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

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Abstract: We construct a balance sheet based network model to study the interconnectedness of US banking system. After a simulation analysis of the buffer effect of contingent convertible (CoCo) debt in controlling contagion in the banking network under a theoretically motivated model, we use 13-F filings made to the US Securities and Exchange Commission (SEC) to calibrate the theoretical model. Our results demonstrate that CoCo debt conversion significantly reduces the average number of bank failures, decreases the ∆CoVaR of the banking system, and thus, mitigates systemic risk. While CoCo debt with dual-trigger is not so efficient as a single trigger design in

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reducing individual bank failures, the former is more effective at protecting the surviving banks, which leads to improved stability from the perspective of the banking system. We claim that the different designs of CoCo triggers result in trade-offs for addressing systemic risk, which may be evaluated in a network model developed in this work.

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

1 Introduction

The 2008 financial crisis highlighted the threat of contagion in bank failures, which could lead to significant systemic risk resulting in a potential collapse of the banking system. The fall of Lehman Brothers, bailout of Bear Stearns and severe financial stress experienced by Citigroup were examples of such threat. In 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 [3]. 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 [21].

Although no CoCo debt has been issued in US so far, banks in Europe started utilizing these instruments for past several years. By end of June 2017, there was more than €125 billion of CoCo debt outstanding in Europe. Between January 2009 to June 2014, €74 billion of CoCo bonds were issued by 37 European banks via 102 issues in twelve countries, including in UK, Switzerland, Spain [31]. In early 2017, Societe Generale sold its first bail-in-able bonds in a Nordic currency, which was part of its issuance plan of reaching $10.7 billion in such securities by the end of 2018, across all currencies [27]. According to a staff memo by Norges Bank (2014) [31], the largest issue of CoCo bonds was by Lloyds, which accounted for 14% of the European market, followed by Credit Suisse at approximately 12%. UBS and Barclays are the third largest CoCo debt issuers with market share of 11% each. The trigger design of current European CoCo bonds are based on a capital adequacy ratios, set at 2% to 8.25%, in terms of CET1 ratio, the Tier 1 ratio, the Total risk-based capital ratio, etc.

Three main features determine how CoCo debt may be used, how their trigger criteria is defined, their conversion mechanism, and how they are held before conversion [21]. Among these features, the trigger criterion is considered the most important, while also being the most complicated [36]. For any design of trigger of CoCo debt, and other design aspects of the instrument, the fundamental
issue is judging the efficacy of the instrument in mitigating systemic risk. In this paper, we study the impact of CoCo debt conversion on mitigating systemic risk of the banking system, and how this impact differs under two different designs of CoCo triggers, namely a single trigger and a dual trigger. In order to address the impact on systemic risk, we incorporate the interconnectedness of the banking system as a network of reduced-form balance sheets.

Between June 2009 and June 2013, $70 billion of CoCo debt was issued with triggers based on regulatory capital ratios. For instance, Credit Suisse’s CoCo debt issuance in February 2011 and Rabobank’s in March 2010 use such trigger [3]. Accounting values were later proposed to approximate the regulatory ratios [21]. However, these measures run the risk of being manipulated by the banks or may end up inevitably lagging the true economic values. In response to these issues, Flannery (2009) [17] and Coffee (2010) [12] proposed to use bank equity prices to identify trigger events, while Duffie (2009) [16] suggested the use of tangible common equity as a percent of tangible assets to measure the liquidity of a single bank in a liquidity crisis. The use of CDS prices for defining CoCo triggers was proposed by Hart and Zingales (2013) [26], while Prescott (2012) [33] refuted the market price design entirely, arguing that such a conversion trigger may get activated even when it is not necessary. In order to utilize the best source of information for CoCo trigger, Calomiris and Herring (2013) [11] proposed a 90-day “quasi-market value of equity ratio” as a signal for conversion.

It is suspected that a single trigger defined on an individual bank’s indicators may not effectively be able to address the systemic risk concerns for the banking system [3]. Therefore, a dual trigger contingent on the aggregate bank losses and an individual bank-specific capital ratio was proposed [34]. This conversion rule, however, only ends up taking effect after the banking sector has already entered into crisis mode. McDonald (2013) [29] included banking industry distress measures into CoCo debt design, with conversion implemented if both a bank’s equity price and banking equity index fall below a threshold. Similarly, Pennacchi et al. (2014) [32] proposed a call option enhanced reverse convertible (COERC) design of CoCo debt. Although CoCo debt is frequently discussed in the context of the banking system, its relevance is not restricted to banking. Allen and Tang (2015) [3] proposed 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 with the objective of forestalling sovereign debt risks.

In 2016, US 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 [25]. If institutional portfolios are too similar, it can trigger fire sales at time of distress, which is an important channel for financial risk contagion contributing to systemic risk [23]. However, the complex and opaque nature of the modern financial system poses a considerable challenge for the analysis of the system’s resilience [5]. Complexity as such is attributed to be the cause of the recent financial crisis, but very few direct measures of the complexity exist [37].

In an attempt to address the complexity due to high degree of interconnections, researchers have applied network science techniques for studying systemic risk. Channels for contagion and amplification of shocks to the financial system are created due to the nature of interconnections among financial institutions [22]. Allen and Gale (2000) [2] pioneered the application of network analysis for evaluating system stability of interconnected financial institutions. More recently, Gai (2013) [19] studied the stability of the financial system by assessing the network structure embedded in the interbank lending of unsecured claims. Anand et al. (2013) [5] developed a statistical model of three layers of financial institutions to illustrate how macroeconomic fluctuations, asset liquidity and network structure interact to determine aggregate credit losses and contagion. A new statistical method was proposed by Gualdi et al. (2016) [23] to assess the significance of overlapping portfolios, measured by the fraction of common asset holdings, for the highest risks of fire sales. Brunetti et al. (2018) [10] proposed a novel approach to estimate the portfolio composition of banks as a function of daily interbank trades and equity returns. The portfolio concentration was used as a measure of bank diversification, while common holdings measured market susceptibility to shocks propagation.

Notwithstanding the benefits of applying network analysis to study the financial system, a lack of publicly available data poses a considerable challenge to these studies. The 13-F filings, also known as the Information Required of Institutional Investment Managers Form, with the US Securities and Exchange Commission (SEC) provide valuable information on 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 [35]. The 13-F filings data do not suffer from survivorship bias because portfolios are reported in each quarter regardless of their surviving another quarter [24]. Researchers have relied on 13-F filings to study the effect of disclosure and confidential treatment of positions of hedge funds. A sample of 250 hedge fund managers’ 13-F filings for the period 1999 to 2006 are used in Aragon et al. (2013) [6] to conclude that positions not disclosed to the public in confidential treatment filings
earn significantly positive abnormal returns over the post-filing period. One shortcoming of using 13-F filings to approximate the overlapping information among financial institutions is that they do not report short positions [24].

Two studies have so far applied 13-F filings to calibrate a network in the financial system. Gualdi et al. (2016) [23] 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. They applied their model to 13-F filings from 1999Q1 to 2013Q4, and found that the proposed proxy of fire sale risk increased again from 2009, after its peak in 2008, to the end of 2013, up to levels not seen since 2007. Guo et al. (2016) [24] analyzed the topology of the network of common asset holdings, with nodes representing managed hedge funds and edge weights capturing the impact of liquidation. The network model of hedge funds was calibrated using quarterly 13-F filings for 2003Q1 to 2012Q3. A cluster analysis revealed that the overlap in the illiquid portion of portfolios of many funds became a significant fraction of the portfolios during the financial crisis period.

CoCo debt is designed to forestall bankruptcy of a debt-issuing bank by internally absorbing losses, and more importantly, to intervene in the spread of the stress of a bank to the entire banking system. Using a network representation, bank holding companies (BHCs) are described as nodes and the inter-bank exposures are captured using the network edges. Failure of one or several BHCs in the network can affect the entire financial system through the network links. Bookstaber and Kenett [9] introduced a multi-layer network as a framework for analyzing the emergence and propagation of risk within the financial system. The layers of their network consist of assets, funding, and collateral. No research has so far applied network analysis to the study of CoCo debt. A banking system can be viewed as a network of 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.

Individual bank’s co-evolution with other banks through their balance sheet connections requires constructing a balance sheet description that is typical for banks, but not too complex. Nier et al. (2007) [30] pioneered the utilization of reduced-form balance sheets to investigate systemic risk dependence on the structure of the banking system. Criticizing central banks’ reliance on highly detailed balance sheet data to establish the precise linkages among financial institutions, Anand et al. (2013) [5] used simplified balance sheet structure with total assets comprising of loans to other banks, loans to firms, equity holdings in firms, and risk-less government securities. Bank’s
liabilities included deposits, interbank borrowing, and the bank’s capital buffer. A reduced-form balance sheet is also used to explore the impact of heterogeneity in the bank size distribution on the stability of the financial system [7]. In this paper, we adapt Anand et al.’s (2013) [5] model for creating a balance sheet based network model to study the interconnectedness of a banking system. Banks are described as nodes and their inter-bank exposures are described by the network links. A reduced-form balance sheet is constructed for each bank based on its key accounting ratios, such as, leverage ratio, debt to deposit ratio, etc., obtained from a typical financial statement. A theoretical network model is developed and implemented using purely simulated data, so that an assessment of failures in one or more banks in the system may be studied due to the linkage of inter-bank debt holdings and channels of common industrial debt exposures. We conduct Monte Carlo simulation analysis to evaluate the effectiveness of specific designs of CoCo debt in controlling systemic risk. Two designs of CoCo debt trigger, namely, a naive single trigger and a dual trigger, are considered and compared.

We calibrate the network using empirical data on inter-bank equity holdings and common equity exposures to specify the banking interconnectedness. The equity data are used as a proxy, as data on interbank debt holdings are not publicly available. The data are extracted from 13-F filings with the US SEC and call reports from the Federal Financial Institutions Examination Council (FFIEC). Our calibrated banking system consists of 36 bank holding companies (BHCs) along the US east coast, as the biggest banks, such as Citigroup, JP Morgan Chase & Co., and Bank of America Corp, are headquartered in this region. The BHCs represent 4 subgroups by size: 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 are aggregated into 11 industrial sectors. The calibrated network model is used to validate the results obtained using the theoretical model.

Our simulation results show that CoCo debt performs well in preventing bank failures and in improving the stability of the banking system, which leads to significant alleviation of systemic stress. We test our theoretical and 13-F specified networks using various financial stress scenarios. Specifically, we consider scenarios where the banking system suffers significant drops in value for its industrial sectors exposure. The theoretical simulation finds an average of 4 fewer bank failures in the presence of single trigger CoCo debt and 2.83 fewer failures in the presence of dual trigger CoCo debt when compared with the baseline case of no CoCo debt issuance. Equity ∆CoVaR at 5th percentile is reduced by 11.95% and 15.52% due to the conversion of CoCo debt with single and dual trigger designs, respectively. In the empirically calibrated network analysis, similar trends of
results are observed. The average number of bank failures is reduced by 1.1834 and 0.1948, and the $\Delta CoVaR$ is reduced by 2.13% and 3.20%, with the help of single and dual trigger CoCo debt, respectively. Although magnitudes of improvements from holding CoCo debt in the empirically calibrated analysis are smaller, they are still statistically significant. Therefore, overall these findings support the effectiveness of CoCo debt in controlling the spread of local stress to the banking system.

In comparing the two designs of triggers, while the single trigger design offers a lower number of average bank failures, the dual trigger design actually outperforms in controlling systemic risk in terms of the $\Delta CoVaR$ measure when the banking sector suffers external shocks. From theoretical simulations under industrial shocks, we observe at the least a 3.56% lower $\Delta CoVaR$ under the dual trigger design compared with the single trigger design. The calibrated network model supports these findings. Therefore, we infer that, while the dual trigger is less efficient than the single trigger design in protecting each individual bank, the former is better for protecting the surviving banks, which leads to improved stability from the perspective of the banking system. This difference resulting from the two designs of CoCo triggers is essentially a trade-off in addressing systemic risk.

The rest of the paper is organized as follows. Section 2 provides detailed discussion of theoretical model construction. In Section 3, we implement the simulation analysis using the theoretical model. Section 4 shows how we modify the model to match the available data and calibrate the models constructed in Section 2 using the empirical data. In Section 5, the calibrated models are used to implement a Monte Carlo simulation analysis, together with presenting our insights and explanations for the results. Finally, our conclusions and discussions of further work are presented in Section 6.

2 Balance Sheet Network Model

Assessing the benefit of CoCo debt issuance requires our model to capture the interconnectedness of the banking system. For this purpose, we develop a balance sheet based network model of the banking system. As such the balance sheets of bank holding companies can be extremely complex, therefore, for the sake of capturing the basic essence of interconnectedness in banking, we utilize a reduced-form of balance sheet in our study containing only the most important information.

As shown in Figure 1, the reduced-form balance sheet model for each bank is composed of six components. Cash & cash equivalents, $C$, government securities, $G$, commercial mortgages, $M$, 
interbank debt holdings, $A^B$, and industry debt holdings, $A^I$, form the asset side of the balance sheet. Deposits, $D$, common debt, $L^B$, CoCo debt, $L^C$, and shareholders’ equity, $E$, form the liability side. Since the value of all assets in a balance sheet equals the value of all liabilities and shareholders equity, we have the following balance sheet identity,

$$ C + G + M + A^B + A^I = D + L^B + L^C + E. \quad (1) $$

Consider a banking system of $N$ banks, with $i^{th}$ bank’s reduced-form balance sheet represented by $C_i$, $A^B_i$, etc. in Equation (1). Banks’ interconnections within the banking system are decomposed as those caused by inter-bank debt holdings, $A^B_i$, and their common exposures, $A^I_i$. Let $w_{ij}$, where $i, j = 1, \ldots, N$, denote the percentage of bank $j$’s common debt held by bank $i$ (over bank $j$’s total common debt). To ensure that all inter-bank debt held remains a consistent fraction of outstanding liabilities of a bank, the sum of these weights for each bank are bounded above by 1. Therefore,

$$ \sum_{i=1}^{N} w_{ij} \leq 1, \forall j = 1, \ldots, N. \quad (2) $$

The value of a bank $i$’s inter-bank debt holdings against other banks, denoted as, $A^B_i$, is given by,

$$ A^B_i = \sum_{j=1}^{N} w_{ij} L^B_j, \quad (3) $$

where $L^B_j$ is the common debt of bank $j$.

The network of bank $i$ also constitutes its common debt holdings against $M$ industrial sectors, aggregated over all non-financial firms. Let $s_{ij}$, where $i = 1, \ldots, N$ and $j = 1, \ldots, M$, denote the fraction of bank $i$’s assets that are debt issued to sector $j$. Therefore, the value of bank $i$’s holdings of debt securities against non-financial firms is given as,

$$ A^I_i = \sum_{j=1}^{M} s_{ij} I_j, \quad (4) $$
where $I_j$ represents the value of a unit exposure to the sector $j$. Large banks are generally more diversified in their loans towards firms, whereas medium and small banks may be more concentrated in specific sectors due to their geographic scope of activities, competitive advantages, or other possible reasons. To incorporate this feature in the model, we randomly generate a subset of sectors that each medium or small bank invests in. As a result, Equation (3) establishes the connections due to inter-bank holding within the banking system, while Equation (4) forms the channels of common exposure connections between banks. The balance sheets evolve over time for each bank, and terms of these evolution are described in the next section.

2.1 Dynamic Evolution

The dynamic evolution of the reduced-form, interconnected balance sheets of the banks occurs due to fundamental factors as well as occurrence of external financial shocks. We begin with the description of the evolution of independent balance sheet terms, followed by that of the dependent terms. Independent terms in the reduced-form balance sheet include industrial debt holdings, cash & cash equivalents, government securities, commercial mortgages, deposits, and bank liabilities.

2.1.1 Cash & Cash Equivalents

In our model, cash & cash equivalents term represents the sum of all highly liquid low-risk assets of a bank. Therefore, this asset component reflects the short-term financing and investing activities of the bank. The cash & cash equivalents support the short-term cash flow needs of the banks, and therefore, we incorporate the regular fluctuations of the cash & cash equivalents by the following jump process,

$$dC_{jt} = C_{jt}dY_{jt},$$

where $Y_{jt}, j = 1, \ldots, N$ are compound Poisson processes. The cumulative size function, $Y_{jt}$, of the compound Poisson process allows us to capture the correlation in the changes in the cash & cash equivalents without dramatically increasing model complexity. $Y_{jt}$ is taken in the form,

$$Y_{jt} = \sum_{k=1}^{N_{jt}} D_k,$$

where $N_{jt}$ is a Poisson point process specific for bank $j$, and $D_k$ are independently identically distributed (i.i.d.) random variables, taken to be Gaussian distributed, measuring each jump size.
In order to capture “shock memory” among different epochs, Equation (6) is modified as
\[ Y_{jt} = \sum_{i=1}^{N_t} X_{ji} D_i, \]  
(7)
where \( N_t \) is a common Poisson point process for all banks and \( X_{ji} \) are i.i.d. Bernoulli distributed random variables. The common Poisson point process allows multiple banks to be affected simultaneously, while the Bernoulli distributed random variables determine specific banks that are stressed by any shock.

### 2.1.2 Interbank Holdings

The evolution in the interbank debt holding levels are modeled using the debt duration and convexity, as well as interest rate dynamics. Interest rates are decomposed into two parts, the base spot rate, \( r_t \), and the credit spread, \( s_t \). The base spot rate is taken to follow the Cox-Ingersoll-Ross dynamics,
\[ dr_t = \alpha r (\bar{r} - r_t) dt + \sigma r \sqrt{r_t} dW_t, \]  
(8)
where \( W_t \) is a standard Wiener process, and the spread term is also taken to follow its own Cox-Ingersoll-Ross dynamics,
\[ ds_t = \alpha s (\bar{s} - s_t) dt + \sigma s \sqrt{s_t} dZ_t, \]  
(9)
where \( Z_t \) is an independent standard Wiener process. The interest rate, \( r^l_t \), relevant for a specific bank with a credit rating of \( l \) is taken as,
\[ r^l_t = r_t + \alpha^l s_t, \]  
(10)
where \( \alpha^l \) is the credit rating coefficient. The interest rate dynamics are used to describe the changes in market value of both common debt and CoCo debt for a bank \( i \) by,
\[ dL^B_{it} = -D^b_i L^B_{it} dr^l_i + \frac{1}{2} C^b_i L^B_{it} dr^l_i^2, \]  
(11)
\[ dL^C_{it} = -D^c_i L^C_{it} dr^l_i + \frac{1}{2} C^c_i L^C_{it} dr^l_i^2. \]  
(12)
This allows us to define the dynamic equivalent of Equation (3) to describe the evolution of the value of interbank debt holding of bank \( i \) as,
\[ A^B_{it} = \sum_{j=1}^{N} w_{ij} L^B_{jt}. \]  
(13)
2.1.3 Industrial Loans

The dynamic evolution of industrial loans in the banks’ balance sheet is associated with an industrial index, \( I_{jt} \), for sector \( j \). Describing individual industrial sector index for its own unique dynamics is beyond the scope of allowable complexity in the network model. Therefore, for comparative simplicity, we use jointly mean reverting jump-diffusion processes to model the industrial sector evolution.

\[
dI_{jt} = \alpha (I_{j\mu} - I_{jt}) dt + \sigma_j I_{jt} dW_{jt} + I_{jt} dJ_{jt},
\]

(14)

where \( W_{jt}, j = 1 \text{ to } M, \) are correlated Wiener processes to capture the correlated movement between different industrial sectors and \( J_{it} \) are compound Poisson processes that incorporate jumps in the value of different industrial sector indexes. The correlation of jump processes across industrial sectors are modeled similarly as the model for cash \& cash equivalents. The dynamic changes of a bank \( i \)'s industrial loans are given in terms of the industrial sector indexes by,

\[
dA_{it}^I = \sum_{j=1}^{M} s_{ij} dI_{jt}.
\]

(15)

Following Equation (1), the evolution of bank \( i \)'s equity value is given by,

\[
E_{it} = C_{it} + G_{it} + M_{it} + A^B_{it} + A^L_{it} - D_{it} - L^B_{it} - L^C_{it}.
\]

(16)

2.1.4 Credit Rating

Credit ratings of banks are used to adjust their applicable interest rates for the valuation of banks’ liability in Equation (10). Due to evolution of quality of assets and other aspects of a bank’s balance sheet, it is plausible that a bank’s credit rating may change over time. Altman’s Z-score (1968) [4] is a statistical tool used to measure the likelihood of a firm’s bankruptcy based on its balance sheet properties, such as working capital, total assets, etc., given by,

\[
Z - \text{Score} = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E,
\]

(17)

where \( A \) is working capital to total assets ratio, \( B \) is the ratio of retained earnings to total assets, \( C \) is EBIT to total assets ratio, \( D \) is market value of equity to total liabilities ratio, and \( E \) is sales to total assets ratio. Given the limited components of our reduced-form balance sheet model, we utilize the evolution of \( A \) and \( D \) to approximate the evolution of the Z-score in Equation (17) for describing credit rating migration of the bank as,

\[
Z - \text{Score}_r = 1.2A + 0.6D.
\]

(18)
We compute the initial credit rating, $Z - Score_r$, for each bank, followed by tracking the score as the bank’s balance sheet evolves. As a bank’s $Z - Score_r$ significantly improves or deteriorates from its initial value, we accordingly upgrade or downgrade the bank’s credit rating. Since all banks are assumed to at least be investment grade, there are no upgrades from the AAA rating and no further downgrades from the BBB rating. The updated credit rating is used for determining the applicable interest rate in Equation (10).

2.2 Financial Shocks & Stress Test

Beyond the evolution of the balance sheet under normal conditions, we also use the reduced-form balance sheet model to evaluate the impact of severe stress scenarios on the banking system. Among stress scenarios, we include sharp declines in either the industrial loans or the cash & cash equivalent holdings of the banks. The first stress shock arrives in the banking sector from the real economy via one (or more) of the industrial sectors. The second type of stress shock is endogenous to the banking sector affecting banks’ liquidity. The level of stress shocks are set at a certain extreme level applied during the balance sheet simulation at pre-determined times. While many such scenarios can be constructed, we test the following scenarios in this paper:

1. A -10% shock to a randomly chosen set of industrial sector indexes at day 20 of a year’s duration for the simulation.

2. -10% shocks to a randomly chosen set of industrial sectors at days 20 and 200 of a year’s duration for the simulation.

3. -10% shocks to randomly chosen industrial sectors and -15% cash shock to a randomly chosen set of large banks, both applied day 20.

The above stress scenarios are reasonable choices given that during the 2000-2002 dot-com bust, the high-tech sector and the related sectors suffered deep losses. On March 10, 2000, the NASDAQ Composite peaked at 5,132.52, thereafter falling 78% in the subsequent 30 months [14]. The 2007-2008 financial crisis was the most severe shock to the US banking system since the 1930s and raised deep concerns regarding liquidity risk [15]. During the financial crisis, after the financial sector suffered the shock, the stress quickly spread to the domestic and overseas real economy. US Dow Jones Industrial Average lost 33.8% of its value in 2008. 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.
2.3 CoCo Debt Triggers

Once a bank’s shareholders’ equity falls below zero, the bank is considered bankrupt. Other banks holding debt of the failing bank recover their principal at a recovery rate. Poorer the recovery rate, greater the propagation effect of financial distress faced by the connected banks. Financial distress can also spread through possible fire-sale of assets when a stressed bank becomes insolvent [8]. When a bank issues CoCo debt, the instrument serves as an emergency capital cushion, which can save the CoCo debt issuing bank from financial distress, and thus help improve stability of the banking system. In our model, $L^C$ represents CoCo debt, and every bank is required to hold a certain amount of CoCo debt in its financing structure, say a fraction of its risky assets comprising of the interbank debt holdings, $A^B$, and common industrial debt exposures, $A^I$. Before being triggered, CoCo debt behaves like common debt, with its value evolving by its duration, convexity and applicable interest rates.

Under certain conditions, CoCo debt conversion to equity is triggered, and we assume that the entire bulk of it automatically converts into common equity of the bank. There is no universally acknowledged best CoCo trigger design, as different designs are stated to have different pros and cons. In this paper, we consider two kinds of trigger designs, a naive bank level single trigger and a dual trigger, and compare their impact on the robustness of the banking system. Under the single trigger design, CoCo debt of a bank converts to common equity once the bank’s own equity-to-asset ratio falls below a certain threshold [18],

$$\frac{E_{it}}{TA_{it}} \leq \alpha_i,$$

(19)

where $E_{it}$ is bank $i$’s equity value, $TA_{it}$ is the total assets value of bank $i$, and $\alpha_i$ is the threshold for minimum capital ratio for the bank $i$. A dual trigger adds a system-level trigger to monitor the equity adequacy from the view of the whole banking system. The system-level trigger is set as follows,

$$\frac{TE}{TA} \leq \beta,$$

(20)

where $TE$ and $TA$ denote the total equity and total assets of the banking system, respectively, and $\beta$ is the trigger threshold value. Under the dual trigger design, CoCo debt conversion of individual banks does not happen unless the system-level trigger is also activated, even if some naive bank-level triggers are already reached. Thus, the two triggers make a trade-off between protection of individual bank failures and the contribution to the stability of the whole banking system.
2.4 Banking Systemic Risk

The core of purpose of CoCo debt is to mitigate systemic risk of the banking system. Therefore, it is crucial to utilize appropriate measures for systemic risk to evaluate the effectiveness of design of CoCo debt. Different risk measures focus on different risk perspectives for assessing systemic risk. The conditional expected default rate is defined as the proportion of all banks in good standing at the beginning that are expected to default in a period of time, conditional on a given event or certain environment. This measure of risk is straightforward and works perfectly when the default event is the main consideration. However, it contains limited information about the status of the surviving banks, and thus, fails to measure the health of the whole banking system.

In this paper, other than the total number of bank failures, we use a widely used systemic risk measure for the banking and network science areas, namely, the co-movement value at risk (CoVaR) [1]. The co-movement value at risk, $CoVaR_q$, is defined as the $q$th percentile of the value of an asset conditional on a given shock experienced by a set of potentially related entities. The measure is designed to evaluate the impact on one entity, given severe outcomes experienced by a set of potentially related entities. Mathematically, it can be expressed as,

$$Pr(E_{it} \leq CoVaR_q^{Shock}|Shock) = q\%,$$  \hspace{1cm} (21)

where $E_{it}$ is the shareholders equity of $i^{th}$ firm and $Shock$ is experienced by a set of potentially related firms. More often than $CoVaR_q$, Delta-CoVaR, $\Delta CoVaR_q$, defined as the difference between the value at risk $VaR_q$ and the conditional value at risk $CoVaR_q^{Shock}$, is used to measure systemic risk, since it eliminates the reference to a baseline. The larger the $\Delta CoVaR_q$, the higher the systemic risk,

$$\Delta CoVaR_q = VaR_q - CoVaR_q^{Shock}.$$  \hspace{1cm} (22)

3 Theoretical Study

We implement the model developed in the previous section using purely synthetic data to conduct a Monte Carlo simulation analysis for a hypothetical banking system. Synthetic data allows us to consider different configurations of the banking system with no data availability limitations.
3.1 Topology of Theoretical Network

Our hypothetical banking network consists of 40 banks, of which 5 are large banks and 35 are medium sized banks. A banking system consisting of 40 banks is not nearly as large as the banking system of large economies, however it is large enough to allow incorporation of essential interconnectedness attributes without making the model too cumbersome to implement and simulate. We use several key financial and accounting ratios from actual banks’ financial statements to generate a realistic reduced-form balance sheet model for each bank. These features are summarized in Table 1. Additionally, we set the total size of interbank debt holdings of a single bank at 15 times the size of its own debt held by other banks. In order to illustrate the clustering in banks’ investments, large banks are assumed to have diversified industrial debt holdings, while medium banks hold debt from a subset of industrial sectors.

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<thead>
<tr>
<th>Key Statistics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage Ratio</td>
<td>10%</td>
</tr>
<tr>
<td>Debt to Deposit Ratio</td>
<td>7.5%</td>
</tr>
<tr>
<td>Average Liability Duration</td>
<td>1.5</td>
</tr>
<tr>
<td>Long Term Base Interest Rate</td>
<td>1.47%</td>
</tr>
<tr>
<td>Long Term BBB Debt Risk Premium</td>
<td>3.43%</td>
</tr>
</tbody>
</table>

The above properties of the banks result in an interconnected banking network, where Table 2 summarizes key network characteristics of the theoretical banking network. An average node degree of 39 for the network, with total number of nodes being 40, suggests that the network is complete. Therefore, both diameter and average path of the network are of length 1. Closeness centrality of a node, as reported in the table, measures centrality of banks in the network, while betweenness centrality measures centrality in a network based on shortest paths between banks. A node with higher betweenness centrality would have a greater contagion impact over the network as longer channels of shock propagation would pass through it. A closeness centrality of 1 and a betweenness centrality of 0 for the theoretical network suggests that all banks are equally highly connected with others in the network. These properties are summarized without accounting for the weights of each edge of the network, and even as a non-weighted network, serve as a reference for the empirically
calibrated network studied later in the paper.

Table 2: Property Measurements of Theoretical Network

<table>
<thead>
<tr>
<th>Avg. Degree</th>
<th>Diameter</th>
<th>Avg. Path</th>
<th>Closeness</th>
<th>Betweenness</th>
<th>Cluster Coef.</th>
<th>Component</th>
<th>Modularity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network</td>
<td>39</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1 weak ; 1 strong</td>
</tr>
</tbody>
</table>

Figure 2: Theoretical Network Visualizations

Figure 2(a) displays the 40 bank network, with each edge depicting inter-bank debt holdings. The banks are classified into three sub-clusters, where network modularity was used to measure the strength of network sub-clusters. Networks with higher modularity have denser connections between nodes within a module, but weaker connections between nodes in different modules. A modularity of 0.101 for the network indicates that the nodes of different sub-clusters still possess dense connections with each other. Figure 2(b) illustrates the connections among banks and the industrial sectors denoting the industrial loans made by the banks to the sectors. The 15 largest nodes represent the 15 industrial sectors, while large and small banks are denoted by labelled smaller nodes. Industrial sectors are grouped into five sub-clusters, with large banks diversified in their loans to almost all sectors, while small banks remain concentrated in specific sectors. This feature is illustrated by different colors in the network visualization.
3.2 Theoretical Simulation Analysis

For each stress test scenario described in Section 2.2, we run 10,000 runs of simulation for the banking system under three cases: banks issuing no CoCo debt, banks issue only single trigger CoCo debt, and banks utilize the dual trigger CoCo debt. The two systemic risk measures described in Section 2.4, namely average number of bank failures and $\Delta CoVaR_q$ for equity value at 5% level, are estimated for each case. Table 3 shows the key statistics from the simulation results under the first stress test scenario, in which the banking system experiences only one industrial shock for the duration of simulation. Panel A of Table 3 reports the average number of bank failures and equity $\Delta CoVaR_q$ for the banking system under the three cases: no CoCo debt, single trigger CoCo debt, and dual trigger CoCo debt. Panel B compares the three cases by reporting the differences in bank failures and $\Delta CoVaR_q$, along with their statistical significance. We find that compared to the case of no CoCo debt issuance, conversion of CoCo debt using either single trigger or dual trigger significantly reduces the average number of bank failures and decreases the $\Delta CoVaR_q$. Thus, CoCo debt mitigates systemic risk for the banking system.

Table 3: Theoretical Results with One Industrial Shock

<table>
<thead>
<tr>
<th>CoCo design</th>
<th>Banking System</th>
<th>Large Banks</th>
<th>Medium Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>1.8817</td>
<td>0.1752</td>
<td>0.9160</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{q,0.05}$</td>
<td>0.1629</td>
<td>0.0830</td>
<td>0.0735</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Difference</th>
<th>Banking System</th>
<th>Large Banks</th>
<th>Medium Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>-1.7064***</td>
<td>-0.9657***</td>
<td>0.7408***</td>
</tr>
<tr>
<td>(46.52)</td>
<td>(-24.38)</td>
<td>(36.98)</td>
<td>(-1.00)</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{q,0.05}$</td>
<td>-0.0799***</td>
<td>-0.0894***</td>
<td>-0.0095*</td>
</tr>
<tr>
<td>(11.10)</td>
<td>(12.61)</td>
<td>(1.88)</td>
<td>(2.75)</td>
</tr>
</tbody>
</table>

Note: Equity amount is normalized by initial equity value
Note: Bootstrap t-statistics are reported in parentheses

As shown in columns (1) and (2) in Panel B of Table 3, introducing single trigger and dual trigger CoCo debt to the banking system reduces the average number of bank failures by 1.7064 and 0.9657, respectively. Meanwhile, equity $\Delta CoVaR_q$ decreases by 7.99% and 8.94%, respectively,
in the presence of single trigger and dual trigger CoCo debt. The coefficients are all significant at the 1% level. These results hold when we consider only the medium banks. For large banks, we do not observe a decrease in average bank failures as no large bank failures are observed in the simulation runs under this stress scenario. However, we do observe a decrease in large banks’ equity $\Delta CoVaR_q$. Therefore, both designs of CoCo debt provide certain protection from systemic risk for the large banks.

Table 4: Theoretical Results with Two Industrial Shocks

<table>
<thead>
<tr>
<th>A: Systemic Risk Measures</th>
<th>Banking System</th>
<th>Large Banks</th>
<th>Medium Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoCo design</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>None</td>
<td>Single</td>
<td>Dual</td>
</tr>
<tr>
<td></td>
<td>4.6103</td>
<td>0.6965</td>
<td>1.7784</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{0.05}$</td>
<td>0.3138</td>
<td>0.1942</td>
<td>0.1586</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B: Significance Test</th>
<th>Banking System</th>
<th>Large Banks</th>
<th>Medium Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>Single-None</td>
<td>Dual-None</td>
<td>Dual-Single</td>
</tr>
<tr>
<td></td>
<td>-3.9138***</td>
<td>-2.8319***</td>
<td>1.0819***</td>
</tr>
<tr>
<td></td>
<td>(-68.90)</td>
<td>(-48.05)</td>
<td>(34.22)</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{0.05}$</td>
<td>-0.1195***</td>
<td>-0.1552***</td>
<td>-0.0356***</td>
</tr>
<tr>
<td></td>
<td>(16.46)</td>
<td>(21.72)</td>
<td>(6.28)</td>
</tr>
</tbody>
</table>

Note: Bootstrap $t$-statistics are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Although both single trigger and dual trigger CoCo debt provide protection to the banking system, their effectiveness is not identical. Differences in their effectiveness are compared in columns (3), (6) and (9) in Panel B of Table 3. In column (3), while the single trigger CoCo protects the banking system better in terms of the number of bank failures, as the single trigger design helps reduce average failures by 0.7408 banks than the dual trigger, it is the dual trigger CoCo debt that outperforms when considering the equity $\Delta CoVaR_q$ of banking system. $\Delta CoVaR_q$ has a 0.95% improvement in the case of dual trigger CoCo debt. Similar results are observed on isolating the results just for the medium banks. However, we do not observe a significant difference for the two designs of CoCo triggers in either preventing bank failures or narrowing down the equity $\Delta CoVaR_q$ for just the large banks, at least for the present stress scenario.

To ensure the robustness of our results, we consider the more severe stress scenario where two industrial shocks are experienced for the duration of simulation (the second stress scenario...
in Section 2.2). Table 4 provides similar results as in Table 3, in the case of stress shocks of greater economic magnitude and higher statistical significance. Financial shocks can occur both for industrial sectors and banks’ other investment activities. In our reduced-form balance sheet for the banks, all of these impacts arising from investments and financing activities must be reflected through the “cash & cash equivalents.” Therefore, we use the third stress scenario of Section 2.2, where we simultaneously apply an industrial shock and a cash shock. The cash shock is applied only to the large banks since they are at the core of the banking system. The results are shown in Table 5.

Table 5: Theoretical Results with Industrial & Cash Shocks

<table>
<thead>
<tr>
<th>A: Systemic Risk Measures</th>
<th>Banking System</th>
<th>Large Banks</th>
<th>Medium Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>CoCo design</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>0.1910</td>
<td>0.8026</td>
<td>0.1840</td>
</tr>
<tr>
<td>Dual</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>0.0098</td>
<td>0.1111</td>
<td>1.8668</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B: Significance Test</th>
<th>Banking System</th>
<th>Large Banks</th>
<th>Medium Banks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Difference</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean of failures</td>
<td>-1.8598***</td>
<td>-1.2482***</td>
<td>0.6116***</td>
</tr>
<tr>
<td></td>
<td>(-46.21)</td>
<td>(-29.42)</td>
<td>(31.44)</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{R,q}$</td>
<td>-0.1490***</td>
<td>-0.2661***</td>
<td>0.1171***</td>
</tr>
<tr>
<td></td>
<td>(18.29)</td>
<td>(-2.52)</td>
<td>(34.32)</td>
</tr>
</tbody>
</table>

Note: Bootstrap $t$-statistics are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We observe that the conversion of both trigger designs increases the stability of the banking system and that of the medium banks in terms of both the systemic risk measures. Since the large banks are directly shocked in this scenario, a positive impact of CoCo debt conversion is observed for protecting large banks from failures. Compared with the first scenario of only one industrial shock, the difference in terms of $\Delta CoVaR_{R,q}$ for comparing the two CoCo designs has changed. We observe that, in column (3) in Panel B of Table 5, the positive effect of dual trigger design is no longer significant at the banking system level. This change is caused by the large bank sub-sample. While the dual trigger CoCo still performs 2.23% better in reducing $\Delta CoVaR_{R,q}$ for medium banks, single trigger CoCo performs better for large banks, beating the dual trigger CoCo case by 11.71%.

The following mechanism are plausible explanations for these finding. Since large banks experi-
ence both the cash and the industrial shocks simultaneously, they are more likely to be the first to suffer financial distress. CoCo debt with dual trigger is less readily converted, as in most cases, the system-level trigger is not reached, even though certain individual banks are at severe risk of failure. As a result, the dual trigger design fails to reduce systemic risk of the large banks subgroup. Thus the size effect results in such discrepancy for the large banks. In general, the theoretical simulations suggest that while the conversion of CoCo debt of both trigger designs increases the stability of the banking system, their performances differ. Single trigger CoCo performs better in protecting individual and earlier stressed banks, whereas dual trigger CoCo is better when we focus on the entire banking system and for mitigating the spillover effects for banks who could suffer in the later phrase of a financial crisis.

3.3 Sensitivity of Simulation Results

In this section, we change several baseline settings used in Section 3.2 for our theoretical simulation to examine the robustness of the results. Leverage ratio of banks is an important indicator for the stability of a banking system, therefore we evaluate the relationship of the leverage ratio with effectiveness of CoCo debt design. This is followed by assessing the implications of changes in the trigger levels of CoCo debt.

3.3.1 Leverage Ratio

The leverage ratio is halved to 5% from the baseline level of 10% and doubled to 20%. Simulations for both single industrial shock and two industrial shocks stress scenarios show that both single and dual trigger CoCo still significantly reduce banking system’s systemic risk. Protecting ability, however, does become weaker as the leverage ratio increases, as one would expect. The difference between the two CoCo trigger designs provides some interesting insights. As seen in Figure 3, the dual trigger CoCo’s ability to protect the banking system by the $\Delta CoVaR$ measure no longer holds when the leverage ratio is high (20%). When the leverage ratio increases, in relative terms the risk from inter-bank debt exposure diminishes, and a shock is less likely to spread through the banking system. As a result, the banks are more likely to be shocked one at a time, rather than be simultaneously affected. Under such circumstances, it is reasonable for the single trigger CoCo design to perform better by the $\Delta CoVaR$ measure also.
3.3.2 Trigger Level

Among the features that define CoCo debt, the trigger level is perhaps the most complicated and controversial. Currently there is no universally accepted CoCo trigger level, either in academic research or financial markets. In Europe, all CoCo instruments issued have triggers based on capital adequacy ratio, varying in terms of ratio type and level [31]. In order to obtain insights on the “optimal” trigger level for CoCo debt designs, we change the trigger levels for both single and dual, ranging from 20% to 60% of the equity ratio. The baseline levels in the earlier section were 60% for dual and 40% for single. Figure (4) shows the sensitivity with the z-axis plotting the difference between dual trigger versus single trigger $\Delta$CoVaR.

Under one or two industrial shocks, the difference (with sign) in $\Delta$CoVaR is negatively correlated
with the level of system level trigger in the dual trigger CoCo design. A higher level of the trigger for the system makes it easier for the single trigger CoCo to convert when a single bank suffers stress. Conversely, a lower dual trigger hinders CoCo conversion even if individual banks may already be in distress. Therefore, the dual trigger outperforms when the system level trigger is higher, but fails to protect the banking system when the system level trigger is lower.

Likewise, Figure (5) shows the change of bank failures in response to the change in trigger levels. As expected, the difference between dual trigger CoCo and single trigger CoCo for average bank failures is positively correlated with the level of system level trigger in the dual trigger design. A lower system level trigger in the dual trigger design restricts the conversion of CoCo debt. Furthermore, when comparing Figures (4) and (5), we find that differences of both $\Delta$CoVaR and bank failures under two CoCo designs are not linearly related with the trigger levels. Specifically, there are two globally optimal region in these plots where the threshold for the dual trigger equals the single trigger at 40%. At this level, the dual trigger CoCo debt is best in terms of $\Delta$CoVaR, while the single trigger CoCo outperforms in saving individual banks. Admittedly, this result is applicable for the present theoretical settings, nevertheless, it provides insight on CoCo debt performance under different trigger levels.
4 Empirical Model and Data Description

Calibrating the network model constructed in Section 2 to identify banks’ interconnectedness requires detailed bank-level data for all the banks. Detailed publicly available data at the required granularity is limited, especially to assess the counterparties of debt holdings of each bank in the model. The advantage of a theoretical model based simulation analysis using synthetic data, as done in Section 3, is the flexibility it provides for model assumptions. However, these theoretical findings must be validated using the most reasonable calibrated model constructed using the available data. The most detailed available data with counterparty information required for our purpose is that available in the 13-F filings with the US Securities and Exchange Commission (SEC). However, 13-F filings provide long positions in equity securities, with unique identifiers for the equity issuers. Therefore, in order to use these data with inter-bank exposures and common exposures information, we must slightly modify the reduced-form balance sheet model developed in Section 2. Therefore, to take advantage of the data available in 13-F filings, we have to make some modifications of the inter-bank network model, which we describe next. We also use the Federal Financial Institutions Examination Council (FFIEC) quarterly call reports data for parts of the balance sheet calibration.

4.1 Reduced-form Balance Sheet Model Modification

The balance sheet, as shown in Equation (16), is modified for the total assets on the balance sheet of a bank holding company (BHC) to include equity securities against other BHCs and non-financial firms. As stated above, the equity holdings against other BHCs and non-financial firms serve as proxies for the inter-bank exposures and common exposures. Total liabilities of each BHC include deposits, $D_{it}$, common debt, $L_{it}^B$, and CoCo debt, $L_{it}^C$, with time varying values determined in terms of respective debt durations and convexities. The dynamic evolution of a BHC $i$’s equity value, $E_{it}$, is given as,

$$E_{it} = C_{it} + G_{it} + M_{it} + E_{it}^B + E_{it}^F - D_{it} - L_{it}^B - L_{it}^C,$$

where $E_{it}^F$ and $E_{it}^B$ denote BHC $i$’s holdings of equity securities against other BHCs and against non-financial firms, respectively. Now, $w_{ij}, i,j = 1,\ldots,N$ and $s_{ij}, i, j = 1,\ldots,N$ in Equations (3) and (4) must represent the percentage of BHC $j$’s equity held by BHC $i$ and the fraction of BHC $i$’s equity exposure to a sector $j$, respectively. $I_{jt}$, which represents an index value for sector $j$, is
assumed to follow a jointly correlated M-dimensional geometric Brownian motion as follows,

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

(24)

The value of government bonds, total mortgage loans, and deposits are assumed to remain constant, while the change of market value of cash & cash equivalents held by BHC \( i \) are assumed to follow dynamics given in Equation (5). The market value of common debt, \( L^B_{it} \), and CoCo debt, \( L^C_{it} \), of a BHC \( i \) with credit rating, \( l \), follow the models given in Equations (11) and (12).

4.2 Data Description

We consider BHCs participating in the US Federal Reserve’s Stress Testing program and smaller BHCs headquartered along US east coast. Additionally, we pursue BHCs with 13-F filings available from SEC’s EDGAR system. Our banking system consists of 36 BHCs, including the largest BHCs, such as, Citigroup, JP Morgan Chase & Co., and Bank of America Corp. We group BHCs into four subgroups based on their total assets, consistent with the Mid-size Bank Coalition of America Research Report (2013) [28] bank-size definition (Table 6).

<table>
<thead>
<tr>
<th>Size</th>
<th>Total Assets</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Super Large BHCs</td>
<td>Greater than $1000 Billion</td>
<td>4</td>
</tr>
<tr>
<td>Large BHCs</td>
<td>Greater than $250 Billion &amp; Less than $1000 Billion</td>
<td>6</td>
</tr>
<tr>
<td>Medium BHCs</td>
<td>Greater than $10 Billion &amp; Less than $1000 Billion</td>
<td>16</td>
</tr>
<tr>
<td>Small BHCs</td>
<td>Less than $10 Billion</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 6: Size of Bank Holding Companies

Besides 13-F data obtained from SEC EDGAR system, the required data for our model calibration are obtained from Federal Financial Institutions Examination Council (FFIEC), Capital IQ and Bloomberg Terminal. The FFIEC quarterly call report data for the 36 banks is obtained for the past 10 years, from 2007Q1 to 2016Q4. These are used to estimate balance sheets’ specific parameters. We obtain Moody’s credit ratings of the 36 BHCs from the Bloomberg terminal, shown in Table 7. Ignoring the rating adjustments for simplicity, we have 21 BHCs with a rating of A, 14 with Baa, and 1 with Ba. 25 of the 36 BHCs participate in the Fed’s Stress Tests program 1.

1https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm
Figure 6: Empirical Network of US BHCs
Table 7: Moody’s Ratings for BHCs

<table>
<thead>
<tr>
<th>BHCs’ Ratings</th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>Baa1</th>
<th>Baa2</th>
<th>Baa3</th>
<th>Ba3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
<td>5</td>
<td>3</td>
<td>13</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>

We aggregate the non-financial firms equity securities reported in the banks’ 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 [20]. Using data from Capital IQ terminal, we assign each non-financial equity security held by the BHCs to one of the following sectors: consumer discretionary, consumer staples, energy, financials, healthcare, industrials, information technology, materials, real estate, telecommunication services, and utilities.

Using data from 13-F filings and call reports yield a potential data bias, since 13-F filings are made 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 commercial mortgages, $M_{it}$, from call reports, together with interbank equity holdings, $E^B_{it}$, and non-financial firm equity holdings, $E^F_{it}$, from 13-F filings. We then 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, obtained from call reports.

$$
\hat{TL}_{it} = \left( \frac{TL_{i,t}}{TA_{i,t}} \right) (C_{it} + G_{it} + M_{it} + E^F_{it} + E^B_{it}),
$$

$$
\hat{D}_{it} = \left( \frac{D_{it}}{TA_{i,t}} \right) (C_{it} + G_{it} + M_{it} + E^F_{it} + E^B_{it}).
$$

where $\frac{TL_{i,t}}{TA_{i,t}}$ is the ratio of total liabilities to total assets and $\frac{D_{it}}{TA_{i,t}}$ is the ratio of deposits to total assets for BHC $i$. The modified total liabilities, $\hat{TL}_{it}$, net of modified deposits, $\hat{D}_{it}$, is set to be the total value of common debt and CoCo debt.

4.3 Topology of US BHCs’ Network

Table 8 summarizes the basic properties of the empirical network consisting of 10 large & super large BHCs, referred to as the core network. The core network is almost complete, with each bank directly connecting with others in the core. This significant level of interconnections between large & super large BHCs is also seen in terms of the higher clustering coefficient, the higher closeness centrality and a strong connected component. Therefore, we expect the financial shocks to spread
faster among super large and large BHCs. Betweenness centrality of the core network is much lower than that of the 36 BHC network. This is reasonable as among the large & super large BHCs, for instance, JP Morgan Chase & Co. or Citigroup, all BHCs are almost of equal importance, with no single BHC standing out as a dominant one. In the network comprised of all BHCs, the super large & large BHCs undoubtedly have a dominant presence with a much higher betweenness centrality of 16.39. This evidence supports the Federal Reserve’s re-proposal on limiting the ties among Wall Street mega-banks in order to address the “too-connected-to-fail” threat.

Table 8: Network of the US Banking System

<table>
<thead>
<tr>
<th>Network</th>
<th>Nodes</th>
<th>Edges</th>
<th>Format</th>
<th>Edge Weights</th>
<th>Self-loop</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Banking System</td>
<td>36</td>
<td>627</td>
<td>Directed</td>
<td>Weighted</td>
<td>Yes</td>
</tr>
<tr>
<td>Core BHCs Network</td>
<td>10</td>
<td>96</td>
<td>Directed</td>
<td>Weighted</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Table 9: Average Value of Network Property Measurements

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample</td>
<td>17.47</td>
<td>4</td>
<td>1.54</td>
<td>0.62</td>
<td>16.39</td>
<td>0.71</td>
<td>1 weak ; 6 strong</td>
</tr>
<tr>
<td>Core</td>
<td>9.6</td>
<td>2</td>
<td>1.03</td>
<td>0.97</td>
<td>0.30</td>
<td>0.97</td>
<td>1 weak ; 1 strong</td>
</tr>
</tbody>
</table>

Figure 8(a) shows the visualization of super large & large BHCs’ (red nodes) industrial equity holdings towards sectors (green nodes), and Figure 8(a) shows the same for the medium & small BHCs. Thickness of the edges indicates a higher percentage of investment from a particular BHC towards a particular sector. Similar to the design for the theoretical network, super large & large BHCs are more diversified for their equity investment, accounting for a majority of common exposures to each industrial sector. Medium & small BHCs, on the other hand, are biased in their equity investment with investment in limited number of sectors. One exception being State Street Bank, which is heavily

Figure 7: Network of Large & Super Large BHCs
invested in all the 11 sectors. State Street Bank happens to be the largest medium BHC by our grouping of BHCs.

![Empirical Network of Common Exposures](image)

(a) Large & Super Large  
(b) Medium & Small

**Figure 8: Empirical Network of Common Exposures**

Network analytics allows us to group the BHCs into three sub-clusters, as shown in Figure 9. By this sub-clusters, systemically important firms, such as JP Morgan Chase & Co., Goldman Sachs and Citigroup are more likely to invest in sectors, such as financial, materials, and consumer discretionary. Bank of America Corp. and Wells Fargo are heavily exposed to industrial, telecommunication services and information technology sectors. Finally, Bank of New York Mellon Corp. and State Street Bank are more connected to sectors such as health care, utilities, energy, and real estate.

### 4.4 Contagion Risk and Correlation Clustering

Financial 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 the lower quartile conditional correlation of returns between the 11 sectors, we identify the strongest downside co-movement connections between the sectors. As shown in Figure 10, 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
Figure 9: Empirical Network of Common Exposures 2
independent in terms of tail-dependencies. Among the connected sectors, when one sector index drops by 1%, indices of other connected sectors on average drop by 0.6%. Through the common equity exposures, $w_{ij}$, a sector shock can propagate to individual BHCs with high common exposure to the affected sectors.

Figure 10: Tail Dependency of Sectors
A similar clustering technique is applied for liquidity shocks, as shown in Figure 11. We calculate equity conditional correlation for the 36 BHCs and classify the 36 BHCs into 3 clusters, as shown in Figure 11. We also have a series of “independent” BHCs that do not possess strong downsize tail-dependency with other BHCs. The size of each node represents the size of the BHCs. Within a cluster, all BHCs suffer liquidity shocks simultaneously at different degrees of 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%.

Figure 11: Tail Dependency of BHC’s Liquidity
5 Empirical Study

We conduct validation analysis using Monte Carlo simulation for the model calibrated in Section 4. Similar to the stress scenarios applied to the theoretical model in Section 3, we apply the following two stress scenarios to test their impact on the reduced-form calibrated network model:

1. -10% shocks to a randomly chosen set of industrial sectors at days 20 and 200 of a year’s duration for the simulation.

2. -10% shocks to randomly chosen industrial sectors and -10% cash shock to a randomly chosen set of large & super large BHCs at days 20 and 200 of a year’s duration for the simulation.

As described in Section 4.4, a sector suffering an industrial shock transmits the shock to connected sectors at 60% of the original shock, while a BHCs suffering a liquidity shock transmits the shock to its connected BHCs at 80% of the intensity of the original shock. The single trigger of the CoCo debt is set at 40% of the bank’s initial equity-to-asset ratio, while the system-level trigger of the dual trigger design is set at 60% of the initial equity-to-asset ratio of the entire banking system. As such any trigger level can be chosen for the two CoCo trigger designs. We pick the 40% and 60% level to let the system-level trigger be relatively more quick to trigger. A very low system level trigger may never be invoked, as seen in Section 3.3.2, until the entire banking system reaches a severely distressed condition. This may be too late for corrective actions.

Table 10 shows key statistics for the empirical analysis when the banking system experiences only industrial shocks. Panel A of Table 10 reports average bank failures and equity $\Delta CoVaR_q$ for the banking system. Panel B compares the differences in average bank failures and $\Delta CoVaR_q$ among three cases, namely, no CoCo debt issuance, single trigger CoCo debt issuance, and dual trigger CoCo debt issuance. Consistent with the findings in the theoretical analysis, conversion of CoCo debt using both single and dual trigger significantly improves the stability of the banking system by reducing both the average bank failures and equity $\Delta CoVaR_q$.

Columns (1) and (2) in Panel B of Table 10 show that average bank failures, when compared with no CoCo debt issuance, reduce by 1.1834 and 0.1948 in presence of single trigger and dual trigger CoCo debt, respectively. These reductions are statistically significant at 1% and 5% level. Equity $\Delta CoVaR_q$ also witnesses a statistically significant reduction of 2.13% and 3.20%, respectively, for the two designs of CoCo debt. For subgroups of BHCs, differing from the findings of the theoretical analysis, the decrease in $\Delta CoVaR_q$,CoVaR from CoCo debt conversion is only significant for the
Table 10: Empirical Result with Two Industrial Shocks

A: Systemic Risk Measures

<table>
<thead>
<tr>
<th>CoCo design</th>
<th>Banking System</th>
<th>Large &amp; Super Large BHCs</th>
<th>Medium &amp; Small BHCs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>3.3417</td>
<td>2.1583</td>
<td>3.1469</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{0.05}$</td>
<td>0.1162</td>
<td>0.0950</td>
<td>0.0842</td>
</tr>
</tbody>
</table>

B: Significance Test

<table>
<thead>
<tr>
<th>Difference</th>
<th>Banking System</th>
<th>Large &amp; Super Large BHCs</th>
<th>Medium &amp; Small BHCs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>-1.1834**</td>
<td>-0.1948**</td>
<td>0.9886***</td>
</tr>
<tr>
<td>(-9.2413)</td>
<td>(-1.7020)</td>
<td>(7.6684)</td>
<td>(-9.7149)</td>
</tr>
<tr>
<td>Equity $\Delta CoVaR_{0.05}$</td>
<td>-0.0213***</td>
<td>-0.0320***</td>
<td>-0.0108*</td>
</tr>
<tr>
<td>(3.5251)</td>
<td>(4.9057)</td>
<td>(1.7147)</td>
<td>(3.9337)</td>
</tr>
</tbody>
</table>

Note: Bootstrap t-statistics are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

large & super large BHC groups, but not so for the medium & small BHC groups. Dual trigger CoCo debt is not found to be effectively reducing bank failures for the medium & small BHCs, as the coefficient of $-0.0380$ in column (8) Panel B is not statistically significant.

Columns (3), (6) and (9) in Panel B of Table 10 report the comparisons for the two designs of CoCo trigger for the entire banking system and for the two subgroups. CoCo debt with a single trigger is better at saving individual banks by an average of 0.9886 at the entire banking system level. In contrast, CoCo debt of dual trigger outperforms single trigger by 1.08%, which is significant at 10% level, in terms of $\Delta CoVaR_q$ reduction. Similar results are observed for large & super large BHCs. For medium & small BHCs, single trigger is still found more effective in preventing BHCs from failing, but the difference in the two designs of CoCo debt for $\Delta CoVaR_q$ is obscure, since the coefficient of $-0.05%$ is not statistically significant.

Table 11 summarizes the results for the second stress scenario, where both industrial and cash shocks occur simultaneously. The results are similar to those observed in Table 10, except that dual trigger CoCo now also starts to be effective for medium & small BHCs by 0.0501 at 10% significance level. Consistent with results from the theoretical analysis, through our empirical validation we conclude that CoCo debt performs well in controlling average bank failures and increasing banking system stability. Conversion of CoCo debt under financial stress significantly reduces both average bank failures and equity $\Delta CoVaR_q$. Furthermore, the dual trigger design more efficiently maintains...
Table 11: Empirical Result with Industrial & Cash Shocks

<table>
<thead>
<tr>
<th>A: Systemic Risk Measures</th>
<th>Banking System</th>
<th>Large &amp; Super Large BHCs</th>
<th>Medium &amp; Small BHCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoCo design</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>None</td>
<td>None</td>
<td>Single</td>
<td>Dual</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>3.3751</td>
<td>2.1636</td>
<td>3.1621</td>
</tr>
<tr>
<td>Equity ∆CoVaR</td>
<td>0.1322</td>
<td>0.1074</td>
<td>0.0950</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B: Significance Test</th>
<th>Banking System</th>
<th>Large &amp; Super Large BHCs</th>
<th>Medium &amp; Small BHCs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Mean of bank failures</td>
<td>-1.2115***</td>
<td>-0.2130**</td>
<td>0.9985***</td>
</tr>
<tr>
<td></td>
<td>(-7.8084)</td>
<td>(-2.6679)</td>
<td>(6.2456)</td>
</tr>
<tr>
<td>Equity ∆CoVaR</td>
<td>-0.0250***</td>
<td>-0.0373***</td>
<td>-0.0125**</td>
</tr>
<tr>
<td></td>
<td>(4.4387)</td>
<td>(6.2811)</td>
<td>(2.1167)</td>
</tr>
</tbody>
</table>

Note: Bootstrap t-statistics are reported in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

the banking system integrity, especially for the large & the super large BHCs, whereas the single trigger design is better at preventing individual BHC failures. The effect of CoCo debt conversion using either trigger design is inconclusive for the medium & the small BHCs.

We find that the balance sheet evolution characteristics of the large BHCs in the empirically calibrated banking network is more volatile than that of medium and small BHCs. This results in the large and super large BHCs hitting the CoCo trigger more frequently, and thus, activating CoCo debt conversion. Moreover, an all-or-nothing CoCo debt conversion creates another drawback, resulting in limited realizations of CoCo debt conversion for medium and small BHCs. Finally, the optimal level of CoCo debt issuance for a specific size of BHC and partial levels of CoCo debt conversion once triggered remain questions that need further investigation.

6 Conclusion and Discussion

The 2008 global financial crisis illustrated the challenge of contagion in bank failures. As a response to the crisis, contingent convertible (CoCo) debt was proposed as a promising tool for alleviating the systemic financial stress of the banking system. CoCo debt automatically converts to equity on appropriately defined triggers. For any design of trigger of CoCo debt, and other design aspects of the instrument, the fundamental issue remains the efficacy of the instrument. In
this paper, we study the impact of CoCo debt conversion on the banking system, and how the impact differs under different designs of CoCo triggers. To measure the interconnectedness of the banking system, we create a network model based on a reduced-form balance sheet, where banks are described as nodes and the debt holdings relations describe the network’s edges.

Our simulation results show that CoCo debt performs well in preventing bank failures and in improving the stability of the banking system, which leads to a significant mitigation of systemic risk in the banking system. We test our theoretically simulated and 13-F calibrated networks with several financial stress scenarios. Moreover, comparing two designs of CoCo debt trigger, we find that while CoCo debt with a single trigger results in lowering average bank failures, it is the dual trigger design that outperforms in controlling systemic risk in terms of $\Delta CoVaR_q$ when external shocks spread through the banking network. The results for the 13-F calibrated empirical network are consistent with these findings. The difference resulting from the two designs of CoCo debt trigger is essentially a trade-off in addressing systemic risk. Consistent findings between the theoretical model, where inter-bank and common exposures are for debt instruments, and the empirical model, where inter-bank and common exposures are for equity instruments, suggests that a mix of debt and equity instruments making the inter-bank and common exposure would find behavior of the network consistent to that found in our analysis.

While we investigated trigger designs for CoCo debt for very large, large, medium and small BHCs under an all-or-nothing conversion approach, an all-or-nothing CoCo debt conversion design may not be optimal for different sizes of banks. A sequence of shocks may require gradual CoCo conversion, and a guideline may also be needed for new CoCo issuance once all the CoCo debt of a bank depletes. Our sensitivity analysis highlighted that appropriate trigger level must also be determined for each type of bank. Although we have shown the positive impact of holding CoCo debt on mitigating banking systemic risk, there is need for caution regarding the self-saving properties of CoCo debt once triggered in the real market. According to Deutsche Bundesbank and Axiom Alternative Investments (2018) [13], these kinds of instruments are “over-engineered” and sometimes bonds that are supposed to make banks stronger may end up causing another crisis due to the degree of such complexity. For instance, their conversion mechanism could range from debt either converting to equity or getting directly written-off. These issues pose challenges that must be investigated in future research.
References


