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Do Social Networks Encourage Risk-taking? Evidence from Bank CEOs

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Note: Part of this work was completed by Hasan while he was a Shimomura Fellow at the Development Bank of Japan.

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Abstract

This paper investigates the impact of CEO's social network on bank risk and observes a significant positive association. Adopting a difference-in-difference approach, using deaths and retirements within networks, it confirms that the findings are causal. It also reports that well-connected bank CEOs take more risk when more of their social ties are linked to informationally opaque firms and when the labor market offers fewer employment options. In addition, diversity of social ties (professional and educational) helps to mitigate the impact on risk. Finally, it reveals an inefficient trade-off between bank risk and return, suggesting that executive social networks lead to excessive bank risk.

Key Words: Risk-taking, social networks, CEOs

JEL Classification: L14, G21, G31.

1. Introduction

The tumultuous events surrounding bank failures during the recent financial crisis have raised significant concerns about the high degree of interconnectedness in the financial system (Allen and Babus, 2008).[1] The substantial costs associated with the too-connected-to-fail (TCTF) have called for regulatory reforms that consider interconnectedness among banking institutions in capital charges.[2] To promote a safe and sound banking system, it is therefore crucial to understand the economic consequences when financial institutions are well connected.

In particular, the interconnectedness of CEOs is quite common and prevalent in the corporate world. Motivated by the increasing importance of financial networks to bank stability (e.g., Allen and Gale, 2000; Leitner, 2005; Hautsch et al., 2014), this paper empirically investigates the risk implications of social connections among bank CEOs. Specifically, we ask whether and to what extent the interconnectedness of bank CEOs in social networks among the corporate elite affects bank risk-taking.

Large financial institutions are often viewed as dominating the business world and forging the makings of a "ruling class" in the United States both economically and politically (Mizruchi, 1982; 2004). Bank executives frequently have personal and professional connections with a wide variety of people and occupy central positions in social networks of the corporate elite. In line with a large amount of sociology literature (e.g., Coleman, 1988; Ellison and Fudenberg 1993; 1995), we propose three channels through which social ties may affect executives' decision-making: the

[1] For instance, the demise of Lehman Brothers immediately led to increased volatility and liquidity shortages for American International Group (AIG). Because AIG is a central player with connections to many other financial institutions, the U.S. government had to bail out AIG the next day for $85 billion to prevent the domino effect of AIG's credit derivative exposure on the rest of the financial system.

[2] In response, the Bank for International Settlements (BIS) considered interconnectedness as a key feature to identify global systemically important banks (G-SIBs) and imposed an additional common equity Tier I surcharge as a capital requirement in Basel III. Common equity Tier I surcharges range from 1% to 3.5%. The goal is to reduce the probability of failure of a G-SIB and limit the extent of a G-SIB's failure on the financial system.

soft information channel, the job market insurance channel, and the groupthink channel. Personal connections provide an effective channel for information exchange, allowing soft information to be spread in social networks (e.g., Burt 1992; Jackson, 2011; Cohen et al., 2008; Cai et al., 2016). Hence, a well-connected bank CEO may be in a prime position to obtain privileged information from her network contacts to aid in decision-making. Such informational advantage reduces uncertainties *ex-ante* and is likely to make bank CEOs feel more comfortable to take high-risk investment projects (though perhaps not excessively risky projects).

Social networks are also a major source of job opportunities (Holzer, 1987; Granovetter, 1995; Calvo-Armengol and Jackson, 2004). Should a manager lose her job due to a failed risky project, having strong social connections significantly facilitates the search for the next job opportunity (Liu, 2014; Faleye et al., 2014). Hence, well-networked bank CEOs may be more risk tolerant because they face less personal downside from risk-taking and enjoy greater upside if their risky projects succeed.

In addition, social network theory suggests that the actions of others affect individual preferences and decisions (e.g., Buskens, 2002). The diffusion of similar ideas can be more pronounced when there is strong homophily (the tendency of individuals to associate and bond with similar people) in social networks (McPherson et al., 2001; Lee et al., 2014). However, homophily may also induce social conformity and "groupthink" that can lead to inefficient decision-making (e.g., Asch, 1951; Janis, 1982; Ishii and Xuan, 2014; Lee et al., 2014; Gompers et al., 2015). Because our sample period from 2000 to 2012 includes the era of high risk-taking by banks leading up to the financial crisis of 2007-2009, it is plausible that bank CEOs take greater risks because they are more closely connected to similar peers and tend to act with a groupthink mindset.

Using a sample of 4,077 bank-year observations for 481 U.S. public banks between 2000 and 2012, we empirically examine how social connections among bank CEOs affect bank risk-taking behavior. We track the employment history of bank CEOs and identify their professional ties to top executives or board members in other companies (including both banks and nonbanks) through overlapping past working relationships. We identify educational ties if a bank CEO and an executive or board member of another company attended the same school and studied in the same degree program (within three years of each other). Following Faleye et al. (2014), we then construct an aggregate measure of connectedness by summing professional and educational ties for each bank CEO.

The main finding of our study is that bank risk increases with the number of CEO social connections. Specifically, a one-standard-deviation increase in CEO social connections translates into a 10 percent decrease in Z-score. Moreover, CEOs' professional ties to other top executives and board members drive bank risk-taking. Social networks do not only influence Z-score, but also the key components of the Z-score. Using alternative measures of bank risk, such as volatility of return on assets (ROA), volatility of return on equity (ROE), and idiosyncratic risk, we report consistent results. To ensure robustness of our findings and draw causal inferences, we adopt several methods to address potential endogeneity issue. First, we include bank fixed effects to control for time-invariant and unobservable bank heterogeneity, and our results still hold. Second, omitted variables capturing factors such as corporate governance, CEO incentive alignment, and managerial ability can potentially lead to a spurious correlation between CEO social connections and risk-taking. Therefore, we rerun our main regression model controlling for bank corporate governance, CEO ownership, compensation sensitivity to stock-price volatility, and general managerial ability. Including these additional controls has no material effect on our main findings.

Third, we use the deaths or retirements of network members as an exogenous shock to the size of an individual bank CEO's network (Fracassi and Tate, 2012; Lee et al., 2015). We employ a difference-in-difference estimator (DID hereafter) and find that banks demonstrate lower risk following exogenous severance of ties among their CEOs.

In the next step, we explore the three abovementioned channels through which CEO connections may affect bank risk-taking. To test the soft information channel, we calculate the percentage of CEO connections to opaque firms. We posit that such connections allow banks to obtain more hard-to-collect information and reduce CEOs' *ex-ante* risk aversion. In line with our prediction, we show that the ability to obtain soft information leads to greater risk. To test the job-market insurance channel, we examine how CEO connections affect risk-taking during adverse CEO labor market conditions. We find that when the overall labor market presents fewer opportunities, CEOs on average take less risk to avoid losing their jobs. Nonetheless, even if the external labor market is poor, well-connected CEOs take more risk than those who do not have strong social networks. The results lend support to the job-insurance channel (Faleye et al., 2014). Last, we show that the positive relation between CEO social networks and bank risk can be mitigated when social networks are more heterogeneous. This suggests that groupthink, driven by homophily in social networks, exerts a positive influence on bank risk.

Although we find evidence that all three channels link CEO social networks to bank risk-taking, the implications of the three channels on bank performance are quite different. For example, the soft information channel suggests that privileged information percolating through social networks allows bank CEOs to make informed decisions and results in superior bank performance. However, the job-market insurance channel suggests that CEOs have incentives to take excessive risk, which can deteriorate bank performance. According to the groupthink channel, bankers simply assimilate with their network peers' decisions when the outcome is unclear, which may have ambiguous implications for bank performance. Therefore, we explore whether higher bank risk-taking translates into better bank performance or higher returns. We adopt two bank performance measures, *ROA* and *profit margin*, to examine empirically the performance implications of bank CEOs' social networks. In general, our findings reveal that the higher risks associated with CEO social networks do not produce higher returns. This inefficient risk-return tradeoff reveals a "dark side" of social networking. It also indicates that the job-security channel is most helpful in explaining bank risk-taking and performance.

The rest of this paper is organized as follows. Section 2 provides a review of related literature and develops the hypotheses. Section 3 details the data, sample, and measures. Section 4 reports the empirical results. Section 5 summarizes and concludes the paper.

2. Related literature and hypotheses development

2.1. Soft information channel

When social agents make decisions without knowledge of the consequences, they often rely on information from their personal relationships (Ellison and Fudenberg, 1993; 1995). The ability for information to flow through a social network has been well documented in finance field. For instance, Hochberg et al. (2007) find that venture capital firms enjoy more deal flows and better performance when they have larger networks of partners. In the bank loan market, Engelberg et al. (2012) show that personal connections between a borrower and a lender result in larger loan amounts, lower interest rates, and less restrictive covenants. In the mergers and acquisitions setting, Cai and Sevilir (2012) find that social ties with target firms facilitate information acquisition by acquirers, which benefits the latter with lower takeover premiums and higher value creation.

Larker et al. (2013) demonstrate that valuable information circulates through networks of board directors. Also, Cohen et al. (2010) find that sell-side analysts perform better if they share an alma mater with key executives of covered firms, which supports the information sharing role of social networks.

According to the information role of social networks, CEOs with more connections are at better position to acquire soft information that is hard to obtain otherwise. For banking business that relies on relationship, soft information is crucial to make risky investment decisions, such as lending to small business and foreign markets. Hence, with more connections, bank CEOs are more informed and can become less risk-averse. More important, information from trustworthy people allows bank CEOs to make decisions more confidently (Borgatti and Cross, 2003). These arguments could suggest that *ex-ante*, having access to information through social networks may reduce CEOs' risk aversion and encourage them to take more risks. Banks with greater connections may find it attractive to invest in higher-risk investments because of CEO's risk appetites. However, enhanced information may enable CEOs to better evaluate the risk and thus limit excessive risk taking. In either situations, the information channel of social networks would suggest higher risk-adjusted performance.

2.2. Job-market insurance channel

CEOs are responsible for making important decisions and bear the negative consequences of unsuccessful investments, such as dismissal (Lehn and Zhao, 2006). However, the existing literature suggests that social networks play an important role in CEO job searches and reemployment. In particular, because information relating to a candidate's abilities and reputation is often subtle and tends to be difficult to verify, prospective employers often avoid using publicly available information sources, preferring to rely on information gleaned from social ties to learn about an individual's qualities (Holzer, 1987; Granovetter, 1995; Calvo-Armengol and Jackson, 2004).

CEOs are connected to other executives and directors through various activities, such as past co-working experience, as well as school or club ties. These connections provide information about executive or board vacancies at other firms and reflect outside employment options (Liu, 2014). Mazerolle and Singh (2004), for example, show that personal connections improve the odds of reemployment following labor market displacement. Berger et al. (2011) find that the number of social ties is a strong predictor of a bank executive's outside appointments. Similarly, Faleye et al. (2014) demonstrate that CEOs' social ties increase tolerance for failed innovation because of the job security provided by social networks. Therefore, social connections may be safety nets that enhance the probability of reemployment should an individual lose his/her job. Applying these insights in our context, it is plausible that a bank CEO can readily access information about outside job vacancies through personal connections. Consequently, *ceteris paribus*, a well-connected bank CEO may be less worried about the personal consequences of undertaking risky investment projects and thus be less risk averse.

2.3. Groupthink channel

Social capital theory predicts that individuals tend to establish social ties on the basis of homophily. That is, individuals tend to socialize or partner with others who share common characteristics, such as ethnicity, age, gender, education, or social status. This phenomenon occurs frequently in social networks (McPherson et al., 2001; Lee et al., 2014), and it is likely to lead to "herd mentality" and groupthink (Asch, 1951; Janis, 1982).

The existing literature documents evidence of such a groupthink mentality. For example, Fracassi (2012) reports that managers in similar industries tend to make similar investment decisions if they are well connected. In addition, Gompers et al. (2015) show that venture capitalists are more likely to form syndicates for joint investments if they share similar ethnic, educational, or career backgrounds. Lee et al. (2014) document that political alignment between executives and directors increase agency problems among managers, which implies that diversity among corporate leaders can benefit shareholders. Houston, Lee and Suntheim (2018) find that board connections in the financial industry foster a groupthink mentality that contributes to higher systemic risk. Likewise, we hypothesize that bank CEOs who share a groupthink mentality as a result of their social network connections tend to undertake risk without challenging each other. Leading up to the crisis of 2008, given many large banks were undertaking security investment without understanding the underlying risk, it is plausible that such activities cause herding behavior among well-connected CEOs and lead to higher risk for those banks. Thus, through the channel of groupthink mentality, more connections with risky firms cause CEOs to take even higher risks. We thus expect, conversely, that diverse social ties mitigate the effect of homophily on bank risk.

3. Data, sample, and measures

3.1. Sample selection

We obtain information on the social network connections of CEOs from the BoardEx database of Management Diagnostics Ltd (BoardEx). We obtain other financial information for our sample banks from bank call reports. Focusing on publicly traded banks in the U.S., we match the BoardEx dataset with call reports to construct our sample. Our procedure yields 4,077 bank-year observations from 2000 to 2012 for 481 unique public banks in the United States.

3.2. Measures

3.2.1. Measures of bank risk

The main dependent measure of our regression analysis is the Z-score, which empirical research widely uses as an indicator of financial stability (Roy, 1952; Laeven and Levine, 2009; Houston et al., 2010). Specifically, $Zscore = (ROA + E/A)/\sigma(ROA)$ where ROA, *E/A*, and $\sigma(ROA)$ are the mean return on assets, the mean equity-to-assets ratio, and the standard deviation of ROA, respectively, in the three-year window. The Z-score has an inverse relationship with bank insolvency risk and captures the likelihood that a bank will go out of business due to insufficient capital to compensate for a decrease in asset value (i.e., $E/A < -ROA$) (Roy, 1952). Following Laeven and Levine (2009), we take the natural logarithm of the Z-score to normalize the distribution.

3.2.2. Measures of CEO social networks

We obtain each CEO's professional and educational background from the BoardEx database. The information includes firms in which those CEOs have worked for, their roles in those firms, years of employment, the universities and degree programs they attended, and when they graduated. Following Fracassi (2016), we map each CEO's professional connections by carefully examining his/her employment history. We consider a connection as a professional tie if a bank CEO and another executive or board member (in another company) worked at the same company prior to their current employment and both were top executives or directors at the previous company.[3] Similarly, we consider a connection as an educational tie if a bank CEO and another executive or director (from another company) graduated from the same school and the same degree program within three years of each other (Cohen et al., 2008). We then count the total number of professional ties, the total number of educational ties, and the total number of professional and educational ties for each bank CEO. In addition, we take the natural logarithms of all three measures to normalize the distribution.

3.2.3. Control variables

Following the existing literature (Laeven and Levine, 2009; Pathan, 2009), we include a set of controls that captures various bank characteristics. *Log(bank size)* is the natural logarithm of bank total assets; *Capital ratio* is bank equity divided by bank total assets; *Deposit ratio* is total deposits divided by bank total assets; *Not rated* is a dummy variable that equals 1 if a bank does not have long-term bond ratings and is zero otherwise. We also control for a set of variables capturing various CEO characteristics (Coles et al., 2006; Berger et al., 2014). *Chairman* is a dummy variable that equals 1 if a CEO is also chairman of the board. *CEO age* is the natural logarithm of CEO age in years. *CEO tenure* is the number of years that a CEO has been working for a particular bank.

3.3. Summary statistics

Table 1 reports the summary statistics of variables used in our regression analyses. The mean value of *Log(Z-score)* is 2.86, which is comparable to numbers reported in prior studies of U.S. banks (e.g., Pathan, 2009). The mean of *Total ties* is about 10. Note that we take a conservative measure

[3] To mitigate the concern that a CEO's connections might include contacts at his or her current job, we exclude connections at the CEO's current employer (Fracassi, 2016).

of CEO networks because we restrict social ties to top executives and board members of other companies. This approach is consistent with Fracassi (2016). The mean values of *Log(Bank size)*, *Capital ratio*, and *Deposit ratio* are 14.68, 0.9, and 0.74, respectively. In our sample, 84 percent of the banks do not have bond ratings, and 44 percent of the CEOs are also chairmen. The average bank CEO in our sample is 57 and has an average tenure of approximately nine years.

[Insert Table 1 about here]

4. Empirical results

4.1. Baseline regression results

In table 2, we report our baseline regression results relating CEO social networks to bank risk. Specifically, we model *Log(Z-score)* as a function of CEO social-network measures, along with variables capturing various bank and CEO characteristics. In addition, we include year fixed effects to absorb economy-wide shocks and timely trends that could affect bank risk. In all regression models, we adopt cluster standard errors to control for the dependence of residuals over time for the same bank (Petersen, 2009). In column 1 of table 2, we document a significantly negative coefficient (-0.041) of *Total ties* (logged). To interpret the economic significance, it means that a 1 percent increase in total ties can lead to 0.041 percent decrease in Z-score.

We further decompose bank CEOs' total network connections into *Professional ties* and *Educational ties*, and we report our results in column 2. We investigate whether one type of network drives the negative relationship between CEO social networks and bank risk. We find a significantly negative coefficient of *Professional ties* and an insignificant coefficient of

Educational ties. The results thus indicate that professional connections convey valuable information that encourages bank CEOs to take risks.

CEOs' professional ties to other top executives and board members drive much of bank risk. In column 3 of table 2, we include bank fixed effects to control for any time-invariant and unobservable heterogeneity across banks. Nonetheless, this alternative model specification does not alter our results in a material way, and we still find a significant and negative coefficient for *Total ties*.

With regard to other control variables, we find that banks with greater assets, higher capital, and higher deposit ratios are more stable. However, we also find that CEO age can affect risk-taking decisions in different ways, and therefore the effects of CEO age and tenure on bank risk are mixed (Berger et al., 1997; Coles et al., 2006). Our results based on the model specification including bank fixed effects are more in line with Coles et al. (2006). Specifically, we find that CEO age and tenure are indeed negatively associated with Z-score.

[Insert Table 2 about here]

4.2. Robustness checks

4.2.1. Alternative measures of bank risk

To ensure the robustness of our main findings, we employ several alternative measures of bank risk and report our results in table 3. We measure *Volatility of ROA* as the standard deviation of return on assets on a yearly basis using quarterly data. Similarly, we measure *Volatility of ROE.* Following Houston et al. (2010), we calculate *Idiosyncratic risk* as the standard deviation of the residuals from a single-index market model using yearly data. In columns 1–4 of table 3, we report our results using *Volatility of ROA, Volatility of ROE,* and *Idiosyncratic risk* as dependent measures, respectively. In all three model specifications, we include the same set of control variables along with year fixed effects and bank fixed effects. Consistent with table 2, we find a positive and significant relationship between total social ties and bank risk.

[Insert Table 3 about here]

4.2.2. Alternative measures of social networks

In this section, we gauge each CEO's social network centrality by using three standard measures, namely degree centrality (number of direct ties one has), closeness (how close one is to others in the network), and betweenness (the chance of linking any two people in the network). In addition to the meaning of interconnectedness, network centrality indicates social status in the network. Higher centrality measures (all three above) suggest more connections and greater power in a status hierarchy (Freeman 1979; Burt, 1982).

According to graph theory, *Degree centrality* is the most straightforward measure of whether a node is in the central position — "in the thick of things" (Scott, 2000). It counts the number of direct ties a CEO has and then normalizes by dividing the maximum possible degrees in an N-actor network in our sample. *Betweenness* captures the extent to which a node lies between others and makes pass-through communications within the network. Hence, a person with high betweenness is an important intermediary who connects other people as a "broker" or "gatekeeper", and is thereby central to the network. *Closeness* captures the degree to which an individual is near all other individuals in a network. It is the inverse of the sum of the shortest distance between each person and every other person in the network.

Table 4 reports baseline regressions using three centrality measures as our independent variables of interest and *Log(Z-score)* as the dependent variable. We find that all three centrality measures have a negative and significant effect on Z-score, which suggests that centrally located CEOs are associated with lower bank stability and higher risk. This is consistent with our baseline results, which use total ties as the measure of social networks.

[Insert Table 4 about here]

4.2.3. Alternative explanations

We perform several additional tests to rule out alternative explanations for our results. For instance, Berger et al., (2014) find that banks with poor governance tend to take greater risks. Fracassi and Tate (2012) find that social networks are associated with weak corporate governance. Therefore, it is possible that our measures of social networks capture weak corporate governance. To address this concern, we add a governance index (Gompers et al., 2003) in column 1 of table 5 and re-estimate the regression.

Saunders et al. (1990) find that banks with larger management ownership exhibit higher risk-taking behavior. We thus include *Management holding*, measured as percentage of shares held by a bank CEO, as an additional explanatory variable in column 2 of table 5. In addition, managerial compensation is an important mechanism for aligning managers' incentives with those of shareholders to maximize shareholder value (Murphy, 1999). We thus add *Vega*, which measures how sensitive bank CEO compensation is to stock-price volatility, in column 3 of table 5 to control for the possibility that CEO compensation packages drive bank risk-taking. It is also possible that our measures of CEO social networks capture management quality (i.e., better CEOs have more social connections). Consequently, we add an index of general managerial ability (Demerjian et al., 2012) in column 4 of table 5. Including these additional controls based on alternative explanations has no material effect on our main findings.

[Insert Table 5 about here]

4.2.4. Difference-in-difference analysis

Although we include bank fixed effects in our baseline estimation to control for the potential omitted-variable problem, an endogeneity issue arises from other possibilities. For example, time-variant unobservables may drive both CEO social networks and bank risk. In addition, given the inherent risk in the lending business, CEOs with more social connections may take more risks in various bank activities in order to expand their networks. In other words, the existence of a potential feedback effect (i.e., reverse causality) prevents us from making causal inferences. Therefore, following existing literature (Fracassi and Tate, 2012), we use the deaths and retirements of executives in bank CEOs' networks as exogenous shocks to perform a difference-in-difference (DID) analysis. The logic is that the size of a bank CEO's network drops for reasons not necessarily related to bank risk when a person connected to a bank CEO dies or retires in a given year.

We identify a treatment group of banks affected by such events; unaffected banks compose our control group. We first collect death or retirement information from BoardEx for all people in the bank CEOs' social networks, if any. We then match this information with our main sample. This process allows us to identify whether any death or retirement events occurred in a CEO's network in a given year.

Affected bank is a dummy variable that equals 1 if a bank is affected by a death or retirement event and its CEO's network size is reduced exogenously; the variable equals zero otherwise. We then identify a matching bank for each treatment bank using a propensity-score-matching method (Irani and Oesch, 2014; Hasan et al., 2014). We run logistic regressions for each matching year (i.e., death or retirement year), where the dependent variable is *Affected bank* and the independent variables include all control variables in the baseline model.

According to the propensity score calculated from the logistic regression, we match each bank in the treatment group with a bank in the control group without replacement. Following Hasan et al. (2014), we use the caliper-matching method, where caliper refers to the difference in the predicted probabilities between the treatment and matching banks. Using matching within a caliper of 10 percent, we identify 246 pairs of matched banks. We use a dummy variable, *Post*, which equals 1 for each full fiscal year after the death or retirement of executives (or board members) in a bank CEO's network, and zero otherwise. We use the standard DID model (see equation 1) to gauge the effect of network shrink on subsequent bank risk:

$$Log(Z\text{-}score)_{i,t} = \beta_0 + \beta_1\ Affected\ bank + \beta_2\ Post + \beta_3\ Affected\ bank \times Post + \Sigma\beta\ (Bank\ characteristics\ and\ CEO\ characteristics)_{t-1} + \varepsilon_{i,t} \quad (1)$$

In this DID model, the variable of interest is the interaction term *Affected bank×Post*. The coefficient on this interaction term captures the difference-in-difference estimate in bank risk between treatment and matching banks across the pre- and post-event sample periods. Given that treatment banks have smaller networks in the post-event periods, we predict a positive coefficient on this interaction term, which indicates that reducing the size of social networks leads to decreased bank risk (or increased bank stability).

In table 6, we report our results using a bank-year sample spanning two one-year periods (column 1) before and after the event (i.e., a two-year window). For a robustness check, we also provide results for four- and six-year windows in columns 2 and 3, respectively. We find a significantly positive coefficient of 0.294 on the interaction variable in column 1. This finding suggests that shrinking CEO social networks reduces bank risk in post-event periods. We find similar results when we use four- and six-year windows.

[Insert Table 6 about here]

4.3. Testing channels linking CEO social networks and bank risk-taking

4.3.1. Soft information channel

According to our information-based hypothesis, social networks provide private/soft information that may reduce the perceived uncertainty of investment projects, thus reducing CEOs' risk aversion and encouraging them to take more risks. If this were true, connections with more opaque firms would provide bank CEOs with more soft information that is hard to collect in the market and hence reduces their risk aversion to a larger extent.

To test this conjecture, we use two proxies to capture the information opacity of the connected firms. The first proxy, *% opaque connections_bid-ask spread*, is constructed using *bid-ask spread*. In particular, we first identify the firms to which a focal bank CEO is connected; we then obtain those firms' stock bid-ask spreads from CRSP. A firm is opaque if its average daily bid-ask spread over a year is higher than the sample median (Amihud et al., 1986). Based on the bid-ask spread definition, we calculate the proportion of firms in a CEO's network that are opaque.

Our second proxy, *% opaque connections_forecast dispersion,* is related to analyst forecast dispersion, calculated as the standard deviation of EPS forecasts among analysts following a firm using IBES data. A firm is opaque if its analyst forecast dispersion in a year is higher than the sample median. We then calculate the proportion of firms in a CEO's network that are opaque based on the analyst forecast dispersion. We expect that a higher proportion of opaque firms in a network provides more soft and private information to CEOs.

In table 7, we replace our total network ties with these two proxies that capture the features of the connecting ties in our main regression. The negative and statistically significant coefficients of those two proxies suggest that having a higher percentage of opaque firms in bank CEOs' networks is associated with a higher level of bank risk. The findings support our hypothesis that CEOs obtain valuable information through their social connections, which reduces their risk aversion and allows them to make informed decisions.

[Insert Table 7 about here]

4.3.2. Job-market insurance channel

The job-market insurance hypothesis argues that CEOs take greater risks because their social networks reduce their job-security concerns (Faleye et al., 2014). If this is true, then the positive relationship between social networks and bank risk should be more pronounced in a worsening job market. To test this conjecture, we use two proxies for CEOs' alternative job opportunities. The first is *High turnover*, which equals 1 if the CEO forced-turnover rate, obtained from Eisfeldt and Kuhnen (2013), in a given year is higher than the sample median, and zero otherwise. A high forced-turnover rate among CEOs is often due to bad economic performance at both the firm and industry levels, which creates a tougher job market for CEOs. The second proxy is *High noncompete*. This measure captures the variations in the enforceability of noncompete agreements that restrict workers from joining or forming rival companies (Garmaise, 2009). We collect the noncompetition index from Garmaise (2009). A higher value indicates fewer job alternatives. We construct *High noncompete*, which equals 1 if the banks' headquarters are in states where noncompetition indices are higher (i.e., they are more restrictive) than the sample median, and zero otherwise.

In table 8, we interact our proxies with *Log (Total ties)*. In both models, the first-order effects of *Total ties* on bank risk remain negative and significant. In addition, we consistently document negative and statistically significant coefficients of the interaction terms between CEO social networks and our proxies for outside job options. The results suggest that CEO social networks increase bank risk-taking more when the job market worsens and job-security insurance benefits of networks increase, thus supporting the job-market insurance channel.

[Insert Table 8 about here]

4.3.3. Groupthink mentality channel

As discussed, social network connections may lead to groupthink and induce bankers to engage in herd behavior regarding trendy investments without understanding the inherent risks. For this reason, we expect CEOs with heterogeneous social networks to be less susceptible to groupthink.

We use two measures to proxy for the heterogeneity of social ties. The first is *Low het_prof*, which equals 1 if professional heterogeneity is smaller than the sample median. Professional heterogeneity is measured as the inverse Herfindahl index and based on different industries and different management expertise of individuals in the network. The second proxy is *Low het_edu*, which equals 1 if educational heterogeneity is lower than the sample median. Educational heterogeneity is measured as the inverse Herfindahl index, based on different educational backgrounds in the network. Overall, a lower heterogeneity score indicates greater homophily.

We expect that the effect of social networks on bank risk is more pronounced when network ties are more homogeneous. To test this, we include two interaction terms, *Log(Total tie)* ×*Low het_prof* and *Log(Total ties)* ×*Low het_edu*, in table 9. Across both columns, the coefficients on *Log(Total ties)* remain significant and negative. In line with our expectations, we find that both interaction terms enter a significant and negative coefficient, which indicates that well-connected CEOs are more likely to take risks when their network connections are homogeneous.

[Insert Table 9 about here]

4.4. The effects of social networks on bank performance

We adopt two measures to gauge bank performance: *ROA* and *Profit margin*. *ROA* is return on assets, which captures accounting-based bank performance for a given year. *Profit margin* is net income divided by total operating income and captures banks' ability to pay expenses and generate net income. The effect of social networks on bank performance also faces endogeneity concerns. To mitigate omitted-variable bias and tease out the reverse effect of performance on social networks, we run difference-in-difference estimations on bank performance. Our difference-in-difference model specification is the same as equation (1), except that we use bank performance measures as dependent variables instead of Z-score. The event variable to examine before and after is the death and retirement of executives in bank CEOs' networks (Fracassi and Tate, 2012).

Affected bank is a dummy variable that equals 1 if a bank is affected by the death or retirement event and its CEO's network size is reduced exogenously; the variable equals zero otherwise. One treatment group has exogenous shocks (*Affected bank* =1). The variable of interest is the interaction term between *Affected bank* and *Post*. *Post* is equal to 1 for the years after the event. It is captured using three alternative windows: [-1,1], [-2,2], and [-3,3] years.

Table 10 reports the difference-in-difference analysis results for bank performance. We find that the coefficients on the interaction term *Affected bank*×*Post* across all models are positive and statistically significant, which suggests that bank performance improves after the exogenous size reduction of its CEO's social network. Combining this finding with our previous finding on bank risk, we conclude that well-connected bank CEOs take greater risks but fail to generate good returns (i.e., they demonstrate an inefficient risk-return trade-off). The result supports the performance implications of the job-market insurance channel, which encourages CEOs to make unsuccessful risky decisions when they have fewer concerns about job security.

[Insert Table 10 about here]

5. Summary and conclusions

Bank risk-taking behavior has long been the focus of academics, policy makers, and practitioners. To promote a sound and safe banking system, regulators have implemented numerous measures to encourage prudent bank practices. Academic researchers also strive to understand the causes and consequences of bank risk-taking behavior. In this study, we use bank CEOs' social networks to explain variations in bank risk-taking behaviors and their associated financial consequences. Our findings indicate that social connectedness encourages bank CEOs to take higher risks and leads to poor performance. Our results are robust to the inclusion of bank fixed effects, analysis based on a difference-in-difference approach, and the adoption of various bank-risk measures. We also perform tests to ensure that alternative explanations such as corporate governance, managerial ownership, compensation, or CEO ability do not drive our main findings.

We explore several channels that link CEO social networks to bank risk. When we evaluate the ways in which social networks affect bank risk, we find that the positive relationship between CEO social networking and bank risk is particularly pronounced for CEOs who are connected with more informationally opaque firms, homogeneous networks with higher odds of groupthink mentality, and in worsening job markets. These findings are consistent with existing studies that show social networks promote the spread of private information and provide network members more reemployment opportunities (Cohen et al., 2008; Liu, 2014).

In general, we present evidence that the higher risks associated with CEO social networks do not translate into higher returns. This inefficient risk-return tradeoff reveals a “dark side” of social networking. We find evidence that connections with a diverse group of individuals significantly alleviate the dark side of social networking for CEOs who are too connected. Overall, our findings suggest markets and regulators may underestimate bank risk if they do not consider the social connections of bank CEOs.

Our study contributes to the literature in the following ways. First, we expand the literature on the determinants of bank risk. Early research focuses on the role of industry competition (Boyd and De Nicolo, 2005), monetary policies (Borio and Zhu, 2012), regulatory policies (Keeley, 1990), ownership structure (Saunders et al., 1990), CEO compensation, and corporate governance (Houston and James, 1995; Fahlenbrach and Stulz, 2011; Berger et al., 2014). Also, Cai et al. (2016) examine bank-loan syndication networks and find that interconnectedness is positively correlated with systemic risk, highlighting the importance of understanding interbank connections. Nonetheless, evidence is still scant regarding the effects of one of the socioeconomic characteristics of bank executives on bank risk-taking. We add to this line of research by identifying a robust positive relationship between CEO social networks and bank risk.

Second, our study provides new insight on the costs and benefits of corporate executive connections. Researchers find that personal connections among managers and firms affect various business activities and outcomes (e.g., Lee et al., 2014; Faleye et al., 2014; Engelberg et al., 2012; Larcker et al., 2013). It is noteworthy that Houston, Lee and Suntheim (2018) find that bank directors' networks facilitate the formation of joint syndicated loan deals and contribute to systemic risks in the banking system. Different from their research design focusing on the systemic-risk-contagion perspective, our study focuses on the individual bank risk driven by bank CEOs' exposure to network information, employment options, and peer influence. Therefore, we provide novel evidence that social networks play a significant role in explaining bank risk-taking behavior.

Finally, our evidence on the inefficient trade-off between risk and return reveals the dark-side of interconnectedness of financial firms. Prior studies explore the dark side of social networking by examining CEO compensation and board independence in industrial sectors (e.g., Fracassi and Tate, 2012; Hwang and Kim; 2009). Our findings imply that the labor market advantage provided by CEO social networks imposes a cost on shareholders because CEOs with lots of connections take greater risks but do not deliver better profitability. Echoing regulatory concerns over firms "too connected to fail," we emphasize the adverse effect of interconnectedness among bank CEOs.

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Appendix A. Variable definitions and sources of data

Variable name	Definition	Data source
A. Bank risk and return		
Log(Z-score)	Logarithm of Z-score, Z-score is computed as the sum of ROA and equity-to-assets divided by the standard deviation of ROA of each bank over past three years.	Call report
Volatility of ROA	The standard deviation of return on assets on a yearly basis using quarterly data.	Call report
Volatility of ROE	The standard deviation of return on equity on a yearly basis using quarterly data.	Call report
Idiosyncratic risk	The standard deviation of residuals from a single-index market model with weekly return as the dependent variable and weekly market return as the independent variable (Houston et al., 2010).	CRSP
ROA	Return (net income) on assets.	Call report
Profit margin	Net income divided by total operating income.	Call report
B. Network measures		
Log(Total tie)	Logarithm of total number of social connections.	BoardEx
Log(Work tie)	Logarithm of total number of social connections with past coworkers.	BoardEx
Log(Education tie)	Logarithm of total number of social connections with schoolmates.	BoardEx
C. Bank characteristics		
Log(Bank size)	Logarithm of total assets.	Call report
Capital ratio	Equity divided by total assets.	Call report
Deposit ratio	Deposit divided by total assets.	Call report
Not rated	A dummy variable that equals 1 if the bank does not have a long-term bond rating, and 0 otherwise.	
D. CEO characteristics		
Chairman	A dummy variable that equals 1 if the CEO is also the chairman of the board.	BoardEx
CEO age	Logarithm of CEO age.	BoardEx
CEO tenure	Number of years the CEO has worked for this bank.	BoardEx
E. Alternative explanations		
Gindex	The Gompers et al. (2003) measure for the strength of shareholder rights.	Risk Metrics
Managerial holding	Percentage of shares held by the bank CEO.	ExecuComp
Vega	Sensitivity of CEO total compensation to stock price volatility.	ExecuComp
General ability	Demerjian et al. (2012)'s measure of managers' general managerial ability.	Demerjian et al. (2012)
F. Variables for interaction terms		
% opaque connections_bid-ask spread	We first identify the firms to which a focal bank CEO is connected. We then obtain those firms' stock bid-ask spreads. A firm is firm if its average daily bid-ask spread over a year is higher than the sample median. We calculate the proportion of firms in a CEO's network that are opaque based on the bid-ask spread definition.	CRSP
% opaque connections_forecast	We first identify the firms to which a focal bank CEO is connected. We then obtain those firms' analyst forecast dispersions, calculated as the standard deviation of EPS forecasts among analysts following a firm. A firm is opaque if its analyst forecast dispersion in a year is higher than the sample median. We then calculate the proportion of firms in a CEO's network that have high analyst forecast dispersion.	IBES
High turnover	Equals 1 if the average CEO forced turnover rate in a given year is higher than the sample median, and 0 otherwise.	Risk Metrics
High noncompete	Equals 1 if the state in which the bank is headquartered allows stricter noncompete agreements than the sample median, and 0 otherwise.	Thomson Financial 13 F
Low het_prof	Equals 1 if professional heterogeneity is smaller than the sample median. Professional heterogeneity is the inverse Herfindahl index based on different industries and different management expertise of individuals in the network.	BoardEx
Low het_edu	Equals 1 if educational heterogeneity is smaller than the sample median. Educational heterogeneity is the inverse Herfindahl index based on different educational backgrounds in the network.	BoardEx
		BoardEx

Table 1. Summary statistics

This table reports the summary statistics of bank risk measures, network measures, bank financial characteristics, CEO compensation, and governance characteristics. Variable definitions are reported in appendix A.

Variable	N	Mean	Median	Standard deviation	P5	P95
Total ties	4,077	9.95	3.00	24.58	1	39
Professional ties	4,077	3.46	2.00	4.72	0.00	11.00
Education ties	4,077	2.39	0.00	14.1	0.00	7.00
Log(Z-score)	4,077	2.86	2.90	1.06	1.12	4.46
Log(Bank size)	4,077	14.68	14.31	1.63	12.79	17.93
Capital ratio	4,077	0.09	0.09	0.04	0.06	0.14
Deposit ratio	4,077	0.74	0.77	0.13	0.53	0.88
Not rated	4,077	0.84	1.00	0.36	0.00	1.00
Chairman	4,077	0.44	0.00	0.50	0.00	1.00
CEO age	4,077	56.96	57	7.24	46.00	68.00
CEO tenure	4,077	8.52	8.5	7.28	2.50	19.50

Table 2. Baseline regression

The dependent variable of three model specifications is *Log(Z-score)*. The variables are defined in appendix A. We estimate models 1 and 2 with OLS; model 3 uses bank fixed effects. Robust standard errors are corrected for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Intendent variables	Dependent variable: Log(Z-score)		
	(1)	(2)	(3)
Log(Total ties)	-0.041**		-0.053**
	(-2.090)		(-2.032)
Log(Professional ties)		-0.056**	
		(-2.404)	
Log(Educational ties)		0.002	
		(0.103)	
Log(Bank size)	0.048***	0.049***	0.027
	(2.940)	(3.021)	(0.576)
Capital ratio	3.447***	3.477***	4.915***
	(6.402)	(6.461)	(8.448)
Deposit ratio	0.509***	0.521***	0.304
	(3.369)	(3.424)	(1.284)
Not rated	-0.094	-0.091	0.072
	(-1.534)	(-1.480)	(0.762)
Chairman	0.087**	0.084**	0.039
	(2.552)	(2.449)	(0.831)
CEO age	0.053***	0.053***	-0.046***
	(2.994)	(2.993)	(-2.808)
CEO tenure	0.053***	0.053***	-0.042***
	(3.004)	(3.004)	(-2.616)
Constant	-1.859	-1.886	4.259***
	(-1.511)	(-1.531)	(3.171)
Observations	4,077	4,077	4,077
Adjusted R-squared	0.114	0.114	0.452
Year fixed effect	Y	Y	Y
Bank fixed effect	N	N	Y

Table 3. Alternative measurement of bank risk

The dependent variables are volatility of ROA, volatility of ROE, and idiosyncratic risk for the three model specifications, respectively. The variables are defined in appendix A. We estimate all regressions with bank fixed effects. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Volatility of ROA	(2) Volatility of ROE	(3) Idiosyncratic risk
Log(Total ties)	0.004**	0.011***	0.012**
	(1.982)	(2.840)	(2.212)
Log(Bank size)	0.015***	0.016*	-0.023*
	(2.991)	(1.789)	(-1.858)
Capital ratio	-0.304***	-1.512***	3.024***
	(-5.037)	(-13.884)	(19.426)
Deposit ratio	0.027	0.030	-0.301***
	(1.093)	(0.679)	(-4.778)
Not rated	-0.016*	0.017	-0.017
	(-1.684)	(0.980)	(-0.691)
Chairman	-0.003	-0.006	-0.006
	(-0.631)	(-0.627)	(-0.500)
CEO age	0.019***	0.003	-0.004
	(11.202)	(1.115)	(-0.919)
CEO tenure	0.019***	0.002	-0.004
	(11.275)	(0.719)	(-0.835)
Constant	-1.411***	-0.289	0.220
	(-10.156)	(-1.152)	(0.621)
Observations	4,077	4,077	4,077
Adjusted R-squared	0.814	0.326	0.669
Year fixed effect	Y	Y	Y
Bank fixed effect	Y	Y	Y

Table 4. Alternative measurement of social networks

The independent variables are professional network's degree centrality, closeness, and betweenness. The dependent variable is *Log(Z-score)* for the three model specifications. The variables are defined in appendix A. We estimate all regressions with OLS. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Log(Z-score)	(2) Log(Z-score)	(3) Log(Z-score)
Degree	-191.043**		
	(-2.029)		
Closeness		-0.508*	
		(-1.886)	
Betweenness			-206.826**
			(-2.049)
Log(Bank size)	0.054***	0.053***	0.045***
	(3.106)	(3.127)	(2.815)
Capital ratio	3.158***	3.239***	3.195***
	(5.978)	(6.142)	(6.023)
Deposit ratio	0.478***	0.526***	0.516***
	(3.052)	(3.333)	(3.279)
Not rated	-0.108*	-0.096	-0.105*
	(-1.707)	(-1.519)	(-1.663)
Chairman	0.082**	0.082**	0.086**
	(2.362)	(2.364)	(2.471)
CEO age	0.038**	0.036**	0.040**
	(2.135)	(2.067)	(2.237)
CEO tenure	0.038**	0.037**	0.040**
	(2.146)	(2.092)	(2.243)
Constant	-0.894	-0.836	-0.965
	(-0.723)	(-0.687)	(-0.779)
Observations	3,990	3,990	3,990
Adjusted R-squared	0.114	0.114	0.114
Year effect	Y	Y	Y
Bank fixed effect	N	N	N

Table 5. Alternative explanations

The dependent variable is *Log(Z-score)* for the four model specifications. The variables are defined in appendix A. We estimate all regressions with OLS. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Log(Z-score)	(2) Log(Z-score)	(3) Log(Z-score)	(4) Log(Z-score)
Log(Total ties)	-0.058**	-0.065**	-0.066**	-0.149*
	(-2.000)	(-1.969)	(-2.017)	(-1.735)
Gindex	0.003			
	(0.306)			
Management holding		-0.072***		
		(-5.718)		
Vega			0.0001	
			(1.343)	
General ability				0.244*
				(1.942)
Log(Bank size)	0.060**	0.096***	0.083**	-0.270
	(2.052)	(2.833)	(2.154)	(-1.100)
Capital ratio	1.121	0.508	0.747	2.810
	(0.948)	(0.374)	(0.529)	(0.581)
Deposit ratio	0.232	0.496	0.488	0.148
	(0.830)	(1.644)	(1.608)	(0.141)
Not rated	-0.044	-0.136	-0.145*	-0.925***
	(-0.597)	(-1.604)	(-1.684)	(-4.070)
Chairman	0.243***	0.269***	0.262***	0.251*
	(3.992)	(3.752)	(3.584)	(1.711)
CEO age	0.006	-0.008	-0.009	-0.005
	(0.330)	(-0.443)	(-0.459)	(-0.154)
CEO tenure	0.014	0.004	0.005	-0.002
	(0.780)	(0.222)	(0.248)	(-0.061)
Constant	7.482***	1.352	1.518	8.349**
	(4.159)	(0.935)	(1.021)	(2.004)
Observations	1,150	972	966	499
Adjusted R-squared	0.122	0.122	0.104	0.259
Year fixed effect	Y	Y	Y	Y
Bank fixed effect	N	N	N	N

Table 6. Difference-in-difference on bank risk

This table presents the results of DID tests on how exogenous shocks to social networks affect bank risk. The dependent variable is *Log (Z-score)*. The variables are defined in appendix A. We estimate all regressions with OLS with difference-in-difference specifications. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Two-Year Window	(2) Four-Year Window	(3) Six-Year Window
Affected firm*Post	0.294**	0.166*	0.149*
	(2.184)	(1.718)	(1.784)
Affected bank	-0.167*	-0.011	-0.045
	(-1.697)	(-0.164)	(-0.787)
Post	-0.208**	-0.160**	-0.190***
	(-2.075)	(-2.328)	(-3.130)
Log(Bank size)	-0.049	-0.012	-0.014
	(-1.282)	(-0.469)	(-0.633)
Capital ratio	2.112	2.070***	1.815***
	(1.166)	(3.452)	(3.469)
Deposit ratio	0.065	0.135	0.113
	(0.198)	(0.682)	(0.672)
Not rated	-0.312**	-0.164*	-0.123
	(-2.378)	(-1.794)	(-1.608)
Chairman	0.216***	0.161***	0.171***
	(2.803)	(2.994)	(3.747)
CEO age	0.053	0.075	0.072**
	(0.878)	(1.521)	(2.278)
CEO tenure	0.060	0.076	0.076**
	(0.994)	(1.558)	(2.435)
Constant	-0.353	-2.399	-1.989
	(-0.088)	(-0.737)	(-0.946)
Observations	492	1,044	1,454
Adjusted R-squared	0.043	0.080	0.086
Year fixed effect	Y	Y	Y
Bank fixed effect	N	N	N

Table 7. Information channel

The dependent variable is *Log(Z-score)*. The variables are defined in appendix A. We estimate all regressions with bank fixed effects. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Log(Z-score)	(2) Log(Z-score)
% opaque connections_bid-ask spread	-0.066*	
	(-1.868)	
% opaque connections_forecast dispersion		-0.127***
		(-4.102)
Log(Bank size)	0.028	0.026
	(0.587)	(0.557)
Capital ratio	4.904***	5.044***
	(8.430)	(8.672)
Deposit ratio	0.284	0.319
	(1.195)	(1.347)
Not rated	0.077	0.046
	(0.809)	(0.486)
Chairman	0.043	0.046
	(0.900)	(0.978)
CEO age	-0.046***	-0.045***
	(-2.785)	(-2.741)
CEO tenure	-0.042***	-0.042**
	(-2.611)	(-2.572)
Constant	4.239***	4.253***
	(3.158)	(3.176)
Observations	4,077	4,077
Adjusted R-squared	0.453	0.455
Year effect	Y	Y
Bank fixed effect	Y	Y

Table 8. Job-security channel

The dependent variable is *Log(Z-score)*. The variables are defined in appendix A. We estimate all regressions with bank fixed effects. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Log(Z-score)	(2) Log(Z-score)
Log(Total ties)	-0.052**	-0.051*
	(-1.997)	(-1.945)
Log(Total ties) × High turnover	-0.049**	
	(-2.020)	
High turnover	0.170***	
	(3.108)	
Log(Total ties) × High noncompete		-0.057*
		(-1.859)
High noncompete		0.066
		(0.840)
Log(Bank size)	0.029	0.029
	(0.618)	(0.616)
Capital ratio	4.940***	4.933***
	(8.493)	(8.478)
Deposit ratio	0.298	0.314
	(1.258)	(1.323)
Not rated	0.067	0.070
	(0.709)	(0.739)
Chairman	0.039	0.038
	(0.834)	(0.799)
CEO age	-0.046***	-0.045***
	(-2.783)	(-2.720)
CEO tenure	-0.042***	-0.041**
	(-2.581)	(-2.514)
Constant	4.050***	4.132***
	(3.019)	(3.073)
Observations	4,077	4,077
Adjusted R-squared	0.453	0.453
Year effect	Y	Y
Bank fixed effect	Y	Y

Table 9. Group-think channel

The dependent variable is *Log(Z-score)*. The variables are defined in appendix A. We estimate all regressions with bank fixed effects. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) Log(Z-score)	(2) Log(Z-score)
Log(Total ties)	-0.072*	-0.068*
	(-1.846)	(-1.716)
Log(Total ties) × Low het_prof	-0.175***	
	(-2.657)	
Low het_prof	0.051	
	(0.915)	
Log(Total ties) × Low het_edu		-0.025
		(-0.402)
Low het_edu		-0.088
		(-1.570)
Log(Bank size)	0.063	0.095
	(0.852)	(1.373)
Capital ratio	9.288***	8.934***
	(10.173)	(10.276)
Deposit ratio	0.341	0.347
	(0.920)	(1.005)
Not rated	-0.159	-0.124
	(-1.159)	(-0.917)
Chairman	0.104	0.040
	(1.453)	(0.594)
CEO age	-0.037	-0.030
	(-1.641)	(-1.316)
CEO tenure	-0.029	-0.024
	(-1.322)	(-1.050)
Constant	3.212*	2.285
	(1.647)	(1.195)
Observations	3,075	3,470
Adjusted R-squared	0.349	0.351
Year fixed effect	Y	Y
Bank fixed effect	Y	Y

Table 10. Difference-in-difference on bank performance

The dependent variables are bank ROA and profit margin, respectively. The variables are defined in appendix A. We estimate all regressions with OLS with difference-in-difference specifications. We correct robust standard errors for bank-level clustering and heteroskedasticity. *T*-statistics are in parentheses. The *, **, *** marks denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	(1) ROA Two-year window	(2) ROA Four-year window	(3) ROA Six-year window	(4) Profit margin Two-year window	(5) Profit margin Four-year window	(6) Profit margin Six-year window
Affected firm*Post	0.004*	0.004**	0.003**	0.106**	0.105***	0.090***
	(1.901)	(2.115)	(2.272)	(2.191)	(2.902)	(3.147)
Post	-0.003	-0.006***	-0.006***	-0.052*	-0.114***	-0.111***
	(-1.465)	(-3.943)	(-5.270)	(-1.704)	(-4.248)	(-5.175)
Affected firm	-0.001	-0.002	-0.001	-0.010	-0.024	-0.015
	(-0.449)	(-1.299)	(-1.490)	(-0.356)	(-1.134)	(-1.035)
Log(Bank size)	-0.001	-0.001***	-0.001***	-0.022**	-0.013*	-0.008
	(-1.567)	(-2.700)	(-3.414)	(-2.042)	(-1.663)	(-1.387)
Capital ratio	0.168***	0.179***	0.198***	3.019***	1.861**	1.232***
	(4.861)	(10.117)	(10.404)	(3.444)	(2.528)	(2.955)
Deposit ratio	-0.013***	-0.013***	-0.013***	-0.312***	-0.157**	-0.094*
	(-2.731)	(-4.263)	(-4.996)	(-2.596)	(-2.187)	(-1.873)
Not rated	-0.004*	-0.006***	-0.006***	-0.044	-0.066**	-0.056***
	(-1.932)	(-3.687)	(-4.587)	(-1.224)	(-2.478)	(-2.729)
Chairman	0.002	0.002**	0.002**	0.053*	0.049**	0.036**
	(1.090)	(2.117)	(2.126)	(1.809)	(2.412)	(2.337)
CEO age	0.000	-0.000	-0.000	0.007	0.024	0.009
	(0.226)	(-0.166)	(-0.393)	(0.354)	(0.921)	(0.617)
CEO tenure	0.000	-0.000	-0.000	0.010	0.025	0.010
	(0.335)	(-0.081)	(-0.313)	(0.526)	(0.979)	(0.666)
Constant	-0.006	0.030	0.039	-0.126	-1.326	-0.428
	(-0.071)	(0.437)	(0.775)	(-0.098)	(-0.776)	(-0.430)
Observations	493	1,044	1,455	493	1,044	1,455
Adjusted R-squared	0.182	0.250	0.375	0.125	0.127	0.130
Year effect	Y	Y	Y	Y	Y	Y