Addressing Systemic Risk Using Contingent Convertible Debt - A Network Analysis

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Abstract: In this paper, we construct a balance sheet based network model to study the interconnected nature of the banking system. After theoretical simulation analysis of the buffer effect of contingent convertible (CoCo) debt in controlling contagion in the banking network, we utilize 13-F filings made to the US Securities and Exchange Commission (SEC) to calibrate the interconnectedness of US banking network. The results demonstrate that the conversion of CoCo debt significantly reduces the average number of bank failures, decreases the ΔCoVaR, and thus mitigates the banking systemic risk. While CoCo debt with a dual-trigger is not so efficient as that with a single trigger in reducing individual bank failures, the former is virtually better at protecting the surviving banks, which leads to improved stability from the perspective of the banking system. We claim that the difference in the design of two CoCo triggers is essentially a trade-off in addressing systemic risk.

Keywords: contingent convertible debt, network model, systemic risk, 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 [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 [20].

Although no CoCo debt has been issued in US so far, banks in Europe have started utilizing this instrument. By the end of June 2017, more than € 125 billion of CoCo bonds were sold in Eurpoe. During the period from January 2009 to June 2014, € 74 billion of CoCo bonds were issued by 37 European banks via 102 issues in twelve countries, including UK, Swiss, Spain, and so on [29]. 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 [26]. On an individual basis, according to a Staff Memo by Norges Bank (2014) [29], the largest issuer of outstanding CoCo Bonds was Lloyds which accounted for 14% of the European market, followed by Credit Suisse with approximately 12%. UBS and Barclays were the third largest with market shares of 11% each. The trigger designs of current European CoCo bonds are all based on a capital adequacy ratio, from 2% to 8.25%, which varies in terms of CET1 ratio, the Tier 1 ratio and the Total risk-based capital ratio.

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 [20]. Among these features, the trigger criterion is considered the most important, while being the most complicated at the same time [35]. 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 two designs of CoCo triggers, namely a single trigger and a dual-trigger concernig systemic risk. To measure the interconnectedness of the banking system, we create a network model based on a reduced form balance sheet.

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 [3]. Later, accounting values were proposed to approximate regulatory ratios [20]. However, these measures may be manipulated by banks or may end up inevitably lagging true economic values. Flannery (2009) [16] and Coffee (2010) [11] proposed to use bank stock prices as trigger events, while Duffie (2009) [15] 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) [25], while Prescott (2012) [31] 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) [10] 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 [3]. Therefore, a dual-trigger contingent on aggregate bank losses and a bank's specific capital ratio was proposed as a CoCo debt trigger [32]. This conversion, however, only ended up taking effect after the sector has already entered a crisis period. McDonald (2013) [28] 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) [30] 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) [3] 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 [24]. 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 [22]. 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 such complexity exist [36].

Researchers have applied network science for studying systemic risk. Channels for contagion and amplification of shocks to the financial system are created due to the interconnections among financial institutions [21]. In 2000, Allen and Gale (2000) [2] pioneered the application of network analysis into the evaluation of the system stability of interconnected financial institutions. Gai (2013) [18] studied the stability of the financial system by associating a network structure of interbank lending with unsecured claims. Anand et al. (2013) [5] 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) [22] to assess the significance of portfolios overlapping quantitatively, in order to identify overlaps that bear the highest risk of fire sales. Brunetti et al. (2018) [9] proposed a novel approach to estimate the portfolio composition of banks as function of daily interbank trades and stock returns. In their research, portfolio concentration is used as a measure of bank diversification and common holdings as a measure of market susceptibility to propagating shocks.

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 [34].

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 [23]. 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) [6] concluded that positions that are not disclosed to the public in confidential treatment filings earn significantly positive abnormal returns over the post-filing 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 [23].

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) [22] 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) [23] 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 [8] 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 first create a balance sheet based network model to study the interconnectedness of the banking system. Banks are described as nodes and the ownership relations are described as edges. A reduced form balance sheet is constructed based on key accounting ratios, such as leverage ratio and debt to deposit ratio, obtained from a typical financial statement in the real world. The theoretical model is developed and applied to purely simulated data so that a failure in one or several banks in the system affects the whole financial system through the linkage of interbank debt holdings and channels of common industrial debt exposures. We conduct Monte Carlo simulation to evaluate the effectiveness of specific designs of CoCo debt in controlling the banking systemic risk. Two designs of CoCo debt trigger, namely, a naive single trigger CoCo and a dual-trigger CoCo, are considered and compared.

After that, we calibrate interbank equity holdings and common equity exposures to approximate the banking interconnectedness, as we lack publicly available data on interbank debt holdings. The data is extracted from 13-F filings made to the US Securities and Exchange Commission (SEC) and call reports from the Federal Financial Institutions Examination Council (FFIEC). We construct a banking system of 36 bank holding companies (BHCs) along the US east coast, as the biggest ones such as Citigroup, JP Morgan Chase & Co., and Bank of America Corp, are headquartered in this region. 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. With the calibrated network model, we replicate our study from the theoretical model to verify the findings.

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 alleviation of the banking systemic stress. We test our simulated and 13-F captured networks with several financial stressed scenarios. Specifically, we consider a scenario in which the banking system suffers a 10% drop in indsutrial sectors twice during one-year simulation. In our theoretical simulation study, we report an average of 4 fewer bank failures in the presence of single trigger CoCo, and 2.83 fewer failures in the presence of dual-trigger CoCo. Meanwhile, equity $\Delta CoVaR$ at 5th percentile is also reduced by 11.95% and 15.52% owing to the conversion of CoCo debt of two trigger designs. In the empirical analysis, similar trends are observed. The average number of bank failure is reduced by 1.1834 and 0.1948, and $\Delta CoVaR$ is reduced by 2.13% and 3.20%, with the help of single trigger and dual trigger CoCo debt, respectively. Although magnitudes of improvements from holding CoCo debt in empirical study are smaller, they are all statistically significant at 1% level (one coefficient is at 5% level). These findings support the effectiveness of CoCo debt in controlling the spread of local stress to the banking system.

Moreover, comparing two designs of trigger, while CoCo debt with a single trigger offers a smaller number of average bank failures, it is the CoCo debt with a dual-trigger that outperforms in controlling systemic risk in terms of the $\Delta CoVaR$ when external shocks are spread in the banking network. In theoretical simulation of two industrial shocks, we observe at the minimal a 3.56% lower $\Delta CoVaR$ under dual-trigger design compared with single trigger design. Similar findings are shown in the calibrated network model. Therefore, it can be inferred that while the dual-trigger is not so efficient as the single trigger in protecting each individual bank, the former is better at protecting the surviving banks, which leads to improved stability from the perspective of the banking system. This difference resulted from two designs of CoCo triggers is essentially a trade-off in addressing systemic risk.

Our paper contributes to the literature mainly in two ways. First, to best of our knowledge, our paper is the first to study the CoCo debt through network model. Our model allows banking connections and thus stress the systemic risk issues in the banking system. Second, we systematically study the impact of different designs of CoCo debt triggers. Although only two types of CoCo triggers are examined in our test, our framework can be easily extended to fit other designs.

The rest of the paper is organized as follows. Section 2 provides detailed discussion of model construction. In Section 3, we implement simulation analysis and obtain theoretical results. Section 4 shows how we modify and calibrate models constructed in Section 2 with empirical data. In Section 5, 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 6.

2 Model and Methodology

2.1 Network Model

In order to describe the interconnected nature of the banking system, we construct a balance sheet based network model. We begin our model by introducing a reduced form of balance sheet, which contains only the most important information in our study.

As shown in Figure 1, for each bank in our model, a reduced form balance sheet is composed of six components. Cash & cash equivalents, C, interbank debt holdings, A^B, and industry debt holdings, A^I, are in the asset side. Deposits, D, interbank liability, L^B, and share holders' equity, E, are in the liability side. Since the value of all assets in a balance sheet is equal to the value of all liabilities, we have the following relation,

$$C + A^B + A^I = D + L^B + E. \tag{1}$$

Consider a banking system of N banks. For each bank i, the reduced form of balance sheet is modeled with subscript i (e.g., C_i, A_i^B, etc.). To calibrate banks' interconnections within the banking system, we decompose the interconnections into two parts, one part caused by interbank debt holdings, A_i^B, and the other caused by their common exposures, A_i^L.

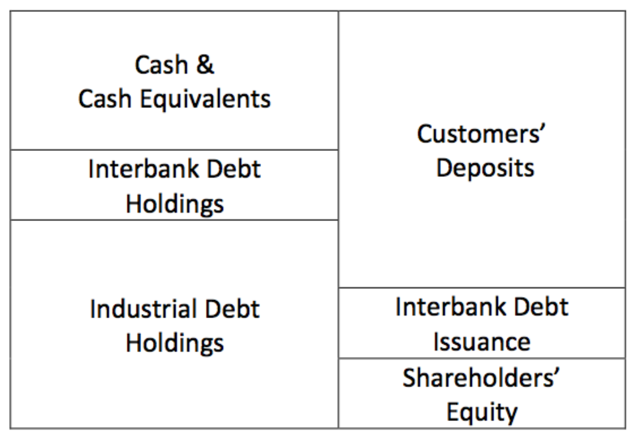

Figure 1: A Sample Reduced Balance Sheet

Let w_{ij}, where $i, j = 1\ to\ N$, denote the percentage of bank j's common debt held by bank i (over bank j's total common debt). To make sure that all liabilities in the network are owned by their holders, the sum of weights for every bank must be equal to 1. In other words,

$$\sum_{i=1}^{N} w_{ij} = 1, \forall j = 1\ to\ N. \tag{2}$$

The value of a bank i's interbank debt holdings against other banks, noted as, A_i^B, is given by,

$$A_i^B = \sum_{j=1}^{N} w_{ij} L_j^B, \tag{3}$$

where L_j^B is the interbank liability of a bank j.

The network of a bank i's debt holdings against industrial sectors, aggregated over all non-financial firms, is formed for N banks and M sectors. Let s_{ij}, where $i = 1$ *to* N and $j = 1$ *to* M, denote the fraction of a bank i's debt exposure to a sector j. The value of a bank i's holdings of debt securities against non-financial firms is given as,

$$A_i^I = \sum_{j=1}^{M} s_{ij} I_j, \tag{4}$$

where I_j represents the value of a singe share invested in a sector j.

Generally speaking, large banks are more diversified in their loans towards firms, whereas medium and small banks are more likely to concentrate on specific sectors for geometric and other possible reasons. To model this property, we put medium and small banks into different groups, and for each group, we randomly generate a subset of sectors in which banks in this group may invest. As a result, Equation (3) establishes the interbank holding connections within the banking system, while Equation (4) forms the channel of common exposure connections.

2.2 Dynamic Evolution

In this section, we extend our previous model to allow for dynamic evolution and external financial shocks. We begin with the evolution of independent balance sheet items and then move to dependent items. Four independent terms in our reduced form balance sheet include industrial debt holdings, cash & cash equivalents, deposits, and interbank liabilities.

2.2.1 Cash & Cash Equivalents

We begin with the dynamic evolution of cash. Note that in our model, the cash term is interpreted as the sum of all highly liquid low-risk assets. Therefore, this term reflects more financing and investing information than the common cash term displayed in a full balance sheet.

Since the cash term stand for low risk assets that are highly liquid, we incorporate regular fluctuations modeled by jump process,

$$dC_{jt} = C_{jt} dJ_{jt}, \tag{5}$$

where dJ_{jt} are compound Poisson processes.

Although cash shocks for different banks in the real world have memory and are correlated with each other, it is difficult to capture those properties precisely here. Therefore, we customize the cumulative size function of the compound Poisson process, Y_{jt}, to allow us to capture the correlation briefly while not to increase the model complexity dramatically.

In general, Y_{jt} is in the form of

$$Y_{jt} = \sum_{i=1}^{N_{jt}} D_i, \tag{6}$$

where N_{jt} is a Poisson point process that is specific for a firm j, and D_i are i.i.d random variables (usually Gaussian distributed) which measure the size of each jump.

To capture "shock memory" among different epochs, Equation (6) is modified as

$$Y_{jt} = \sum_{i=1}^{N_t} X_{ji} D_i, \tag{7}$$

where N_t is a Poisson point process, and X_{ji} are i.i.d. Bernoulli distributed random variables. Common Poisson point processes allow multiple banks to be affected simultaneously, and the Bernoulli distributed random variables determine specific banks that are stressed.

2.2.2 Interbank Holdings

The evolution of interbank debt holdings is approximated with debt duration, convexity and the interest rate dynamics. The interest rate is decomposed into two parts, the base rate, r_t, and the credit spread, s_t,

$$dr_t = \alpha_r(\bar{r} - r_t)dt + \sigma_r \sqrt{r_t} dW_t, \tag{8}$$

$$ds_t = \alpha_s(\bar{s} - s_t)dt + \sigma_s \sqrt{s_t} dZ_t. \tag{9}$$

The interest rate, r_t^l, for a bank with a credit rating of l is taken as,

$$r_t^l = r_t + \alpha^l s_t, \tag{10}$$

where α^l is the credit rating coefficient.

The dynamic change of market value of interbank debt for a bank i is then given by,

$$dL_{it}^b = -D_i^b L_{it}^b dr_t^l + \frac{1}{2} C_i^b L_{it}^b dr_t^{l2}. \tag{11}$$

As defined in Equation (4), the value of interbank debt holding held by a bank i is taken as,

$$A_{it}^B = \sum_{j=1}^{N} w_{ij} L_{jt}^B, \tag{12}$$

2.2.3 Industrial Loans

The dynamic evolution of industrial loans is associated with the change of a single share's value, I_{jt}, invested in a sector j. Describing the details of debt investment in different industrial sectors is far beyond the scope of this paper. For simplicity, we use joint mean reversion jump-diffusion processes to model the share value of debt in different industrial sectors.

$$dI_{jt} = \alpha(I_{j\mu} - I_{jt})dt + \sigma_j I_{jt} dW_{jt} + I_{jt} dJ_{jt}, \tag{13}$$

where W_{jt}, $j = 1$ *to* M, are correlated Wiener processes that capture correlations among different industrial sectors, and J_{it} are compound Poisson processes that capture regular jumps within different industrial sectors. To calibrate the correlation of the jump processes across industrial sectors, we apply the similar method as we do in modeling the evolution of cash & cash equivalents. The dynamic change of a bank i's industrial loans is given by,

$$dA^I_{it} = \sum_{j=1}^{M} s_{ij}(dI_{jt} + dI^s_{jt}), \tag{14}$$

where dI^s_{jt} is the change of a share debt value in industry j at time t, resulting from industrial shocks.

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

$$E_{it} = C_{it} + A^B_{it} + A^I_{it} - D_{it} - L^B_{it}. \tag{15}$$

2.2.4 Credit Rating

Since we have defined credit rating in our model (Equation (10)), it is natural to think about what will happen if bank credit ratings are allowed to change over time. The Altman Z-score (1968) [4] is a statistical tool used to measure the likelihood that a company will go bankrupt based on balance sheet items, such as working capital, and total assets.

$$Z - Score = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E, \tag{16}$$

where A is the ratio of working capital to total assets, B is the ratio of retained earnings to total assets, C is the ratio of EBIT to total assets, D is the ratio of market value of equity to total liabilities, and E the ratio of sales to total assets.

Given the limitation of our model, we can only compute A and D to approximate Z-score and use it as a measure for credit rating migration,

$$Z - Score_r = 1.2A + 0.6D. \tag{17}$$

We first compute the initial measure of credit rating, $Z - Score_r$, for each bank. During the simulation, once a bank's $Z - Score_r$ reaches 90% (or 111%) of its initial value, we will downgrade (or upgrade) its credit rating, and use the updated Z-Score value to replace the initial one. Since all banks are rated between AAA and BBB, there is no upgrade for AAA rating, and no downgrade for BBB rating.

2.3 Financial Shocks & Stress Test

Besides the regular evolution of balance sheet items we modeled above, we also demonstrate how the model can be used to set up stress testing for our banking system. In stress test scenarios, we include sharp declines of either industrial loans or cash holdings, by a certain extreme amount at a predetermined time.

According to Dodd-Frank Act Stress Test 2017 report [33], the adverse and severely adverse scenarios used in stress test are not forecasts, but rather hypothetical scenarios designed to assess the strength of banking organizations and their resilience to an unfavorable economic environment. Therefore, we created and tested the following scenarios:

1. -10% shocks to a random number of industrial sectors at day 20.
2. -10% shocks to a random number of industrial sectors at day 20 and day 200.
3. -10% shocks to a random number of industrial sectors and -15% cash shock to a random number of large banks, both at day 20.

The stress testing scenarios we create are reasonable choices given the regulatory requirements and historical financial crises. On March 10, 2000, the NASDAQ Composite peaked at 5,132.52, but fell 78% in the following 30 months [13]. The 2007-2008 financial crisis was the biggest shock to the US banking system since the 1930s and raised deep concerns regarding liquidity risk [14]. 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. 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.

2.4 Bank Failures and CoCo Debt

Once the shareholders' equity value of a bank falls below zero, the bank is considered to be bankrupt. Other banks that hold the debt issued by the failing one get their debt repaid at a recovery rate. Such a propagation effect increases the financial distress faced by connected banks. Moreover, the financial distress can also spread through possible fire-sale of assets when the stressed bank is insolvent [7].

When a bank holds CoCo debt, it can serve as an emergency liquidity cushion, which will protect the debt-issuing bank from financial distress, and thus increase the banking system stability. In our model, L^C represents the CoCo debt. Every bank is required to hold a certain amount of CoCo debt which equals to a fraction of its risky assets that comprise the interbank debt holdings, A^B, and common debt industrial exposures, A^I. Before triggered, CoCo debt behaves like common debt, and its book value remains constant.

Under certain conditions, CoCo debt will be triggered, and its entire bulk automatically converts into common equity shares. There is no CoCo trigger design that is universally acknowledged as the best one, as different designs will show different pros and cons when it comes to different financial stress. In this paper, we take account of two kinds of trigger designs, namely, a naive bank level single trigger and a dual-trigger, and compare their impact on the robustness of the banking system.

Under the design of a single trigger, CoCo debt of a bank is converted into common equities once its own equity-to-asset ratio fall bellow a certain threshold [17]

$$\frac{E_{it}}{TA_{it}} \leq \alpha_i, \tag{18}$$

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

A dual-trigger adds a systemic trigger at the outer layer to monitor the equity adequacy from the view of the whole banking system. This systemic trigger is set as follows,

$$\left\langle \frac{E}{TA} \right\rangle_t \leq \beta, \tag{19}$$

where TE and TA denotoe the total equity and total asset of banking system, repsectively. β is the threshold value. Under such a design, CoCo debt conversion of individual banks can not happen unless the systemic trigger is activated first, even if naive bank triggers are already reached. Thus, we make a trade-off between the protection of individual bank failures and the contribution to the stability of the whole banking system, given the conversion of CoCo debt.

2.5 Banking Systemic Risk

The core of our research is to address systemic risk of the banking system, it is crucial to define an appropriate measure for it. Different risk measures focus on different risk prospectives, yet not all of them work for systemic risk. The conditional expected default rate is defined as the proportion of all individuals in good standing at the beginning that are expected to default, conditional on a given event or environment. This measure of risk is straightforward and works perfectly when the default event is the main consideration. However, it contains little information on the status of the surviving banks, and thus fails to measure the health of the whole system.

In this paper, apart from counting the number of bank failures, we use a widely acknowledged systemic risk measure in banking and network science areas, namely, the conditional value at risk (CoVaR) [1]. The conditional value at risk, $CoVaR_q$, is defined as the qth percentile of the value of the portfolio conditional on a given shock. Mathematically, it can be expressed as,

$$Pr(X_i \leq CoVaR_q^{Shock} | Shock) = q\%. \tag{20}$$

More often, people use $\Delta CoVaR_q$, the difference between value at risk VaR_q and conditional value at risk $CoVaR_q^{Shock}$, to measure systemic risk since it ignores the impact of baseline. The larger the $\Delta CoVaR_q$, the higher the risk,

$$\Delta CoVaR_q = CoVaR_q - CoVaR_q^{Shock}. \tag{21}$$

3 Theoretical Simulation

In this section, we apply our model to purely Monte Carlo simulated data. The size of our simulated banking network is set to be 40, with 5 large banks and 35 medium ones. On one hand, the size of 40 is large enough to contain relevant interactive information; one the other, it is not too expensive to simulate. We calibrate several key financial and accounting ratios from a bank's financial statement and use them to generate a reduced form balance sheet for the purpose of simulation. These features are listed in Table 1.

We set two additional rules to make our reduced balance sheet more representative. First, the total size of interbank debt holdings of a single bank is set to be 15 times the size of its own debt issuance held by others. Second, to illustrate the clustering nature of bank investments, large banks are assumed to have a diversified industrial debt holdings, whereas medium banks only hold debt from a subset of industrial sectors.

Table 1: Captured Key Statistics for a Typical Balance Sheet

Key Statistics	Value
Leverage Ratio	10%
Debt to Deposit Ratio	7.5%
Average Liability Duration	1.5
Long Term Base Interest Rate	1.47%
Long Term BBB Debt Risk Premium	3.43%

The stress test scenarios are described in Section 2.3. In each scenario, we run 10,000 times of simulations for the banking system under three cases: without CoCo debt, with single trigger CoCo debt, and with dual-trigger CoCo debt. Two systemic risk measures, the average number of bank failures and ΔCoVaR for equity value at 5% level, are estimated for each case.

Table 2 shows the key statistics for the theoretical result under the first stress test scenario, in which the banking system is experienced with only one industrial stress. Panel A of Table 2 reports the average number of bank failures and equity ΔCoVaR in the banking system under three cases: with no CoCo debt, with conversion of single trigger CoCo debt, and with conversion of dual-trigger CoCo debt. Panel B compares three cases by reporting the differences of bank failures and ΔCoVaR, along with their statistical significance. As one would expect, we find that compared to the case where no CoCo debt is held, the conversion of CoCo debt, with either single trigger or dual-trigger, significantly reduces the average number of bank failures, decreases the ΔCoVaR, and thus mitigates the banking systemic risk in the banking system level.

Table 2: Theoretical Results with One Industrial Shock

A: Systemic Risk Measures	Banking System			Large Banks			Medium Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single	Dual	None	Single	Dual	None	Single	Dual
Mean of bank failures	1.8817	0.1752	0.9160	0.0001	0	0	1.8816	0.1752	0.9160
Equity $\Delta CoVaR_{0.05}$	0.1629	0.0830	0.0735	0.1218	0.1035	0.1052	0.1948	0.0717	0.0619

B: Significance Test	Banking System			Large Banks			Medium Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single
Mean of bank failures	-1.7064***	-0.9657***	0.7408***	-0.0001	-0.0001	0.0000	-1.7063***	-0.9656***	0.7408***
	(-46.52)	(-24.38)	(36.98)	(-1.00)	(-1.00)	(.)	(-46.53)	(-24.38)	(36.98)
Equity $\Delta CoVaR_{0.05}$	-0.0799***	-0.0894***	-0.0095*	-0.0183**	-0.0166**	0.0017	-0.1232***	-0.1329***	0.-0097*
	(11.10)	(12.61)	(1.88)	(2.75)	(2.54)	(-0.27)	(13.48)	(15.54)	(1.70)

Note: Equity amount is normalized by initial equity value

Note: Bootstrap t-statistics are reported in parentheses

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

As shown in column (1) and (2) in Panel B of Table 2, introducing single trigger and dual-trigger CoCo debt to the system reduces the average number of bank failures by 1.7064 and 0.9657. Meanwhile, equity ΔCoVaR is decreased by 7.99% and 8.94% in the presence of single trigger CoCo and dual-trigger CoCo, respectively. The coefficients are all significant at 1% level. The results are similar when we consider only the medium banks. For large banks, we do not observe a decrease in bank failures because no large bank fails in this stress test. However, we do observe a decrease in large banks' equity ΔCoVaR. Therefore, we conclude that both types of CoCo debt provide certain protection for the large banks.

Although both single trigger CoCo debt and dual-trigger CoCo debt provide protection to the banking system, their effectiveness are not the same. Differences in their protection are compared in Column (3), (6) and (9) of Panel B in Table 2. According to Column (3), while the single trigger CoCo protects the banking system better in terms of the number of bank failures, (single trigger design helps to save 0.7408 more banks than dual-trigger one), it is the dual-trigger CoCo that outperforms when considering the equity ΔCoVaR of banking system, witnessing a 0.95% improvement (a reduction of 0.95% in ΔCoVaR). Similar results are observed within medium banks. However, we do not observe a difference of two designs of CoCo trigger in either preventing bank failures or narrowing down equity ΔCoVaR within large banks.

Table 3: Theoretical Results with Two Industrial Shocks

A: Systemic Risk Measures	Banking System			Large Banks			Medium Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single	Dual	None	Single	Dual	None	Single	Dual
Mean of bank failures	4.6103	0.6965	1.7784	0	0	0	4.6103	0.6965	1.7784
Equity $\Delta CoVaR_{0.05}$	0.3138	0.1942	0.1586	0.2574	0.2017	0.1996	0.3660	0.1915	0.1282

B: Significance Test	Banking System			Large Banks			Medium Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single
Mean of bank failures	-3.9138***	-2.8319***	1.0819***	0.0000	0.0000	0.0000	-3.9138***	-2.8319***	1.0819***
	(-68.90)	(-48.05)	(34.22)	(.)	(.)	(.)	(-68.90)	(-48.05)	(34.22)
Equity $\Delta CoVaR_{0.05}$	-0.1195***	-0.1552***	-0.0356***	-0.0557***	-0.0578***	-0.0021	-0.1744***	-0.2378***	-0.0633***
	(16.46)	(21.72)	(6.28)	(9.09)	(9.77)	(0.39)	(19.90)	(27.37)	(9.46)

Note: Bootstrap t-statistics are reported in parentheses

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

To insure the robustness of our results, we also provide the results where we doubled the industrial shocks. Table 3 provides similar results as in Table 2, only with larger economic magnitude and higher statistic significance. Further, financial shocks may take place at both industrial sectors and other investment activities. Since we are creating a reduced form balance sheet, all of those impacts resulting from investing and financing activities but not captured by our balance sheet model are reflected in the term of "cash & cash equivalents". Therefore, in the following test we allow industrial shock and cash shock to happen simultaneously.

We give external cash shocks only to large banks since they are the center of the banking system in our simulation study, as described in Section 2.3. The results are shown in Table 4. Likewise, we observe that the conversion of both trigger designs increases the stability of banking system and that of medium banks in terms of the two systemic risk measures. Moreover, since large banks are directly shocked in this scenario, we can confirm the positive impact of CoCo debt conversion on protecting large banks from failures.

However, compared with scenario 1 of only one industrial stress, the differences when comparing two CoCo designs in terms of ΔCoVaR have changed. We observe that, in column (3) of Panel B Table 4, the positive effect of dual-trigger design is no longer significant in banking system level. This change is caused by the large bank subsample. While the dual trigger CoCo still performs 2.23% better in reducing ΔCoVaR for medium banks, single trigger CoCo performs better for large banks, beating dual trigger CoCo by 11.71%. We infer the following mechanism behind this finding. Since large banks are receiving both cash and industrial shocks together, they are more likely to be the first ones that become financially distressed. The CoCo debt with a dual-trigger finds it difficult to convert, as in most cases, the systemic trigger is not achievable, though an individual bank is already in danger. As a result, the design of dual-trigger fails to reduce systemic risk for the subgroup of large banks. It is the size effect that results in such a discrepancy for large banks, and thus a limitation of our theoretical model.

Table 4: Theoretical Results with Industrial & Cash Shocks

A: Systemic Risk Measures	Banking System			Large Banks			Medium Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single	Dual	None	Single	Dual	None	Single	Dual
Mean of bank failures	2.0508	0.1910	0.8026	0.1840	0.0008	0.0111	1.8668	0.1902	0.7915
Equity $\Delta CoVaR_{0.05}$	0.3447	0.1682	0.1817	0.5645	0.2984	0.4154	0.2008	0.0726	0.0503

B: Significance Test	Banking System			Large Banks			Medium Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single
Mean of failures	-1.8598***	-1.2482***	0.6116***	-0.1832***	-0.1729***	0.0103***	-1.6766***	-1.0752***	0.6014***
	(-46.21)	(-29.42)	(31.44)	(-25.88)	(-24.04)	(7.63)	(-45.87)	(-27.64)	(31.12)
Equity $\Delta CoVaR_{0.05}$	-0.1765***	-0.1630***	0.0135	-0.2661***	-0.1490***	0.1171***	-0.1282***	-0.1505***	-0.0223***
	(21.87)	(20.42)	(-2.52)	(34.32)	(18.29)	(-16.61)	(13.94)	(17.79)	(3.98)

Note: Bootstrap t-statistics are reported in parentheses

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

In general, our theoretical simulations suggest that while the conversion of CoCo debt of both trigger designs increases the stability of the banking system, their performances are different. Single trigger CoCo performs better in protecting individual and earlier stressed banks, whereas dual-trigger CoCo is a better choice when we focus on the whole banking system, and those banks who suffer in the later phrase of financial stress. Therefore, we claim that there should be a trade-off in the risk management objective when considering different designs of CoCo debt.

4 Empirical Adoption and Data Collection

In this section, we calibrate the network model constructed in Section 2. However, to the best of our knowledge, there is no publicly available data for inter-debt holdings among financial institutions. To measure this interbank connectedness, the 13-F filings made to the US Securities and Exchange Commission (SEC) provide valuable information on inter-equity holdings among US financial institutions. Therefore, to take advantage of 13-F filings, we modify and approximate the network model of interbank debt holdings with that of interbank equity holdings.

4.1 Model Modification

The balance sheet, as shown in Equation (15), is modified in the following ways: total assets on the balance sheet of a bank holding company (BHC) include cash & cash equivalents, C_{it}, government bonds, G_{it}, total loans, A^L_{it}, and equity securities against other BHCs and non-financial firms. Total liabilities of each BHC include deposits, D_{it}, common debt, L^b_{it}, and CoCo debt, L^c_{it}, with time varying value determined in terms of debt durations and convexities. The dynamic evolution of a BHC i's equity value, E_{it}, is given as,

$$E_{it} = C_{it} + G_{it} + A^L_{it} + E^f_{it} + E^b_{it} - L^b_{it} - L^c_{it} - D_{it}, \tag{22}$$

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

The value of government bonds, total loans, and deposits are assumed to follow a linear trend, while the change of market value of cash & cash equivalents held by a BHC i is assumed to follow a geometric brownian motion. The market value of common debt, L^b_{it}, and CoCo debt, L^c_{it}, of a BHC i with credit rating, l, can be approximated as follows,

$$dL^b_{it} = -D^b_i L^b_{it} dr^l_t + \frac{1}{2} C^b_i L^b_{it} dr^{l2}_t, \quad \forall i = 1 \ to \ N, \tag{23}$$

$$dL^c_{it} = -D^c_i L^c_{it} dr^l_t + \frac{1}{2} C^c_i L^c_{it} dr^{l2}_t, \quad \forall i = 1 \ to \ N, \tag{24}$$

where D^b_i and D^c_i denote durations of common debt and CoCo debt, respectively. Similarly, C^b_i and C^c_i represent convexities of common debt and CoCo debt, respectively.

Different from w_{ij} and s_{ij} denoted in Equation (3) and Equation (4), here we define w_{ij}, $i, j = 1$ to N, and s_{ij}, $i = 1$ to N and $j = 1$ to M, as the percentage of a BHC j's equity securities held by a BHC i and the fraction of a BHC i's equity exposure to a sector j, respectively. The value of a BHC i's equity holdings against other BHCs, noted as E^b_{it}, can be calculated as,

$$E^b_{it} = \sum_{j=1}^{N} w_{ij} E_{jt}, \quad \forall i = 1 \ to \ N, \tag{25}$$

where E_{jt} is the equity value of a BHC j. Equity holdings against non-financial firms, E^f_{it}, is

$$E^f_{it} = \sum_{j=1}^{M} s_{ij} I_{jt}, \quad \forall i = 1 \ to \ N, \tag{26}$$

where I_{jt} represents an index value for a sector j, assumed to follow another jointly correlated geometric brownian motions since we are modeling equity securities,

$$dI_{jt} = u_j I_{jt} dt + \sigma_j I_{jt} dW_t, \quad \forall j = 1 \ to \ M. \tag{27}$$

4.2 Data Collection

After exploring both the BHCs participating in the Fed's Stress Testing program and BHCs along US east coast, we determine BHCs based on availability of 13-F filings in the SEC EDGAR system.

We construct a banking system of 36 BHCs along the US east coast, as the biggest BHCs such as Citigroup, JP Morgan Chase & Co., and Bank of America Corp, are headquartered in this region. BHCs are grouped into four subgroups based on their total assets. Consistent with the Mid-size Bank Coalition of America Research Report (2013) [27], the size definition is shown in Table 5.

Table 5: 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

Our data acquisition relies on four resources, namely, US SEC EDGAR system, Federal Financial Institutions Examination Council (FFIEC), Capital IQ terminal, and Bloomberg terminal. From the FFIEC, we collect the quarterly textual call reports of 36 banks for the past 10 years, from 2007Q1 to 2016Q4, to construct balance sheets and estimate corresponding parameters. The interbank equity holdings and common equity exposures are calibrated using the data from SEC 13-F filings. From a Bloomberg terminal, we obtain Moody's Ratings of the 36 BHCs in our banking system, as shown in Table 6. We ignore the rating adjustments for simplicity and thus, have 21 BHCs with ratings of A, 14 with Baa, and 1 with Ba.

Table 6: Moody's Ratings for BHCs

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

For 36 BHCs in our network model, 25 of them participate in the Fed's Stress Testing program. The network of the Fed's Stress Testing BHCs is relatively complete. Table 7 and Table 8 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[1].

Table 7: 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

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,

[1]https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm

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 significant difference. 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.

Table 8: 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

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 [19]. 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.

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,

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

The total liabilities to total assets ratio and deposit to total assets ratio are obtained from call reports, respectively. The modified common debt, $\hat{L}_{it}^b$, is computed as the difference between the modified total liabilities, $\hat{TL}_{it}$, and the modified deposits, $\hat{D}_{it}$.

5 Empirical Study

In this section, we conduct Monte Carlo simulation for the modified model calibrated in Section 4. Similar to stress test scenarios in the Theoretical part, we tested the following two scenarios:

1. -10% shocks to a random number of industrial sectors at day 20 and day 200.

2. -10% shocks to a random number of industrial sectors and -10% cash shock to a random number of large & super large BHCs at day 20 and day 200.

One sector suffering an industrial shock is transmitted to connected sectors at 60% of the original shock, while one BHCs suffering a cash shock is transmitted to connected BHCs at 80% of the original one. The single trigger is set to be 40% of the initial equity-to-asset ratio while the systemic trigger for the dual-trigger design is set to be 60% of the initial equity-to-asset ratio of the whole banking system.

Table 9 shows the key statistics for the empirical result when the banking system is experienced with only industrial shocks. Panel A of Table 9 reports the average number of bank failures and equity ΔCoVaR in the banking system. Panel B compares the differences in bank failures and ΔCoVaR among three cases: with no CoCo debt, with conversion of single trigger CoCo debt, and with conversion of dual-trigger CoCo debt. Consistent with our findings in theoretical part, the conversion of CoCo debt, with either single trigger or dual-trigger, significantly improves the stability of the banking system by reducing both the average number of bank failures and equity ΔCoVaR.

Table 9: Empirical Result with Two Industrial Shocks

A: Systemic Risk Measures	Banking System			Large & Super Large BHCs			Medium & Small BHCs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single	Dual	None	Single	Dual	None	Single	Dual
Mean of bank failures	3.3417	2.1583	3.1469	1.7489	1.0608	1.5921	1.5928	1.0975	1.5548
Equity $\Delta CoVaR_{0.05}$	0.1162	0.0950	0.0842	0.1510	0.1202	0.1053	0.0447	0.0443	0.0437
B: Significance Test	Banking System			Large & Super Large BHCs			Medium & Small BHCs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single
Mean of bank failures	-1.1834***	-0.1948**	0.9886***	-0.6881***	-0.1568*	0.5313***	-0.4953***	-0.0380	0.4573***
	(-9.2413)	(-1.7020)	(7.6684)	(-9.7149)	(-1.8935)	(8.4882)	(-7.4704)	(-1.3339)	(6.5160)
Equity $\Delta CoVaR_{0.05}$	-0.0213***	-0.0320***	-0.0108*	-0.0312***	-0.0461***	-0.0149**	-0.0007	-0.0011	-0.0005
	(3.5251)	(4.9057)	(1.7147)	(3.9337)	(6.1343)	(2.0871)	(0.2660)	(0.3623)	(0.2054)

Note: Bootstrap t-statistics are reported in parentheses

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

As shown in column (1) and (2) in Panel B of Table 9, the average number of bank failures, compared when no CoCo debt is held, are reduced by 1.1834 and 0.1948, in the presence of single trigger CoCo and dual-trigger CoCo. The coefficient are significant in 1% and 5% level. Also, the equity ΔCoVaR witnesses a reduction of 2.13% and 3.20%, respectively, owing to the conversion of two types of CoCo debt. The coefficients are both significant at 1% level. For subgroups of BHCs, different from the results in theoretical part, the decrease in ΔCoVaR from the conversion of CoCo debt is only significant within large & super large BHCs but not significant for medium & small ones. Also, dual-trigger CoCo does not effectively reduce the bank failures for medium & small BHCs since the coefficent of -0.0380 in column (8) Panel B is not statistically significant.

Column (3), (6) and (9) in Panel B of Table 9 report the comparisons of two designs of CoCo trigger for banking system and two subgroups. CoCo debt of single trigger is better at saving individual banks by an average of 0.9886 from the banking sytem level. In contrast, CoCo debt of dual-trigger outperforms single trigger by 1.08%, whith is significant at 10% level, in terms of ΔCoVaR reduction. Similar results are observed within large & super large BHCs. For medium & small BHCs, single trigger is still the winner in preventing BHCs from failing but the difference in two designs given ΔCoVaR is obscure since the coefficient of -0.05% is not statistically significant.

Table 10: Empirical Result with Industrial & Cash Shocks

A: Systemic Risk Measures	Banking System			Large & Super Large BHCs			Medium & Small BHCs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single	Dual	None	Single	Dual	None	Single	Dual
Mean of bank failures	3.3751	2.1636	3.1621	1.7590	1.0636	1.5961	1.6161	1.1000	1.5660
Equity $\Delta CoVaR_{0.05}$	0.1322	0.1074	0.0950	0.1722	0.1374	0.1193	0.0466	0.0466	0.0459
B: Significance Test	Banking System			Large & Super Large BHCs			Medium & Small BHCs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single	Single-None	Dual-None	Dual-Single
Mean of bank failures	-1.2115***	-0.2130**	0.9985***	-0.6954***	-0.1629**	0.5325***	-0.5161***	-0.0501*	0.4660***
	(-7.8084)	(-2.6679)	(6.2456)	(-9.6613)	(-2.4686)	(8.4566)	(-8.7689)	(-1.8033)	(6.4194)
Equity $\Delta CoVaR_{0.05}$	-0.0250***	-0.0373***	-0.0125**	-0.0351***	-0.0531***	-0.0183***	-0.0003	-0.0009	-0.0006
	(4.4387)	(6.2811)	(2.1167)	(4.9412)	(6.3115)	(2.7287)	(0.1047)	(0.2998)	(0.2422)

Note: Bootstrap t-statistics are reported in parentheses

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

Table 10 summarizes the results under second scenario where industrial shocks and cash shocks happen simultaneously. The results are similar to what we have observed in Table 9 except that dual-trigger CoCo also saves medium & small BHCs by 0.0501, significant at 10% level.

Consistent with theoretical results in Section 3, in empirical study CoCo debt performs well in controlling bank failures and increase system stability. With the conversion of CoCo debt under financial stress, both the average number of bank failures and equity ΔCoVaR are reduced significantly. Further, the design of a dual-trigger is more efficient in maintaining the banking system health, especially for the group of large & super large BHCs, whereas the design of a single trigger is better at preventing individual BHCs from failure. However, the effect of CoCo debt conversion of either trigger deigns is obscure within medium & small BHCs. Due to the data limitation, the evolution of large BHCs calibrated among empirical banking network is more volatile than that of medium and small ones. It is easier for large & super large BHCs to achieve the trigger threshold and thus, activate the conversion. Moreover, the design of all-or-nothing conversion mechanism is another drawback since an optimal amount of CoCo debt held and how much to convert once triggered for individual BHC remain a research question under investigation.

6 Conclusion and Discussion

The global financial crisis of 2008 illustrated the challenge of contagion of bank failures. As a response to the crisis, contingent convertible (CoCo) debt appeared promising in alleviating the financial stress of the banking system, by automatically converting into 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 ownership relations are described as 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 alleviation of the banking systemic stress. We test our simulated and 13-F captured networks with several financial stressed scenarios. Moreover, comparing two designs of trigger, while CoCo debt with a single trigger offers a smaller number of average bank failures, it is the CoCo debt with a dual-trigger that outperforms in controlling systemic risk in terms of the $\Delta CoVaR$ when external shocks are spread in the banking network. The result of empirical 13-F captured network study is consistent with these result in directions. This difference resulted from two designs of CoCo triggers is essentially a trade-off in addressing systemic risk. These findings support the effectiveness of CoCo debt in controlling the spread of local stress to the banking system.

Our main contributions are to apply the network model to study CoCo debt and to calibrate the network model of the banking system, with both simulated and 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 conversion may not be the optimal one for different banks. Also, the appropriate trigger level should be further explored.

Indeed, although we have shown the positive impact of holding CoCo debt on mitigating banking systemic risk, we have to be cautious about their self-saving properties once triggered in the real market. According to Deutsche Bundesbank and Axiom Alternative Investments (2018) [12], this kind 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 is different: debt is either converted to equity or directly written-off. Trigger levels also vary between and within countries, and can even be different for banks and their subgroups. Those issues all challenge the overall impact of CoCo debt when issued in the US. We leave these investigations for future research.

References

[1] Tobias Adrian and Markus K. Brunnermeier. Covar. *American Economic Review*, 106(7):1705–1741, 2016. Predicting and measuring a financial institution's contribution to systemic risk that internalizes externalities and avoids procyclicality.

[2] Franklin Allen and Douglas Gale. Financial contagion. *Journal of political economy*, 108(1):1–33, 2000.

[3] Linda Allen and Yi Tang. What's the contingency? a proposal for bank contingent capital triggered by systemic risk. *Journal of Financial Stability*, 26:1–14, 2016.

[4] Edward I Altman. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, 23(4):589–609, 1968.

[5] Kartik Anand, Prasanna Gai, Sujit Kapadia, Simon Brennan, and Matthew Willison. A network model of financial system resilience. *Journal of Economic Behavior & Organization*, 85:219–235, 2013.

[6] George O Aragon, Michael Hertzel, and Zhen Shi. Why do hedge funds avoid disclosure? evidence from confidential 13f filings. *Journal of Financial and Quantitative Analysis*, 48(05):1499–1518, 2013.

[7] Efraim Benmelech and Nittai K Bergman. Bankruptcy and the collateral channel. *The Journal of Finance*, 66(2):337–378, 2011.

[8] Richard M Bookstaber and Dror Y Kenett. The multilayer structure of the financial system. Technical report, Office of Financail Research, 2016.

[9] Celso Brunetti, Jeffrey H. Harris, and Shawn Mankad. Bank holdings and systemic risk. The Board of Governors of the Federal Reserve System, 2018.

[10] Charles W Calomiris and Richard J Herring. How to design a contingent convertible debt requirement that helps solve our too-big-to-fail problem. *Journal of Applied Corporate Finance*, 25(2):39–62, 2013.

[11] John C Coffee. Bail-ins versus bail-outs: Using contingent capital to mitigate systemic risk. *Available at SSRN*, 2010.

[12] Nicholas Comfort and John Glover. Riskiest bank debt could spark market turmoil, bundesbank says @(online). Technical report, Bloomberg, March 2018. Available at `https://www.bloomberg.com/news/articles/2018-03-27/riskiest-bank-debt-could-spark-market-turmoil-bundesbank-says`.

[13] Wikipedia contributors. Dot-com bubble — wikipedia, the free encyclopedia, 2017. [Online; accessed 14-December-2017].

[14] Wikipedia contributors. Financial crisis of 2007?2008 — wikipedia, the free encyclopedia, 2017. [Online; accessed 14-December-2017].

[15] Darrell Duffie. Contractual methods for out-of-court restructuring of systemically important financial institutions. *Submission Requested by the US Treasury Working Group on Bank Capital, draft of November*, 9, 2009.

[16] Mark J Flannery. Market-valued triggers will work for contingent capital instruments. *Solicited Submission to US treasury working group on bank capital*, 2009.

[17] Mark J Flannery. Contingent capital instruments for large financial institutions: A review of the literature. *Annu. Rev. Financ. Econ.*, 6(1):225–240, 2014.

[18] Prasanna Gai. Systemic risk measurement and macroprudential policy: Implications for new zealand and beyond. *New Zealand Economic Papers*, 47(1):95–110, 2013.

[19] GICS. Global industry classication standard. Technical report, MSCI, Standard & Poor, March 2014. Available at `https://web.archive.org/web/20141219200846/http://www.msci.com/resources/factsheets/MSCI_Global_Industry_Classification_Standard.pdf`.

[20] Paul Glasserman and Behzad Nouri. Contingent capital with a capital-ratio trigger. *Management Science*, 58(10):1816–1833, 2012.

[21] Paul Glasserman and H Peyton Young. How likely is contagion in financial networks? *Journal of Banking & Finance*, 50:383–399, 2015.

[22] Stanislao Gualdi, Giulio Cimini, Kevin Primicerio, Riccardo Di Clemente, and Damien Challet. Statistically validated network of portfolio overlaps and systemic risk. *Scientific reports*, 6, 2016.

[23] Weilong Guo, Andreea Minca, and Li Wang. The topology of overlapping portfolio networks. *Statistics & Risk Modeling*, 33(3-4):139–155, 2016.

[24] Jesse Hamilton. Fed plans second effort at limiting banks' ties to one another @(online). Technical report, GARP, March 2016. Available at `http://www.garp.org/#!/risk-intelligence/all/all/a1Z400000031qT0EAI`.

[25] Oliver Hart and Luigi Zingales. How to make a bank raise equity. *Financial Times, February*, 7:2010, 2010.

[26] Leo Laikola. Societe generale tests first bail-in bonds in a nordic currency. Technical report, GARP, January 2017. Available at `http://www.garp.org/#!/risk-intelligence/all/all/a1Z40000003NfWLEA0`.

[27] MBCA. Comparisions ans similarities between mid-size and small banks. Technical report, The Mid-size Bank Coalition of America (MBCA), 2013.

[28] Robert L McDonald. Contingent capital with a dual price trigger. *Journal of Financial Stability*, 9(2):230–241, 2013.

[29] Kjell Bjorn Nordal and Nicolas Stefano. Contingent convertible bonds (cocos) issued by european banks. Technical report, Norges Bank, 2014. Available at `https://www.norges-bank.no/contentassets/7e3b516fc71a4f0aad2d4fd471d2282estaff_memo_19_2014.pdf`.

[30] George Pennacchi, Theo Vermaelen, and Christian CP Wolff. Contingent capital: The case of coercs. *Journal of Financial and Quantitative analysis*, 49(03):541–574, 2014.

[31] Edward S Prescott. Contingent capital: the trigger problem. *Available at SSRN*, 2012.

[32] Raghuram Rajan and Rodney Ramcharan. Financial fire sales: evidence from bank failures, 2014.

[33] Federal Reserve. Dodd-frank act stress test 2017: supervisory stress test methodology and results. *Accessed June*, 2017.

[34] SEC. Form 13f-reports filed by institutional investment managers, July 2017.

[35] Suresh Sundaresan and Zhenyu Wang. On the design of contingent capital with a market trigger. *The Journal of Finance*, 70(2):881–920, 2015.

[36] Steve Y Yang and Esen Onur. Interest rate swap market complexity and its volatility implication. *Available at SSRN*, 2017.