in this category enjoy a subsidy from having this safety net and have more incentives to take on more risk (Chesney et al., 2010).

3.4 CEO Networks and Bank Risk

In order to assess the effect of CEO networks, we regress bank risk on the SN score and control variables listed in the four regression specifications as follows:

[4] The SAS code used to calculate the KMV-Merton model is provided by Bharath and Shumway (2008) and is available at: http://www-personal.umich.edu/~shumway/papers.dir/nuiter99_print.sas

$$EDF = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \varepsilon \quad (13)$$

$$TR = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \varepsilon \quad (14)$$

$$SYSR = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \varepsilon \quad (15)$$

$$IDIOR = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \varepsilon \quad (16)$$

Where

EDF is calculated from KMV-Merton model, where a bank's probability of default is equivalent to the likelihood that the option will expire unexercised and the firm's shareholders will default;
TR is the standard deviation of the daily bank stock returns in each year;
IDIOR is the standard deviation of the error terms in Eq. (12);
SYSR is the coefficient of *Rmt* (i.e. $\beta 1$) in Eq. (12);
SN is the equal-weighted average of a CEO's social centrality: degree, closeness, and betweenness;
POWER is the ratio of CEO total compensation to the sum of all top five executives' total compensation;
%CEO_OWN is the percentage of shares outstanding held by a CEO;
LNTA is the natural log of total assets at the end of the 2006 fiscal year;
CV is calculated as the sum of the market value of equity plus the book value of liabilities divided by the book value of total assets;
CAPITAL is computed as the book value of bank equity as a percentage of total assets;
DIVER is calculated as one minus the sum of the squared fraction of operating income from interest and the squared fraction of net operating income from non-interest sources;
MERGER is a dummy variable for M&A, equals one for a bank that is involved with any take-over activities in a year, zero otherwise;
TBTF is a dummy variable that takes a value of one if a bank either has to submit to an April 2009 stress test conducted by the Federal Reserve Board or is in the largest market capitalization decile as of 2006.

3.5 CEO Ownership and CEO Power

To explore the possibility that the *SN* effect is different in banks with powerful CEOs and high CEO ownership, we interact *POWER* and *%CEO_OWN* with the SN dummy. The model specifications are as follows:

$$EDF = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \beta_{10} SN * POWER + \beta_{11} SN * \%CEO\_OWN + \varepsilon \quad (17)$$

$$TR = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \beta_{10} SN * POWER + \beta_{11} SN * \%CEO\_OWN + \varepsilon \quad (18)$$

$$SYSR = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \beta_{10} SN * POWER + \beta_{11} SN * \%CEO\_OWN + \varepsilon \quad (19)$$

$$IDIOR = \alpha_0 + \beta_1 SN + \beta_2 POWER + \beta_3 \%\_CEO\_OWN + \beta_4 LNTA + \beta_5 CV + \beta_6 CAPITAL + \beta_7 DIVER + \beta_8 I2MERGER + \beta_9 TBTF + \beta_{10} SN * POWER + \beta_{11} SN * \%CEO\_OWN + \varepsilon \quad (20)$$

Where
EDF, *TR*, *IDIOR*, *SYSR*, *SN*, *POWER*, *%CEO_OWN*, *LNTA*, *CV*, *CAPITAL*, *DIVER*, *MERGER*, and *TBTF* are all defined as above.

3.6 Endogeneity

One major method to account for endogeneity is to include instruments in the model. Unfortunately, there are no valid instruments to econometrically account for such potential endogeneity in social network studies. Hence, following the other studies on social network (e.g., Fracassi and Tate, 2012; Chikh and Filbien, 2011; Renneboog and Zhao, 2011; Berger, et al, 2013), we alleviate the endogeneity concerns by using lagged bank characteristics and CEO characteristics to control for bank risk-taking during the crisis. Arguably, reverse causality, causality running from bank risk-taking behavior to CEO social networks, is not a major problem in this empirical research setting for two reasons. First, we use CEOs' social networks as of 2006 to explain bank risk during the crisis (2007-2008). Hence, there is at least a one-year lag between the dependent variable and independent variables. This approach eliminates a direct contemporaneous endogenous effect. Second, most of the social links among bank CEOs were initiated long before the financial crisis. As such, it is hard to argue that the causality runs from bank risk taking to CEO social networks.

4. Empirical Results

4.1 CEO Networks and Bank Risk

This section reports OLS regression results based on Equations (13) – (16). These models investigate the impact of social networks on various measures of bank risk including *EDF*, *TR*, *IDIOR*, and *SYSR*. Model 1 of Table 3 documents the results for *EDF*. Model 1 is well-fitted with an overall R^2 of 30.99% with statistically significant F-values. With regard to social networks, the results show that, after controlling for bank characteristics and other CEO characteristics, a higher *SN* score is statistically significant and negatively associated with *EDF*. Specifically, it demonstrates that an increase in *SN* score ranking (e.g., from low to medium, or from medium to high) would decrease bank *EDF* by 7.3%. The results suggest that banks with well-connected CEOs are less likely to default during the financial crisis.

The coefficients on other bank and CEO characteristics are also insightful. For example, *LNTA* is statistically significant and positively correlated to *EDF*, indicating that a larger bank tends to be exposed to more risk. *CV* is positively related to *EDF*, contrasting with the notion that *CV* represents an opportunity cost of bank insolvency and should be negatively associated with bank risk. Table 3 also shows that *CAPITAL* is statistically significant and negatively associated with *EDF*, supporting the view that the high concentration of debt reduces bank risk. This is because debt serves an important market monitoring mechanism in disciplining bank managers (Allen, et al., 1998). The coefficient on the *TBTF* dummy is positive, providing evidence that the "too big to fail" policy increases moral hazard problems for big banks.

The results from models (2), (3), and (4) are in general similar to those in model (1). Specifically, model (2) of Table 3 reports that an increase in *SN* score would decrease bank *TR* by 2%. This result suggests that CEO social networks contribute to less total bank risk during the financial crisis. In other words, banks with well-connected CEOs are relatively stable banks during the financial crisis. Model (3) indicates that *SN* is negatively associated with *IDIOR*. However, the *SN* coefficient is not statistically significant, suggesting that the *SN* effect may not be a main consideration for investors to build an efficient portfolio. Moreover, model (4) shows that an increase in *SN* score would decrease bank *SYSR* by 3.2%. Interesting, in this model, the *MERGER* dummy is negatively and significantly associated with *SYSR*, indicating that merger activity decreases bank systematic risk.

Table 3: CEO Networks and Bank Risk

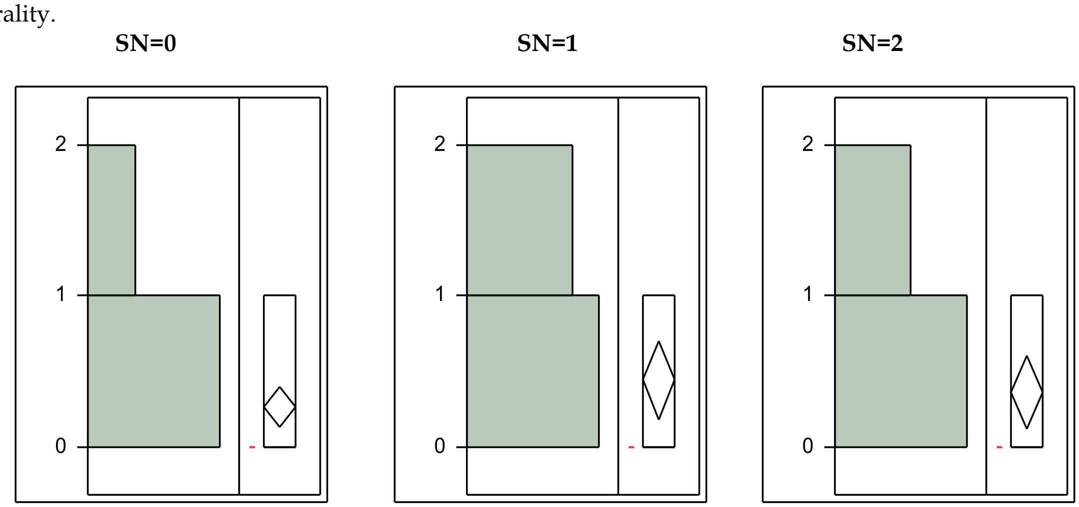
Explanatory variables	(1)	(2)	(3)	(4)
	EDF	TR	IDIOR	SYSR
SN	-0.073***	-0.020**	-0.022	-0.032**
POWER	-0.234	-0.654	-0.865	-0.234
%CEO_OWN	-1.303	-0.876	-0.532	-0.321
LNTA	0.043**	0.065	0.014	0.044**
CV	2.32***	0.012***	0.007***	0.003
CAPITAL	-1.434**	0.654**	-1.54**	-0.343**
DIVER	0.083	0.02**	0.03	-0.23
MERGER	-0.165	0.012	0.15	-0.04**
TBTF	0.064**	0.013	0.231	-0.033
Intercept	3.876***	-3.821***	-2.242***	-0.349
Adj R-Sq	0.08	0.07	0.09	0.08
F-value	2.17**	2.09**	2.01**	2.04**
Obs	56	61	61	61

Notes: This table reports the OLS regression results of social networks (SN) on Expected Default Frequency *(EDF),* Total risk *(TR),* Idiosyncratic risk *(IDIOR),* and Systematic risk *(SYSR).* Expected Default Frequency *(EDF)* is calculated from the KMV-Merton model, where a bank's probability of default is equivalent to the likelihood that the option will expire unexercised and the firm's shareholders will default. Total risk *(TR)* is the standard deviation of the daily bank stock returns in each year. Idiosyncratic risk *(IDIOR)* is the standard deviation of the error terms in Eq. (12). *Systematic risk (SYSR)* is the coefficient of *Rmt* (i.e. $\beta 1$) in Eq. (12). TR, IDIOR, and SYSR are all averaged over 2007-2008. All other control variables are defined the same as in Table 1. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

Overall, the results support the notion that CEO networks have a positive effect on bank risk taking. A possible explanation is that social network provides efficient information to bank CEOs, and enable them to accurately identify market risk and to set the right course of action, resulting in less risk taking during the financial crisis.

Figure 2: CEO Networks and CEO Insider Trading Occurrence

The figure shows the frequency of the CEO insider trading by social networks (SN) during 2007-2008. SN=0 indicates low social centrality; SN=2 means high social centrality. SN=1 refers to a medium level of social centrality.



4.2 CEO Networks and Insider Trading

Since we uncover evidence that well-connected bank CEOs are involved with less risk-taking, we further assess whether well-connected CEOs tend to reduce equity holdings in 2006, just prior to the crisis. Figure 2 illustrates that CEOs with a low *SN* score have a low frequency of reducing equity holdings. This result support the view that well-connected bank CEOs have better knowledge of an upcoming financial crisis and thus trade out of their equity position and thereby minimize their personal wealth losses. Table 4 shows the results from a nonparametric Wilcoxon Signed Rank test. The evidence is consistent with Figure 2, suggesting that CEO social networks have a significantly positive impact on insider trading in 2006, and hence reduce the CEOs' personal wealth loss in the wake of the financial crisis.

Table 4: CEO Networks and Insider Trading

Test Statistics[a]	
The frequency of CEO insider trading by CEO networks	
t-score	2.12**
a. Wilcoxon Signed Ranks Test	

Notes: The table reports the Wilcoxon Signed Rank test that hypothesizes about the relative proportion of insider trading falling into two social network subgroups: high (*SN*=2) - low (*SN*=0). 33 observations in the high group, and 32 observations in the low group. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

Table 5: The Interactive Effects of CEO Power and CEO Ownership on Bank Risk

Explanatory variables	(1)	(2)	(3)	(4)
	EDF	TR	IDIOR	SYSR
SN	-0.041**	-0.013**	-0.014	-0.017
POWER	-0.399	-0.787	-0.926	-0.661
%CEO_OWN	-1.678	-0.635	-0.520	-0.247
LNTA	0.053**	0.015	0.011	0.068***
CV	3.650***	0.005***	0.007***	0.003
CAPITAL	-1.734**	0.791**	-1.051**	0.396
DIVER	0.082	0.01**	0.230	-0.210
MERGER	-0.077	0.011*	0.190	-0.02***
TBTF	0.063***	0.130	0.103	-0.037
SN*POWER	-0.340	-0.009	-0.003	-0.432**
SN*%CEO_OWN	0.684	0.034	0.000	0.043
Intercept	4.232***	-3.674***	-3.786***	-0.443
Adj R-Sq	0.080	0.070	0.070	0.080
F-value	2.470**	2.180**	2.000**	2.070**
Obs	56	61	61	61

Notes: This table reports the OLS regression results of social networks (*SN*) on Expected Default Frequency *(EDF)*, Total risk *(TR)*, Idiosyncratic risk *(IDIOR)*, and Systematic risk *(SYSR)*. Expected Default Frequency *(EDF)* is calculated from the KMV-Merton model, where a bank's probability of default is equivalent to the likelihood that the option will expire unexercised and the firm's shareholders will default. Total risk *(TR)* is the standard deviation of the daily bank stock returns in each year. Idiosyncratic risk *(IDIOR)* is the standard deviation of the error terms in Eq. (12). Systematic risk *(SYSR)* is the coefficient of Rmt (i.e. $\beta 1$) in Eq. (12). *TR*, *IDIOR*, and *SYSR* are all averaged over 2007-2008. CEO power (*POWER*) is the ratio of CEO total compensation to the sum of all top five executives' total compensation. CEO ownership (*%CEO_OWN*) is the percentage of shares outstanding held by a CEO. All other control variables are defined the same as in Table 1. *T* statistics are reported in parenthesis. Significance at the 10%, 5% and 1% levels is indicated by *, ** and ***, respectively.

4.3 CEO Ownership and CEO Power

The empirical evidence shows a negative relationship between CEO networks and bank risk taking. However, it is likely that the CEO networks effect is more pronounced in banks where CEOs are powerful and hence have the capability to make strategic decisions. Similarly, the effect is also possible to be more evident when bank CEOs' interests are better aligned with shareholders. Table 5 reports the coefficients of interaction terms on *SN* with *POWER*, and *SN* with *%CEO_OWN*. For CEO power, the interaction terms are all negative and are statistically significant in terms of *SYSR*. The results further confirm our conjecture that CEO networks have an impact on CEOs' risk choices, given that a powerful CEO is more likely to exert an influence on such choices. However, for CEO ownership, the results regarding the interactive effect of CEO network and CEO ownership are not statistically significant using all four risk measures.

5. Conclusion

We investigate the impact of CEO networks on bank risk during the recent financial crisis and test whether CEO networks have a bearing on CEO insider trading at the onset of the crisis. To pursue these tests, we construct a unique dataset of CEO networks based on 97 bank CEOs' social ties, which allows us to assign a *SN* score to each CEO.

We provide evidence that CEO networks in 2006, the year prior to the financial crisis, are related to bank risk-taking ex post during the financial crisis. We find that after controlling for bank and other CEO characteristics, a higher *SN* score is associated with lower bank risk. An increase in the *SN* score (e.g., from low to medium, or from medium to high) would decrease *EDF* by 7.3%, decrease *TR* by 2.0%, and decrease *SYSR* by 3.2% at the 1% or 5% significance levels.

In addition, the CEO social network effect is magnified with CEO power, indicating that a well-connected bank CEO uses his internal dominance to influence corporate risk choices, and hence undertake less risk during the financial crisis. Furthermore, CEO social networks have a significantly positive impact on insider trading that occurred in 2006, reducing CEOs' personal wealth loss in the wake of the financial crisis. Overall, the results suggest that CEO social networks provide an efficient information channel to bank CEOs, enable them to accurately evaluate industry risks, resulting in lower risk levels for both corporate and personal wealth during the financial crisis. In addition, the CEO networks effect is intensified in banks with powerful CEOs.

The empirical results of this study should be of interest to policy makers, who could focus their limited monitoring sources on bank CEOs whose social network traits put them at greater risk of failure. The evidence provided here is also expected to be of interest to boards, especially those members who sit on the nominating committees, to evaluate CEO candidates in terms of social network characteristics. This study is also of interest to CEOs themselves by unraveling the mystery of whether CEO social networks are truly beneficial.

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