Addressing Systemic Risk Using Contingent Convertible Debt – A Network Analysis *

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Abstract

We utilize 13-F filings made to the US Securities and Exchange Commission (SEC) and call reports from the Federal Financial Institutions Examination Council (FFIEC) to construct interbank equity holdings and common equity exposures of 36 US bank holding companies (BHCs). The calibrated network model is applied to evaluate the effectiveness of contingent convertible (CoCo) debt in controlling the banking systemic risk when shocks are experienced by individual BHCs or the banking system. The results demonstrate that CoCo debt performs well in certain conditions in reducing BHCs' probability of default and in preventing bank failures due to industrial shocks and liquidity stress.

Keywords: contingent convertible debt, systemic risk, network model, 13-F filings

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1 Introduction

The global financial crisis of 2008 illustrated the challenge of contagion of bank failures, which may lead to potential systemic risk causing collapse of the banking system. For instance, the fall of Lehman Brothers, the bailout of Bear Stearns and the financial stress experienced by Citigroup. As a response to the crisis, a form of debt that automatically converts into equity on appropriately defined triggers, called contingent convertible (CoCo) debt , has been frequently discussed [2]. The 2010 Dodd-Frank Act called for the regulators to study the potential effectiveness of CoCo debt and Basel Committee on Banking Supervision defined several trigger events [15]. Some banks in Europe have started utilizing this instrument. For instance, in early 2017, Societe Generale sold its first bail-in-able bonds in a Nordic currency, which is part of its issuance plan of reaching $10.7 billion in such securities by the end of 2018, across all currencies [21].

According to Glasserman and Nouri (2012) [15], three main features determine how CoCo debt can be utilized in the financial system, their trigger criteria, conversion mechanism, and how they are held before conversion. Among these features, the trigger criterion is considered the most important, while being the most complicated at the same time [29]. Between June 2009 and June 2013, $70 billions of CoCo debt has been issued with triggers based on regulatory capital ratios, for instance Credit Suisse's issuance in February 2011 and Rabobank's in March 2010 [2]. Later, accounting values were proposed to approximate regulatory ratios [15]. However, these measures may be manipulated by banks or may end up inevitably lagging true economic values. Flannery (2009) [11] and Coffee (2010) [7] proposed to use bank stock prices as trigger events, while Duffie (2009) [10] suggested using tangible common equity as a percent of tangible assets to measure liquidity of a single bank in a liquidity crisis. The use of CDS prices for CoCo triggers was introduced by Hart and Zingales (2013) [20], while Prescott (2012) [25] refuted the market price design entirely, showing that such a conversion trigger may get activated even when it is not necessary. In order to capture the best source of information on triggering, Calomiris and Herring (2013) [6] proposed a 90-day "quasi-market value of equity ratio" as a signal for conversion.

A single trigger based on individual banks' measure may not be able to address systemic risk concerns for the banking system [2]. Therefore, a dual-trigger contingent on aggregate bank losses and a bank's specific capital ratio was proposed as a CoCo debt trigger [26]. This conversion, however, only ended up taking effect after the sector has already entered a crisis period. McDonald (2013) [23] included banking industry distress measures into CoCo design, with conversion implemented if both a bank's stock price and banking index fall below a threshold. Similarly, Pennacchi et al. (2014) [24] proposed a call option enhanced reverse convertible (COERC) as a design of CoCo debt. Although CoCo debt is frequently in discussion for the banking system, their relevance is not restricted to the banking. Allen and Tang (2015) [2] proposed a dual-trigger CoCo debt with different triggers set for banks, broker-dealers and insurance companies. Consiglio and Zenios (2016) have argued for a CoCo debt design consisting of a 30-day moving average of CDS spreads as a trigger event with the objective of forestalling sovereign debt risks.

In 2016, the Federal Reserve re-proposed long-delayed rules to limit the ties among Wall Street banks in order to address the "too-connected-to-fail" threat [19]. If institutional portfolios are too similar, fire sales may get triggered, which is an important channel for financial risk contagion and, therefore, contributes to systemic risk [17]. However, the complex and opaque nature of the modern financial system poses a considerable challenge for the analysis of the system's resilience [3]. Complexity as such is attributed to be the cause of the recent financial crisis, but very few direct measures of such complexity exist [30].

Researchers have applied network science for studying systemic risk. Channels for contagion and amplification of shocks to the financial system are created due to interconnections among financial institutions [16]. In 2000, Allen and Gale (2000) [1] pioneered the application of network analysis into the evaluation of the system stability of interconnected financial institutions. Gai (2013) [13] studied the stability of the financial system by associating a network structure of interbank lending with unsecured claims. Anand et al. (2013) [3] presented a statistical model involving three layers of financial institutions to illustrate how macroeconomic fluctuations, asset liquidity and network structure interact to determine aggregate credit losses and contagion. Measured by a fraction of common asset holdings, a new statistical method was proposed by Gualdi et al. (2016) [17] to assess the significance of portfolios overlapping quantitatively, in order to identify overlaps that bear the highest risk of fire sales.

Despite the advantage of applying network models to study the financial system, the lack of publicly available data presents considerable challenge to the calibration of networks. The 13-F filings, also known as the Information Required of Institutional Investment Managers Form, from the Securities and Exchange Commission (SEC) provides valuable information of interbank equity holdings among financial institutions in the United States. An institutional investment manager that exercises investment discretion over $100 million or more in Section 13(f) securities is required to report its quarterly holdings on Form 13-F to the SEC within 45 days of each quarter-end [28].

The data from 13-F filings do not suffer from survivorship bias because portfolios are reported in each quarter regardless of their surviving after the next quarter [18]. Researchers usually rely on 13-F filings to study the effect of disclosure and confidential treatment of positions of hedge funds. Having studied 13-F filings filed by a sample of 250 hedge fund managers over the period from 1999 to 2006, Aragon et al. (2013) [4] concluded that positions that are not disclosed to the public in confidential treatment filings earn significantly positive abnormal returns over the postfiling period. However, one obvious problem of using 13-F filings to approximate the overlapping information among financial institutions is that they ignore the short positions, and only disclose long positions [18].

To the best of our knowledge, so far only two papers have applied 13-F filings to calibrate a network for the financial system. Gualdi et al. (2016) [17] proposed a new measure of portfolio overlap based on null statistical network models, using the average number of links between institutions (i.e., the number of statistically similar portfolio overlaps) to measure the risk of fire sales. Having applied their model to a historical database of SEC 13-F filings from 1999Q1 to 2013Q4, they found that the proposed proxy of fire sale risk increased again from 2009, after the peak in 2008, to the end of their dataset (2013) up to levels not seen since 2007. Guo et al. (2016) [18] analyzed the topology of the network of common asset holdings, where nodes represent the managed hedge funds and edge weights capture the impact of liquidation. Their network model of hedge funds was calibrated with quarterly 13-F filings data from 2003Q1 to 2012Q3. The cluster analysis found that the overlap for many funds in their illiquid portfolios became a significant fraction of their portfolios during the financial crisis period.

CoCo debt is designed to forestall bankruptcy of the debt-issuing bank by internally absorbing losses, and more importantly, to intervene in the spread of the stress of an individual bank to the whole banking system. Network analysis provides valuable insights in studying the financial system. In a network model, bank holding companies (BHCs) are described as nodes and the ownership relations are described as edges. Failure that happens in one or several BHCs in the system will affect the whole financial system through the network. Bookstaber and Kenett [5] introduced a multilayer network as a framework for analyzing the emergence and propagation of risk within the financial system. Their layers of the network encompass assets, funding, and collateral. However, no research has so far applied network models to study CoCo debt. The banking system can be viewed as a network formed by BHCs and non-financial firms, connected through their assets, liabilities and equities. CoCo debt incorporated into a BHC's balance sheet is held as common debt until a specially designed trigger for conversion is invoked.

In this paper, we utilize 13-F filings made to the US Securities and Exchange Commission (SEC) and call reports from the Federal Financial Institutions Examination Council (FFIEC) to construct interbank equity holdings and common equity exposures. We construct the banking system of 36 BHCs headquartered in regions along the US east coast since the biggest BHCs are headquartered in those areas, for instance JP Morgan Chase & Co. and Citigroup in New York and Bank of America Corp. in North Carolina. The BHCs are further classified into 4 subgroups, namely, 4 super large BHCs, 6 large BHCs, 16 medium BHCs and 10 small ones. The common exposures of 36 BHCs towards non-financial firms are aggregated into 11 industrial sectors. The calibrated network model is applied to evaluate the effectiveness of a specially defined CoCo debt in controlling the banking systemic risk. The CoCo debt for each BHC gets triggered once its equity-to-asset ratio drops below a customized threshold when faced with financial stress.

Our simulation results show that CoCo debt performs well in reducing the probability of default and in preventing bank failures, which leads to a significant alleviation of the banking systemic stress. We create three financial scenarios where industrial sector indices may drop by 40% and a liquidity stress will cause a sudden reduction of 20% in a BHC's cash holdings. Under each scenario, the number of insolvent BHCs shows a significant decrease in the presence of conversion of CoCo debt. The sharp decrease of probability of default, measured by Expected Default Frequency (EDF), a firm-specific, forward-looking measure, also justifies the effectiveness of CoCo debt conversion in controlling the spread of local stress to the banking system.

The rest of the paper is organized as follows. Section 2 provides detailed discussion of model construction. Section 3 shows the data we used in the paper, illustrates the methodology in extracting information from 13-F filings and call reports, and discusses how we calibrate our model with empirical data. In Section 4, the calibrated models are used to implement Monte Carlo simulation, together with our insights and explanations to the results. Finally, our conclusions and discussions of further work are presented in Section 5.

2 Model and Methodology

We construct networks of interbank equity holdings and common equity exposures of BHCs towards non-financial firms. The common equity exposures of each BHC towards non-financial firms are identified by different industries the firms belong to, and aggregated into those industrial sectors.

2.1 Evolution of Equity

Suppose there are N BHCs and M industrial sectors. Total assets on the balance sheet of each BHC include cash & cash equivalents, C_{it}, government bonds, G_{it}, total loans, A_{it}^L, and equity securities against other BHCs and non-financial firms. Total liabilities of each BHC include deposits, D_{it}, common debt, L_{it}^b, and CoCo debt, L_{it}^c, with time varying value determined in terms of debt durations and convexities. With the above assets and liabilities, the dynamic evolution of a BHC i's equity value, E_{it}, recorded on its balance sheet is given as:

$$E_{it} = C_{it} + G_{it} + A_{it}^L + E_{it}^f + E_{it}^b - L_{it}^b - L_{it}^c - D_{it}, \tag{1}$$

where E_{it}^f and E_{it}^b denote a BHC i's holdings of equity securities against other BHCs and against non-financial firms, respectively.

2.2 Evolution of Interest Rate

As shown in Equation (1), the evolution of equity value of a BHC i depends on the value of its assets and liabilities. To model the dynamic evolution of assets and liabilities, we first need to capture interest rate dynamics. Suppose that the base interest rate, r_t, and credit spread, s_t, follow the following two stochastic processes,

$$dr_t = \alpha_r(\bar{r} - r_t)dt + \sigma_r\sqrt{r_t}dW_t, \tag{2}$$

$$ds_t = \alpha_s(\bar{s} - s_t)dt + \sigma_s\sqrt{s_t}dZ_t, \tag{3}$$

where $\bar{r}$ and $\bar{s}$ are long-term means, α_r and α_s are mean reversion ratios, and σ_r and σ_s are volatility coefficients, respectively, of base interest rate and credit spread.

The interest rate applicable to a BHC with credit rating, l, at time t is taken as,

$$r_t^l = r_t + \alpha^l s_t, \tag{4}$$

where α^l is the credit rating coefficient.

2.3 Evolution of Liabilities

Consistent with the balance sheet (Equation (1)), total liabilities of a BHC i consist of deposits, common debt and CoCo debt. The market value of deposits is assumed to follow a linear trend,

$$\frac{dD_{it}}{D_{it}} = k_i^D dt, \quad \forall i = 1 \ to \ N, \tag{5}$$

where D_{i0} is the initial market value of a BHC i's deposits.

The market value of common debt, L_{it}^b, and CoCo debt, L_{it}^c, of a BHC i with credit rating, l, can be approximated as follows,

$$dL_{it}^b = -D_i^b L_{it}^b dr_t^l + \frac{1}{2}C_i^b L_{it}^b dr_t^{l2}, \quad \forall i = 1 \ to \ N, \tag{6}$$

$$dL_{it}^c = -D_i^c L_{it}^c dr_t^l + \frac{1}{2}C_i^c L_{it}^c dr_t^{l2}, \quad \forall i = 1 \ to \ N, \tag{7}$$

where D_i^b and D_i^c denote durations of common debt and CoCo debt, respectively. Similarly, C_i^b and C_i^c represent convexities of common debt and CoCo debt, respectively.

2.4 Evolution of Assets

Cash & cash equivalents, government bonds, loans, holdings of equity securities from other BHCs, as well as from non-financial firms, aggregated by sectors constitute the assets of a BHC.

2.4.1 Evolution of Government Bonds & Total Loans

The market value of government bonds and total loans of a BHC i follow the following linear trend,

$$\frac{dG_{it}}{G_{it}} = k_i^G dt, \quad \forall i = 1 \ to \ N, \tag{8}$$

$$\frac{dA_{it}^L}{A_{it}^L} = k_i^A dt, \quad \forall i = 1 \ to \ N, \tag{9}$$

where G_{i0} and A_{i0}^L are the initial market value of government bonds and total loans of a BHC i, respectively.

2.4.2 Evolution of Cash & Equivalents

The change of market value of cash & cash equivalents held by a BHC i is assumed to follow a geometric brownian motion,

$$\frac{dC_{it}}{C_{it}} = u_i dt + \sigma_i dW_t, \quad \forall i = 1 \ to \ N, \tag{10}$$

where u_i is the drift rate and σ_i is the volatility rate.

2.4.3 Interbank Equity Holdings

Consider the network model of interbank equity holdings of N BHCs. We denote w_{ij}^b, $i, j = 1 \ to \ N$, as the percentage of a BHC j's equity securities held by a BHC i. Therefore, the value of a BHC i's equity holdings against other BHCs, noted as E_{it}^b, can be calculated as,

$$E_{it}^b = \sum_{j=1}^{N} w_{ij}^b E_{jt}, \quad \forall i = 1 \ to \ N, \tag{11}$$

where E_{jt} is the equity value of a BHC j.

2.4.4 Common Equity Exposures towards Non-financial Firms

The network model of a BHC i's equity holdings against industrial sectors, aggregated over all non-financial firms, is formed for N BHCs and M sectors. Let w_{ij}^f, $i = 1 \ to \ N$ and $j = 1 \ to \ M$, denote the fraction of a BHC i's equity exposure to a sector j. The value of a BHC i's holdings of equity securities against non-financial firms, E_{it}^f, is given as,

$$E_{it}^f = \sum_{j=1}^{M} w_{ij}^f I_{jt}, \tag{12}$$

where I_{jt} represents an index value for a sector j, assumed to follow the following stochastic process,

$$dI_{jt} = u_j I_{jt} dt + \sigma_j I_{jt} dW_t, \quad \forall j = 1 \ to \ M. \tag{13}$$

2.5 Financial Shocks

In order to consider stress events for the banking system, two kinds of financial shocks are considered, namely, liquidity shock and industrial shock. Multiple shocks of either kind can happen within a single period. BHCs are grouped into clusters by their conditional equity correlations. Within a cluster, all BHCs suffer shocks, but with different severity. Specifically, when cash holdings of a particular BHC decrease by 1% due to liquidity stress, other BHCs connected to it within a cluster also suffer a decrease in their cash holdings by, say, 0.8%.

Shocks to industrial sectors follow a joint-correlation structures of sector indices. This allows simulating financial contagion between sectors. When one sector index drops by 1%, indices of other highly correlated sectors also drop by certain amount, say 0.6%. Through the network of common equity exposures, w_{ij}^f, a sector shock can propagate to individual BHCs with high common exposure to the sector.

Let $f(k;\lambda)$ and U denote the frequency and the severity of financial shocks, respectively.

$$f(k;\lambda) \sim \mathcal{P}(\lambda), \quad U \sim N(\mu,\sigma), \quad \mu \in [-1,0],$$

where $\mathcal{P}(.)$ and $N(.)$ represent cumulative distribution functions of Poisson distribution and Gaussian distribution, respectively.

2.6 Contingent Convertible Debt - Trigger Criterion

We consider all-or-nothing CoCo triggers, where the entire bulk of CoCo debt held automatically converts into common equity shares. In order to maintain a minimum level of loss-absorbency (a sufficiently low probability of default (PD)), CoCo debt is taken to convert when a BHC's equity to assets ratio declines to reach a certain threshold value [12],

$$\frac{E_{it}}{A_{it}} \leq \alpha_i, \tag{14}$$

where E_{it} is a BHC i's equity value, A_{it} is the total assets value of the BHC i and α_i is the threshold of minimum capital ratio for the BHC i.

2.7 Measuring Systemic Risk

The Moody's KMV (Kealhofer, McQuown, and Vasicek) approach uses a concept called "distance to default" and translates it into an estimate of probability of default and recovery rate. Expected Default Frequency (EDF) is a forward-looking measure of the probability that a firm will default over a specified period of time (typically one year).

As an extension of Merton's model, the default point of KMV model is a linear combination of short-term and long-term debt of the firm. For our model, we define the default threshold at time t for a BHC i as,

$$default_{i,t} = D_{i,t} + 0.5 * L^b_{i,t} + 0.5 * L^c_{i,t}, \tag{15}$$

where $D_{i,t}$, $L^b_{i,t}$, and $L^c_{i,t}$ represent the value of the BHC i's deposits, common debt and CoCo debt, respectively.

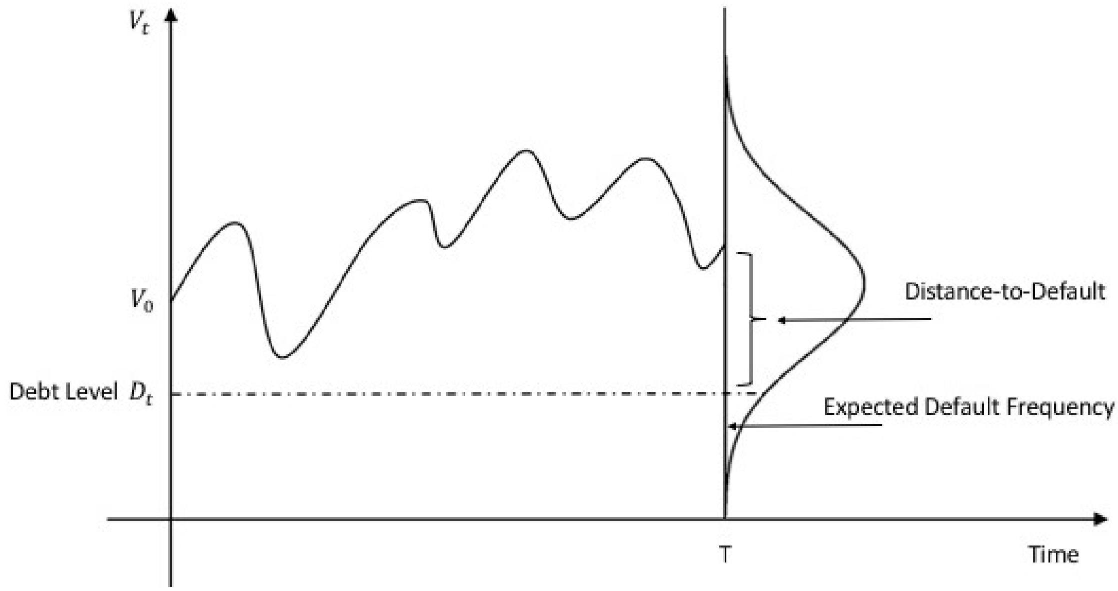

Figure 1: Evolution in Firm Value relative to Debt Level over Time

The Distance-to-Default (DD) calculates the number of standard deviations between the mean of total asset distribution and the default threshold. The $EDF_{i,t}$ for a BHC i at time t is calculated as,

$$EDF_{i,t} = N(-DD), \tag{16}$$

where $N(.)$ is the cumulative distribution function of the standard normal distribution.

3 Data Collection and Calibration

This section provides detailed discussions of data extraction and model calibration. Our data acquisition relies on four resources, namely, US Securities and Exchange Commission (SEC) EDGAR system, Federal Financial Institutions Examination Council (FFIEC), Capital IQ terminal, and Bloomberg terminal. From the Bloomberg terminal, we obtain the historical daily data for base interest rate, r_t, BHCs' credit ratings and sector indices, during the period from 2014-01-01 to 2016-12-31.

As shown in Figure 2, after exploring both the BHCs participating in the Fed's Stress Testing program and BHCs along US east coast, we determine BHCs included in our banking system study based on availability of 13-F filings in the SEC EDGAR system. We collect call reports data from the FFIEC to construct BHCs' balance sheets and estimate corresponding parameters. The network model of interbank equity holdings and common equity exposures is calibrated using the data from 13-F filings.

3.1 13-F Filings & Network Construction

The 13-F filings report issuers of securities, security type, number of shares held, and the market value of each security [27]. The types of securities that must be reported include exchange traded and NASDAQ-quoted stocks, equity options and warrants, shares of closed-end investment companies, etc.. All long positions in such securities with more than 10,000 shares or with market values exceeding $200,000 must be reported. Short positions, shares of open-end funds, and private securities may not be disclosed.

From the SEC EDGAR system[1], we collected the 13-F filings in textual format for all 36 US BHCs. After parsing, cleaning and tokenizing the 13-F filing data, we extracted the interbank equity holdings information. The 36 BHCs are grouped into four subgroups based on their total assets. Consistent with the Mid-size Bank Coalition of America Research Report (2013) [22], the definition of BHCs' size is shown below,

Table 1: Size of Bank Holding Companies

Size	Total Assets	Number
Super Large BHCs	Greater than $1000 Billion	4
Large BHCs	Greater than $250 Billion & Less than $1000 Billion	6
Meidum BHCs	Greater than $10 Billion & Less than $1000 Billion	16
Small BHCs	Less than $10 Billion	10

Besides interbank equity holdings, we aggregate equity securities against non-financial firms reported in 13-F filings into different industrial sectors according to The Global Industry Classification Standard (GICS). GICS is used as a basis for S&P and MSCI financial market indices for assigning each company to an industrial sector, according to the definition of its principal business activity [14]. Using a Capital IQ terminal, we assign each non-financial security held by BHCs to one of the following sectors: Consumer Discretionary, Consumer Staples, Energy, Financials, Healthcare, Industrials, Information Technology, Materials, Real Estate, Telecommunication Services, and Utilities.

[1] SEC EDGAR: https://www.sec.gov/edgar/searchedgar/companysearch.html

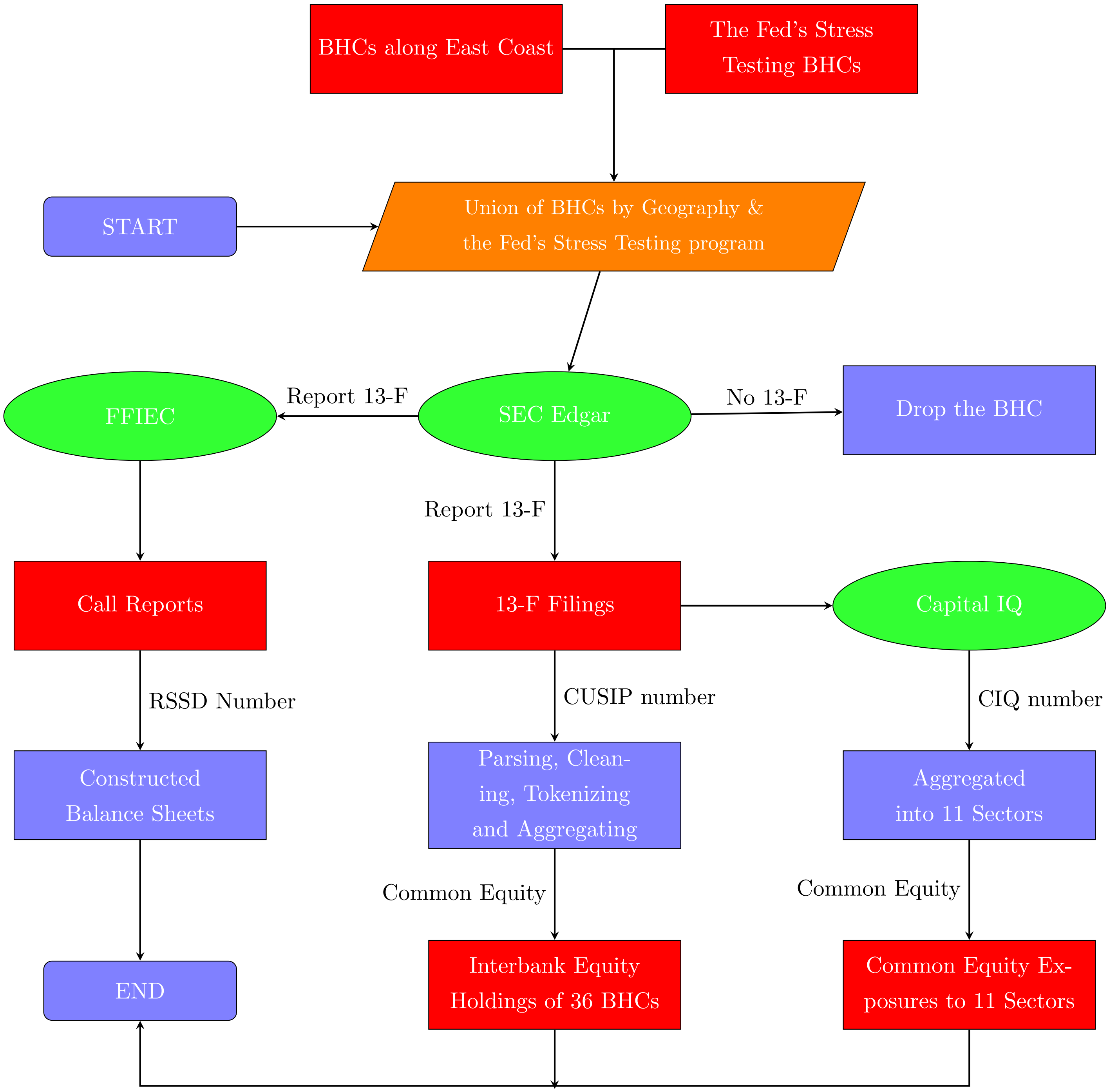

Figure 2: Flowchart of Data Extraction

Figure 3 plots the network of the banking system we have constructed - a directed, weighted network, with 36 nodes, 629 edges, and self-loops. The self-loops represent the holdings of each BHC of its own equity securities. The size of each node represents the BHC size.

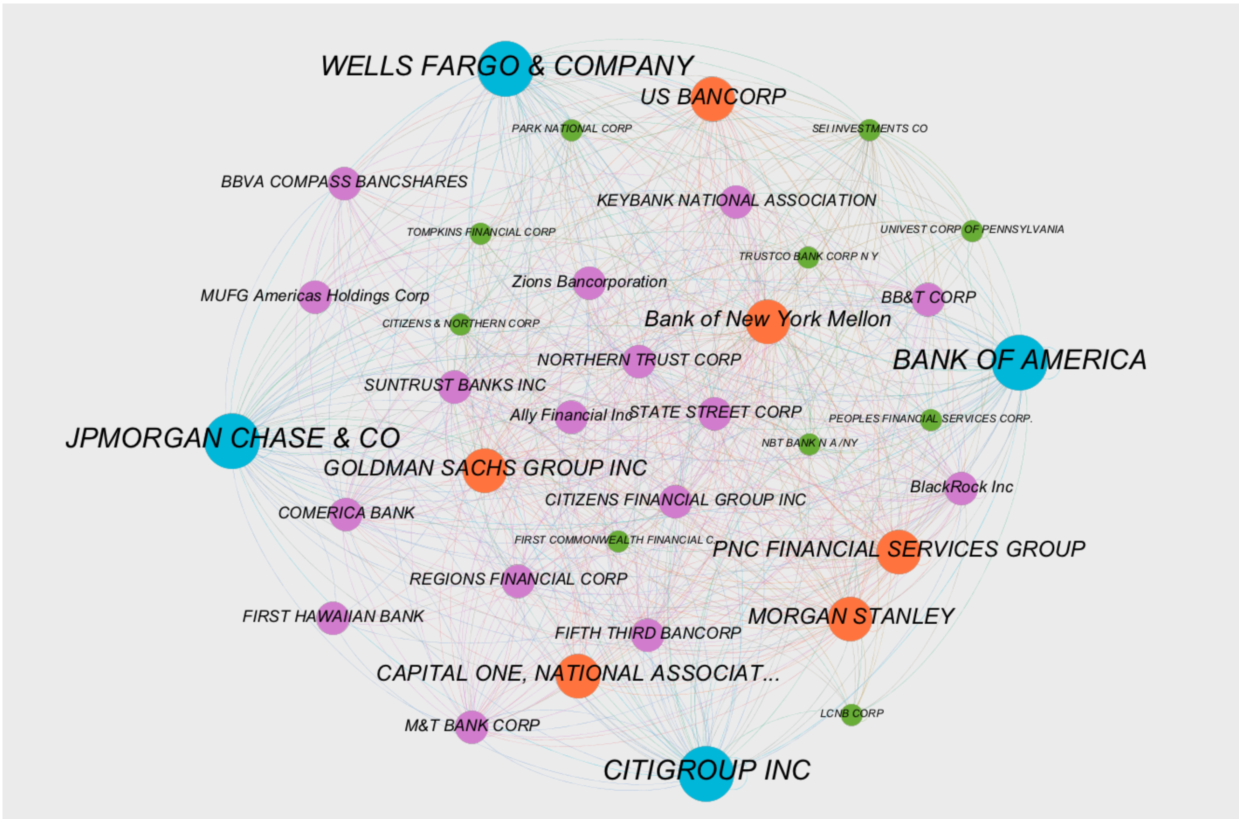

Figure 3: Network of US Banking System

3.2 Call Reports & Balance Sheet Construction

Officially known as the Report of Condition and Income for banks and Thrift Financial Report for thrift banks, a call report must be filed by all regulated financial institutions in the US on a quarterly basis. The call reports contain detailed financial statements information for the banks. Banks are required to file no later than 30 days after the end of each quarter. From the FFIEC, we collect the quarterly textual call reports of 36 banks in our banking system for the past 10 years - from 2007Q1 to 2016Q4. Taking advantage of RSSD, a unique ID for each bank, we identify different time-series sequences for cash & cash equivalents, government bonds, total loans, common debt and deposits, as shown in Table 2. A weighted average of long-term debt, medium-term debt, and short-term debt from call reports constitute the common debt, L^b_{it}, of a BHC. In Table 3, we estimate durations and convexities for long, medium and short-term debt for each BHC assuming them to be zero coupon bonds.

Table 2: Call Report Items

Types	Call Report Files	RSSD	Example Items
Total Assets	RC: Balance Sheet	RCFD2170	Total Assets
Total Liabilities	RC: Balance Sheet	RCFD2948	Total Liabilities
Cash & Cash Equivalents	RC: Balance Sheet	RCFD0081	Currencies and Coins
Government Securities	RC-B: Securities	RCFD0213	U.S. Treasury securities
Total Loans	RC: Balance Sheet	RCFD5369	Loans and Leases held for sale
Deposits	RC: Balance Sheet	RCON2200	Domestic: with and without interest
Long-term Debt	RC: Balance Sheet	RCON3200	Subordinated notes and debentures
Medium-term Debt	RC-M: Memoranda	RCFDF057	Federal Home Loans 3-5 Years
Short-term Debt	RC-D: Trading Liabilities	RCON3548	Total Trading Liabilities

Table 3: Debt from Call Reports

Types	Term-to-Maturity	Approximation	Discounting Rate
Short	1 -3 years	2-year Zero-coupon	2-year Treasury Zero Coupon Rate
Medium	3 - 5 years	4-year Zero-coupon	4-year Treasury Zero Coupon Rate
Long	>5 years	10-year Zero-coupon	10-year Treasury Zero Coupon Rate

$$D_i^b = \sum_{j=1}^{3} \eta_{i,j} D_{i,j}, \quad j = 1, 2, 3,$$

$$C_i^b = \sum_{j=1}^{3} \eta_{i,j} C_{i,j}, \quad j = 1, 2, 3,$$

where $D_{i,1}$ and $C_{i,1}$ denote the duration and convexity of the short-term debt of bank i, respectively; $D_{i,2}$ and $C_{i,2}$ for the medium-term debt and $D_{i,3}$ and $C_{i,3}$ for the long-term debt.

Utilizing the data from 13-F filings and call reports yield a potential data bias since 13-F filings are filed by BHCs, while call reports are filed by commercial banks. To resolve this discrepancy, we first construct total assets, $TA_{i,t}$, using cash & cash equivalents, C_{it}, government bonds, G_{it}, and loans, A_{it}^L, from call reports, together with interbank equity holdings, E_{it}^b, and non-financial firm holdings, E_{it}^f, from 13-F filings. We scale down the total liabilities, $TL_{i,t}$, and deposits, D_{it}, using the ratio of total liabilities to total assets and the ratio of deposits to total assets, respectively, taken from call reports.

$$
\begin{aligned}
T\hat{L}_{it} &= \frac{TL_{it}}{TA_{it}}(C_{it} + G_{it} + A_{it}^{L} + E_{it}^{f} + E_{it}^{b}), \\
\hat{D}_{it} &= \frac{D_{it}}{TA_{it}}(C_{it} + G_{it} + A_{it}^{L} + E_{it}^{f} + E_{it}^{b}).
\end{aligned}
$$

The modified total debt, $\hat{L_{it}^{b}}$, is computed as the difference between the modified total liabilities, $T\hat{L}_{it}$, and the modified deposits, $\hat{D}_{it}$.

3.3 CoCo Debt Allocation

As defined in Section 2 (Equation (14)), we consider all-or-nothing CoCo triggers, α_i, where the entire bulk of CoCo debt held automatically converts into common equity shares. We assume that the conversion trigger of a BHC i, α_i, equals to 60% of its equity-to-asset ratio at 2016Q4.

Currently, US BHCs hold no CoCo debt in their balance sheets. Therefore, we assume that BHCs allocate part of their common debt to CoCo debt. Since CoCo debt is riskier than common debt by serving as a buffer for bank failures, the CoCo debt duration, D_i^c, and convexity, C_i^c, are assumed to be 50% higher than those of common debt,

$$D_i^c = 1.5 * D_i^b \quad \forall i = 1, 2, ...36, \tag{17}$$

$$C_i^c = 1.5 * C_i^b, \quad \forall i = 1, 2, ...36. \tag{18}$$

It is reasonable to assume that the super large, large and medium BHCs participating in the Fed Stress Testing program should hold a larger percentage of CoCo debt than the small BHCs. Table 4 shows the percentage of common debt that BHCs allocate to hold as CoCo debt. For instance, the super large BHC, like Bank of America, sets 50% of its current common debt as CoCo debt, while a small BHC sets 30% of its common debt as CoCo debt.

Table 4: General CoCo Debt Holdings for BHCs

Bank Size	Super Large	Large	Medium	Small
CoCo Ratio	50%	50%	50%	30%

Common debt levels, as implied in our model, for several BHCs, including Goldman Sachs, Morgan Stanley, Bank of New York Mellon, State Street Bank, Northern Trust Corporation and Tompkins Financial Corporation are negligible. For instance, common debt obtained from call reports data for Morgan Stanley only accounts for 2% of its total assets, while the common debt for other five BHCs is also relatively small. In these cases, even if all common debt is held as CoCo debt, the conversion of CoCo debt to equity is too small to make a difference. We adopt a more aggressive CoCo debt holding for these banks. We ensure that all these banks have approximately 9.54%

CoCo debt to asset ratio, by adequately allocating common debt or common debt and deposits to CoCo debt.

Table 5: Modifications to CoCo Debt for Six BHCs

BHCs	Debt-to-Asset Ratio $\geq$ 9.54%?	Allocation from Deposits?
Goldman Sachs	YES	0
Morgan Stanley	NO	8.22%
Bank of New York Mellon	NO	1.97%
State Street Bank	YES	0
Northern Trust Corporation	YES	0
Tompkins Financial Corporation	NO	5.08%

3.4 Industrial Sectors

A BHC i's equity security holdings consist of interbank equity holdings, E_{it}^{b}, and equity holdings from non-financial firms, E_{it}^{f}, aggregated into 11 sectors. Table 6 summarizes the historical daily data of each sector index from 2014-01-01 and 2016-12-31. All sector indices data are obtained from S&P Dow Jones Indices.[2]

Table 6: Industrial Sector Indices

Sectors	Empirical Data
Consumer Discretionary	S&P 500 CONSUMER DISCRETIONARY INDEX
Consumer Staples	S&P 500 CONSUMER STAPLES INDEX
Energy	S&P 500 ENERGY INDEX
Financials	S&P 500 FINANCIALS INDEX
Healthcare	S&P 500 HEALTH CARE INDEX
Industrials	S&P 500 INDUSTRIALS INDEX
Information Technology	S&P 500 INFORMATION TECHNOLOGY INDEX
Materials	S&P 500 MATERIALS INDEX
Real Estate	S&P 500 REAL ESTATE INDEX
Telecommunication Services	S&P 500 TELECOMMUNICATION SERVICES INDEX
Utilities	S&P 500 UTILITIES INDEX

[2]S&P Dow Jones Indices: http://us.spindices.com/indices/equity/sp-500-consumer-discretionary-sector

3.5 Interest Rates & Credit Ratings

From the Bloomberg terminal, we obtain Moody's Ratings of the 36 BHCs in our banking sytem, as shown in Table 7. We ignore the rating adjustments for simplicity and thus, have 21 BHCs with ratings of A, 14 with Baa, and 1 with Ba.

Table 7: Moody's Ratings for BHCs

Ratings	A1	A2	A3	Baa1	Baa2	Baa3	Ba3
Number	5	3	13	5	4	5	1

We use the daily data of 6-month US Treasury bill rate to model the base interest rate, r_t. The credit spread is computed as a product of a credit adjustment factor, β_i, and the base credit spread, s_t. The base credit spread, s_t, is calibrated by BofA Merrill Lynch BB US Option-Adjusted Spread (OAS), the daily observations from 2014-01-01 to 2016-12-31. The credit adjustment factor, β_i, is approximated using the historical data of BofA Merrill Lynch US Option-Adjusted Spreads with credit ratings of BB, BBB and A. The higher the credit rating, the lower the adjustment factor.

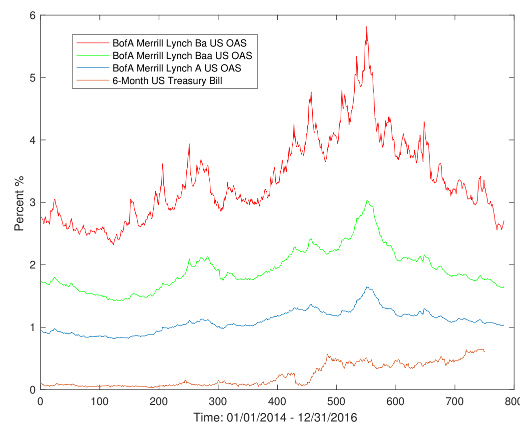

Figure 4: T-bill Rate & OAS

Figure 4 shows the time series of the 6-month US Treasury bill rate and BofA Merrill Lynch US Option-Adjusted Spreads. Let β_i denote the credit adjustment factor for OAS spreads, OAS_i, for i = 1, 2, 3, with credit ratings of A, Baa, and Ba, respectively,

$$\beta_i = E(\frac{OAS_i}{OAS_3}), \quad \forall i = 1, 2, 3,$$

where $E(.)$ denotes the expected value function.

Table 8: Credit Spreads

Credit Ratings	Empirical Data	β	Spreads ($\beta * s_t$)
Ba	BofA Merrill Lynch BB US Option-Adjusted Spread	1	1*s_t
Baa	BofA Merrill Lynch BBB US Option-Adjusted Spread	0.5655	$0.5655 * s_t$
A	BofA Merrill Lynch A US Option-Adjusted Spread	0.3815	$0.3815 * s_t$

3.6 Correlation Clustering

Two kinds of financial shocks are considered in our model, namely, liquidity shock and industrial shock. Shocks to a sector or a BHC inevitably affect other sectors or BHCs that are highly connected with them. To measure this shock propagation, we apply tail-dependency analysis.

By calculating lower quartile conditional correlation of returns between 11 sectors, we sort them by their absolute value in a descending order. Cut-off of the ordered conditional correlations set at 0.7 allows us to identify the most significant tail-dependencies.

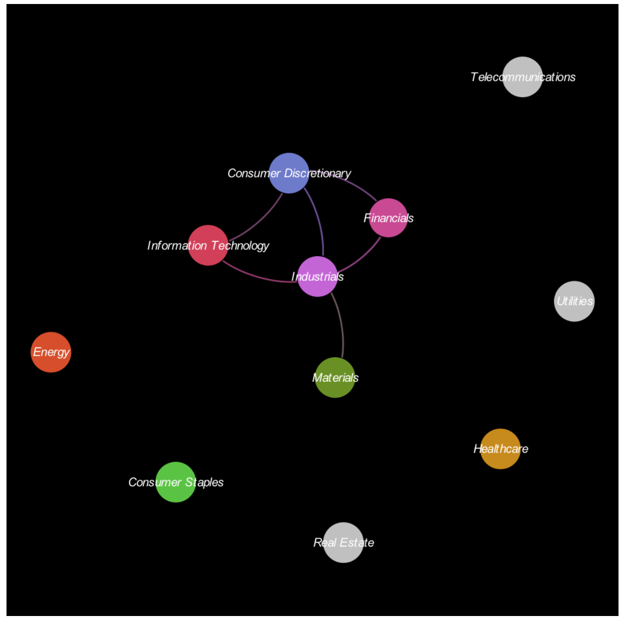

Figure 5: Tail Dependency of Sectors

As shown in Figure 5, five industrial sectors, namely, Consumer Discretionary, Financials, Industrials, Information Technology and Materials, are highly correlated in their tails, while the other six sectors remain relatively independent. Among the connected sectors, when one sector index drops by 1%, indices of other connected sectors drop by 0.6%. Through the network of common equity exposures, w_{ij}^f, a sector shock can propagate to individual BHCs with high common exposure to the sectors.

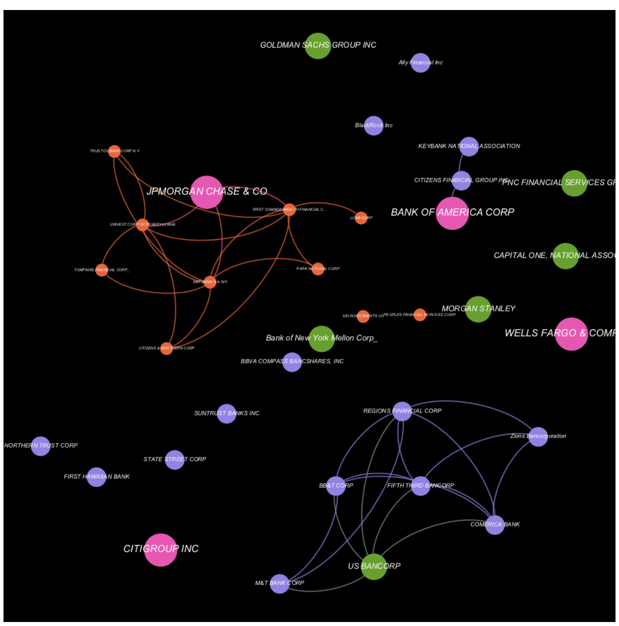

Figure 6: Tail Dependency of BHC's Liquidity

A similar clustering technique is applied to liquidity shocks, as shown in Figure 6. We calculate equity conditional correlation of 36 BHCs. As shown in Figure 6, 36 BHCs are classified into 3 clusters, along with a series of "independent" BHCs. The size of each node represents the size of the BHCs, namely, super large, large, medium and small ones. Within a cluster, all BHCs suffer shocks, but with different severity. Specifically, when cash holdings of a particular BHC decreases by 1% due to liquidity stress, other connected BHCs also suffer a decrease in their cash holdings by 0.8%.

3.7 Simulation of Financial Shocks

During the simulation process, the frequency of financial shocks, either from liquidity or industrial sectors, are modeled by a Poisson distribution with parameter, λ, while the severity of shocks is modeled by a Gaussian distribution $U \sim N(u, \sigma)$, where u is a negative number between -1 and 0.

To determine the likelihood of industrial shocks, we rely on the calibrated process (Equation (13)) for sector index evolution,

$$dI_{jt} = u_j I_{jt} dt + \sigma_j I_{jt} dW_t, \quad \forall j = 1 \text{ } to \text{ } M.$$

We use volatility rate, σ_j, to approximate a sector j's "riskiness" and define a volatility-based probability of industrial shocks experienced by a sector j,

$$P_{sector}(j) = \frac{\sigma_j}{\sum_{k=1}^{k=11} \sigma_k}, \quad \forall j = 1 \text{ } to \text{ } 11. \tag{19}$$

The cash holdings of a BHC fluctuate due to the bank's business activities, either from financing or from investing. The stock price correlations are taken as proxy for the correlations of BHCs' cash holdings. Calculation using the stock volatility, σ_i, of a BHC i, from its historical data is applied to cash shocks.

Intuitively, we would expect that the larger the BHC, the more likely it will suffer severe financial shocks, and the more significantly it will impact the whole banking system. To adjust for this "size effect", an asset-weighted volatility-based probability that implies the probability of the primary BHC "chosen" to suffer liquidity shocks is,

$$P_{bank}(i) = \frac{M_i \sigma_i}{\sum_{k=1}^{k=36} M_k \sigma_k}, \quad \forall i = 1 \text{ } to \text{ } 36, \tag{20}$$

where σ_i and M_i represent the equity volatility and market capitalization of a BHC i, respectively.

4 Model Implementation and Results

4.1 Topology of The Fed's Stress Testing BHCs

In the model defined and constructed in the previous sections, 25 of 36 BHCs participate in the Fed's Stress Testing program. As shown in Figure 7, the network of the Fed's Stress Testing BHCs is relatively complete. Table 9 and Table 10 summarize and compare the network of all the 36 BHCs and the network of only BHCs that participate in the Fed's Stress Testing program.

Compared with the network of 36 BHCs, the network of BHCs participating in the Fed's Stress Testing program does not show significant differences in terms of the average degree, diameter, average path length and the clustering coefficient of the network. The betweenness of the network, which is a measure of centrality in a network based on the shortest path, shows some differences. The smaller the betweenness, the more connected the network. The betweenness of the network of BHCs participating in the Fed's Stress Testing program is much lower than that of the network of 36 BHCs. Therefore, we expect the financial shocks to spread faster among super large, large and medium BHCs. It also justifies the Federal Reserve's re-proposal to limit the ties among Wall Street banks in order to address the "too-connected-to-fail" threat.

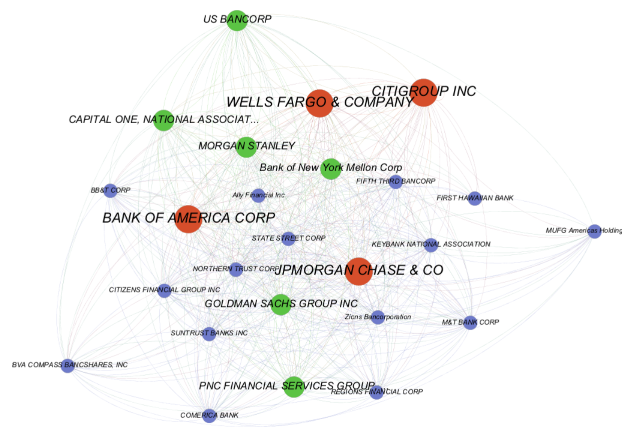

Figure 7: The Fed's Stress Testing BHCs

Table 9: Network of the US Banking System

Network	Nodes	Edges	Format	Edge Weights
The Banking System (Sample)	36	627	Directed	Weighted
Fed Stress Testing BHCs (Fed)	25	497	Directed	Weighted

Table 10: Average Value of Network Property Measurements

Network	In&Out Degree	Diameter	Path Len.	Betweeness	Cluster Coef.	Component
Sample	17.47	4	1.54	16.39	0.711	1 weak ; 6 strong
Fed	19.88	3	1.172	3.96	0.868	1 weak ; 2 strong

4.2 Simulation Results

We conduct a Monte Carlo simulation using the model calibrated in Section 3. We create three scenarios with different levels of severity and frequency of both liquidity stress and industrial shocks. The purpose of the simulation analysis is to develop insights on the co-evolution of the BHCs and to measure the systemic risk, including the number of bank failures and the probability of default. To evaluate the implication of CoCo debt conversion in controlling systemic risk when the BHCs are faced with financial shocks, in each scenario, we compare the post-shock condition of the banking system in the presence and absence of CoCo debt conversion.

Scenario 1 In this scenario, the industrial sectors suffer a financial shock once every 5 years, $\mathcal{P}(5)$, while the liquidity shocks occur annually, $\mathcal{P}(1)$, on average. The industrial shock is taken to have a mean of 40% drop, with 10% standard deviation. One sector suffering shocks is transmitted to connected sectors at 60% of original shock. Likewise, the liquidity shock is taken to have an average of 20% drop, with 5% standard deviation. One BHC suffering liquidity stress is transmitted to connected BHCs at 80% of original liquidity shock.

Table 11: Scenario 1: Expected Default Frequency for Single BHCs

BHCs	No CoCO	With CoCo	Change of EDF
JPMORGAN CHASE & CO	13.2547%	0.0044%	-99.9671%
BANK OF AMERICA CORP	2.0645%	0.0223%	-98.9195%
WELLS FARGO & COMPANY	0.0172%	0.0000%	-99.8195%
CITIGROUP INC	0.0000%	0.0000%	-98.3200%
GOLDMAN SACHS GROUP	35.3312%	20.6603%	-41.5240%
MORGAN STANLEY	43.3733%	0.1486%	-99.6574%
US BANCORP	0.0000%	0.0000%	-99.8069%
PNC FINANCIAL SERVICES GROUP	0.0000%	0.0000%	-91.7700%
BANK OF NEW YORK MELLON	0.0000%	0.0000%	-26.9368%
CAPITAL ONE, NATIONAL ASSOCIATION	0.0000%	0.0000%	–91.7789%

Table 11 summarizes the simulated Expected Default Frequencies (EDFs) of ten super large and large BHCs of our banking system. CoCo debt conversion during financial stress decreases the EDFs of four super large BHCs, JP Morgan & Chase, Bank of America, Wells Fargo and Citigroup, by 99%. Of the other six large BHCs, four witness an EDF drop of 99%. The worst case of improvement is seen for Bank of New York Mellon, with an EDF decrease of only about 27% after CoCo debt conversion.

Figure 8 shows the distribution of the number of BHCs that fail in 10,000 runs of simulation and Table 12 summarizes the statistics of the bank failures. The distributions of bank failures show a significant concentration around zero, as would be expected, since bank failures are rare events. In absence of holding any CoCo debt, on average, 2.5 BHCs fail. Half of the failing BHCs are either large or super large. In contrast, with the conversion of CoCo debt during financial stress, the average number of BHCs failing is sharply reduced to 0.6.

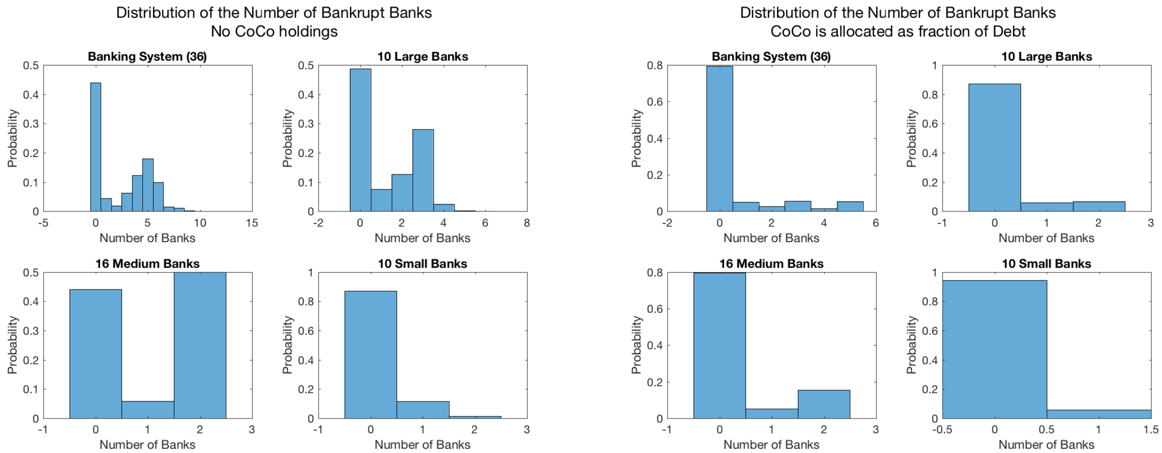

Figure 8: Left: Without CoCo Debt Right: With CoCo Conversion

Table 12: Scenario 1: Statistics for Bank Failures

Bank Size	System (36)	Super & Large (10)	Medium (16)	Small (10)
Without CoCo (Mean)	2.4970	1.2920	1.0590	0.1460
Without CoCo (S.d.)	2.5122	1.3974	0.9685	0.3934
With CoCo (Mean)	0.6130	0.1965	0.3585	0.0580
With CoCo (S.d.)	1.3864	0.5432	0.7330	0.2338

Scenario 2 In this scenario, the frequency of industrial shocks increases from every 5 years to every 2 years, $\mathcal{P}(2)$, and the frequency of liquidity shocks from every 1 year to every 6 months, $\mathcal{P}(0.5)$. The severities of both financial shocks remain the same as in Scenario 1.

Table 13: Scenario 2: Statistics for Bank Failures

Bank Size	System (36)	Super & Large (10)	Medium (16)	Small (10)
Without CoCo (Mean)	3.0035	1.5670	1.1680	0.2685
Without CoCo (S.d.)	2.7699	1.5293	0.9660	0.5344
With CoCo (Mean)	1.0150	0.3580	0.5370	0.1200
With CoCo (S.d.)	1.7667	0.7121	0.8579	0.3250

Table 13 summarizes the statistics of bank failures and Figure 9 shows the distribution of the number of BHCs that fail in 10,000 runs of simulation. Consistent with our prediction, on average, more BHCs are affected under this scenario. In the absence of holding CoCo debt, more than 3 BHCs fail, while with CoCo debt conversion, only 1 BHC fails on average. This is a significant reduction of 67%. Table 14 summarizes the simulated EDFs of the largest ten BHCs of our banking system.

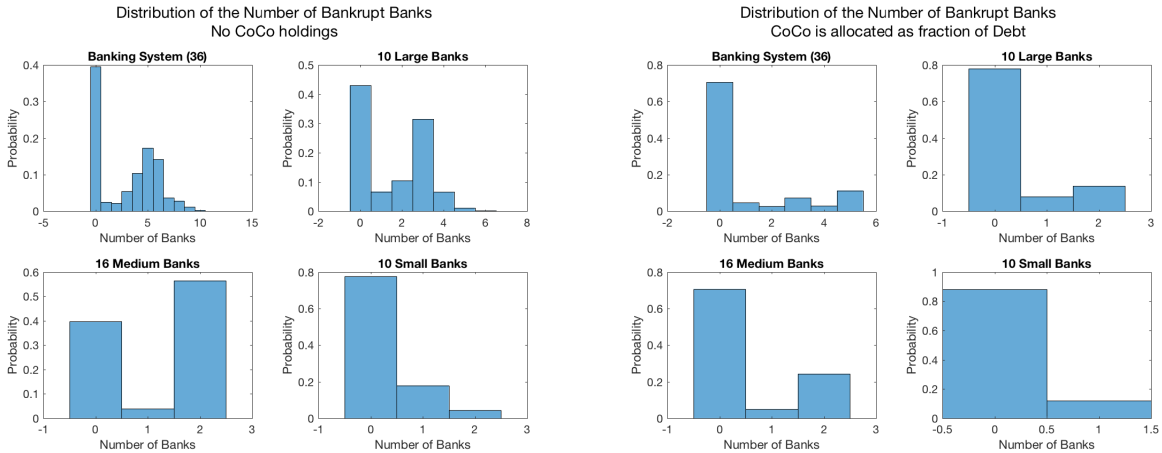

Figure 9: Left: Without CoCo Debt Right: With CoCo Conversion

Table 14: Scenario 2: Expected Default Frequency for Single BHCs

BHCs	No CoCO	With CoCo	Change of EDF
JPMORGAN CHASE & CO	25.4098%	0.0245%	-99.9036%
BANK OF AMERICA CORP	12.2473%	0.0938%	-99.2339%
WELLS FARGO & COMPANY	0.7520%	0.0004%	-99.9491%
CITIGROUP INC	0.0000%	0.0000%	-82.7530%
GOLDMAN SACHS GROUP	37.6737%	27.9878%	-25.7100%
MORGAN STANLEY	44.0197%	0.4203%	-99.0451%
US BANCORP	0.0000%	0.0000%	-95.0812%
PNC FINANCIAL SERVICES GROUP	0.0079%	0.0000%	-100.0000%
BANK OF NEW YORK MELLON	41.5928%	34.6616%	-16.6645%
CAPITAL ONE, NATIONAL ASSOCIATION	0.0000%	0.0000%	-99.7158%

Scenario 3 In the third scenario, we assume that industrial shocks and liquidity shocks occur more frequently, say once every year and once every six months, respectively. Under this scenario, CoCo debt conversion performs less well in reducing bank failures and probability of default, compared to the previous two scenarios. Nevertheless, 8 of 10 large and super large BHCs have a reduction of more than 80% in their default probabilities. The worst case, for instance, of Goldman Sachs and Bank of New York Mellon, still benefit from holding CoCo debt, with their probabilities of default dropping by more than 10%.

On average, more than four BHCs face the threat of bank failure. Since two of the failing BHCs are large or super large BHCs, the bank failure in this scenario will inevitably shake the US banking industry. Contrary to the appalling post-shock condition when no CoCo debt is held, the banking stress is significantly alleviated through CoCo debt conversion. Only 1.6 BHCs fail when CoCo debt converts during financial stress.

Table 15: Scenario 3: Expected Default Frequency for Single BHCs

	No CoCO	With CoCo	Change of EDF
JPMORGAN CHASE & CO	34.3541%	0.3790%	-98.8967%
BANK OF AMERICA CORP	28.6407%	3.4864%	-87.8271%
WELLS FARGO & COMPANY	17.2216%	0.0053%	-99.9613%
CITIGROUP INC	0.0000%	0.0000%	-86.2328%
GOLDMAN SACHS GROUP	40.8964%	35.2398%	-13.8317%
MORGAN STANLEY	45.4740%	1.1038%	-97.5728%
US BANCORP	0.0000%	0.0000%	-81.3378%
PNC FINANCIAL SERVICES GROUP	0.0000%	0.0000%	-98.7709%
BANK OF NEW YORK MELLON	43.7299%	39.1547%	-10.4624%
CAPITAL ONE, NATIONAL ASSOCIATION	0.0000%	0.0000%	-99.9086%

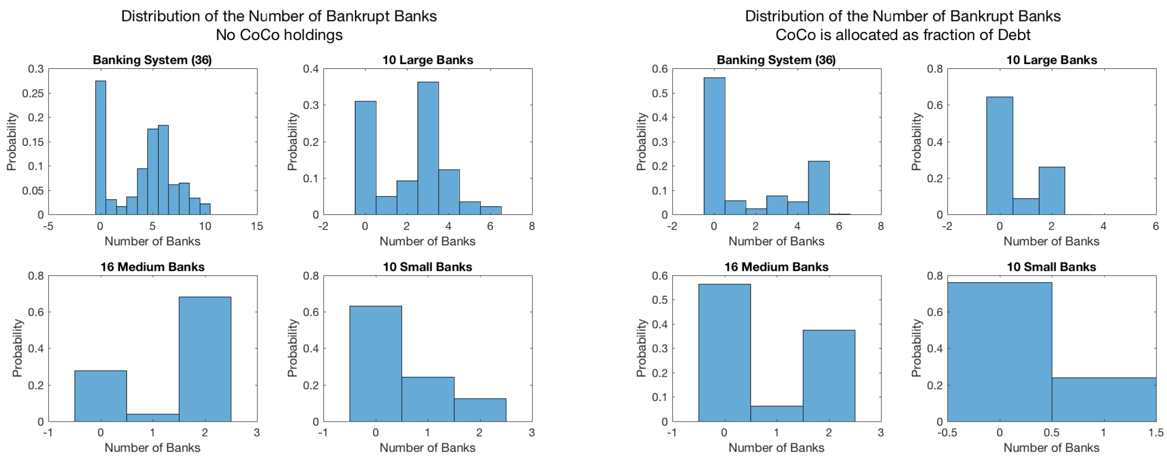

Figure 10: Left: Without CoCo Debt Right: With CoCo Conversion

Large and super large BHCs are more likely to face bank failures than medium and small ones when suffering industrial and liquidity stress. The lower betweenness of the network of the BHCs that participate in the Fed's Stress Testing program suggests that financial shocks propagate faster along the linkage between them. On the contrary, in the absence of CoCo debt conversion, small BHCs of our banking system manage to maintain solvency during the financial stress. Finally, the distribution of bank failures for medium BHCs shows an obvious bimodal distribution, where failures peak at 0 and 2. As we defined in Section 2 (Equation (12)), w_{ij}^{f}, measures the equity exposure of a BHC i to a sector j. Large and super large BHCs may have a more diversified portfolio by investing in all the 11 sectors, while in contrast, medium BHCs are likely to have an industrial bias by only investing in a subset of sectors. Therefore, medium BHCs would expect a huge loss once industrial shocks are experienced by sectors to which they are highly exposed, but be spared from financial stress when shocks strike other sectors.

Table 16: Scenario 3: Statistics for Bank Failures

Bank Size	System (36)	Large (10)	Medium (16)	Small (10)
Without CoCo (Mean)	4.0340	2.1370	1.4045	0.4925
Without CoCo (S.d.)	2.9994	1.6798	0.8929	0.7065
With CoCo (Mean)	1.6740	0.6235	0.8115	0.2390
With CoCo (S.d.)	2.1307	0.8855	0.9500	0.4266

Under all 3 scenarios, although the impact of CoCo debt conversion during financial stress is consistently positive, for some specific BHCs due to the way we implement CoCo debt in their balance sheets, the reduction in the default probabilities is smaller. For instance, EDF of Bank of New York Mellon only decreases by 27% in the best case, and 10% in the worst case by CoCo debt conversion. Also, as the shocks become more severe, the limitations of our chosen design of CoCo debt trigger, of all-or-nothing, start to magnify. This is most evident for some BHCs, such as, for Goldman Sachs. The EDF of Goldman Sachs reduces by more than 40% in the presence of CoCo debt conversion when the industrial sectors suffer a financial shock once every 5 years, but decreases by only 13% when the industrial shocks occur semiannually, other things being equal.

We created 3 scenarios similar to historically observed financial shocks. We took BHCs to suffer significant liquidity stress as the liquidity shock is taken to have an average of 20% drop. We considered industrial shocks with an average decline of 40% and with the spread of shocks to other sectors. For instance, five industrial sectors, such as, Financials, Industrials, Information Technology, are modeled with significant correlations in their tails during financial stress, with a sector suffering the shock transmitting its impact to connected sectors at 60% of the original shock. These are reasonable choices given that during 2000-2002 dot-com bust, the high-tech sector collapsed. On March 10, 2000, the NASDAQ Composite peaked at 5,132.52, but fell 78% in the following 30 months [8]. The 2007-2008 financial crisis was the biggest shock to the US banking system since the 1930s and raised deep concerns regarding liquidity risk [9]. The financial sector first suffered the stress and quickly it spread to domestic and overseas financial markets, as the US Dow Jones Industrial Average lost 33.8% of its value in 2008. Also, the automotive industry, especially the US manufacturing industrials were affected the most, as the market share of the "Big Three", General Motors, Ford, and Fiat Chrysler (FCA US), declined from 70% in 1998 to 53% in 2008.

5 Conclusion

The global financial crisis of 2008 illustrated the challenge of contagion of bank failures, which may lead to potential systemic risk causing collapse of the banking system. As a response to the crisis, a self-saving instrument called contingent convertible (CoCo) debt appeared promising in alleviating the financial stress of the banking system, by automatically converting into equity on appropriately defined triggers.

In this paper, we utilized 13-F filings made to the US Securities and Exchange Commission (SEC) and call reports from the Federal Financial Institutions Examination Council (FFIEC) to construct interbank equity holdings and common equity exposures. We constructed a banking system consisting of 36 bank holding companies (BHCs) headquartered in regions along the US east coast, such as in New York, Connecticut and New Jersey states. The BHCs were classified into 4 subgroups, namely, 4 super large BHCs, 6 large BHCs, 16 medium BHCs and 10 small ones. The common exposures of the 36 BHCs towards non-financial firms were aggregated into 11 industrial sectors. The calibrated network model was applied to evaluate the effectiveness of a specially defined CoCo debt in controlling the bank failures and the banking systemic risk.

We considered all-or-nothing CoCo debt triggers, where the entire bulk of CoCo debt held automatically converts into common equity shares. In order to maintain a minimum level of loss-absorbency (a sufficiently low probability of default (PD)), CoCo debt is taken to convert when a BHC's equity to assets ratio drops below 60% of its equity-to-asset ratio at 2016Q4. The simulation results show that under 3 scenarios we created with both industrial shocks and liquidity stress, the number of insolvent BHCs shows a significant decease in presence of the CoCo debt conversion. Further, the sharp decrease in probabilities of default of BHCs, measured by Expected Default Frequency, when BHCs allocate part of common debt to CoCo debt in their balance sheets also supports the effectiveness of CoCo debt in controlling the spread of local stress to the banking system.

Two main contributions of this paper are to apply the network model to study CoCo debt and to calibrate the network model of the banking system with empirical data extracted from the SEC EDGAR 13-F filings. Major limitations of results are that we were not able to extract full information from call reports to construct our balance sheets, and the design of all-or-nothing CoCo debt trigger may not be the optimal one for different BHCs. Also, to measure the systemic risk, a more thorough and accurate measure should be explored. Finally, it would be interesting and important to investigate how CoCo debt would work to prevent the cascading series of default events due to the overlapping portfolios of bank holding companies during financial crisis. We leave these investigations for future research.

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