Financial Contagion: Bank Characteristics Matter

Sharif Mazumder and Louis R. Piccotti[1]

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Abstract

We systematically examine how bank characteristics are related to a bank's financial contagion risk exposure. Examining capital requirements and bank size, we find that tier 1 capital requirements are negatively associated with a bank's contagion exposure, while bank size is positively associated. The association between bank size and financial contagion is non-linear, meaning larger banks contribute more than their medium and smaller competitors. Banks with greater financial constraints are less exposed to contagion. Geographic distance between banks is negatively related to contagion, and we find evidence that institutional ownership is positively related to banks' contagion exposures. Finally, we find that board and CEO attributes that reduce banks' risk-taking incentives are negatively associated with contagion risk exposure.

Keywords: Financial contagion, Systemic risk, Corporate finance, Corporate governance

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[1] Mazumder is with the Haile College of Business, Northern Kentucky University, Highland Heights, KY 41076 (a portion of this paper was completed while Mazumder was with the Department of Finance, Spears School of Business, Oklahoma State University, Stillwater, OK 74078, e-mail: mazumderm1@nku.edu); Piccotti is with the Department of Finance, Spears School of Business, Oklahoma State University, Stillwater, OK 74078, e-mail: louis.r.piccotti@okstate.edu. We thank Haluk Ünal (the editor) and an anonymous referee as well as Leonid Pugachev for valuable comments and suggestions. We also thank for comments of Karen Jang (discussant at FMA 2020). All errors are the authors' sole responsibility.

1. Introduction

Banks (as well as other financial intermediaries) have been shown to be special through their unique regulatory environment, their effects on the credit supply (Duchin, Ozbas, & Sensoy, 2010; Ivashina & Scharfstein, 2010), their tendencies for financial contagion propagation (Allen & Gale, 2000; Leitner, 2005), and their effects on the equity risk premium (Adrian, Etula, & Muir, 2014; Piccotti, 2017). While there is now a vast body of literature studying how to econometrically measure financial contagion (Billio et al., 2012; Diebold & Yılmaz, 2014; Adrian & Brunnermeier, 2016; Acharya et al., 2017; Duffy et al., 2019; and Piccotti, 2017; among many others), there is still little understanding of the relationship between bank characteristics and their contribution to financial contagion. The contribution of this paper is to provide a systematic analysis of bank characteristics on financial contagion. Among hundreds of characteristics, we focus on bank characteristics that the existing literature supports as factors of contagion, e.g., bank size, financial constraints, competitiveness, easiness and incentives of monitoring, corporate governance, and CEO characteristics (Allen & Gale, 2000; Acemoglu et al., 2012; Bostandzic & Weiß, 2018; Wagner, 2007; Battaglia &Gallo, 2017; Ahmed, Sihvonen, & Vahamaa, 2019).

Since the financial crisis of 2007, a considerable amount of attention has been devoted to how individual banks contribute to the systemic risk of the global financial system.[2] The heterogeneous regulatory requirements in different regions cause significant variation in bank characteristics as well as in policies. The study of Bostandzic and Weib (2018) characterizes how banks from one region are more responsible for contributing to global systemic risk than banks from other regions. However, banks in the same jurisdiction can also differ due to heterogeneous

[2] We take on the definition for systemic risk from Engle, Jondeau, and Rockinger (2012) and Hovakimian, Kane, and Laeven (2012) to be the propensity for a bank to be undercapitalized when the financial system as a whole is undercapitalized.

characteristics. These heterogeneities in bank fundamentals may also be associated with banks' risk-taking incentives, especially in the tail. It is puzzling why some banks are affected differently by contagious shocks than others. Intuitively, bank characteristics vary due to different business models and interconnected sources of income. According to the FDIC, four US banks failed in 2019 with total assets of $214.1 million.[3] This begs the question of why the collapse of Lehman Brothers in 2008 affected the financial system differently than the four banks that collapsed in 2019.[4] It is important to distinguish between bank characteristics that produce higher returns and those that offer higher returns in compensation for higher contagion risk. The central aim of this paper is to provide a systematic analysis of the effects of bank characteristics on financial contagion.

We measure financial contagion following Piccotti, 2017, $FC_t^{(i)}$ hereafter. $FC^{(i)}$ has the nice property that it captures upside contagion, in addition to downside contagion, which is important when there is procyclical leverage in the financial sector (Adrian & Shin, 2014). Another advantage of the $FC_t^{(i)}$ measure is that it is dynamic, whereas the $CoVaR$ and MES measures are static in nature (though Brownlees & Engle, 2017 develop a dynamic conditional expected capital shortfall measure). Using $FC^{(i)}$, we test the following bank characteristics' contribution to the financial contagion for the sample period of 1960 to 2017.

First, we examine how bank size, capital requirements, financial constraints, and competition affect the contagion exposure of banks. By financial constraint[5], we mean the financing frictions that affect banks' abilities to lend and may hinder the flow of funds to their

[3] Source: https://www.fdic.gov/bank/individual/failed/banklist.html
[4] The impact of the filing of Bankruptcy by Lehman Brothers was severe. The Dow Jones index dropped by 4.4% on September 15,2008.
[5] We use two proxies to capture financial constraints, liquid asset ratio and KZ index. We explain these two methods in subsequent sections.

potential borrowers. In this context, financially constrained banks may be lending suboptimally because the banks' equity capital is limited and building internal funds is a costly process that takes time (Bucher et al., 2013). Allen and Gale (2000) and Leitner (2005) model financial contagion as propagating from bank to bank as insufficiently capitalized banks experience cascading defaults. An implication of this is that banks that are relatively better capitalized (that is, they have higher tier 1 capital ratios) are expected to have a lower contagion exposure than relatively undercapitalized banks, which is what we find in our sample. The effect, with respect to capital ratios, is not monotonic, however. We further explore the nonlinearity in the association and find that there is a U-shaped association, meaning that the banks' larger buffer of core capital increases financial contagion (Jiang, Zhang, & Sun, 2020). When we examine banks' size, we find a positive relationship between size and banks' contributions to financial contagion. The notion of "too big to fail" encourages banks to take additional risk as banks' subsidies in case of default motivate them to involve risky ventures. Evaluation of non-linear association reveals that larger banks contribute more to the financial contagion than their smaller counterparts. Therefore, if banks get subsidized for being large, they appear to be incentivized to take on an increased level of risk. Larger banks are involved in market-based activities (Leaven et al., 2014); thus, banking systems have grown and have become increasingly global and interconnected. In other words, banks with less financial constraints interconnect more with each other through their common claims.

We also study the effect that banks' proximities to each other have on financial contagion. Aharony and Swary (1996) show that solvent banks with headquarters closer in geographic proximity to failing banks' headquarters tend to have greater contagious linkages. Bostandzic and Weiß (2018) suggest that one of the primary reasons that European banks have higher marginal contributions to systemic risk than U.S. banks is because of their higher relative interconnectedness. Aït-Sahalia, Cacho-Diaz, and Laeven (2015) provide additional evidence that geographic distance matters for contagious linkages by documenting mutually exciting jump processes in international equities. Thus, presumably, the higher proximity of banks increases the interdependence and interconnectedness to each other. As a measure of the geographic proximity of banks, we use the inverse of the number of banks in a city[6], and we find that this measure is negatively related to a bank's contribution to financial contagion. This result suggests that when there are more banks in a geographic location, there are more contagious linkages.

Second, we examine how ease of monitoring and monitoring incentives are related to financial contagion. The existing literature presents that the ownership structures of banks may affect financial performance and risk-taking incentives (Ellul & Yerramilli, 2013; IMF, 2014). Erkens, Hung, and Matos (2012) find that financial firms with higher institutional ownership experienced worse stock returns in the 2007-2008 financial crisis. Laeven and Levine (2009) separately show that banks with more concentrated shareholder ownership are riskier. Alternatively, as a competing monitoring hypothesis, Callen and Fang (2013) show that institutional investors reduce banks' left tail risks. Studies have also shown that institutional investors can experience contagious events amongst each other (Boyson, Stahel, & Stulz, 2010; and Dudley & Nimalendran, 2011). In a cross-sectional study, Battaglia and Gallo (2017, BG hereafter) find a negative association between institutional ownership and systemic risk during the crisis of 2007. However, the time-series patterns of the association have been ignored. The findings of the IMF (2014) suggest that institutional investors' monitoring effects decrease the banks' risk-taking incentives. Still, the association between bank interconnectedness and co-value-at-risks has been overlooked. We test the relationship between bank-level institutional ownership and banks'

[6] The findings are robust if we control for the number of population in the city.

contagion and find a contradicting result with BG in both magnitude and direction. We find a positive relationship between the level of institutional ownership and banks' contributions to financial contagion. Our results are consistent with the view that institutional investor contagion passes through to banks. At the same time, however, if institutional investors reduce banks' left tail risk, then banks may optimally increase their contagion exposures to maximize returns while minimizing changes to their overall risk.

Third, we empirically show how banks' governance and CEO characteristics affect banks' contagion exposures. We focus on bank opaqueness, board attributes, and CEO attributes. Fortin, Goldberg, and Roth (2010) show that banks with stronger governance are less risky (have a lower standard deviation of returns), while Erkens, Hung, and Matos (2012) find that financial firms with more independent board members had worse stock returns during the financial crisis. Beltratti and Stulz (2012) also challenge whether poor governance was a primary cause of the financial crisis. Pathan (2009) finds that smaller boards are associated with less risk-taking by banks, while BG find that European banks' risks increase at a diminishing rate regarding board size. Our study supplements BG's cross-sectional study by investigating the association of board characteristics with financial contagion. We add to the debate by providing evidence that banks' financial contagion exposure increases with bank opacity, increases with the percentage of independent board members, decreases with average board member age, and decreases with the spread between the highest tenure and lowest board tenure. We find conflicting evidence with respect to board size and bank financial contagion exposure. Our investigation of which CEO attributes (risk-taking or risk averting) contribute to financial contagion yields that banks with aged and higher share ownership are associated positively. In contrast, CEO duality associates negatively, which is consistent with the hypotheses. Another salient characteristic of a bank is its opaqueness of financial reporting. Banks' asset class holdings and their proprietary information of the assets are the main reasons why banks are opaque. The opacity of reporting creates a new friction that makes monitoring costly and is associated with higher risk-taking, contributing to financial contagion risk.

Our study analyzes bank-level characteristics on financial contagion; hence, the endogeneity issue may become a prominent concern that biases the observed association. In our study, we address the potential endogeneity problem through several ways. Endogeneity can arise due to reverse causality. To address this problem, we take the lag of independent variables to predict financial contagion or systemic risk. Taking lagged independent variables in the identification primarily helps to mitigate the causal inference problem, if any. Moreover, we use the propensity score matching method, difference-in-difference method, and non-parametric tests. In addition, endogeneity can also arise from unobserved omitted variables. To overcome this issue, we take firm fixed effects[7] along with year fixed effects. The firm-fixed effect approach takes care of firm-level time-invariant effects in the models. Thus, adopting these two approaches help our results to be more robust against potential endogeneity problems.

Most closely related to our study is Bostandzic and Weiß (2018, BW hereafter). BW compare and contrast why some banks in the U.S. and Europe are more exposed to systemic risk and contribute more to systemic risk. BW conclude that European banks are more susceptible to global systemic risk. Their analysis examines the country-specific characteristics and finds that more stringent capital regulation decreases the exposure of banks to systemic risk. This paper contributes to the existing literature in several respects. First, as far as it could be ascertained, this

[7] In some of the tables, we industry fixed effects instead of firm fixed effects because the variable of interest has little time series variations, such as board composition, CEO characteristics.

is the first study to analyze banks' characteristics that affect financial contagion, while existing studies focus on systematic risk or tail risk (e.g., $CoVaR$ and MES). Second, with respect to previous and more recent studies on the topic, which mainly focus on the effect of a single determinant on systematic risk (for example, corporate governance (Battaglia & Gallo, 2017), interconnectedness (Grilli et al., 2015), industry characteristics (Chiu, Pena, & Wang, 2015), bank opacity (Jones, Lee, & Yeager, 2013)), we incorporate several characteristics, including size, financial constraints, geographic proximity, ease of monitoring, corporate governance, and CEO attributes, and their contribution to financial contagion in a single study. Thirdly, using an extended sample period enables us to analyze crisis and non-crisis periods simultaneously. Finally, our sometimes-conflicting results with the predicted hypotheses open a window to look at the associations more rigorously.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the relevant literature and describes the testable hypotheses. In section 3, we discuss the dataset. Section 4 presents our empirical results, while section 5 presents the endogeneity tests. Section 6 presents the robustness checks. We conclude in section 7.

2. Related Literature

Financial contagion is one of the most discussed financial economics topics due to its severe effect on the economy. Researchers have long developed the theoretical corpus; later, others test with empirical settings about the financial contagion or systemic risk's main mechanism (Rochet & Tirole, 1996a; Allen & Gale, 2000; and Archaya, 2001). The literature of contagion can be segregated into several strands. One segment of literature looks at the specific sources of contagion, such as balance sheet contagion (Allen & Gale, 2000; Elsinger, Lehar, & Summer, 2006; Elliot et al., 2014) and the role of disclosure on financial contagion (Alvarez & Barlevy, 2015; Konig-Kersting et al., 2021). Another strand of literature analyzes financial contagion regarding liquidation costs (Duffy et al., 2019), payment and clearing house (Rochet & Tirole, 1996), informational contagion (Chen, 1999; Bae, Karolyi, & Stulz, 2003), and information channels of financial contagion (Trevino, 2020). Though the literature on financial contagion is vast, studies of which factors or bank characteristics contribute to financial contagion are still sparse. In the existing literature, researchers focus mostly on some of the bank-level factors that are responsible for contributing to systemic risk, such as banks' size (O'Hara & Shaw, 1990; Acharya & Yorulmazer, 2008) and growth opportunities (Matutes & Vives, 2000). Besides the size and growth opportunities, the non-core activities of banks are also associated with systemic risk (Brunnermeier, Dong, & Palia, 2012), i.e., collateral channel (Benmelech & Bergman, 2011). The existing studies find a positive association between bank size and systemic risk (Laeven et al., 2014). The notion of "too big to fail" encourages larger banks to take more risks because large banks get a subsidy if they fail. Thus, the association of bank size and contagion is non-linear and convex. The existing literature is minimal in this empirical setting.

In relation to banks' size, larger banks are less financially constrained due to "too big to fail" subsidies. The interconnectedness of banks becomes stronger when banks connect with each other through common financial claims (Allen & Gale, 2000; Sáez & Shi, 2004). If a bank is financially unconstrained, it can extend more loans to other banks (Adrian & Shin, 2014). The intuition lies behind financially unconstrained banks shifting their income source from traditional to nontraditional. DeYoung and Torna (2013) find that banks having substantial income sources from nontraditional activities (stakeholder activities) tend to take more risks in their traditional banking activities. It is common to assume that financially constrained banks only have access to non-contingent finance that is fully insured against the risk of becoming constrained; thus, they have less financial amplification effects (Krishnamurthy, 2003). A supplement of the existing literature showing how unconstrained banks increase financial contagion can be an essential contribution.

Next, banks' interconnectedness increases when they are in the same geography (Aharony & Swary, 1996; Bostandzic & Weiß, 2018; and Aït-Sahalia, Cacho-Diaz, & Laeven, 2015). Banks' concentration and contribution to systemic risk is also discussed heavily (such as Allen & Gale, 2000). Arguably, banks in the same region share similar clients and information. Therefore, more proximate banks are more interconnected in portfolio investments and information sharing. In the information circulation context, depositors who lack the ability to evaluate the quality of the banks put more contingencies even on the non-distressed banks if any failure happens in the locality. The proximity of banks is also a proxy for competition among those banks. Previous literature is inconclusive about competition and bank risk-taking (Allen & Gale, 2004). Jimenez, Lopez, and Saurina (2013) conduct a study on Spanish banks and find that competition increases banks' risk-taking incentives. Micro-level evidence from individual banks suggests that lower bank competition is negatively associated with bank risk-taking (Beck et al., 2010). This paper complements the existing literature by analyzing banks' proximity on financial contagion.

Furthermore, banks' complexity and involvement of non-core activities also contribute to systemic risk (Herring & Carmassi, 2014). Complexity and involvement in non-core activities make banking activities more opaque. Banks are assumed to be more opaque (Blau et al., 2017) due to a higher propensity of analyst disagreement and split opinions (Morgan, 2002) about them. Flannery, Kwan, and Nimalendran (2013) further state that the recent financial crisis was magnified due to the opaque nature of the banking industry. Research on bank opacity and its impact on banks' stock returns reveals that opaque banks are more profitable, and bank opacity creates systemic risk (Jones, Lee, & Yeager, 2013). Fosu et al. (2017) find that the opacity of banks increases banks' risk-taking incentives, and the risk-taking incentives are accentuated by the degree of banking market competition. Allen and Gale (2000) suggest that insufficient information may also create another channel of financial contagion. Therefore, the level of the financial opaqueness of a bank is expected to provide explanatory power for a bank's contribution to financial contagion.

Opaqueness leads to more costly monitoring activities (Nier, 2005). Separation of ownership and management gives rise to agency problems between parties. On the one hand, the atomistic nature of equity holdings may increase the problem as none of the shareholders feel motivated to monitor the managers. Thus, higher institutional ownership decreases the risk-taking incentives of a bank. Some other studies find the opposing result that a higher concentration of banks' ownership is associated positively with banks' risk-taking (Leaven & Levine, 2009). Arguably, contagion among institutional investors (Boyson, Stahel, & Stulz, 2010; Dudley & Nimalendran, 2011) can pass through to banks, leading to further contagion. On the other hand, larger shareholders, especially those who have technical knowledge and incentives to monitor, increase their monitoring role and decrease the agency problem (Callen & Fang, 2013). Extant literature suggests that strong monitoring reduces the incentive of taking on more risky projects (IMF, 2014; Ellul & Yerramilli, 2013). Though the existing literature on institutional ownership and risk taking is vast, few studies examine the association between institutional ownership and financial contagion.

Banks' governance and its association with risk-taking incentives are discussed in the literature quite heavily. Fortin et al. (2010) suggest that banks characterized by strong governance mechanisms take more risk. The size of boards is also associated with the risk-taking incentives of banks. Pathan et al. (2009) find that banks with smaller board sizes are associated with increased risk-taking corporate decisions. Several other papers study the association of US banks' management structures with their stability and find no association (Berger et al., 2012). Anecdotal evidence suggests that CEOs' heterogeneous characteristics drive corporate actions and firms' performance (Adams, Almeida, & Ferreira, 2005). Kaplan, Klebanov, and Sorensen (2012) find that CEOs' general abilities and execution skills are positively related to firms' performance. Other studies find that certain characteristics, such as CEO power and CEO overconfidence, may be detrimental to firms' performance and corporate policies (Malmendier & Tate, 2005). Some CEO characteristics, which promote CEOs to take on more risky projects include age (Serfling, 2014) and gender (Faccio et al., 2016). In contrast, some CEO attributes that are negatively associated with risk-taking incentives include CEO duality (Pathan, 2009), ownership (Kim & Lu, 2011), and entrenchment (Berger, Ofek, & Yermack 1997). We expect that CEO attributes that promote risk-taking also relate positively to their bank's financial contagion exposure. Alternatively, CEO characteristics that discourage risk-taking incentives help reduce their bank's financial contagion exposure.

3. Data

We collect monthly bank stock price data (SIC codes 6000-6199 and share codes 10-11) from the CRSP monthly stock file. Small-minus-big (SMB), high book/market-minus-low book/market (HML), and up-minus-down (UMD) factor portfolio return data are from the website of Professor Ken French[8]. COMPUSTAT reports accounting data, either quarterly or annually. To procure a higher frequency of non-missing data, we use annual accounting data from

[8] For details, please see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

COMPUSTAT. Our sample period extends from 1960 to 2017, and the details of the data and variables are presented in Table B.1. We calculate the monthly firm-level contagion measure, $FC_t^{(i)}$, detailed in Appendix I.A.I. In this framework, financial contagion is the covariation in bank stock returns that is in excess of the factor model implied return covariation. The estimation procedure consists of three steps, with the portion of bank returns explained by the factor model filtered out in the first step, the excess covariances estimated in the second step, and the excess covariances aggregated and scaled by the bank sector return variance in the third step. Since the COMPUSTAT data is yearly and our contagion data is monthly, we take the yearly average of contagion for each bank to get each bank's annual measure of contagion. In addition, we use two measures of systemic risk, $CoVar$ and MES, which are computed as described in Appendix I.A.I. We collect CEO attributes data from Execucomp. BoardEx[9] provides the board composition data. Moreover, institutional ownership data is obtained from Thompson Reuters' 13F.[10] Our final sample consists of 17,746 firm-year observations[11]. To mitigate the effects of outliers, we winsorize the data at the 1st and 99th percentiles.

Table 1 presents the summary statistics for the key variables used in our study. The mean and median bank's contribution to financial contagion (banks' marginal contributions, $FC^{(i)}$) are 0.00054 and 0.00001, respectively. That is, the mean bank increases the fraction of return variance of the value-weighted portfolio of banks due to residual covariances by 0.054 percentage points. The size of financial firms in our study is highly positively skewed with the mean bank's total

[9] BoardEx is a comprehensive database of board members' curricula vitae that reports professional education and degree information, past employment history, current employment status, and positions held in other firms. BoardEx provides data from 1998.

[10] Thompson Reuters institutional holding database reports Consolidated Holdings (Type 1), Institutional Holdings (Type 2), and Mutual Fund Holdings (Type 3). We consider both institutional holding (Type 2) and mutual fund holding (Type 3) to calculate the institutional holding percentage.

[11] Since we use various databases to test our hypotheses, the sample size may vary from table to table.

assets being \$12,952.67 million, while the median bank's total assets is \$1,034.60 million. The mean (median) tier 1 capital ratio is 7.21% (8.50%), while the mean (median) total capital ratio is 9.55% (11.65%). Our sample firms' loans to assets ratio is slightly negatively skewed with a mean of 0.64 and a median of 0.66. The mean (median) deposits to assets ratio is 0.75 (0.78), and the ratio of noninterest income to revenue is negatively skewed with a mean of 0.14 and a median of 0.12. Finally, our sample's mean and median number of banks per year are 503 and 546, respectively.

[Insert Table 1 about here]

4. Empirical Results

4.1 Financial contagion and banks' characteristics

Our first tests relate financial contagion (bank i's yearly average contribution to aggregate financial contagion) to firm-level controls. The baseline regression model is:

$$Contagion_{i,t+1} = \alpha + \gamma \cdot Controls_{i,t} + d_i + d_t + \epsilon_{i,t+1} \tag{1}$$

where $Contagion_{i,t+1}$ is the yearly average of bank i's financial contagion exposure, $FC_t^{(i)}$ at time $t+1$, γ is the coefficient vector on the control variables, d_i denotes the firm or industry[12] fixed effects (to capture the industry and firm-specific unobserved variation), d_t represents year fixed effects (to capture the year specific unobserved variation), and $\epsilon_{i,t+1}$ is the residual term. The controls are: natural log of total assets ($Ln\ (Asset)$), total asset square ($Total\ Asset\_sqr$), core capital ($Tier\ 1\ capital$), core capital square ($Tier1\ Capital\_sqr$), loan ratio ($LoantoAsset$), deposit ratio ($DeposittoAsset$), noninterest income ratio ($NoninttoRvenue$), profit margin ($NitoAsset$), market-adjusted return ($Excess\_mkt$), number of banks ($\#bank$), stock volatility

[12] Industry is defined as Fama and French 49 industry.

($Std.Dev\ of\ Stock\ Return$), and liquidity ($ProNotrade$). Definitions for each of the variables can be found in Table A.1.

Table 2 presents the results of estimating our control regression in Equation (1). Banks' contributions to aggregate financial contagion are positively related to their total assets, noninterest income to total revenue, stock return volatility, and negatively related to tier 1 capital ratio. These results are largely in line with the effects outlined by Allen and Gale (2000) that financial contagion can have on cascading defaults in the banking sector. First, banks are subject to higher regulation regarding the capital adequacy ratio. The capital adequacy ratio is considered as a buffer that absorbs the unprecedented adverse shock. Despite the large volume of banking literature, the association of capital adequacy and its contribution to the financial contagion is ambiguous. The capital adequacy ratio, tier 1 capital ratio, refers to the required minimum level of capital held by banks at a given time. We include tier 1 capital as a capital adequacy ratio and find the association to be negative with financial contagion. The results are consistent with the moral hazard model that banks can decrease capital adequacy and increase risk-taking. In other words, undercapitalized banks take more risk to capitalize deposit insurance schemes. The negative association is consistent with Caiazza et al. (2018) and Hogan (2015). They find that the association of tier 1 capital is negative with banks' risk-taking through the nonperforming loan ratio and stock market return volatility. Thus, our results complement the existing study that higher tier 1 capital reduces contribution to financial contagion. The existing literature further explores the nonlinearity component of the association between capital adequacy ratio and risk-taking (Calem & Rob, 1999; Jiang, Zhang, & Sun, 2020). Consistent with this methodology, we also include a quadratic term in our model and find a U-shaped association. As a bank's capital increases, it first reduces its contribution to the financial contagion and then contributes more to it.

[Insert Table 2 about here]

Next, we take several other bank-level controls. First, the total loan outstanding as a percentage indicates how loaned up a bank is, and it also indicates the low liquidity of banks. The higher the ratio, the riskier the banks are. However, we do not find any significant association between loan ratio and financial contagion. Next, we control the deposit ratio, total deposits to total assets. In particular, banks with high deposit ratios are subject to higher confidence of a large body of depositors. Moreover, these banks are more connected as these banks are big. Thus, a bank that retains higher deposits from individuals or other banks is typically more vulnerable to financial shocks, even though the bank may not be directly affected by the shock. Consistent with this view, the deposit ratio is positively and significantly associated with financial contagion. Prior to the financial crisis of 2007, banks earned a higher proportion of their profits from noninterest income. The literature is inconclusive about the association between noninterest income and financial contagion[13]. In our model, the association between noninterest income and financial contagion is positive. The result is consistent with the findings of Brunnermeier, Nathan Dong, and Palia (2020) and Bostandzic and Weiss (2018). This suggests that a shock initially affects a subset of financial firms and eventually spills over to other financial firms in the same network. Next, we control profitability to see whether a previous years' performance increases banks' financial contagion. Previous findings of Weib et al. (2014) argue that high values of profitability can shield from the risk of default. On the other hand, higher profitability could also be extended to the successful engagement of risky ventures that may suddenly contribute to the banks' financial contagion. We find evidence of the alternative explanation that banks' profitability is positively associated with financial contagion.

[13] Noninterest income includes income from trading and securitization, investment banking, advisory fees, brokerage commissions, venture capital, fiduciary services, and so on.

Investors have recognized that economic conditions frequently undergo abrupt changes, such as low volatility characterizes economic growth and high volatility characterizes economic contraction. Kupiec and Guntay (2016) find that systematic risk produces asymptotic left tail dependence in stock return distributions. To deeply understand the stock market's influence on financial contagion, we included several stock return-related variables: excess market return, the standard deviation of stock return, and liquidity (number of days traded). Volatility (the standard deviation of the prior year's stock return) and liquidity (proportion of the number of trading days) have positive loadings for affecting financial contagion. Riskier banks, in general, engage in relatively riskier investments or more complicated financial contracts with other banks. As a result, banks' financial contagion increases with the increased overall riskiness of the banks, which we proxy by the standard deviation of stock returns. Lastly, we include the number of banks in the sample year because banks are interrelated in interbank networks; thus, the failure of one bank may have a chain reaction on the total banking network. However, we did not find any significant association between the number of banks and financial contagion in most models.

4.2 Bank size, financial constraints, competitiveness and their effects on financial contagion

4.2.a. Size effect

Along with the control variables mentioned above, we also take control of bank size and find a positive association with contagion (consistent with Allen and Gale, 2000; 2004 and Laeven et al., 2014). In the recent housing crisis, large banks were the epicenter of the crisis, and their distress damaged the economy significantly. Due to the sophisticated nature of the banking system, larger banks usually connect more with others in the network, which results in higher dependencies on other banks' financial claims. In addition, large banks have increased in size, complexity, and market-based activities, making larger banks more interconnected. Laeven et al. (2014) suggest that larger banks may have a more fragile business model (with higher leverage and market-based activities) and create more systemic risk. Therefore, larger banks, by nature, are more exposed to financial contagion.

Similarly, under the policy of "too big to fail," large financial firms have an advantage over smaller firms in the regulatory environment, which may increase the risk-taking incentives of large banks (Boyd et al., 1994) and subsequently increase the contagion exposure of larger banks. Larger banks respond highly to "too big to fail" because the creditors of large banks perceive that they will be bailed out in case of distress. Thus, a large bank's cost of debt is lower. This makes large banks riskier, using more leverage and unstable funding. Laeven et al. (2014) explore the optimal size of banks as big banks are not always socially optimal. Even though there remain economies of scale in operating, large banks contribute more significantly to financial contagion. Consistent with this argument, a non-linear association between bank size and financial contagion can be further explored. In model (2) of Table 2, we include quadratic terms of the bank's total assets scaled by million USD to capture the curvature of the association. The coefficient of $Total\ Asset\_sqr$ is positive and significant, meaning that the association is convex. The convex association validates that larger banks contribute more to financial contagion compared to smaller banks.

4.2.b. Financial constraints

In the previous section, we argue that when banks have more assets, they become more connected because they have higher lending and borrowing capacities with other banks. With this reasoning, financially unconstrained banks become more connected in the financial network

(Gong, Hu, & Ligthart, 2015). We explore more about the size effect in the context of whether financial contagion exposures are different for financially constrained versus unconstrained banks. We use two proxies for financial constraints for robustness. First, every year, we rank banks based on their liquid asset ratio (LAR) and assign them as financially constrained (unconstrained) if the bank remains in the bottom (top) tercile.[14] The intuition for considering the liquid asset ratio as a proxy for financial constraints is due to its demonstration of how easily financial firms can meet their short-term obligations. Second, we use the Kaplan and Zingales (1997) index (KZ Index) and assign a bank as being financially constrained (unconstrained) if it remains in the top (bottom) tercile. [15]

Columns (1) and (2) in Table 3 present the regression results for the two proxies defined above, respectively, when we use $FC_t^{(i)}$ as the dependent variable. Banks that are less financially constrained contribute significantly more to financial contagion for the KZ index and liquid asset ratio (LAR) models.

[Insert Table 3 about here]

4.2.c. Geographic proximity as a measure of competitiveness

[14] LAR is liquid asset over total asset. We define liquid asset consistent with Basel III. Liquid assets are the sum of level 1, level 2A, and level 2B. Level 1 assets include Federal Reserve bank balances, foreign resources that can be withdrawn quickly, securities issued or guaranteed by specific sovereign entities, and U.S. government issued or guaranteed securities. Level 2A assets include securities issued or guaranteed by specific multilateral development banks or sovereign entities, and securities issued by U.S. government-sponsored enterprises. Level 2B assets include publicly-traded common stock and investment-grade corporate debt securities issued by non-financial sector corporations. If COMPUSTAT reports any item missing in that fiscal year, we consider it as zero.

[15] $KZ\ index = -1.001909 * cashflow\ to\ capital\ + 0.2826389 * tobin\_q + \ 3.139193 * (Longterm\ debt + Short\ term\ debt)/\ capital_{ta-1}\ - 39.3678 *\ dividend\ to\ capital\ -\ 1.314759 *\ cash/capital_{t-1}$. Kaplan and Zingales (1997) classify firms into constrained and unconstrained firms. The higher the index the higher the financial constraints.

Generally, banks in the same region are exposed to similar economic conditions and shocks. The higher geographic proximity of banks can promote higher connections among each other for managing liquidity and information sharing. However, the interconnectedness of the banks may have contrasting implications. On the one hand, higher interconnectedness plays an important role in mitigating liquidity problems. On the other hand, if one bank fails, then the shock can transmit to the other banks. This section provides evidence that banks having head offices in the same city are prone to greater financial contagion.[16] We create a variable $Inverse\_proximity_{i,t} = \frac{1}{\#\ city_{i,t}}$, where $Inverse\_proximity_{i,t}$ serves as a proxy for the inverse geographic proximity and $\#\ city_{i,t}$ is the number of banks per city per year. A higher value means less densely populated and *vice versa*.

In Table 4, we present results from examining how banks' geographic proximities to one another affect their contributions to financial contagion. Our measure of geographic proximity is the inverse of the number of banks per city per year. Therefore, if contagion is inversely related to the distance between banks, then our inverse distance measure and bank financial contagion measure are expected to be negatively related. Since the coefficient on the inverse of the number of banks measure is negative, we find a positive relationship between the number of banks in a city and contagious linkages, which is consistent with our conjecture that the number of banks in a city is positively related[17] to the level of financial contagion. Our results relate to the prior work of Aharony and Swary (1996), who provide evidence that contagious linkages are higher among

[16] COMPUSTAT reports City as the headquarter city for each bank. To calculate the number of banks per city per year, we consider this variable. We consider head office location as a geographic proximity as the nontraditional activities are done from the head office rather than a branch office. Since non-interest income to revenue is positively associated, we are taking head office location to calculate geographic proximity measure. We also control for population and report the results in IA.10.
[17] In Table IA.7 of the Internet Appendix, we present results controlling for city population size and the results are qualitatively similar.

solvent banks that have headquarters closer in geographic proximity to failing banks, while Aït-Sahalia, Cacho-Diaz, and Laeven (2014) provide evidence that equities markets in close geographic proximity to one another experience mutually exciting jump intensities. In column 2, we include the nonlinearity components of assets and capital. We find robust evidence.

[Insert Table 4 about here]

4.3 Monitoring and financial contagion

4.3.a. Bank opacity as a proxy of monitoring cost

Due to the complex nature of banks' balance sheets, banks are subject to greater analyst disagreement and split ratings (Morgan, 2002). Previous research argues that the recent financial crisis of 2007-2008 magnified the problem of banks' opaqueness (Flannery, Kwan, & Nimalendran, 2013). They also find that banks' financial opacity rises significantly during financial crises. There are inherent reasons why banks are opaque; one of the reasons is that they hold assets that have proprietary information. In a monitoring context, the monitoring cost for opaque firms is higher. The higher monitoring cost hurts shareholders' incentives to monitor banks properly, which may result in higher financial contagion. Banks are vulnerable in several other channels too. Banks are susceptible to the classical "lemon problem" without deposit insurance if depositors cannot distinguish healthy banks from weak banks. Moreover, banks that hold opaque assets even as a diversification strategy may be subject to higher systemic risk if other banks pursue the same diversification strategy to invest in opaque assets (Wagner, 2010). Therefore, we expect that financial opacity contains explanatory power for banks' financial contagion exposures.

We use two proxies for financial opacity,[18] with their details contained in Table B.1. Table 5 reports the results from regressing banks' financial contagion contributions on their associated financial opacity measures with controls. Column (1) shows that firm opacity is significantly positively related to average contagion levels, $FC_t^{(i)}$. Column (2) reports the results with alternative firm opacity proxies as a robustness check, and the results continue to be significant.

[Insert Table 5 about here]

4.3.b. Institutional ownership as a proxy of monitoring incentives

Next, we examine the effect that institutional ownership has on a bank's level of financial contagion. In each year, we calculate the percentage of firms' market values held by institutional investors in total ($\%InstHolding$).[19] Previous researchers have documented contagion among institutional investors (Boyson, Stahel, & Stulz, 2010; Dudley & Nimalendran, 2011), which could cause banks to become contagiously linked through a portfolio re-balancing channel (Fleming, Kirby, & Ostdiek, 1998), through a flight to the quality channel (Kodres & Pritsker, 2002; Kyle & Xiong, 2001), or through a collateral channel (Benmelech & Bergman, 2011), among other possible channels. Conversely, Callen and Fang (2013) show that institutional investors monitor firms and reduce firms' 1-year-ahead crash risk. In this case, institutional ownership and a bank's contagion level are negatively related.

[18] We slightly modify Maffett (2012) to create bank opacity index as follows: average percentile rank of (1- forecast accuracy), (1-analyst following), and forecast diversity. In the second measure, we create $Firm\ Opacity\_alt$ of average percentile rank of (1-raw accuracy), (1-analyst forecast), raw diversity. Maffett (2012) uses two additional variables to create firm opacity: Big 5 auditors and discretionary smoothness. These two variables are not available for a sufficient number of firm years in our sample. Therefore, we ignore these two variables. The mean value of our modified firm opacity measure is similar to that of Maffett (2012). For details, please see *Table A.1*.

[19] Thompson Reuters reports institutional holding data beginning in 1997. Our sample period in this section, therefore, is reduced to 1997 to 2017. Consequently, our sample size is reduced to 4,739 observations.

Our results contradict the findings of BG in sign. While BG find a negative association with institutional ownership, we find a positive association[20] between institutional ownership and financial contagion. The sample size was reduced significantly due to the inclusion of institutional investors in the model. Thus, understanding the new sample is worthwhile to compare the results with the previous results. Panel A of Table 6 shows that firms' fundamental characteristics in the sample are quite similar to the aggregate sample. For all models in panel B of Table 6, we find a positive relationship[21] between banks' contagion levels and their level of institutional holdings along with the control variables in equation (1), which is consistent with the relation found by Erkens, Hung, and Matos (2012) and Laeven and Levine (2009) during the financial crisis period. Our results support two contemporary views of institutional holdings: a contagion pass-through channel and a monitoring channel. First, our results are consistent with the contagion pass-through hypothesis, which is that contagion among institutional investors passes through to the banks they hold. Second, our results also shed light on the monitoring channel. If institutional investors reduce the left tail risk of banks, then these banks are less risky, and it may be optimal for them to increase their exposure to other banks in the process of maximizing their risk-adjusted returns.

[Insert Table 6 about here]

4.4.Corporate governance and Financial Contagion

[20] We control the NBER recession period to know whether the association is driven by the recession period or not. We find that the results are robust with the original results of table 6. The National Bureau of Economic Research (NBER) provides the US Business Cycle Expansions and Contractions data at http://www.nber.org/cycles/cyclesmain.html.

[21] We re-examine the relationship between banks' contagion levels and their level of institutional holdings, both mutual fund holdings and other institutional holdings, and present the results in Table IA.9 of the Internet Appendix. We re-examine the relationship between banks' contagion levels and their level of mutual fund holdings only and present the results in Table IA.9 of the Internet Appendix.

Corporate governance literature has long advocated the importance of board structure and composition to ensure that boards fulfill their fiduciary role effectively on behalf of shareholders. Extant literature emphasizes two important roles of the board, which are monitoring and advising. The monitoring channel of the board argues that greater board independence improves CEO monitoring (Goyal & Park, 2002). Furthermore, the means with which outside board members improve the firm's investment policy is through the advising channel (Kim et al., 2014). However, corporate governance studies often ignore banks and utilities due to these firms' additional regulations. In a cross-sectional study, BG show the association among the board characteristics and systemic risk during the financial crisis of 2007-2008. They find that board independence and the number of board meetings are negatively associated with systemic risk, while the board size is positively associated with systemic risk.

In contrast, when bank boards are examined during the financial crisis, banks with more independent boards and larger boards are found to be riskier and have worse stock returns (Erkens, Hung, & Matos, 2012 and Pathan, 2009). We expand the literature by examining how board attributes are related to banks' contributions to financial contagion and systemic risk in panel regression settings. We argue that the analysis of the time series pattern needs to be further stressed to validate the association. We test the following five board characteristics[22]: percentage of independent board members ($\%IndDir$), number of board members ($\#BoardMember$), average age of board members ($AvgAge$), average tenure of the board members ($AvgTenu$), and board tenure range ($HTmLT$).

[22] Board attributes data is from BoardEx. BoardEx reports data from 1998. We merge BoardEx data with COMPUSTAT data using ISIN and CUSIP. After merging and ignoring missing board attributes data, our sample for this section contains 2,314 firm-year observations.

In Table 7 panel B, we find mixed evidence[23] as to the relation between board attributes and the financial contagion exposure of a bank. In contrast to BG, we find that the coefficient on $\%IndDir$ is positive and significant. We control for the recession year[24] to disentangle the relationship of board independence during the recession period and the non-recession period. The interaction effect of $\%IndDir$ and recession-year dummy is insignificant, meaning that the independent director has little effect on financial contagion during the financial crisis. This result can be interpreted as the banks' shareholders being incentivized to take higher risks in the presence of moral hazard problems. Thus, board independence is positively associated with financial contagion. However, $AvgAge$ and $HTmLT$ display negative associations with financial contagion. The negative relation between the average age of the board members and financial contagion exposure suggests that more aged members have more conservative views. The $HTmLT$ variable measures the diversity on the board. Previous studies of corporate governance provide evidence of the effectiveness of board diversity on firm performance (Carter & Simkins, 2003 and Garcia-Meca et al., 2015). Our results supplement the existing claims by examining banking firms. The coefficient on $HTmLT$ is negatively associated with financial contagion, which means that board diversity improves the board's effectiveness to reduce banks' risk exposures. $AvgTenu$ serves as a proxy of the board members' entrenchment on the board, where a longer tenure of board members on average suggests that board members are more entrenched. We do not find a robust significant association between $AvgTenu$, $\#BoardMember$, and financial contagion. However,

[23] We take industry and year fixed effect in this table as firms less likely to change the composition of the boards frequently. For example the correlation between $\%IndDir$ and lag $\%IndDir$ is almost 87%. Hence there is not too much variation in the firm-level for the board attributes. Taking the firm fixed effect will lose the significance of the variable of interest.

[24] We also control for the after year of recession to control the monitoring effect of independent directors after the recession, and find that the result are robust with our present results.

in model 2 (when we consider nonlinearity components as controls), we find that $AvgTenu$ is negatively associated because more entrenchment helps reduce risk and provides them with job and wealth safety. $\#BoardMember$ is positively associated with financial contagion, making it consistent with the findings of BG.

[Insert Table 7 about here]

Table 8 panel B presents the regression results of financial contagion on CEO attributes and controls. We generally find consistent results of CEO attributes and their association with the financial contagion. We hypothesize that certain CEO attributes, such as age and share ownership, are positively associated with financial contagion or systemic risk as these attributes increase short-term risk-taking incentives. On the other hand, the attributes that enhance CEO entrenchment, i.e., total compensation and CEO tenure, are hypothesized to be associated negatively with financial contagion. In both cases, we find mixed results[25]. The significantly positive association between financial contagion and CEO share ownership can be interpreted as equity-based compensation increasing managers' short-term risk-taking incentives to align with the shareholders (Pathan, 2009). CEO duality is negatively related, which means that the risk-averse entrenched CEOs take less risk; thus, systemic risk is negatively associated. In column 2, we include non-linear components along with the original controls. We find similar results except for the coefficient of share ownership, Shr_own_10000, which becomes insignificant.

[Insert Table 8 about here]

5. Endogeneity Tests

[25] We test whether the results are driven by the CEOs' conservative attitude during recession year controlling for the recession year dummy but find almost similar results, which means that the results are not driven by the recession year dummy.

Banks' policies and financial contagion may cause simultaneity. Moreover, omitted variable bias may also result in an endogenous association among our variables of interest and financial contagion. We take several precautions to address the endogeneity issue. First, we take the lagged dependent variable of interest in each of our models. Second, to address the firm-level unobserved variation, we take bank-level fixed effects along with the year fixed effects. We acknowledge that while these two strategies are commonly used in the literature, they still may not fully address the models' causal inference problems. Along with the strategies mentioned above, we take other methods to address the endogeneity issues, such as propensity score matching (PSM), difference-in-difference (DID), and non-parametric analysis. All the approaches are widely used to address the simultaneous causality problem. First, panel A of table 9 reports the financial constraints model. If a firm's choice of financial constraint is endogenous, then drawing causal inference is problematic. We address this concern by using the PSM technique as suggested by Caliendo and Kopeinig (2008). We match each treatment observation without replacement with a unique control observation using a caliper of 5% to find the closest match. After matching, we get 3,204 matching firms. We continue to find that financially unconstrained firms contribute to financial contagion and systemic risk.

In panel B, we adopt two strategies to address endogeneity in the model related to geographic proximity. First, we use a non-parametric approach. More precisely, we rank our variables of interest from the smallest to the largest, with the smallest observations having rank 1, the second smallest rank 2, and so on (Conover and Iman, 1981). Then we run the regression using the ranked variables instead of the original variables. We find consistent results with our main results showing that the associations between financial contagion and systemic risk with geographic proximity are positive. Second, we use the difference-in-difference (DID) approach.

We use the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 as a natural experiment. According to the act, banks are allowed to branch across state lines. Moreover, banks can merge or acquire other banks outside of their home state. We use IBBEA as an exogenous shock of the geographic proximity model because with the passage of IBBEA, banks' competition within a state has been reduced. This reduced competition negatively affects systemic risk because banks are not highly centered within a region after IBBEA. Thus, it reduces banks' interconnectedness. We conjecture that the resulting increased geographic dispersion negatively relates to systemic risk since banks need not share common clients in the same region. Consistent with our belief, we find that the interaction effect of IBBEA dummy (IBBEA dummy is 1 if datapoint is later than the year 1994) and inverse geographic proximity is positive, which means that the association between systemic risk and geographic proximity reduces with the passage of the act.

In panels C through F, we use the same non-parametric tests that we use in panel B to rank our variable of interest. In all the models, we find that the associations of interest are consistent with our main results.

[Insert Table 9 about here]

6. Robustness

A more detailed analysis of bank types unveils banks' common nature and their contributions to the financial contagion. Within the sample, we segregate the samples into three sub-samples: commercial banks, savings institutions, and investment banks. Though these three categories of banks' operations are similar, the types of clients these banks serve are different. Commercial banks deal with business customers who are, by nature, big entities seeking billions of dollars in loans for construction projects. On the other hand, saving banks and credit unions are not for profit financial cooperatives. Another sub-category, investment banks, are financial advisors to the corporations and help their clients to raise money, negotiate a merger, or arrange a private placement of bonds. Thus, various types of banks contribute to financial contagion and systemic risk differently.

Table 10 reports the regression results for all the models segregating into three sub-samples. In all the models, we find that the variables of interest are statistically significant and the coefficient signs are consistent with our hypotheses for the commercial bank sample.[26] The results are intuitive as the operations of commercial banks highly interconnect one commercial bank with others. Thus, these banks are more responsible for the overall systemic risk. On the other hand, in columns (4) to (6), we did not find a significant association among the variables of interests and systemic risk for the savings institutes in most cases. Columns (7) to (9) report the results of the sub-samples of investment banks.[27] We find weak evidence of association in this sub-sample.

[Insert Table 10 about here]

Next, we create sub-samples by year. Since our sample period is long, the sub-sample analysis offers deeper insights both into corporate and regulatory policy implementation. Table 11 reports the regression results for all the models using the sub-sample analysis of the year. We create three sub-samples: from 1960 to 1990, 1991 to 2006, and 2007 to 2017. In almost all the models, we find that the associations are significant both in magnitude and direction for the pre-housing crisis periods. Interestingly, the associations weaken during and after the housing crisis.

[26] The data points of borad characteristics and CEO characteristics become very small when we categorize the sample into three sub-categories. Thus, we did not test the sub-sample analysis for these two sections as performing tests with reduced sample size may end up with bias results due to non-representing smaller sample size.

[27] We create a sub-sample of investment banks if the SIC codes are 6211 for the firms. By nature, some variables in this sub-sample are missing, such as loan ratio, deposit ratio, and noninterest revenue. Thus, we drop these independent variables when we run regressions. Due to lack of data availability of investment banks, panel C and panel D of this sub-sample are empty.

Central banks, regulators, and policymakers were forced to take extraordinary measures after the housing crisis. Consequently, banks nowadays are highly capitalized; thus, less money is passing to the financial systems. Hence, after the housing crisis, the association among the bank-level factors and financial contagion has become weak.

[Insert Table 11 about here]

As a final measure of robustness, we explore how social connectedness may contribute to financial contagion or systemic risks. We argue that personal connections influence financial transactions among banks. Houston, Lee, and Suntheim (2017) find that banks with shared social connections partner more often when involved in syndicated loans. Hence, banks with higher social connections may contribute more greatly to financial contagion or systemic risks. Table 12 reports the regression results of social connectedness on financial contagion or systemic risks. We measure social connections ($SocialConnectedness$) by collecting data from BoardEx. BoardEx reports network size (number of overlaps from employment, other activities, and education) of directors. To construct social connectedness, we take the log of the total network size of all directors of a bank. In columns (1) and (2), we find that the association of $SocialConnectedness$ is positively associated with $FC_t^{(i)}$ and $CoVaR$. Thus, banks' social connectedness can contribute positively to financial contagion or systemic risks.

[Insert Table 12 about here]

In table 13, we include the systemic risk of tail events along with the financial contagion for the sake of robustness. We present four alternative specifications for the $FC_t^{(i)}$ and systemic risk measure: the yearly average financial contagion measure using the CAPM and 4-factor model in the first step of the $FC_t^{(i)}$ measure, marginal expected shortfall measure (MES) of Acharya et al. (2010), and the $CoVaR$ measure of Adrian and Brunnermeier (2016) as a systemic risk measure.

Conceptually, the last two measures are different than the financial contagion measure because $FC_t^{(i)}$ captures both upside and downside risk exposures. On the other hand, MES and $CoVar$ only capture the left tail exposures. We present a comparative analysis of these measures in Table 13. In panel A, we find that financially unconstrained firms, higher institutional ownership firms, and opaque firms are associated with higher financial contagion and systemic risk, which is consistent with our prior results. On the other hand, $inverse\_proximity$ is negatively associated with all four measures. Overall, these results suggest that our results are generally robust for using alternative specifications of financial contagion and systemic risk.

In panels B and C, we report the results of board characteristics and CEO attributes on alternative contagion and systemic risk measures. We generally find that $\%IndDir$ and $\#BoardMember$ are positively related, and $HTmLT$ is negatively related to financial contagion and systemic risk. However, $AvgTenu$ is insignificant for all the models. In panel C, we report the effects that CEO attributes have on financial contagion. We find that CEO age and female CEO are positively associated with contagion, while CEO tenure as a measure of entrenchment is negatively associated with systemic measures in columns 3 and 4. Overall, these results continue to provide evidence in support of our main results.

[Insert Table 13 about here]

7. Conclusion

Banks are special in the sense that their contagious linkages affect the consumption opportunity set through their expansion or contraction of credit. While many studies now exist which examine how to measure financial contagion econometrically, few studies have examined how financial contagion is related to bank characteristics. We advance the literature by systematically examining how bank characteristics are related to their contagion exposures. Specifically, we examine capital ratios, financial constraints, institutional holdings, geographic bank density, firm opacity, cash flow shocks, CEO characteristics, and board characteristics.

Our study advances the literature along two veins. First, our paper connects the financial contagion literature with banks' policy attributes. We find that banks' contagion exposures are positively associated with banks' total assets, total capital requirements, noninterest income, and stock return volatility. The effect of capital requirements on banks' contagion exposures is not monotonic; tier 1 capital is negatively related to banks' contagion exposures. These results support and extend the findings of extant studies, which have primarily focused on the financial crisis period.

Next, we study whether financial constraints contribute to contagion exposures using three proxies for financial constraints and we find robust evidence that more financially constrained banks have lower levels of financial contagion exposure. We have also advance geographic proximity (clustering) literature. We find that greater geographic density increases financial contagion, which indicates that banks' greater geographic clustering enhances banks' dependencies on each other. Finally, our study contributes to the financial reporting literature by using two proxies for financial opacity to show that firms' financial opacity associates positively with their financial contagion exposure.

The second vein through which we advance the literature is by examining how a bank's governance affects its financial contagion exposure. We examine the effect of institutional ownership on the contagion exposure of a bank, and we find that the institutional ownership relates positively, which suggests that contagion amongst institutional investors passes through to the financial institutions' stock holdings. Alternatively, this result could also be consistent with institutional investors' monitoring of banks reducing banks' left tail risks, which incentivizes banks to take on more risk. Related to a bank's board, we find that the average age of directors and board tenure range are, respectively, negatively and positively associated with financial contagion. We also inspect whether CEO attributes affect a bank's financial contagion exposure but do not find a robust relationship. Our results together provide comprehensive evidence regarding how a bank's corporate profile affects its contagion exposure. Future research can benefit from further exploring the intersection of corporate finance and financial contagion.

Appendix A.1

Variable Description

Variable	Definition
$AvgAge$	The average age of directors. *Source- BoardEx*
$Bank\_Opacity$	The average scaled percentile rank of (1-Forecast Accuracy), (1-Analyst Following), Forecast Diversity
$Bank\_Opacity\_alt$	The average scaled percentile rank of (1-Raw Accuracy), (1-Analyst Following), and the standard deviation of forecast diversity. *Source- I/B/E/S*
CEO_dual	Dummy variable equal to 1 if the CEO serves as both CEO and Chairman. *Source- BoardEx.*
$Deposit\ to\ asset\ ratio$	Total deposit to the total asset. (DPTC+DPTB)/AT. *Source: Compustat*
$Earnings\ Surprise$	$(EPS_t - EPS_{t-1})/P_{t-1}$. *Source: Compustat*
$Excess\_market$	The yearly average of excess market returns *Source: Ken. French website*
$FC_t^{(i)}$, COVAR, MES, CATFIN, $FC_t^{(i,CAPM)}$, $FC_t^{(i,FF4f)}$	Yearly average contagion or systemic risk measure described in Appendix I.A.I.
$Female\ CEO$	A dummy variable equal to 1 if the CEO of a firm is a female. *Source- Execucomp*
$FinUnc$	A dummy variable is one if a financial firm is in financial unconstraint banks. Financial unconstraint is measured by three criteria, such as Liquid Asset Ratio (LAR), total capital and KZ index. *Source: Compustat*
$Forecast\ Accuracy$	"... the percentile-ranked residual value from a regression of *Raw Accuracy* on *Earnings Surprise* and *Forecast Bias*, where *Raw Accuracy* is the absolute value of the forecast error multiplied by −1, scaled by the stock price at the end of the prior fiscal year and where the forecast error is the analysts' mean annual earnings forecast less the actual earnings…"- Maffett (2012). *Source: I/B/E/S summary*
$Forecast\ Bias$	$(Mean\ eps\ forecast - actual\ forecast)/\ P_{t-1}$. *Source: I/B/E/S summary.*
$Forecast\ Diversity$	"…The percentile-ranked residual value from a regression of *Raw Diversity* on *Earnings Surprise* and *Forecast Bias*, where *Raw Diversity* is the standard deviation of analysts' forecasts of the firm's earnings in the following year, normalized by the mean forecast and then divided by the square root of the number of analysts following that firm.…" -Maffett (2012). *Source: I/B/E/S summary*
$HTmLT$	Maximum director tenure minus minimum director tenure. *Source: BoardEx*
$Inverse\_proximity$	One divided by the number of banks per city. *Source: Compustat*
$\%IndDir$	The percentage of directors who are independent on a board. *Source: BoardEx*
$\%\ InstHolding$	The percentage of the bank's common stock that is held by mutual funds or institutional investors. *Source: Thompson Reuters.*
$KZ\ Index$	Kaplan and Zingales (1997) index $KZ\ index = -1.001909 * cashflow\ to\ capital + 0.2826389 * tobin\_q + 3.139193 * (Longterm\ debt + Short\ term\ debt)/\ capital_{ta-1} - 39.3678 * dividend\ to\ capital - 1.314759 * cash/capital_{t-1}$.
LAR	LAR is a liquid asset over the total asset. We define liquid assets consistent with Basel III. Liquid assets are the sum of level 1, level 2A, and level 2B. Level 1 assets include Federal Reserve bank balances, foreign resources that can be withdrawn quickly, securities issued or guaranteed by specific sovereign entities, and U.S. government-issued or guaranteed securities. Level 2A assets include securities issued or guaranteed by specific multilateral development banks or sovereign entities, and securities issued by U.S. government-sponsored enterprises. Level 2B assets include publicly traded common stock and investment-grade corporate debt securities issued by non-financial sector corporations. If COMPUSTAT reports any item missing in that fiscal year, we consider it as zero. *Source: Compustat*
$Loan\ to\ asset\ ratio$	Total loan to the total asset. [LCABG+LCUACU+LLOT+IALTI+MTL]/AT. *Source: Compustat*
$Nonint\ to\ Revenue$	Non-interest income to total revenue. INITB/REVT. S*ource: Compustat*
$Liquidity$	Current assets (item 4) divided by current liabilities (item 5). *Source: Compustat*
ln_age	Natural log of CEO age. *Source: Execucomp*
ln_TC	Natural log of total compensation of CEO (tdc2). *Source: Execucomp*
$NI\ to\ asset$	Net income to the total assets. NI/AT. *Source: Compustat*
$Ln(Asset)$	Ln(Total Asset). *Source: Compustat*
N_{cf}	Cash flow news innovations using the Campbell and Shiller (1988) decomposition.
N_{dr}	Discount rate innovations using the Campbell and Shiller (1988) decomposition.
$Recession\_year$	A dummy of one if the year is a recession year defined by NBER. *Source: NBER*
$SocialConnectedness$	Log of total network size of directors of a bank. *Source: BoardEx*
Shr_own_10000	The percentage of ownership stake that a CEO has in the firm scaled by 10000. *Source: Execucomp*
Std_stock_return	The firm's standard deviation of daily stock returns over year t. Source: *CRSP*
$Tier\ 1\ Capital\ ratio$	Risk-adjusted capital ratio-Tier1. COMPUSTAT variable- CAPR1. *Source: Compustat*
$Tier1\ Capital\_sqr$	Risk-adjusted capital ratio-Tier1 square scaled by 1 million. *Source: Compustat*
$Total\ Capital\ ratio$	Risk-adjusted capital ratio- combined. COMPUSTAT variable- CAPR3. *Source: Compustat*
$Total\ Asset\_sqr$	Total Asset Square scaled by 1 million. *Source: Compustat*
$\#BoardMember$	The number of board members on a board. *Source: BoardEx*
$\#Bank$	The number of banks per year. *Source: Compustat*

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, *80*(5), 1977-2016.

Acharya, V. (2001). *A Theory of Systemic Risk and Design of Prudential Bank Regulation, New York University* (Doctoral dissertation, Ph. D. Dissertation).

Acharya, Viral V., Pedersen, Lasse H., Philippon, Thomas and Richardson, Matthew. (2017). Measuring systemic risk, *Review of Financial Studies* 30, 2-47.

Acharya, V. V., & Yorulmazer, T. (2008). Cash-in-the-market pricing and optimal resolution of bank failures. *The Review of Financial Studies*, *21*(6), 2705-2742.

Adams, R. B., Almeida, H., & Ferreira, D. (2005). Powerful CEOs and their impact on corporate performance. *The Review of Financial Studies*, *18*(4), 1403-1432.

Adrian, Tobias and Brunnermeier, Markus K. (2016). CoVaR, *American Economic Review* 106, 1705-1741.

Adrian, Tobias, Etula, Erkko, and Muir, Tyler. (2014). Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557-2596.

Adrian, Tobias and Song Shin, Hyun. (2014). Procyclical leverage and value-at-risk, *Review of Financial Studies* 27, 373-403.

Aharony, Joseph and Swary, Itzhak. (1996). Additional evidence on the information-based contagion effects of bank failures, *Journal of Banking & Finance* 20, 57-69.

Ahmed, S., Sihvonen, J., & Vähämaa, S. (2019). CEO facial masculinity and bank risk-taking. *Personality and Individual Differences*, *138*, 133-139.

Aït-Sahalia, Yacine, Cacho-Diaz, Julio, and Laeven, Roger J.A. (2015). Modeling financial contagion using mutually exciting jump processes. *Journal of Financial Economics* 117, 585-606.

Allen, Franklin and Gale, Douglas. (2000). Financial contagion, *Journal of Political Economy* 108, 1-33.

Allen, F., & Gale, D. (2004). Competition and financial stability. *Journal of money, credit and banking*, 453-480.

Alvarez, F., & Barlevy, G. (2015). *Mandatory disclosure and financial contagion* (No. w21328). National Bureau of Economic Research.

Bae, K. H., Karolyi, G. A., & Stulz, R. M. (2003). A new approach to measuring financial contagion. *The Review of Financial Studies*, *16*(3), 717-763.

Battaglia, Francesca and Gallo, Angela. (2017). Strong boards, ownership concentration, and EU banks' systemic risk-taking: evidence from the financial crisis, *Journal of International Financial Markets, Institutions & Money* 46, 128-146.

Basel Committee. (2010). Principles for enhancing corporate governance. *Basel Committee on Banking Supervision. Basel*.

Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *The Journal of Finance*, *65*(5), 1637-1667.

Beltratti, Andrea and Stulz, René M. (2012). The credit crisis around the globe: why did some banks perform better?, *Journal of Financial Economics* 105, 1-17.

Benmelech, Efraim and Bergman, Nittai K. (2011). Bankruptcy and the collateral channel, *Journal of Finance* 66, 337-378.

Berger, P. G., Ofek, E., & Yermack, D. L. (1997). Managerial entrenchment and capital structure decisions. *The Journal of Finance*, *52*(4), 1411-1438.

Billio, Monica, Getmansky, Mila, Lo, Andrew W. and Pelizzon, Loriana. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors, *Journal of Financial Economics* 104, 535-559.

Blau, B. M., Brough, T. J., & Griffith, T. G. (2017). Bank opacity and the efficiency of stock prices. *Journal of Banking & Finance*, *76*, 32-47.

Boot, A. W., & Schmeits, A. (2000). Market discipline and incentive problems in conglomerate firms with applications to banking. *Journal of financial intermediation*, *9*(3), 240-273.

Bostandzic, Denefa and Weiß, Gregor N.F. (2018). Why do some banks contribute more to global systemic risk?. *Journal of Financial Intermediation* 35, 17-40.

Boyd, John H., and Gertler, Mark. (1994). The role of large banks in the recent US banking crisis. *Federal Reserve Bank of Minneapolis Quarterly Review* 18, 2-21.

Boyson, Nicole M., Stahel, Christof, W. and Stulz, René M. (2010). Hedge fund contagion and liquidity shocks, *Journal of Finance* 65, 1789-1816.

Brownlees, Christian and Engle, Robert F. (2017). SRISK: a conditional capital shortfall measure of systemic risk, *Review of Financial Studies* 30, 49-79.

Brunnermeier, M. K., Dong, G. N., & Palia, D. (2020). Banks' noninterest income and systemic risk. *The Review of Corporate Finance Studies*, *9*(2), 229-255.

Bucher, M., Dietrich, D., & Hauck, A. (2013). Business cycles, bank credit and crises. *Economics Letters*, *120*(2), 229-231.

Calem, P., & Rob, R. (1999). The impact of capital-based regulation on bank risk-taking. *Journal of Financial Intermediation*, *8*(4), 317-352.

Callen, Jeffrey L. and Fang, Xiaohua. (2013). Institutional investor stability and crash risk: monitoring versus short-termism?, *Journal of Banking & Finance* 37, 3047-3063.

Campbell, John Y. and Shiller, Robert J. (1988). The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-228.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57-82.

Caiazza, S., Cotugno, M., Fiordelisi, F., & Stefanelli, V. (2018). The spillover effect of enforcement actions on bank risk-taking. *Journal of Banking & Finance*, *91*, 146-159.

Carter, David A., Simkins, Betty J. and Simpson, W. Gary. (2003). Corporate governance, board diversity, and firm value. *Financial Review* 38, 33-53.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31-72.

Chen, Y. (1999). Banking panics: The role of the first-come, first-served rule and information externalities. *Journal of Political Economy*, *107*(5), 946-968.

Chiu, W. C., Peña, J. I., & Wang, C. W. (2015). Industry characteristics and financial risk contagion. *Journal of Banking & Finance*, *50*, 411-427.

Conover, W. J., & Iman, R. L. (1981). Rank transformations as a bridge between parametric and nonparametric statistics. *The American Statistician*, *35*(3), 124-129.

DeYoung, R., & Torna, G. (2013). Nontraditional banking activities and bank failures during the financial crisis. *Journal of Financial Intermediation*, *22*(3), 397-421.

Diebold, Francis X. and Yılmaz, Kamil. (2014). On the network topology of variance decompositions: measuring the connectedness of financial firms, *Journal of Econometrics* 182, 119-134.

Duchin, Ran, Ozbas, Oguzhan and Sensoy, Berk A. (2010). Costly external finance, corporate investment and the subprime mortgage crisis, *Journal of Financial Economics* 97, 418-435.

Dudley, Evan and Nimalendran, Mahendrarajah. (2011). Margins and hedge fund contagion, *Journal of Financial and Quantitative Analysis* 46, 1227-1257.

Duffy, J., Karadimitropoulou, A., & Parravano, M. (2019). Financial contagion in the laboratory: Does network structure matter?. *Journal of Money, Credit and Banking*, *51*(5), 1097-1136.

Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, *104*(10), 3115-53.

Ellul, A., & Yerramilli, V. (2013). Stronger risk controls, lower risk: Evidence from US bank holding companies. *The Journal of Finance*, *68*(5), 1757-1803.

Elsinger, H., Lehar, A., & Summer, M. (2006). Risk assessment for banking systems. *Management science*, *52*(9), 1301-1314.

Engle, Robert, Jondeau, Eric and Michael Rockinger. (2012). Systemic risk in europe, Swiss Finance Institute, Research Paper Series No. 12-45.

Erkens, David H., Hung, Mingyi and Matos, Pedro. (2012). Corporate governance in the 2007-2008 financial crisis: evidence from financial institutions worldwide, *Journal of Corporate Finance* 18, 389-411.

Faccio, M., Marchica, M. T., & Mura, R. (2016). CEO gender, corporate risk-taking, and the efficiency of capital allocation. *Journal of Corporate Finance*, *39*, 193-209.

Fama, Eugene F. and French, Kenneth R. (1993). Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Flannery, Mark J., Kwan, Simon H. and Nimalendran, Mahendrarajah. (2013). The 2007–2009 financial crisis and bank opaqueness. *Journal of Financial Intermediation* 22, 55-84.

Fleming, Jeff, Kirby, Chris and Ostdiek, Barbara. (1998). Information and volatility linkages in the stock, bond, and money markets, *Journal of Financial Economics* 49, 111-137.

Forbes, Kristin J. and Rigobon, Roberto. (2002). No contagion, only interdependence: measuring stock market co-movements, *Journal of Finance* 57, 2223-2261.

Fortin, Rich, Goldberg, Gerson M. and Roth, Greg. (2010). Bank risk-taking at the onset of the current banking crisis, *Financial Review* 45, 891-913.

Fosu, S., Ntim, C. G., Coffie, W., & Murinde, V. (2017). Bank opacity and risk-taking: Evidence from analysts' forecasts. *Journal of Financial Stability*, *33*, 81-95.

García-Meca, Emma, García-Sánchez, Isabel-María and Martínez-Ferrero, Jennifer. (2015). Board diversity and its effects on bank performance: An international analysis. *Journal of Banking & Finance* 53, 202-214.

Gertler, M., & Bernanke, B. (1989). Agency costs, net worth and business fluctuations. In *Business cycle theory*. Edward Elgar Publishing Ltd..

Gong, D., Hu, S., & Ligthart, J. E. (2015). Does corporate income taxation affect securitization? Evidence from OECD banks. *Journal of Financial Services Research*, *48*(3), 193-213.

Goyal, Vidhan K. and Park, Chul W. (2002). Board leadership structure and CEO turnover. *Journal of Corporate Finance* 8, 49-66.

Grilli, R., Tedeschi, G., & Gallegati, M. (2015). Markets connectivity and financial contagion. *Journal of Economic Interaction and Coordination*, *10*(2), 287-304.

Herring, R. J., & Carmassi, J. (2014). Complexity and systemic risk. *The Oxford handbook of banking*, 77.

Hogan, T. L. (2015). Capital and risk in commercial banking: A comparison of capital and risk-based capital ratios. *The Quarterly Review of Economics and Finance*, *57*, 32-45.

Houston, J. F., Lee, J., & Suntheim, F. (2018). Social networks in the global banking sector. *Journal of Accounting and Economics*, *65*(2-3), 237-269.

Hovakimian, A., Kane, E. J., & Laeven, L. (2012). *Tracking variation in systemic risk at us banks during 1974-2013* (No. w18043). National Bureau of Economic Research.

International Monetary Fund, 2014. Global Financial Stability Report: Risk-taking, Liquidity, and Shadow Banking, October

Ivashina, Victoria and Scharfstein, David. (2010). Bank lending during the financial crisis of 2008, *Journal of Financial Economics* 97, 319-338.

Jiang, H., Zhang, J., & Sun, C. (2020). How does capital buffer affect bank risk-taking? New evidence from China using quantile regression. *China Economic Review*, *60*, 101300.

Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking?. *Journal of Financial Stability*, *9*(2), 185-195.

Jones, J. S., Lee, W. Y., & Yeager, T. J. (2013). Valuation and systemic risk consequences of bank opacity. *Journal of Banking & Finance*, *37*(3), 693-706.

Kaplan, Steven N. and Zingales, Luigi. (1997). Do investment cash-flow sensitivities provide useful measures of financing constraints, *Quarterly Journal of Economics* 112, 169-215.

Kaplan, Steven N., Klebanov, Mark M. and Sorensen, Morten. (2012). Which CEO characteristics and abilities matter?. *The Journal of Finance* 67, 973-1007.

Kim, E. H., & Lu, Y. (2011). CEO ownership, external governance, and risk-taking. *Journal of Financial Economics*, *102*(2), 272-292.

Kim, Kyonghee, Mauldin, Elaine and Patro, Sukesh. (2014). Outside directors and board advising and monitoring performance. *Journal of Accounting and Economics* 57, 110-131.

Kodres, Laura E. and Pritsker, Matthew. (2002). A rational expectations model of financial contagion, *Journal of Finance* 57, 769-799.

König-Kersting, C., Trautmann, S. T., & Vlahu, R. (2021). Bank instability: Interbank linkages and the role of disclosure. *Journal of Banking & Finance*, 106353.

Krishnamurthy, A. (2003). Collateral constraints and the amplification mechanism. *Journal of Economic Theory*, *111*(2), 277-292.

Kupiec, P., & Güntay, L. (2016). Testing for systemic risk using stock returns. *Journal of Financial Services Research*, *49*(2), 203-227.

Kyle, Albert S. and Xiong, Wei. (2001). Contagion as a wealth effect, *Journal of Finance* 56, 1401-1440.

Laeven, Luc and Levine, Ross. (2009). Bank governance, regulation and risk-taking, *Journal of Financial Economics* 93, 259-275.

Laeven, M. L., Ratnovski, M. L., & Tong, M. H. (2014). *Bank size and systemic risk*. International Monetary Fund.

Leitner, Yaron. (2005). Financial networks: contagion, commitment, and private sector bailouts, *Journal of Finance* 60, 2925-2953.

Maffett, Mark. (2012). Financial reporting opacity and informed trading by international institutional investors. *Journal of Accounting and Economics* 54, 201-220.

Malmendier, U., & Tate, G. (2005). CEO overconfidence and corporate investment. *The journal of finance*, *60*(6), 2661-2700.

Matutes, C., & Vives, X. (2000). Imperfect competition, risk-taking, and regulation in banking. *European economic review*, *44*(1), 1-34.

Morgan, Donald P. (2002). Rating banks: Risk and uncertainty in an opaque industry. *American Economic Review* 92, 874-888.

Newey, Whitney K. and West, Kenneth D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Nier, E. W. (2005). Bank stability and transparency. *Journal of Financial Stability*, *1*(3), 342-354.

O'hara, M., & Shaw, W. (1990). Deposit insurance and wealth effects: the value of being "too big to fail." *The Journal of Finance*, *45*(5), 1587-1600.

Pathan, Shams. (2009). Strong boards, CEO power and bank risk-taking, *Journal of Banking & Finance* 33, 1340-1350.

Piccotti, Louis R. (2017). Financial contagion risk and the stochastic discount factor, *Journal of Banking & Finance* 77, 230-248.

Rochet, J. C., & Tirole, J. (1996). Interbank lending and systemic risk. *Why Are there So Many Banking Crises?*, 140.

Sáez, Lawrence and Shi, Xianwen. (2004). Liquidity pools, risk sharing, and financial contagion, *Journal of Financial Services Research* 25, 5-23.

Serfling, M. A. (2014). CEO age and the riskiness of corporate policies. *Journal of Corporate Finance*, *25*, 251-273.

Tirole, J., & Rochet, J. C. (1996). Controlling Risk in Payment Systems. *Journal of Money, Credit and Banking*, *28*, 832-62.

Trevino, I. (2020). Informational channels of financial contagion. *Econometrica*, *88*(1), 297-335.

Wagner, W. (2010). Diversification at financial institutions and systemic crises. *Journal of Financial Intermediation*, *19*(3), 373-386.

Weiß, G. N., Bostandzic, D., & Neumann, S. (2014). What factors drive systemic risk during international financial crises?. *Journal of Banking & Finance*, *41*, 78-96.

Table 1

Summary statistics

This table presents the summary statistics for the variables used in our study. The sample period is from 1960 to 2017. Yearly contagion is the average yearly contagion measure of $FC_t^{(i)}$, and variable descriptions are contained in Table A.1.

Name of variable	Mean	Median	SD	1%	99%
$FC_t^{(i)}$	0.00054	0.00001	0.00258	-0.00022	0.01203
SMB	0.00120	0.00018	0.00874	-0.01825	0.01789
HML	0.00246	0.00996	0.01136	-0.02289	0.03032
$Risk\ Free$	0.00315	0.00381	0.00224	0.00000	0.00893
UMD	0.00664	0.00783	0.01449	-0.05321	0.02564
$Average\ excess\ market\ return$	0.00591	0.00882	0.01486	-0.03682	0.02571
$Total\ Asset$	12952.67000	1034.60000	92206.15000	13.78000	214921.50000
$Tier\ 1\ Capital\ Ratio$	7.21000	8.50000	6.69170	0.00000	23.40000
$Total\ Loan$	5314.42000	416.53000	45696.87000	0.00000	71364.27000
$Loan\ to\ Asset$	0.63890	0.65470	0.14760	0.09312	0.90755
$Deposit\ to\ Asset$	0.74830	0.77430	0.12570	0.18270	0.91650
$Non-interest\ income\ to\ revenue$	0.13978	0.11929	0.12061	-0.00267	0.55649
$Net\ income\ to\ Asset$	0.00589	0.00890	0.41259	-0.10610	0.18812
$\#\ Bank$	503.00000	546.00000	167.16000	33.00000	737.00000
$\%InsHolding$	0.409	0.225	0.475	0	0.90
$\%IndDir$	0.793	0.818	0.115	0.462	1

Table 2

Control regression

This table reports the panel regression results from regressing yearly contagion and systemic risk on the firm characteristics. The panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier$ 1 $capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	$FC_t^{(i)}$	$FC_t^{(i)}$
	(1)	(2)
$Ln(Asset)$	0.0012***	0.0009***
	(2.9764)	(3.2828)
$Total\ Asset\_sqr$		0.0038***
		(3.3159)
$Tier1\ Capital\ Ratio$	-0.8751	-27.0890**
	(-0.2317)	(-2.1080)
$Tier1\ Capital\_sqr$		1.0951**
		(2.2267)
$LoantoAsset$	-0.0004	-0.0001
	(-1.3166)	(-0.4095)
$DeposittoAsset$	0.0009*	0.0011**
	(1.7404)	(2.2588)
$NoninttoRevenue$	0.0018**	0.0010**
	(2.4287)	(2.4372)
$NitoAsset$	0.0053**	0.0050**
	(2.2015)	(2.4956)
$Excess\_mkt$	-0.0040	-0.0034
	(-0.9322)	(-0.9441)
$\#bank$	0.0000	0.0000
	(0.1507)	(0.7507)
$Std.Dev\ of\ Stock\ Return$	0.0081***	0.0065***
	(2.6376)	(2.9820)
$ProNotrade$	0.0006***	0.0004***
	(2.7505)	(3.1631)
Constant	-0.0090***	-0.0082***
	(-3.4295)	(-3.6926)
Observations	11,353	11,353
Adjusted R-squared	0.6535	0.6964
Firm FE	YES	YES
Year FE	YES	YES

Table 3

Financial contagion and financial constraints

This table reports the panel regression results from regressing yearly contagion and systemic risk on financial constraint measures along with firm characteristics. The panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$. $FinUnc$, financially unconstrained, is a dummy variable equal to 1 if the firm belongs in the top tercile of liquidity asset ratio, total capital ratio, and the bottom tercile of the KZ index. The following control variables are included. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	$FC_t^{(i)}$	
	(1)	(2)
$FinUnc_{KZ}$	0.0002***	
	(4.6093)	
$FinUnc_{LAR}$		0.0001***
		(2.7250)
$Ln(Asset)$	0.0009***	0.0009***
	(11.2828)	(11.3080)
$Total\ Asset\_sqr$	0.0038***	0.0038***
	(3.6990)	(3.6855)
$Tier1\ Capital\ Ratio$	-26.4943***	-25.4372***
	(-4.7910)	(-4.6557)
$Tier1\ Capital\_sqr$	1.0425***	0.9873***
	(4.7023)	(4.5039)
$LoantoAsset$	-0.0001	0.0001
	(-0.5529)	(0.4519)
$DeposittoAsset$	0.0010***	0.0009***
	(3.8972)	(3.9566)
$NoninttoRevenue$	0.0010***	0.0010***
	(4.0354)	(4.0555)
$NitoAsset$	0.0048***	0.0053***
	(3.5282)	(3.8971)
$Excess\_mkt$	-0.0039	-0.0034
	(-1.1198)	(-1.0280)
$\#bank$	0.0000	-0.0000**
	(1.0496)	(-1.9887)
$Std.Dev\ of\ Stock\ Return$	0.0065***	0.0063***
	(4.5956)	(4.5040)
$ProNotrade$	0.0004***	0.0004***
	(5.1835)	(4.8428)
Constant	-0.0081***	0.0050
	(-7.7976)	(0.8527)
Observations	11,353	11,347
Adjusted R-squared	0.6965	0.6896
Firm FE	YES	YES
Year FE	YES	YES

Table 4

Financial contagion and geographic proximity

This table reports the panel regression results from regressing yearly contagion and systemic risk on the banks' geographic proximity along with the other firm characteristics. The panel regressions are run with the fixed effect models. The dependent variable is the yearly average of $FC_t^{(i)}$. $Inverse\_proximity$ is 1 divided by the number of banks per city. $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier$ 1 $capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

	$FC_t^{(i)}$
VARIABLES	(1)
$Inverse\_proximity$	-0.0005***
	(-5.2237)
$Ln(Asset)$	0.0008***
	(21.0709)
$Total\ Asset\_sqr$	0.0050***
	(4.8134)
$Tier1\ Capital\ Ratio$	-36.5427***
	(-5.0405)
$Tier1\ Capital\_sqr$	1.5534***
	(5.3933)
$LoantoAsset$	0.0007***
	(4.6207)
$DeposittoAsset$	0.0001
	(0.6005)
$NoninttoRevenue$	0.0001
	(0.5955)
$NitoAsset$	0.0040**
	(2.5046)
$Excess\_mkt$	0.0031
	(0.7026)
$\#bank$	0.0000
	(0.4682)
$Std.Dev\ of\ Stock\ Return$	0.0089***
	(6.2788)
$ProNotrade$	0.0004***
	(4.7350)
Constant	-0.0048***
	(-12.0696)
Observations	11,307
Adjusted R-squared	11,307
Year FE	0.5949
City FE	YES

Table 5

Financial contagion and bank opacity

This table reports the panel regression results from regressing yearly contagion and systemic risk on bank opacity along with the other firm characteristics. The dependent variable is the yearly average of $FC_t^{(i)}$. $Firm\ Opacity$ is an index of average percentile rank of (1-forecast accuracy), (1-analyst forecast), and forecast diversity. $Firm\ Opacity\_alt$ is an index of average percentile rank of (1-raw accuracy), (1-analyst forecast), and raw diversity. The following control variables are included. $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	$FC_t^{(i)}$	
	(1)	(2)
$Firm\ Opacity$	0.0003**	
	(2.5421)	
$Firm\ Opacity\_alt$		0.0003**
		(1.9985)
$Ln(Asset)$	0.0009***	0.0009***
	(11.2828)	(11.3080)
$Total\ Asset\_sqr$	0.0038***	0.0038***
	(3.6990)	(3.6855)
$Tier1\ Capital\ Ratio$	-26.4943***	-25.4372***
	(-4.7910)	(-4.6557)
$Tier1\ Capital\_sqr$	0.9786**	0.9873***
	(2.5378)	(4.5039)
$LoantoAsset$	-0.0001	0.0001
	(-0.5529)	(0.4519)
$DeposittoAsset$	0.0010***	0.0009***
	(3.8972)	(3.9566)
$NoninttoRevenue$	0.0010***	0.0010***
	(4.0354)	(4.0555)
$NitoAsset$	0.0048***	0.0053***
	(3.5282)	(3.8971)
$Excess\_mkt$	-0.0039	-0.0034
	(-1.1198)	(-1.0280)
$\#bank$	0.0000	-0.0000**
	(1.0496)	(-1.9887)
$Std.Dev\ of\ Stock\ Return$	0.0065***	0.0063***
	(4.5956)	(4.5040)
$ProNotrade$	0.0004***	0.0004***
	(5.1835)	(4.8428)
Constant	-0.0081***	0.0050
	(-7.7976)	(0.8527)
Observations	11,353	11,347
Adjusted R-squared	0.6965	0.6896
Firm FE	YES	YES
Year FE	YES	YES

Table 6

Financial contagion and institutional holdings

This table reports the panel regression results from regressing yearly contagion and systemic risk on the institutional ownerships along with the other firm characteristics. Panel A shows the summary statistics of the reduced sample. In panel B, the panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$. $\%\,InstHolding$ is the percentage of the bank's common stock that is held by institutional investors (mutual funds). $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1997 to 2017.

Panel A: Summary Statistics

Name of variable	Mean	Median	SD	1%	99%
Total Assets (million)	12,293.21	1,275.80	95,823.75	122.684	189,138.00
$Tier1\ Capital$	11.40	11.150	4.892	0	24.54
$Loan\ to\ Asset$	0.655	0.670	0.131	0.200	0.888
$Deposit\ to\ Asset$	0.738	0.755	0.104	0.418	0.900
$Non-interest\ income\ to\ revenue$	0.153	0.133	0.105	-0.003	0.556
$Net\ income\ to\ Asset$	0.0068	0.0058	0.014	-0.038	0.023
$\#\ Bank$	577	602	100.12	392	737

Panel B: Regression results

	$FC_t^{(i)}$	
		Including non-linear controls
VARIABLES	(1)	(2)
$\%InsHolding$	0.0002**	0.0001***
	(2.3306)	(2.6899)
$Ln(Asset)$	0.0000**	0.0000**
	(2.3515)	(2.3515)
$Total\ Asset\_sqr$		0.0006***
		(2.7800)
$Tier1\ Capital\ Ratio$	-4.1330	-18.1171*
	(-0.6300)	(-1.6473)
$Tier1\ Capital\_sqr$		0.6144*
		(1.6541)
Controls	YES	YES
Constant	0.0019**	0.0015***
	(2.0735)	(3.7212)
Observations	3,939	3,939
Adjusted R-squared	0.6949	0.6965
Year FE	YES	YES
Firm FE	YES	YES

Table 7

Financial Contagion with Board attributes

This table reports the panel regression results from regressing yearly contagion and systemic risk on board attributes and control firm characteristics. Panel A shows the summary statistics of the reduced sample. In panel B, the panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$. $\%IndDir$ is the percentage of directors who are independent on a board. $AvgAge$ is the average age of board members per firm. $HTmLT$ is the difference between the highest tenure and the lowest tenure. $\#BoardMember$ represents the number of board members on a board on average. $AvgTenu$ is the average tenure of the board members. $Recession\_year$ is a dummy variable if the year is a recession year. $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1998 to 2017.

Panel A: Summary Statistics

Name of variable	Mean	Median	SD	1%	99%
Total Assets (million)	10,565.97	1,215.326	112,208.60	181.738	62,336.42
$Tier1\ Capital$	11.72	11.480	3.952	0	23.04
$Loan\ to\ Asset$	0.665	0.674	0.120	0.310	0.888
$Deposit\ to\ Asset$	0.762	0.778	0.087	0.465	0.893
$Non-interest\ income\ to\ revenue$	0.159	0.146	0.093	-0.003	0.511
$Net\ income\ to\ Asset$	0.0053	0.007	0.011	-0.042	0.020
$\#\ Bank$	520	546	79.603	392	704

Panel B: Regression

	$FC_t^{(i)}$	
VARIABLES		Including non-linear controls
	(1)	(2)
$\%IndDir$	0.0007**	0.0003*
	(2.4144)	(1.6846)
$Recession\_year$	-0.0013*	-0.0066*
	(-1.7178)	(-1.7934)
$Recession\_year$* $\%IndDir$	0.0014	0.0010
	(1.4484)	(1.2417)
$\#BoardMember$	0.0021	0.0026***
	(1.6269)	(2.6258)
$AvgAge$	-0.0017*	-0.0013*
	(-1.8863)	(-1.9094)
$AvgTenu$	0.0026	0.0018
	(1.5086)	(1.2203)
$HTmLT$	-0.0029***	-0.0017***
	(-3.3744)	(-2.6069)
Controls	YES	YES
Constant	0.0133***	-0.0097*
	(3.1018)	(-1.8816)
Observations	2,314	2,314
Adjusted R-squared	0.1974	0.4633
Ind FE	YES	YES
Year FE	YES	YES

Table 8

Financial Contagion and CEO attributes

This table reports the panel regression results from regressing yearly contagion and systemic risk on CEO attributes and firm characteristics. Panel A shows the summary statistics of the reduced sample. In panel B, the panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$. $\ln\_Age$ is the natural log of the age of the CEO. Shr_own is the percentage ownership stake that a CEO has in the firm scaled by 10000. $\ln\_TC$ is the natural log of the total compensation. CEO_dual is a dummy variable equal to 1 if the CEO is both chairman and CEO. $Female\_CEO$ is a dummy variable equal to 1 if the CEO is a female. $\ln\_CEO\_tenure$ is the natural log of the number of years a CEO is incumbent. The following control variables are included. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1992 to 2017.

Panel A: Summary Statistics

Name of variable	Mean	Median	SD	1%	99%
Total Assets (million)	48,841.97	8,099.84	226,549.40	1,029.77	1,527,015
$Tier1\ Capital$	11.90	11.76	3.76	0	21.50
$Loan\ to\ Asset$	0.631	0.660	0.1390	0.133	0.901
$Deposit\ to\ Asset$	0.731	0.753	0.107	0.405	0.888
$Non-interest\ income\ to\ revenue$	0.217	0.200	0.135	-0.003	0.556
$Net\ income\ to\ Asset$	0.007	0.009	0.012	-0.059	0.031
$\#\ Bank$	490	476	82.11	392	704

Panel B: Regression

VARIABLES	$FC_t^{(i)}$	
		Including non-linear controls
	(1)	(2)
$\ln\_Age$	0.0012**	0.0009**
	(2.4417)	(2.5115)
Shr_own_10000	0.3205**	0.0259
	(2.1271)	(0.3393)
$\ln\_TC$	-0.0002	0.0003**
	(-1.3352)	(2.4510)
CEO_dual	-0.0005**	0.0000
	(-2.2050)	(0.1076)
$Female\_CEO$	0.0005**	0.0003***
	(2.3360)	(2.7477)
$\ln\_CEO\_tenure$	-0.0003**	-0.0002***
	(-2.4658)	(-3.1298)
Controls	YES	YES
Constant	-0.0140**	-0.0064
	(-2.1147)	(-0.8942)
Observations	791	791
Adjusted R-squared	0.4201	0.7369
Ind FE	YES	YES
Year FE	YES	YES

Table 9

Endogeneity Test

This table reports regression results of endogeneity tests for all the models. The dependent variable is the yearly average of $FC_t^{(i)}$. Panel A reports the propensity score matching regression when the treatment sample is firms that are not financially constrained. We match the sample using total asset size and deposit ratio applying caliper 5% with the nearest neighbor method. Panel B reports endogeneity test results for the model of geographic proximity. We use two types of tests: non-parametric tests and DID. In the Non-parametric test, we rank our variables of interest from the smallest to the largest, with the smallest observations having rank 1, the second smallest rank 2, and so on (Conover and Iman, 1981). Then we run the regression using the ranked variables instead of the original variables. Columns 1 through 3 reports non-parametric test and columns 4 to 6 report the result of DID. IBBEA dummy is 1 if the data point is the year 1994. Panel C reports the non-parametric tests regression results of the bank opacity model. Panel D reports the non-parametric tests regression results of the institutional holding model. Panel E reports the non-parametric tests regression results of the board characteristics model. Panel F reports the non-parametric tests regression results of CEO characteristics model. Along with the transformed variable of interests, the following control variables are included. $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period varies from panel to panel because of the data availability.

Panel A: Financial Constraint			
	DID	Propensity Score Matching (PSM)	Non-Parametric Test
Variables	$FC_t^{(i)}$	$FC_t^{(i)}$	$FC_t^{(i)}$
$FinUnc_{LAR}$		0.00020***	
		(3.37219)	
Controls		Yes	
Observations		6,408	
Adjusted R-squared		0.71858	
Firm FE		YES	
Year FE		YES	
Panel B: Geographic Proximity			
$Rank\_Inverse\_proximity$			0.00012***
			(4.90340)
$Inverse\_proximity$	-0.0011***		
	(-8.4398)		
IBBEA Dummy	0.0627		
	(1.3627)		
IBBEA Dummy x $Inverse\_proximity$	0.0009***		
	(7.4417)		
Controls	Yes		
Observations	11,307		11,307
Adjusted R-squared	0.59790		0.59790
Firm FE	YES		YES
Year FE	YES		YES
Panel C: Bank Opacity			
$Rank\_Firm\ Opacity$			0.0003***
			(2.5726)
Controls			Yes
Observations			4,886
Adjusted R-squared			0.7277
Firm FE			YES

Year FE	YES
Panel D: Institutional Holdings	
$Rank\_\%\ InstHolding$	0.0001*
	(1.9613)
Controls	Yes
Observations	3,939
Adjusted R-squared	0.6963
Firm FE	YES
Year FE	YES
Panel E: Board Characteristics	
$Rank\_\%IndDir$	0.0188*
	(1.7777)
$Recession\_year$	-0.0069*
	(-1.8721)
$Recession\_year$* $Rank\_\%IndDir$	0.0806
	(1.2322)
$Rank\_\#BoardMember$	0.2647***
	(2.5806)
$Rank\_AvgAge$	-0.0016**
	(-2.0568)
$Rank\_AvgTenu$	0.0015
	(1.5383)
$Rank\_HTmLT$	-0.0121***
	(-2.7138)
Controls	Yes
Observations	2,314
Adjusted R-squared	0.4641
Ind FE	YES
Year FE	YES
Panel F: CEO Characteristics	
$Rank\_ln\_Age$	0.1549**
	(2.4973)
$Rank\_Shr\_own\_10000$	-0.0005
	(-0.4318)
$Rank\_\ln\_TC$	0.0019
	(1.5182)
$Rank\_CEO\_dual$	0.0000
	(0.1444)
$Female\_CEO$	0.0003**
	(2.3160)
$Rank\_ln\_CEO\_tenure$	-0.2370***
	(-3.2624)
Controls	Yes
Observations	791
Adjusted R-squared	0.7319
Ind FE	YES
Year FE	YES

Table 10

Robustness Test: Sub-sample Analysis by Bank type

This table reports the regression results of all the models splitting the samples in three sub-samples: commercial banks, savings institutes, and investment banks. The dependent variable is the yearly average of $FC_t^{(i)}$. Panel A reports the regression results of the financial constraints model. Panel B reports regression results for the model of geographic proximity. Panel C reports the regression results of the bank opacity model. Panel D reports the regression results of the institutional holding model. $FinUnc_{LAR}$, financially unconstrained, is a dummy variable equal to 1 if the firm belongs in the top tercile of liquidity asset ratio. $Inverse\_proximity$ is 1 divided by the number of banks per city. $Firm\ Opacity\_alt$ is an index of average percentile rank of (1-raw accuracy), (1-analyst forecast), and raw diversity. $\%\ InstHolding$ is the percentage of the bank's common stock that is held by institutional investors (mutual funds). The following control variables are included. $Ln\ (Asset)$ is the natural logarithm of the total assets $Total\ Asset\_sqr$ is the total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period varies from panel to panel because of the data availability.

	Commercial Bank	**Savings Institutions**	**Investment Bank**
	(1)	(2)	(3)
Panel A: Financial Constraint			
$FinUnc_{LAR}$	0.0003***	0.0000	0.0002
	(4.5516)	(0.7163)	(0.5522)
Controls	Yes	Yes	Yes
Observations	7,769	3,438	790
Adjusted R-squared	0.6952	0.8698	0.5556
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Panel B: Geographic Proximity			
$Inverse\_proximity$	-0.0004***	0.0001**	-0.0007
	(-3.1675)	(2.5175)	(-1.5598)
Controls	Yes	Yes	Yes
Observations	7,729	3,438	781
Adjusted R-squared	0.6274	0.8579	0.4418
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Panel B: Firm Opacity			
$Firm\ Opacity$	0.0005***	0.0000	
	(2.8820)	(1.3185)	
Controls	Yes	Yes	
Observations	3,622	1,207	
Adjusted R-squared	0.7307	0.9635	
Firm FE	YES	YES	
Year FE	YES	YES	
Panel D: Institutional Holdings			
$\%\ InstHolding$	0.0002**	-0.0000	
	(2.2777)	(-0.2201)	
Controls	Yes	Yes	
Observations	2,561	1,338	
Adjusted R-squared	0.7015	0.8188	
Firm FE	YES	YES	
Year FE	YES	YES	

Table 11

Robustness Test: Sub-Sample by Time

This table reports regression results of all the models splitting the samples in three sub-samples by time: from 1960 to 1990, from 1991 to 2006, and from 2007 to 2018 (Housing crisis and post-crisis). The dependent variable is the yearly average of $FC_t^{(i)}$. Panel A reports the regression results of the financial constraints model. Panel B reports regression results for the model of geographic proximity. Panel C reports the regression results of the bank opacity model. Panel D reports the regression results of the institutional holding model. $FinUnc_{LAR}$, financially unconstrained, is a dummy variable equal to 1 if the firm belongs in the top tercile of liquidity asset ratio. $Inverse\_proximity$ is 1 divided by the number of banks per city. $Firm\ Opacity\_alt$ is an index of average percentile rank of (1-raw accuracy), (1-analyst forecast), and raw diversity. $\%\ InstHolding$ is the percentage of the bank's common stock that is held by institutional investors (mutual funds). The following control variables are included. $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period varies from panel to panel because of the data availability

	From 1960 to 1990	**From 1991 to 2006**	**Housing Crisis and Post Crisis**
	(1)	(2)	(3)
Panel A: Financial Constraint			
$FinUnc_{LAR}$	-0.0003*	0.0001***	0.0000
	(-1.6946)	(2.7146)	(0.5770)
Controls	Yes	Yes	Yes
Observations	1,378	7,062	2,907
Adjusted R-squared	0.7446	0.8779	0.8637
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Panel B: Geographic Proximity			
$Inverse\_proximity$	-0.0019***	-0.0003***	-0.0001
	(-3.2755)	(-4.9815)	(-0.6214)
Controls	Yes	Yes	Yes
Observations	1,338	7,062	2,907
Adjusted R-squared	0.6961	0.5380	0.6425
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Panel C: Bank Opacity			
$Firm\ Opacity$	0.0008	0.0001	0.0005**
	(1.2415)	(0.9104)	(1.9685)
Controls	Yes	Yes	Yes
Observations	221	2,964	1,701
Adjusted R-squared	0.8011	0.8833	0.8574
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Panel D: Institutional Holdings			
$\%\ InstHolding$		0.0002*	0.0000
		(1.9548)	(0.1224)
Controls		Yes	Yes
Observations		2,172	1,767
Adjusted R-squared		0.9163	0.9713
Firm FE		YES	YES
Year FE		YES	YES

Table 12

Robustness Test: Social Connections and financial contagion

This table reports the regression results of social connections on financial contagion. The dependent variable is the yearly average of $FC_t^{(i)}$. $SocialConnectedness$ is a log of the total board of directors connections. $Ln\,(Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively.

VARIABLES	$FC_t^{(i)}$
$SocialConnectedness$	0.0029***
	(2.7941)
$Ln(Asset)$	0.0004***
	(8.4017)
$Total\ Asset\_sqr$	0.0062***
	(5.9436)
$Tier1\ Capital\ Ratio$	-37.9566***
	(-3.4040)
$Tier1\ Capital\_sqr$	1.3053***
	(3.1605)
$LoantoAsset$	-0.0002
	(-1.3719)
$DeposittoAsset$	-0.0002
	(-1.4390)
$NoninttoRevenue$	0.0007***
	(3.8551)
$NitoAsset$	0.0024
	(1.2569)
$Excess\_mkt$	0.0058
	(1.2674)
$\#bank$	0.0000***
	(5.0278)
$Std.Dev\ of\ Stock\ Return$	0.0072***
	(3.4862)
$ProNotrade$	0.0003***
	(3.3937)
Constant	-0.0133***
	(-3.1508)
Observations	4,314
Adjusted R-squared	0.5703
Year FE	YES
Ind FE	YES

Table 13

Robustness Test: Yearly $CoVaR$, MES, FC^{CAPM}, and FC^{FF4f} and bank characteristics

This table reports the panel regression results from regressing alternative contagion measures, MES, and CoVaR on firm characteristics, board attributes, and CEO attributes. The dependent variable is the yearly average of *yearly contagion (CAPM), yearly contagion (4-factors), MES,* and *CoVaR* . Panel A reports regression results of bank characteristics. $FinUnc_{LAR}$, financially unconstrained, is a dummy variable equal to 1 if the firm belongs in the top tercile of liquidity asset ratio. $\%\ InstHolding$ is the percentage of the bank's common stock that is held by institutional investors. $Inverse\_proximity$ is 1 divided by the number of banks per city. $Firm\ Opacity$ is an index (alternative) of average percentile rank of (1- raw accuracy), (1-analyst forecast), and raw diversity. Panel B reports the regression with the board characteristics. $\%IndDir$ is the percentage of directors who are independent on a board. $AvgAge$ is the average age of board members per firm. $HTmLT$ is the difference between the highest tenure and the lowest tenure. $\#BoardMember$ represents the number of board members on a board on average. $AvgTenu$ is the average tenure of the board members. In panel C, we regress with CEO attributes. Age is the age of the CEO. Shr_own is the percentage ownership stake that a CEO has in the firm. $\ln\_TC$ is the natural log of total compensation. CEO_dual is a dummy variable equal to 1 if the CEO is both chairman and CEO. $Female\_CEO$ is a dummy variable equal to 1 if the CEO is a female. CEO_tenure is the number of years a CEO is incumbent. The following control variables are included in all models. $Ln\ (Asset)$ is the natural logarithm of the total assets. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period of Panel A is 1973 to 2017. The sample period of panel B is 1998 to 2017. The sample period of panel C is 1992 to 2017.

VARIABLES	(1)	(2)	(3)	(4)
	CoVaR	MES	FC^{CAPM}	FC^{FF4f}
Panel A:Bank characteristics				
FUC_{LAR}	0.0001***	0.0000	0.0002***	0.0001***
	(2.8843)	(1.4110)	(4.2578)	(3.7665)
$\%\ InstHolding$	0.0002***	0.0001***	0.0001***	0.0001**
	(2.6198)	(3.2184)	(2.6431)	(2.3948)
$Inverse\_proximity$	-0.0002***	-0.0001***	-0.0004***	-0.0005***
	(-4.5670)	(-3.1892)	(-4.3442)	(-5.1019)
$Firm\ Opacity$	0.0005**	0.0004***	0.0004**	0.0003**
	(2.2603)	(2.6662)	(2.5300)	(2.1748)
Panel B: Board Attributes				
$\%IndDir$	0.0002**	0.0001***	0.0006**	0.0004**
	(2.5300)	(2.730)	(2.1477)	(2.1962)
$\#BoardMember$	0.001**	0.0004**	0.0028***	0.0019***
	(2.370)	(2.12)	(2.6576)	(2.7469)
$AvgAge$	-0.0002	-0.0001	-0.0014	-0.0011*
	(-1.210)	(-0.380)	(-1.5545)	(-1.7960)
$AvgTenu$	-0.0002	-0.0001	0.0014	0.0016
	(-0.610)	(-1.170)	(0.6931)	(1.3213)
$HTmLT$	-0.0004**	-0.0001	-0.0017**	-0.0014***
	(-2.110)	(-0.8298)	(-2.0478)	(-2.6876)
Panel C: CEO Attributes				
$\ln\_Age$	0.0005**	0.0005**	0.0013***	0.0007*
	(2.5615)	(2.3127)	(3.0123)	(1.8833)
Shr_own_10000	-0.0160	-0.0132	0.0036	0.0208
	(-0.2883)	(-0.2609)	(0.0336)	(0.2659)
$\ln\_TC$	-0.0000	-0.0002	0.0002	0.0004**
	(-0.2482)	(-1.2216)	(1.2095)	(2.1190)
CEO_dual	0.0000	-0.0001	-0.0001	0.0001
	(0.5864)	(-0.6128)	(-0.4159)	(0.3112)
$Female\_CEO$	0.0002*	-0.0000	0.0003	0.0004***
	(1.6590)	(-0.3621)	(1.5346)	(2.7391)
$\ln\_CEO\_tenure$	-0.0000	-0.0000	-0.0002**	-0.0002***
	(-0.7513)	(-0.7484)	(3.0123)	(-2.6020)

FOR ONLINE PUBLICATION ONLY

Online Supplementary Appendix: Financial Contagion: Bank Characteristics Matter

Appendix I.A.I: Empirical estimation

I.A.1 Financial Contagion

Following Piccotti (2017), we measure financial contagion using the state-space methodology, and we assume that bank returns are explained by the Fama and French (1993) 3-factor model (with the factors being excess market returns, returns on the small-minus-big portfolio, and returns on the high book/market-minus-low book/market portfolio):

$$r_{t,i} = \alpha_{t,i} + \mathbf{f}_t'\mathbf{b}_{t,i} + e_{t,i}, \tag{IA.1}$$

for $i \in \{1,2,\dots,N\}$, $t = \{1,2,\dots,T_i\}$. $r_{t,i}$ is the observed return for bank i at time t, $\alpha_{t,i}$ is the bank's expected return that is unrelated to systematic risks, $\mathbf{f}_t$ is the (3×1) vector of factor returns at time t, $\mathbf{b}_{t,i}$ is the (3×1) vector of factor loadings, and $e_{t,i} \sim N\left(0, \sigma_{t,i}^2\right)$ is the idiosyncratic shock (orthogonal to $\mathbf{f}_t$) that bank i receives at time t. $N(\cdot)$ denotes the normal distribution. In the presence of financial contagion, the idiosyncratic shocks have non-zero covariances. Bank i's time-varying α and time-varying factor loadings $\mathbf{b}$ evolve according to:

$$\begin{bmatrix} \alpha_{t,i} \\ \mathbf{b}_{t,i} \end{bmatrix} = \begin{bmatrix} \rho_{\alpha,i} & \mathbf{0}' \\ \mathbf{0} & \mathbf{R}_i \end{bmatrix} \begin{bmatrix} \alpha_{t-1,i} \\ \mathbf{b}_{t-1,i} \end{bmatrix} + \boldsymbol{\eta}_{t,i}, \tag{IA.2}$$

where $\rho_{\alpha,i}$ is the autoregressive parameter for the time-varying alpha, $\mathbf{0}$ is the (3×1) vector of zeros, $\mathbf{R}_i$ is the (3×3) diagonal matrix of autoregressive parameters for the factor loadings, and $\boldsymbol{\eta}_{t,i} \sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\eta},i}\right)$ is the (4×1) vector of parameter innovations. $\boldsymbol{\eta}_{t,i}$ and $e_{t,i}$ are uncorrelated. We assume that $\boldsymbol{\Sigma}_{\boldsymbol{\eta},i}$ is diagonal, which restricts the parameters' residual innovations to be uncorrelated. As it is written, Equation (IA.2) states that α and $\mathbf{b}$ are described by an uncorrelated AR(1) process, and we estimate Equations (IA.1)-(IA.2) with the Kalman filter.

The portion of bank returns that are not explained by the factor model is the estimated residuals, conditioned on the time $t-1$ information set:

$$\hat{e}_{t|t-1,i} = r_{t,i} - \hat{\alpha}_{t|t-1,i} - \mathbf{f}_t'\hat{\mathbf{b}}_{t|t-1,i}. \tag{IA.3}$$

The estimated residuals $\hat{e}_{t,i}$ attained from Equation (IA.3) are compared to the residuals of the remaining banks in the bank portfolio through regressing $\hat{e}_{t,i}$ on the returns on the bank portfolio, without an intercept term (since $\mathbb{E}_{t-1}\{\hat{e}_{t|t-1,i}\} = 0$, a bias is not introduced). That is:

$$\hat{e}_{t|t-1,i} = z_{t,i} r_{t,I}^{(i)} + u_{t,i}, \tag{IA.4}$$

where $r_{t,I}^{(i)} = \sum_{j \neq i} w_{t,j} r_{t,j}$ is the return on the bank portfolio with the i'th bank's stock return removed from it (therefore, $\sum_{j \neq i} w_{t,j} < 1$). Bank i's stock return is removed from the bank portfolio return so that a spurious correlation between $\hat{e}_{t,i}$ and itself is not captured in the regression in Equation (IA.4). $z_{t,i}$ is the time-varying coefficient to be estimated, which follows an AR(1) process:

$$z_{t,i} = \rho_{z,i} z_{t-1,i} + \omega_{t,i}, \tag{IA.5}$$

where $\rho_{z,i}$ is the autoregressive parameter and $\omega_{t,i} \sim N(0, \Sigma_{\omega,i})$ is the residual innovation term. We assume that $z_{t,i}$ follows an AR(1) process in order to capture time-varying financial contagion. We use the Kalman filter to estimate Equations (IA.4)-(IA.5).

We use the time t filter to estimate $z_{t|t,i}$ to attain realized financial contagion (rather than the 1-period-ahead out-of-sample estimated contagion that would be attained using the time $t-1$ filter to attain $z_{t|t-1,i}$, for example). The resulting estimate for $\hat{z}_{t|t,i}$ is:

$$\hat{z}_{t|t,i} = \frac{\sum_{j\neq i} \mathbb{CV}_t\{\hat{e}_{t,i}, e_{t,j}\}}{\sigma^2_{t,r_I^{(i)}}}. \tag{IA.6}$$

Since $\sigma^2_{t,r_I^{(i)}}$ differs for each i, the $\hat{z}_{t|t,i}$ coefficients need to be adjusted so that there is a common denominator, which allows the coefficients to be aggregated across banks. Therefore, we multiply each $\hat{z}_{t|t,i}$ coefficient by $\sigma^{-2}_{t,r_I}\sigma^2_{t,r_I^{(i)}}$.

When the value-weighted sum of the adjusted $z_{t|t,i}$ coefficients are taken, the fraction of the bank portfolio return variance that is attributable to financial contagion is attained:

$$FC_t = \sum_i FC_t^{(i)} = \frac{C}{A+B+C}, \tag{IA.7}$$

where

$$FC_t^{(i)} = w_{t,i} z_{t|t,i} \frac{\sigma^2_{t,r_I^{(i)}}}{\sigma^2_{t,r_I}}, \tag{IA.8}$$

$$A = \sum_{l=1}^{3} \widehat{\mathbb{V}}_t\{f_{t,l}\}\left(\sum_i \left(w_{t,i}b_{t,l,i}\right)^2 + 2\sum_{i,j:i<j} w_{t,i}w_{t,j}b_{t,l,i}b_{t,l,j}\right), \tag{IA.9}$$

$$B = \sum_i w^2_{t,i}\widehat{\mathbb{V}}_t\{e_{t,i}\}, \tag{IA.10}$$

$$C = 2 \sum_{i,j:i<j} w_{t,i} w_{t,j} \widehat{\mathbb{CV}}_t\{e_{t,i}, e_{t,j}\}. \tag{IA.11}$$

FC_t is bounded between -1 and $+1$ shows (in his Internet Appendix) that FC_t is robust to stochastic volatility biases (see Forbes & Rigobon, 2002) and factor model specification. We show in Table 10 and Table 11 that our main results are robust to the factor model specification that is used to filter bank returns in Equation (IA.1).

Figure I.A.1 presents the time series of aggregate financial contagion (FC_t), using the Piccotti (2017) estimator. A list of the ten financial institutions with the greatest sample mean marginal contributions to aggregate financial contagion is presented in Table I.A.1. Financial contagion generally makes up between 20% to 40% of the banking sector's return variance with an upward trend over our sample period. Formally, the trend equation, with Newey and West (1987) heteroskedasticity and autocorrelation consistent t-statistics in parentheses, is:

$$FC_t = \underset{(34.1800)}{0.2321} + \underset{(5.3000)}{0.0013} \times \frac{j}{12} + u_t,$$

where FC_t is the aggregate financial contagion measure and $j = 1,2,3, \ldots$ is a monthly trend variable. The trend equation shows that financial contagion unconditionally makes up 23.21% of the value-weighted bank portfolio's return variance, and the coefficient on the trend variable indicates that aggregate financial contagion has increased by 0.13 percentage points per year on average over our sample period. Noticeably, the contagion time series spikes within almost all the recession periods defined by NBER. Financial contagion increases gradually during the recession and reaches its peak during the recessionary period when the contraction is larger. However, when the recessionary periods are shorter, average financial contagion increases during the recovery period, which validates the gradual spread of contagion to the broader financial networks that were initiated during the contraction.

[Insert Table I.A.1 and Figure I.A.1 about here]

I.A.2 CoVaR and MES

Extant studies have proposed several alternative measures to estimate systemic risk, such as $CoVaR$ (Adrian & Brunnermeier, 2016) and marginal expected shortfall (MES, Archaya et al., 2017). For robustness, we re-examine how bank characteristics contribute to financial contagion when financial contagion is measured by $CoVaR$ and MES.

$CoVaR$ measures an individual bank's contribution to the fragility of the financial sector. We define the $CoVaR$ between a banks' stock returns and the value-weighted bank portfolio, $CoVaR_{t,q}^{j|I}$, as:

$$q\% = \mathbb{P}\left\{r_{t,j}\middle|r_{t,I}^{(j)} \leq CoVaR_{t,q}^{j|I}\right\}, \tag{IA.12}$$

where $\mathbb{P}\{x|y\}$ denotes the conditional probability of x conditioned on y, $q\%$ is the $q\%$-quantile, which we set at 5% (the 5th percentile), $r_{t,j}$ is the monthly return on bank j, $r_{t,I}^{(j)}$ is the monthly return on the value-weighted bank portfolio with the contribution of bank j subtracted out, and we use a 60-month rolling window to calculate the return percentiles so that our $CoVaR$ measure is dynamic. We multiply $CoVaR_{q,t}^{j|i}$ by -1 so that a higher $CoVaR$ indicates greater systemic risk. We form the aggregate $CoVaR$ measure, $CoVaR_{t,q}$, to be:

$$CoVaR_{t,q} = \sum_{j} w_{t,j} CoVaR_{t,q}^{j|I}, \tag{IA.13}$$

where $w_{t,j}$ is the weight of bank j in the value-weighted bank portfolio.

MES measures the expected loss that bank j has, conditional on $r_{t,I}^{(j)}$ being below its $q\%$ threshold (the 5th percentile in our study). Formally, we define MES for bank j at time t as:

$$MES_{t,q}^{j|I} = \mathbb{E}\left\{r_{t,j}\middle|r_{t,j}^{(j)} \leq VaR_{t,q}^{I}\right\}, \tag{IA.14}$$

where $VaR_{t,q}^{I}$ is the q% VaR threshold for the value-weighted bank portfolio (minus the return contribution of bank j), and we use a 60-month rolling window so that our MES measure is dynamic. We multiply $MES_{t,q}^{j|I}$ by -1 so that a higher MES indicates greater systemic risk. Our aggregate MES measure is:

$$MES_{t,q} = \sum_{j} w_{t,j} MES_{t,q}^{j|I}. \tag{IA.15}$$

Table IA.3 and IA.5 presents the correlation matrix between the, $FC_t^{(i)}$, aggregate financial contagion measure (FC in Appendix I.A.I), aggregate $CoVaR$, aggregate MES. Figure IA.2 Panels (c)-(d) contain the time series plots for the aggregate contagion measures.

[Insert Figure IA.2 about here]

Appendix I.A.II. Aggregate Financial Contagion, Cash Flow News, and Discount Rate News

We measure discount rate news and cash flow news using the Campbell and Shiller (1988) methodology. The VAR model we use is:

$$\mathbf{z}_{t+1} = \mathbf{a} + \boldsymbol{\Gamma}\mathbf{z}_t + \mathbf{u}_{t+1}, \tag{IA.16}$$

where $\mathbf{z}_t = \left(r_{m,t}, r_{f,t}, yld_t\right)'$ is the explanatory vector, $r_{m,t}$ is the market return, $r_{f,t}$ is the risk-free rate, and yld_t is the dividend yield on the S&P 500. $\mathbf{a}$ and $\boldsymbol{\Gamma}$ are, respectively, (3×1) and (3×3) coefficient matrices, and $\mathbf{u}_{t+1}$ is the (3×1) residual vector. Innovations in cash flow news ($N_{cf,t+1}$) and discount rate news ($N_{dr,t+1}$) are:

$$N_{cf,t+1} = \mathbf{e}_1' \left(\mathbf{I}_3 + \boldsymbol{\Lambda}\right)\mathbf{u}_{t+1}, \tag{IA.17}$$

$$N_{dr,t+1} = \mathbf{e}_1' \boldsymbol{\Lambda}\mathbf{u}_{t+1}, \tag{IA.18}$$

$$\boldsymbol{\Lambda} = \rho\boldsymbol{\Gamma}\left(\mathbf{I}_3 - \rho\boldsymbol{\Gamma}\right)^{-1}, \tag{IA.19}$$

where $\mathbf{e}_1$ is the (3×1) standard basis vector with a 1 as its first element and 0's as the remaining elements, $\rho = \frac{1}{1+\exp\left(\overline{DP}\right)}$, and $\overline{DP}$ is the mean log dividend-price ratio. The VAR results are presented in Table C.1.

[Insert Table IA.2 about here]

Figure IA.3 contains plots of cash-flow news innovations in Panel (a) and discount rate news innovations in Panel (b), which are derived from Equations (IA.17)-(IA.19). We smooth the time series using the formula $MA_t(x) = \psi x_t + (1 - \psi)x_{t-1}$, where the smoothing parameter $\psi = 0.109101$ corresponds to a half-life of 6 months. Both time series show a contrasting pattern throughout the sample period, as expected. During bad economic times, the expected growth is low, and there is a high-risk premium. At the same time, economic uncertainty increases the discount rate news innovation and decreases the cash flow news innovations (Bansal et al., 2014). In Figure IA.3, we find the consistent pattern that during economic contractions, cash flow news innovations are negative, and, at the same time, discount rate news innovations are positive. Table IA.3 presents the correlation matrix for the (unfiltered) cash flow news innovations, discount factor innovations, unexpected market returns, and financial contagion levels.

[Insert Figure IA.3 about here]

Financial contagion levels are significantly positively correlated with contemporaneous unexpected market returns, and cash flow news innovations are significantly negatively correlated with lagged unexpected market returns and cash flow news innovations. Financial contagion levels and discount rate news innovations do not have significant correlations contemporaneously or when the lag of discount rate news innovations is considered. The alternating correlation signs between unexpected market returns, cash flow news innovations, and financial contagion can be explained by banks optimally becoming more connected during good times (positive contemporaneous correlation) and then financial contagion risk being decreased when a good state of the world is observed (negative lagged correlation). This empirical observation is also found by Adrian and Shin (2014) and Piccotti (2017).

[Insert Table IA.4 about here]

We relate financial contagion (bank i's yearly average contribution to aggregate financial contagion) to cash flow news and discount rate news innovations with firm-level controls included. The regression model is:

$$Contagion_{i,t+1} = \alpha + \beta_1 N_{cf,t} + \beta_2 N_{dr,t} + \gamma \cdot Controls_{i,t} + d_i + d_t + \epsilon_{i,t} \qquad \text{(IA.20)}$$

where $N_{cf,t}$ is the cash flow news innovation at year t, $N_{dr,t}$ is the discount rate news innovations at year t, γ is the coefficient vector on the control variables, d_i denotes the firm or industry[28] fixed effects (to capture the industry and firm-specific unobserved variation), d_t represents year fixed effects (to capture the year specific unobserved variation), and $\epsilon_{i,t}$ is the residual term. In Table IA.4, we regress banks' per annum mean financial contagion levels on per annum mean cash flow news innovations, per annum mean discount rate news innovations, and controls. We present the results for four different model specifications with various fixed effects and clustering treatments. Note that, since $N_{cf,t}$ and $N_{dr,t}$ are common to all banks at time t, the coefficients on these variables are statistically insignificant by design, when year fixed effects are included (if this were not so, then the model would be misspecified). As expected, cash flow news innovations and discount rate news innovations only enter significantly related to financial contagion when firm fixed effects are included, while year fixed effects and firm clustered standard errors are excluded. In Table IA.5, we present a correlation matrix of all the systemic measures.

[Insert Table IA.5 about here]

[28] Industry is defined as Fama and French 49 industry.

Appendix I.A.III Other Bank characteristics

I.A.III.A. Cash flow shocks and financial contagion exposures

Since financial firms are believed to be more susceptible to sudden cash flow shocks, regulators and stakeholders keep a close watch on how well they meet their immediate liquidity needs. Therefore, a cash flow shock may lead a bank to issue additional contingent instruments (such as repos and commercial paper, for example). This network of financial claims causes banks to become dependent on each other, which results in contagion. To test for how cash flow shocks affect banks' contagion exposures, we regress financial contagion on a cash flow shock variable and controls. We follow Guay and Harford (2000) and measure the size of the bank's cash flow shock as:

$$cashflow_{shock,j} = \frac{CF_{-1:0,j} - CF_{-4:-2,j}}{CF_{-4:-2,j}}, \tag{IA.21}$$

where $CF_{t_1:t_2,j}$ denotes bank j's average cash flow in years t_1 to t_2. Table IA.6 reports the regression results, and we do not find a significant association between the size of a bank's cash flow shock and the bank's financial contagion exposure.

[Insert Table IA.6 about here]

I.A.III.B. Recessions and financial contagion

Generally, financial shocks initially affect fewer financial firms and eventually propagate to the broader financial network (Allen & Gale, 2000). In Figure IA.1 (as well as in Figure IA.2), we see that financial contagion exposures increase at the beginning of recessionary periods and reach their peaks during the recession if the contraction period is longer in duration. For shorter recessionary periods, contagion exposures reach their peaks in the post-recession period. We examine if there is a difference in financial contagion exposure prior to or following a recessionary period in Table IA.7. However, we do not find a significant relationship between the before (or after) recession dummy variable with financial contagion. This suggests that recessions do not affect banks' optimal contagion exposures following them. In Table IA.8, we interact the recession dummy variable with cash flow news (N_{cf}) and discount rate news(N_{dr}). Both the interactions are positive and significant, when only year fixed effects are included in the regression. However, the results are not robust when we consider both year and firm fixed effects.

[Insert Table IA.7 and IA.8 about here]

References

Adrian, Tobias and Song Shin, Hyun. (2014). Procyclical leverage and value-at-risk, *Review of Financial Studies* 27, 373-403.

Allen, Franklin and Gale, Douglas. (2000). Financial contagion, *Journal of Political Economy* 108, 1-33.

Bansal, Ravi, Kiku, Dana, Shaliastovich, Ivan and Yaron, Amir. (2014). Volatility, the macroeconomy, and asset prices. *The Journal of Finance* 69, 2471-2511.

Campbell, John Y. and Shiller, Robert J. (1988). The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-228.

Guay, Wayne and Harford, Jarrad. (2000). The cash-flow permanence and information content of dividend increases versus repurchases. *Journal of Financial Economics* 57, 385-415.

Piccotti, Louis R. (2017). Financial contagion risk and the stochastic discount factor, *Journal of Banking & Finance* 77, 230-248.

Table I.A.1

Financial contagion rank

This table presents the top 10 most systemic financial institutions (identified by their CRSP PERMNO) during our sample period. Panel A contains the sample mean marginal contributions to aggregate financial contagion, and Panel B contains the names of the financial institutions. FC_{capm}, FC_{ff3f}, and FC_{ff4f} respectively denote the marginal financial contagion contribution $FC^{(j)}$ when the CAPM, Fama and French 3-factor model, and Carhart 4-factor model are used to filter common factor exposure out of bank returns. $CoVaR^{j|I}$ and $MES^{j|I}$, respectively, denote the Adrian and Brunnermeier (2016) and Archaya et al. (2017) systemic risk measures as described in Appendix A.2. The sample period is 1960 to 2017. If the end is equal to 20171231, then it indicates that the financial institution is still in existence at the end of our sample.

Panel A: Marginal financial contagion contribution rank

Rank	PERMNO	$FC^{(j)}_{ff3f}$	PERMNO	$FC^{(j)}_{capm}$	PERMNO	$FC^{(j)}_{ff4f}$	PERMNO	$CoVaR^{j\|I}$	PERMNO	$MES^{j\|I}$
1	70519	0.021	70519	0.027	70519	0.019	11367	0.027	70519	0.012
2	47896	0.019	47896	0.022	47896	0.018	70519	0.026	59408	0.008
3	59408	0.016	59408	0.019	27297	0.015	59176	0.016	59176	0.007
4	27297	0.015	27297	0.015	83440	0.015	59408	0.014	47896	0.007
5	83440	0.015	41718	0.015	59408	0.014	47896	0.013	41718	0.005
6	41718	0.014	11367	0.014	11367	0.013	10970	0.011	11367	0.005
7	11367	0.014	38703	0.014	41718	0.013	82654	0.009	38703	0.004
8	59176	0.012	59176	0.012	59176	0.012	69032	0.009	27297	0.004
9	10970	0.011	78946	0.011	10970	0.011	83835	0.009	89199	0.004
10	26550	0.011	10970	0.011	38703	0.010	52919	0.008	88239	0.003

Panel B: Top systemically risky financial institutions

PERMNO	Start	End	Name	PERMNO	Start	End	Name
59176	19721214	20171231	AMERICAN EXPRESS CO	27297	19600525	19830805	FIRST CHARTER FINL CORP
83440	19960508	20001201	ASSOCIATES FIRST CAPITAL CORP	26550	19721214	20171231	FIRST INTERSTATE BANCORP
59408	19721214	20171231	BANK OF AMERICA CORP	47896	19690305	20171231	JPMORGAN CHASE & CO
10970	19251231	19800131	C I T FINANCIAL CORP	52919	19710727	20081231	MERRILL LYNCH & CO INC
41718	19650315	19960329	CHASE MANHATTAN CORP	69032	19860321	20171231	MORGAN STANLEY DEAN WITTER & CO
70519	19861029	20171231	CITIGROUP INC	82654	19951016	20171231	ROYAL BANK CANADA MONTREAL QUE
11367	19251231	19680816	COMMERCIAL CR CO	83835	19960830	20171231	TORONTO DOMINION BANK ONT
78946	19930223	19970530	DEAN WITTER DISCOVER & CO	88239	20000516	20150116	U B S AG
89199	20011003	20171231	DEUTSCHE BANK A G	38703	19621210	20171231	WELLS FARGO & CO NEW

Table IA.2

VAR parameter estimates

This table presents the results from OLS estimation of the following vector autoregression (VAR) model:

$$\mathbf{z}_{t+1} = \mathbf{a} + \boldsymbol{\Gamma}\mathbf{z}_t + \mathbf{u}_{t+1}$$

where $\mathbf{x}_t = \left(r_{m,t}, r_{f,t}, yld_t\right)'$. $r_{m,t}$ is the market return, $r_{f,t}$ is the risk-free rate, and yld_t is the dividend yield on the S&P 500. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

	a	$r_{m,t}$	$r_{f,t}$	yld_t	N	R^2
MRKT	-0.003	0.069*	-2.553***	0.581***	695	0.020
	(-0.557)	(1.837)	(-2.900)	(2.867)		
Rf	0.000	0.000	0.956***	0.005*	695	0.945
	(0.064)	(-0.915)	(76.657)	(1.896)		
DIV	0.000**	-0.015***	0.032	0.988***	695	0.992
	(2.555)	(-16.616)	(1.538)	(207.869)		

Table IA.3

Correlation matrix

This table presents the correlation matrix of variables. t-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

	$u_{m,t}$	$N_{cf,t}$	$N_{dr,t}$	FC_t	$u_{m,t-1}$	$N_{cf,t-1}$	$N_{dr,t-1}$	FC_{t-1}
$u_{m,t}$	1.000	0.901***	-0.372***	0.149***	0.002	-0.025	-0.057	-0.018
		(38.885)	(-10.261)	(3.934)	(0.049)	(-0.652)	(-1.512)	(-0.463)
$N_{cf,t}$		1.000	0.067*	0.167***	0.003	-0.054	-0.122***	-0.017
			(1.768)	(4.423)	(0.085)	(-1.411)	(-3.233)	(-0.441)
$N_{dr,t}$			1.000	0.015	0.003	-0.058	-0.130***	0.005
				(0.397)	(0.069)	(-1.521)	(-3.434)	(0.120)
FC_t				1.000	-0.073*	-0.069*	0.021	-0.368***
					(-1.930)	(-1.813)	(0.555)	(-10.142)
$u_{m,t-1}$					1.000	0.901***	-0.371***	0.149***
						(38.863)	(-10.241)	(3.935)
$N_{cf,t-1}$						1.000	0.068*	0.167***
							(1.795)	(4.428)
$N_{dr,t-1}$							1.000	0.015
								(0.407)
FC_{t-1}								1.000

Table IA.4

Financial contagion with cash flow shock and discount rate shock

This table reports the panel regression results from regressing yearly contagion and systemic risk on the firm characteristics. The panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$, CoVaR, and MES. $N_{cf,}$ and N_{dr} are cash flow news and discount rate news. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	$FC_t^{(i)}$	CoVaR	MES
	(3)	(4)	(5)
N_{cf}	0.1388	-0.0086	0.0029
	(1.3821)	(-0.4240)	(0.1808)
N_{dr}	3.1811	-0.1825	0.1126
	(1.2160)	(-0.3766)	(0.3830)
$Ln(Asset)$	0.0009***	0.0005***	0.0003***
	(3.2829)	(9.5567)	(9.2506)
$Total\ Asset\_sqr$	0.0038***	0.0046***	0.0049***
	(3.3161)	(7.3500)	(6.6309)
$Tier1\ Capital\ Ratio$	-27.0890**	-17.0887***	-6.3877***
	(-2.1081)	(-5.3910)	(-3.9062)
$Tier1\ Capital\_sqr$	1.0951**	0.6442***	0.4017***
	(2.2268)	(4.6725)	(5.2922)
$LoantoAsset$	-0.0001	-0.0002**	0.0000
	(-0.4095)	(-2.2913)	(0.3010)
$DeposittoAsset$	0.0011**	0.0006***	0.0005***
	(2.2589)	(3.3816)	(4.2522)
$NoninttoRevenue$	0.0010**	0.0003	0.0002
	(2.4373)	(1.2624)	(1.5312)
$NitoAsset$	0.0050**	0.0051***	0.0027***
	(2.4957)	(6.8549)	(3.9348)
$Excess\_mkt$	-0.0034	-0.0040*	-0.0011
	(-0.9441)	(-1.7709)	(-0.9892)
$\#bank$	0.0000	0.0000	0.0000*
	(0.7319)	(0.5216)	(1.8976)
$Std.Dev\ of\ Stock\ Return$	0.0065***	0.0006	0.0021***
	(2.9822)	(0.9124)	(2.8210)
$ProNotrade$	0.0004***	0.0002***	0.0001***
	(3.1632)	(4.6374)	(4.3679)
Constant	-0.0312	-0.0050	-0.0058**
	(-1.2873)	(-1.1038)	(-2.1116)
Observations	11,352	11,352	11,352
Adjusted R-squared	0.6964	0.7401	0.7692
Firm FE	YES	YES	YES
Year FE	YES	YES	YES

Table IA.5

Financial contagion measure correlation matrix

This table presents the correlation matrix between commonly used financial contagion measures.

	FC_{FF3F}	FC_{capm}	FC_{FF4F}	MES	$CoVaR$
FC_{FF3F}	1.000				
FC_{capm}	0.834	1.000			
FC_{FF4F}	0.925	0.672	1.000		
MES	0.020	0.151	-0.056	1.000	
$CoVaR$	0.415	0.488	0.390	0.607	1.000

Table IA.6

Yearly contagion, cash flow shock, and bank characteristics

This table reports the panel regression results from regressing yearly contagion on banks' cash flow shocks and firm characteristics. The dependent variable is the yearly average of $FC_t^{(i)}$. $Cashflow_{shock}$ is calculated following Guay and Harford (2000). $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in the previous year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	$FC_t^{(i)}$
$Cashflow_{shock}$	-0.0000
	(-0.8374)
$Ln(Asset)$	0.0013***
	(11.2068)
$Total\ Asset\_sqr$	0.0036***
	(3.5232)
$Tier1\ Capital\ Ratio$	-20.9044***
	(-2.8464)
$Tier1\ Capital\_sqr$	0.6382**
	(2.3475)
$LoantoAsset$	-0.0002
	(-0.7972)
$DeposittoAsset$	0.0016***
	(4.7777)
$NoninttoRevenue$	0.0014***
	(4.0976)
$NitoAsset$	0.0078***
	(4.6077)
$Excess\_mkt$	-0.0195
	(-0.8011)
$\#bank$	-0.0001***
	(-14.4845)
$Std.Dev\ of\ Stock\ Return$	0.0092***
	(4.7773)
$ProNotrade$	0.0011
	(1.6136)
Constant	0.0096***
	(8.0179)
Observations	8,829
Adjusted R-squared	0.7061
Firm FE	YES
Year FE	YES

Table IA.7

Yearly contagion, recession, bank characteristics

This table reports the panel regression results from regressing yearly contagion on recession dummies and firm characteristics. The dependent variable is the yearly average of $FC_t^{(i)}$. $Beforerecession\_dummy$ is equal to 1 if the year of the observation is one year before the recession and equal to 0 otherwise. $Afterrecession\_dummy$ is equal to 1 if the year of the observation is one year after the recession and is equal to 0 otherwise. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	(1) Before Recession	(2) After Recession
$Ln(Asset)$	0.0018***	0.0020***
	(3.2957)	(3.2425)
$Total\ Asset\_sqr$	0.0128**	0.0024
	(2.1996)	(0.7650)
$Tier1\ Capital\ Ratio$	41.6924	29.4232
	(0.6044)	(0.4599)
$Tier1\ Capital\_sqr$	-4.0786	-3.3938
	(-1.1666)	(-1.1754)
$LoantoAsset$	-0.0007	-0.0009
	(-0.4328)	(-0.4978)
$DeposittoAsset$	0.0029	0.0048*
	(1.5503)	(1.9263)
$NoninttoRevenue$	0.0010	0.0038*
	(0.5741)	(1.7927)
$NitoAsset$	0.0156**	0.0099
	(2.1019)	(0.7965)
$Excess\_mkt$	-0.0117	-0.0472
	(-0.2577)	(-1.1805)
$\#bank$	-0.0000***	-0.0000***
	(-3.4119)	(-5.9784)
$Std.Dev\ of\ Stock\ Return$	0.0037	0.0074
	(0.6033)	(0.7365)
$ProNotrade$	-0.0005	0.0020
	(-0.4054)	(1.2790)
N_{cf}	0.1683**	-0.1169*
	(2.3692)	(-1.7433)
N_{dr}	0.0643	0.7034***
	(0.6803)	(3.5506)
Constant	-0.0063	0.0004
	(-1.6341)	(0.0746)
Observations	1,193	1,179
Adjusted R-squared	0.5839	0.3662
Firm FE	YES	YES
Year FE	YES	YES

Table IA.8

Yearly contagion and recession interaction with cash flow shock and discount rate shock

This table reports the panel regression results from regressing yearly contagion on the recession interaction terms and firm characteristics. The dependent variable is the yearly average of $FC_t^{(i)}$. $Recession\_year$ is a dummy variable equal to 1 if the year is a recession year and equal to 0 otherwise. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. $N_{cf,}$ and N_{dr} are cash flow news and discount rate news innovations, respectively, using the Campbell and Shiller (1988) decomposition. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	(1)	(2)	(3)
$Recession\_year$	-0.0033	-0.0018	0.0170**
	(-1.5925)	(-1.3197)	(2.0730)
$N_{cf} * Recession\_year$	0.6651*	0.5231**	-1.5537*
	(1.8988)	(2.0239)	(-1.7087)
$N_{dr} * Recession\_year$	1.0837*	0.8535**	-4.3212*
	(1.9062)	(2.0347)	(-1.8424)
Constant	0.0032	0.0021	0.0050
	(1.5502)	(1.6159)	(0.8098)
Observations			
Adjusted R-squared	15,771	15,771	11,352
Controls	0.1561	0.6027	0.6964
Firm FE	NO	NO	YES
Year FE	NO	YES	YES

Table IA.9

Financial contagion and institutional holdings: both mutual funds and other institutional holdings

This table reports the panel regression results from regressing yearly contagion and systemic risk on firm characteristics. The panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$, CoVaR, and MES. $\% \, InstHolding$ is the percentage of the bank's common stock that is held by institutional investors. $Ln\,(Asset)$ is the natural logarithm of the total assets of a firm.. $Total\ Asset\_sqr$ is the total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

VARIABLES	$FC_t^{(i)}$	CoVaR	MES
	(1)	(2)	(3)
$\% \, InstHolding$	0.0001***	0.0000	-0.0000
	(2.6899)	(0.1232)	(-1.3705)
$Ln(Asset)$	0.0000	0.0001***	0.0000***
	(0.7009)	(3.5585)	(3.4098)
$Total\ Asset\_sqr$	0.0021	0.0031**	0.0057***
	(0.7841)	(2.2009)	(4.5581)
$Tier1\ Capital\ Ratio$	-7.7926**	-2.7691*	0.9760
	(-2.2829)	(-1.9110)	(0.6953)
$Tier1\ Capital\_sqr$	0.2006**	0.1089**	0.0249
	(2.2860)	(2.4508)	(0.7373)
$LoantoAsset$	-0.0000	-0.0000	0.0000
	(-0.7054)	(-0.4375)	(0.7440)
$DeposittoAsset$	-0.0001	0.0002**	0.0001**
	(-0.9562)	(2.0010)	(2.1561)
$NoninttoRevenue$	-0.0001	-0.0001	0.0000
	(-1.0820)	(-0.7892)	(0.4956)
$NitoAsset$	0.0006*	0.0006***	0.0000
	(1.7776)	(3.1207)	(0.0344)
$Excess\_mkt$	0.0016	0.0001	-0.0004
	(1.3714)	(0.1537)	(-0.8478)
$\#bank$	-0.0000**	-0.0000	-0.0000
	(-2.0980)	(-1.3671)	(-0.7226)
$Std.Dev\ of\ Stock\ Return$	0.0004	-0.0006*	-0.0001
	(1.5020)	(-1.9050)	(-0.3080)
$ProNotrade$	0.0000	0.0000*	0.0000*
	(0.8356)	(1.7521)	(1.8505)
Constant	0.0068**	0.0015	0.0002
	(2.1159)	(1.0259)	(0.2526)
Observations			
Adjusted R-squared	4,739	4,739	4,739
Firm FE	0.7661	0.9225	0.9079
Year FE	YES	YES	YES

Table IA.10

Financial contagion and geographic proximity: adjusted for population

This table reports the panel regression results from regressing yearly contagion and systemic risk on the firm characteristics. The panel regressions are run with the fixed effect model. The dependent variable is the yearly average of $FC_t^{(i)}$, CoVaR, and MES. $Inverse\_proximity$ is 1 divided by the number of banks per city times the natural log of the population of the town[29]. $Ln\ (Asset)$ is the natural logarithm of the total assets of a firm. $Total\ Asset\_sqr$ is total assets square scaled by 1 million to capture the nonlinearity. $Tier\ 1\ capital$ is the core capital of a financial institution. $Tier1\ Capital\_sqr$ is the core capital square scaled by 1 million USD to capture the nonlinearity. $LoantoAsset$ is total loans over the total assets. $DeposittoAsset$ is total deposits to the total assets. $NoninttoRvenue$ is revenue earned other than interest scaled by total revenue. $NitoAsset$ is net income scaled by the total assets. $Excess\_mkt$ is the market-adjusted average yearly return. $\#bank$ is the number of banks per year. $Std.Dev\ of\ Stock\ Return$ is the standard deviation of stock returns in the previous year. $ProNotrade$ is the total number of nontrading days in a year. Standard errors are heteroscedasticity adjusted robust (Huber-White estimators). ***, **, and * indicate that the coefficients are statistically significant at 1%, 5%, and 10% levels, respectively. The sample period is 1960 to 2017.

	$FC_t^{(i)}$	CoVaR	MES
VARIABLES	(3)	(5)	(6)
$Inverse\_proximity$	-0.0260*	-0.0178**	0.0011
	(-1.8389)	(-2.1037)	(0.1246)
$Ln(Asset)$	0.0009***	0.0007***	0.0004***
	(5.0647)	(13.1320)	(8.9857)
$Total\ Asset\_sqr$	0.0050***	0.0045***	0.0035***
	(4.8134)	(4.0810)	(4.1524)
$Tier1\ Capital\ Ratio$	-55.0529***	-38.7068***	-18.7772***
	(-2.6324)	(-5.2873)	(-4.0214)
$Tier1\ Capital\_sqr$	45.6980***	31.1296***	20.7285***
	(3.1159)	(6.1173)	(5.3017)
$LoantoAsset$	-0.0002	-0.0005**	-0.0002
	(-0.3385)	(-2.3598)	(-1.4498)
$DeposittoAsset$	-0.0009	-0.0012***	-0.0008**
	(-1.2652)	(-3.9177)	(-2.5212)
$NoninttoRevenue$	0.0008	0.0009***	0.0006***
	(1.0407)	(3.2264)	(2.9356)
$NitoAsset$	0.0089*	0.0104***	0.0061**
	(1.8686)	(3.7095)	(2.3097)
$Excess\_mkt$	0.0045	0.0006	0.0014
	(0.5555)	(0.0920)	(0.3671)
$\#bank$	-0.0000	0.0000**	0.0000***
	(-1.4285)	(2.1371)	(4.9636)
$Std.Dev\ of\ Stock\ Return$	0.0168***	0.0121***	0.0105***
	(2.8300)	(4.3664)	(3.0642)
$ProNotrade$	0.0006**	0.0005***	0.0003***
	(2.5205)	(3.5721)	(3.7197)
Constant	-0.0048***	-0.0117***	-0.0107***
	(-3.1799)	(-3.0372)	(-5.9613)
Observations	6,129	6,129	6,129
Adjusted R-squared	0.4752	0.4552	0.2977
Year FE	YES	YES	YES
City FE	YES	YES	YES
Clustering	YES	NO	NO

[29] We measure the Inverse_proximity = $\left(\frac{1}{\#\ of\ Bank\ per\ City}\right) * \ln(Population)$. A higher the value means that less densely located a bank is. Since, population is highly positively skewed, we take natural log of population.

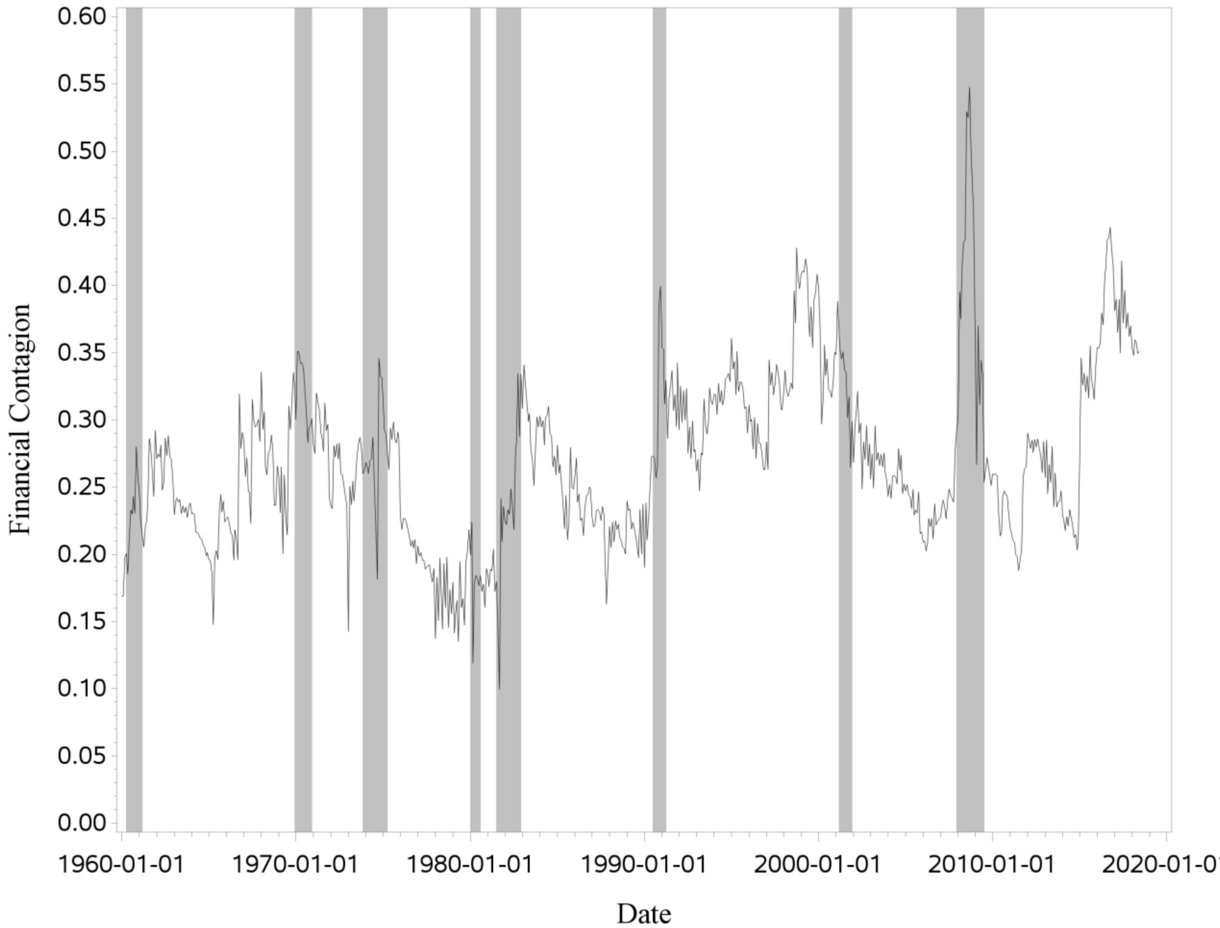
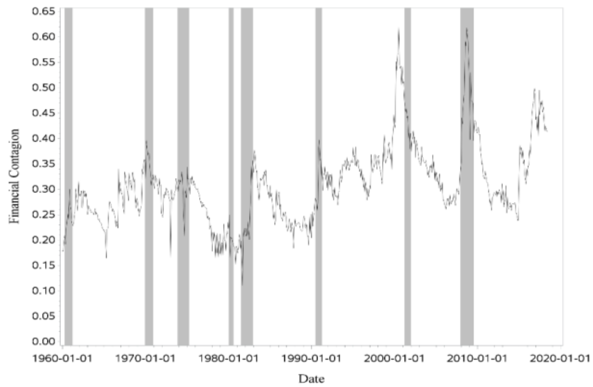


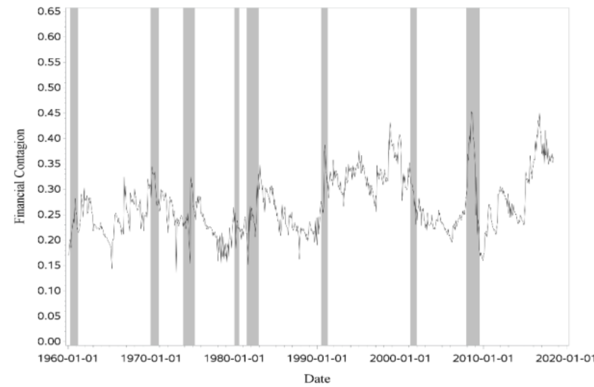
Figure I.A.1

Financial Contagion Estimates

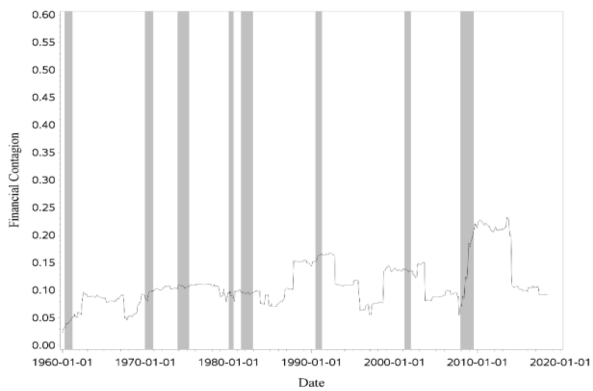
Month-end aggregate financial contagion estimates (as a fraction of the return variances of the bank indexes) using the $FC_t^{(i)}$methodology are presented. See Appendix A for a description of the construction of this measure. NBER recessionary dates are shaded. The sample period is 1960 to 2017.



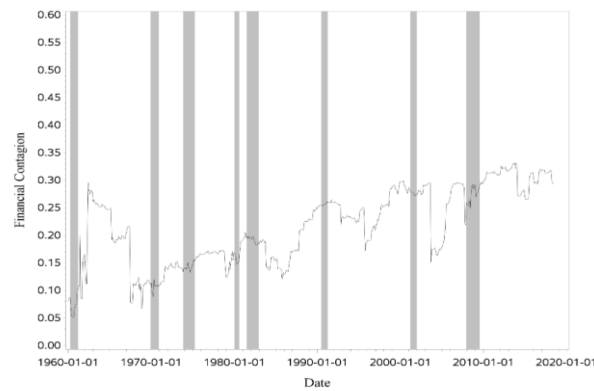
(a)



(b)



(c)

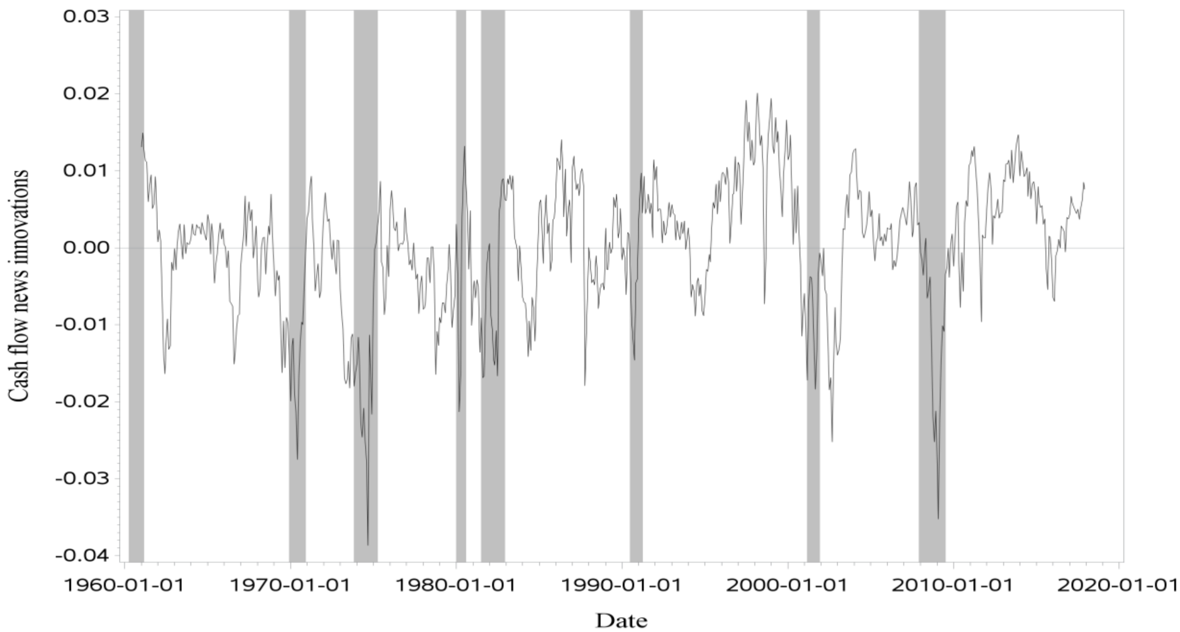


(d)

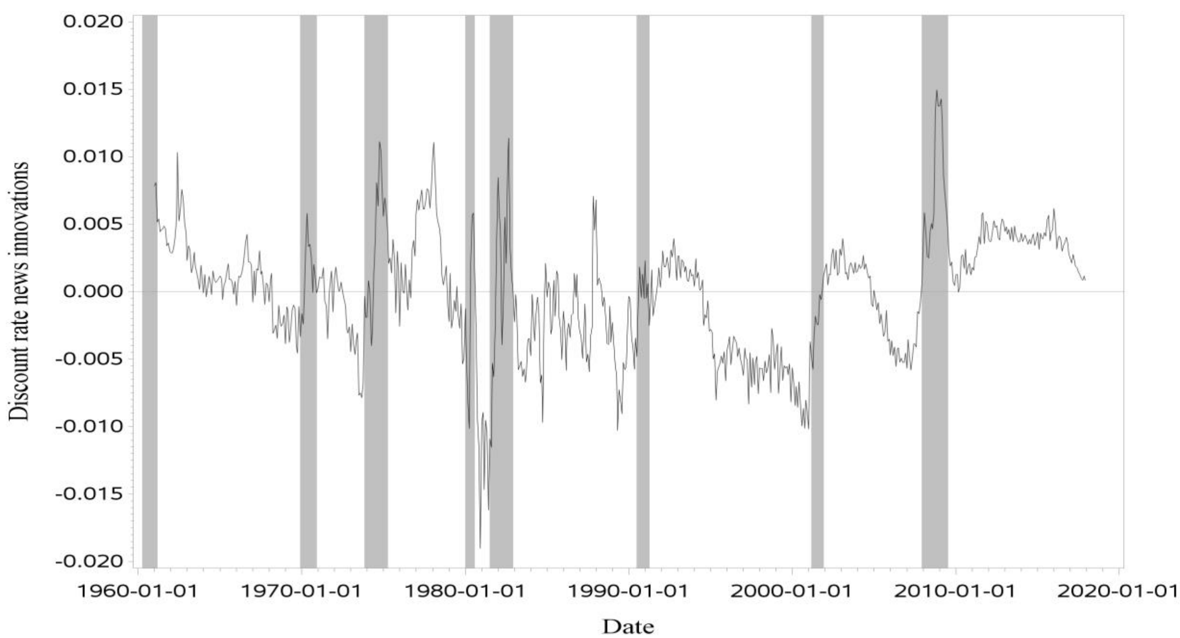
Figure IA.2

Alternative financial contagion measures

This figure presents time series plots of the financial contagion measure $FC_t^{(i)}$ using the market model to filter the effects of common factor exposures out of bank returns in Panel (a) and using the Carhart (1997) 4-factor model to filter the effects of common factor exposures out of bank returns in Panel (b). Panel (c) presents the market-value weighted total marginal expected shortfall measure, and Panel (d) presents the market-value weighted total CoVaR measure.



(a)



(b)

Figure IA.3

Cashflow news and discount rate news innovations

Cash flow news innovations are presented in Panel (a), and discount rate innovations are presented in Panel (b) using the Campbell and Shiller (1988) decomposition (see Appendix C for details). The time series are smoothed using the formula $MA_t(x) = \psi x_t + (1-\psi)x_{t-1}$, where the smoothing parameter $\psi = 0.109101$, which corresponds to a half-life of 6 months. NBER recession dates are shaded. The sample period is 1960 to 2017, and the first 12 observations (months) are deleted for the moving average's burn-in period.