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Addressing Systemic Risk Using Contingent Convertible Debt - A Network Analysis

Research Highlights

1. Develop a reduced-form network model for bank inter-connectedness.
2. Implement the network model for a simulation analysis of systemic risk.
3. Evaluate the theoretical performance of contingent convertible debt.
4. Empirically calibrate the network modeling using 13 F and other bank data.
5. Validate the effectiveness of contingent convertible debt for systemic risk.

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

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Abstract: We construct a balance sheet network model to study the interconnectedness of a banking system. A simulation analysis of the buffer effect of contingent convertible (CoCo) debt in controlling contagion in a theoretical banking network model is followed by calibrating the model using 13F filings. We find that CoCo debt conversion significantly mitigates systemic risk, with a dual-trigger CoCo debt design being more effective in protecting the surviving banks. A two-tranche CoCo debt design combines the benefits of single and dual-trigger CoCo debt. The trade-offs in different designs of CoCo triggers can be evaluated in a network simulation model, as developed in this work.

Keywords: finance, contingent convertible debt, systemic risk, 13F filings, network model, simulation analysis

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JEL Codes: G21, D85, C15, G32

1 Introduction

The 2008 financial crisis highlighted the threat of contagion in bank failures, which could lead to significant systemic risk of a potential collapse of the banking system. The fall of Lehman Brothers, bailout of Bear Stearns and severe financial stress experienced by Citigroup are 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. CoCo debt holds the potential of reducing systemic risk by recapitalizing stressed banks [6] and its appropriate design can likely reduce firms' incentives to take on tail risk [29]. In the US, the 2010 Dodd-Frank Act calls for the regulators to study the effectiveness of CoCo debt, while internationally, Basel Committee on Banking Supervision defines several trigger events for these instruments [42]. Academics mostly agree that the instrument can enable banks to raise buffer capital at a lower cost compared to equity issuance [45].

Three main features determine how CoCo debt may be used, namely, its conversion trigger criteria, the conversion mechanism, and the form in which it exists prior to conversion [42]. Among the three features, the trigger criteria are considered to be the most important and the most complicated, as an ideal trigger design should be objective, informative, timely, and independent of regulators' interventions or manipulations [62]. For any design of a CoCo debt instrument, the fundamental challenge is evaluating the efficacy of the instrument in mitigating systemic risk. In this paper, we study the impact of CoCo debt conversion on mitigating the systemic risk of a banking system, and how this impact differs under different designs of CoCo triggers, namely a single trigger, a dual trigger, and a double tranche. In order to assess the impact of CoCo debt conversion on systemic risk, we incorporate the interconnectedness of the banking system as a network of reduced-form balance sheets.

Almost 37 European banks had already issued CoCo debt by the end of 2017, with most using capital adequacy ratios to define the conversion triggers. During the pandemic of 2020, the value of CoCo bonds issued by European banks declined dramatically, thus testing the purpose and design of these instruments. Some banks, such as ING, Swedbank, planned to redeem their CoCo issues to smoothen worries. This raises new questions regarding the callability design embedded in these instruments, as regulatory pressure continued to urge banks to not hand over huge sums of cash to bondholders when they don't need to. Using accounting values for defining triggers was proposed to approximate the regulatory ratios [42]. However, accounting-based measures run the risk of being manipulated by the banks or end up lagging the true economic values. Pennacchi and Tchistyi (2019) [57] argue that CoCo debt triggers must be market values based in order to achieve timely conversions. Flannery (2009) [39] and Coffee (2010) [31] propose to use bank equity prices to identify trigger events, while Duffie (2009) [35] suggests the use of tangible common equity as a percent of tangible assets.

The use of CDS prices for defining CoCo triggers is suggested by Hart and Zingales (2013) [49], while Calomiris and Herring (2013) [25] propose a 90-day "quasi-market value of equity ratio" as a signal for conversion in order to utilize the best source of information for CoCo trigger. However, Prescott (2012) [59] refutes the market-value based design entirely, arguing that such a conversion trigger could get activated even when it is not necessary. A market-value based trigger can also imply that the equity holders are unable to choose an optimal conversion policy, where Sundaresan and Wang (2015) [62] demonstrate that market-value based trigger CoCo debt does not lead to a unique competitive equilibrium, unless ex ante value transfer at conversion is not expected. Davis et al. [34] provide experimental evidence by testing hypothetical CoCo debt data under different trigger regime scenarios. Tian (2016) [63] includes a call provision into the contract, where CoCo debt issuer has the right to redeem the contingent capital at any time, and proves that a unique price equilibrium exists if and only if the pre-conversion CoCo debt value is greater than its call option value.

It is suspected that CoCo conversion trigger defined in terms of a single bank's indicators would not effectively address the systemic risk concerns for the banking system [6]. Acharya et al. (2016) [1] argue that even when individual bank's risks are properly dealt with, the banking system may remain, or could be induced to become, fragile and vulnerable to large financial shocks. Therefore, a dual trigger contingent on both the aggregate banks' losses and an individual bank-specific capital ratio is proposed by Rajan and Ramcharan (2014) [60]. This conversion rule, however, ends up taking effect only after the banking sector has already entered a crisis mode. McDonald (2013) [54] includes 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) [58] propose a call option enhanced reverse convertible (COERC) design of CoCo debt.

In 2016, US Federal Reserve re-proposed long-delayed rules to limit the ties among Wall Street banks to address the "too-connected-to-fail" threat [48]. If institutional portfolios are too similar, it can trigger fire sales at a time of distress, which is an important channel for financial risk contagion contributing to systemic risk [46]. However, the complex and opaque nature of the modern financial system poses a considerable challenge for the analysis of the system's resilience [8]. Gofman (2017) [44] concludes that restricting interconnectedness among banks can improve stability.

In an attempt to address complexity arising from the 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 occur due to the nature of interconnections among the financial institutions [43]. Allen and Gale (2000) [4] pioneered the application of network analysis for evaluating system stability of interconnected financial institutions. Eisenberg and Noe (2001) [36] assess the extent of financial contagion arising from the structure of interbank liabilities in a network analysis. More recently, the framework of Eisenberg and Noe (2001) [36] has been generalized to account for more realistic cases [15] [27]. Banerjee et al. (2018) [13] provide bounds for price of debt where financial networks encode firm interconnection through debt claims, Banerjee et al. (2018) [12] develop a generalized extension for financial contagion under discrete and continuous time dynamics, and Kusnetsov et al. (2019) [52] evaluate systemic risk under interbank liabilities of multiple maturities.

Anand et al. (2013) [8] develop 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. Brunetti et al. (2018) [21] developed a novel approach to estimate the portfolio composition of banks from the daily interbank trades and equity returns, while Bookstaber and Kenett [19] use a multi-layer network framework, with layers representing assets overlaps, funding activity, and collateral based connections, for analyzing the emergence and propagation of risk within the financial system. Gualdi et al. (2016) [46] propose a new statistical method to assess the significance of overlapping portfolios, measured by the fraction of common asset holdings, for the highest risks of fire sales. Studies have examined correlation networks, and compared them with physical networks, of banks to find that correlation networks can forecast financial crises, while physical networks are able to forecast liquidity issues [22]. A socially optimal design of financial networks is also evaluated to tackle the trade-off between risk sharing and contagion [23].

Notwithstanding the benefits of applying network analysis to study the financial system, a lack of publicly available data to completely define the network structure poses a considerable challenge to these studies. The simulation analysis techniques utilized in our work are designed to analyze systems defined using partially available information. Banks' 13F filings with the US Securities and Exchange Commissions (SEC), also known as the Information Required of Institutional Investment Managers Form, provide valuable information on interbank equity holdings among US financial institutions[1]. The 13F filings data do not suffer from survivorship bias as portfolios are reported in each quarter regardless of a bank surviving another quarter, however the reports do not include short positions [47].

Two studies have applied 13F filings data to calibrate a financial system network. Gualdi et al. (2016) [46] propose 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. Guo et al. (2016) [47] analyze 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 is calibrated using quarterly 13F filings from 2003Q1 to 2012Q3. A cluster analysis reveals that the overlapping illiquid portions of the funds' portfolios become 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 its losses, and more importantly, to intervene in the spread of the stress of a bank to the entire banking system. A network representation describes banks as nodes and their inter-bank exposures as network edges. Failure of one or several BHCs in the network can affect the entire financial system through the network links. Our paper is the first, to best of our knowledge, to apply network analysis to the study of CoCo debt, where a banking system is viewed as a network of BHCs and non-financial firms connected due to their assets and liabilities. In this network, 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) [55] 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) [8] use a simplified balance sheet structure.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 [14]. In this paper, we adapt Anand et al.'s (2013) [8] model for creating a balance

[1]An institutional investment manager who exercises investment discretion over $100 million in Section 13(f) securities is required to report its quarterly holdings in Form 13F to the SEC within 45 days of each quarter end. See the SEC website for more information `https://www.sec.gov/fast-answers/answers-form13fhtm.html`.

sheet network model to study the interconnectedness of a banking system. Banks are denoted as nodes of the network and the inter-bank exposures are represented by network links. For a theoretical analysis of a banking network, a reduced-form balance sheet is constructed for each bank using key accounting ratios, such as leverage ratio, debt to deposit ratio, etc., obtained from typical banks' financial statements. Simulation analysis is an ideal tool to assess the behavior of a system under various conditions, when the actual system may not be experimented with, as well as when exhaustively complete data to describe the system may not be available [61] [40] [9].The theoretical banking network model is implemented and analyzed using simulation analysis to assess the impact of one or more bank failures on the system due to the inter-bank debt holdings linkages and channels of common industrial debt exposures. Through this analysis, we evaluate the effectiveness of specific designs of CoCo debt in controlling systemic risk, where two designs of CoCo debt trigger, namely, a single trigger and a dual trigger, are considered and compared with a dual tranche design of CoCo debt.

We apply the banking network model to a specific set of US banks and calibrate the network for these banks using empirical data on inter-bank equity holdings and common equity exposures to specify banking interconnectedness. In the empirical analysis, equity exposures are used as a proxy, as data for complete pairwise debt exposures between banks are not available [26]. The data are extracted from 13F 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 36 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 from the theoretical analysis.

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 the theoretical and 13F specified networks using various financial stress scenarios. Specifically, we consider scenarios where the banking system suffers significant drops in the value of its industrial sectors exposure. The theoretical simulation finds an average of 3.92 fewer bank failures in the presence of single trigger CoCo debt and 3.23 fewer failures in the presence of dual trigger CoCo debt when compared with the baseline case of no CoCo debt issuance. Equity

$\Delta CoVaR$ at 5^{th} percentile is reduced by 11.47% and 13.91% 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. We evaluate a two-tranche design of CoCo debt, which holds the promise of combining the advantages of the single trigger and dual trigger CoCo debt design. We find that a two-tranche CoCo debt design does balance the trade-off by protecting individual banks and reducing the systemic risk of the banking system, but a single choice of tranche depth may not work for all banks and stress scenario types. 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 CoCo debt triggers, while the single trigger design offers a lower number of average bank failures, the dual trigger design outperforms in controlling systemic risk in terms of the $\Delta CoVaR$ measure when the banking sector suffers external shocks. From theoretical simulations under more severe industrial shocks, we observe a 2.44% lower $\Delta CoVaR$ under the dual trigger design compared with the single trigger design. The calibrated network model supports these findings. 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. Thus the trade-off in the two designs of CoCo triggers for systemic risk reduction must be optimally constructed, possibly in a multiple tranche CoCo issuance.

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

2 Balance Sheet Network Model

Assessing the benefits of CoCo debt requires our model to capture the interconnectedness of the banking system. For this purpose, we develop a balance sheet network model of the banking system. As such the balance sheets of bank holding companies can be extremely complex; however, for the sake of capturing the basic essence of interconnectedness between banks, we utilize a reduced-form of balance sheet in our study.

Figure 1 shows the reduced-form balance sheet of a bank composed of nine components. Cash &

<table>
<tr><td>Cash &
Cash Equivalents</td><td rowspan="3">Customers' Deposits</td></tr>
<tr><td>Government Bonds</td></tr>
<tr><td rowspan="2">Commercial
Mortgage</td></tr>
<tr><td rowspan="2">Common Debt</td></tr>
<tr><td rowspan="2">Interbank Debt
Holdings</td></tr>
<tr><td>CoCo Debt</td></tr>
<tr><td>Industrial Debt
Holdings</td><td>Shareholders' Equity</td></tr>
</table>

Figure 1: A Simple Reduced-form Balance Sheet is composed of nine components.

cash equivalents, C, government securities, G, commercial mortgages, M^C, interbank debt holdings, A^B, and industry debt holdings, A^I, form the assets 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,

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

Consider a banking system of N banks, with the i^{th} bank's reduced-form balance sheet being represented by C_i, A_i^B, etc. in Equation (1). Banks' interconnections within the banking system are decomposed as those caused by interbank debt holdings, A_i^B, and their common exposures, A_i^I. Interbank holdings of CoCo debt can also be a possible link for systemic risk propagation, however this propagation is highly dependent on the CoCo conversion structure and its value transfer mechanism, which is not included in our model. Therefore, we assume that CoCo debt issued by a bank is not held by other banks.

Let $w_{ij} \geq 0$, $\{i, j \in 1, \ldots, N\}$, denote the fraction of bank j's common debt held by bank i, over bank j's total common debt. To ensure that all interbank 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,

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

The value of bank i's inter-bank debt holdings against other banks, denoted 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 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 $s_{ij} \geq 0$, $\{i \in 1, \ldots, N; j \in 1, \ldots, M\}$, 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,

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

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 interbank holding within the banking system, while Equation (4) forms the channels of common exposure connections among banks. Lastly, in cases where CoCo debt holding is required, bank i is taken to hold CoCo debt equivalent to 5% of market value of its total risky assets, namely, $L_i^C = 5\% \times (A_i^B + A_i^I)$. The balance sheets evolve over time for all banks, and the evolution of each term is 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 cash & cash equivalents, government securities, commercial mortgages, industrial debt holdings, 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 thus, we incorporate the regular fluctuations of the cash & cash equivalents by the following jump process,

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

where $Y_{jt}, \{j \in 1, \ldots, N\}$ 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,

$$Y_{jt} = \sum_{k=1}^{N_{jt}} \lambda_k, \tag{6}$$

where N_{jt} is a Poisson point process specific for bank j, and λ_k are independent identically distributed (i.i.d.) random variables, taken to be Gaussian, measuring each jump size. In order to capture "shock memory" among different epochs, Equation (6) is modified as

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

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 a shock.

2.1.2 Interbank Holdings

The evolution of interbank debt holdings 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 Cox-Ingersoll-Ross dynamics [33],

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

where W_t is a standard Wiener process, and the spread term is also taken to follow its own Cox-Ingersoll-Ross dynamics,

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

where Z_t is an independent standard Wiener process. The interest rate, r_t^l, relevant for a specific 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 interest rate dynamics are used to describe the changes in market value of both common debt and CoCo debt for a bank i by,

$$dL_{it}^B = -D_i^b L_{it}^B dr_t^l + \frac{1}{2} C_i^b L_{it}^B \left(dr_t^l\right)^2, \tag{11}$$

$$dL_{it}^C = -D_i^c L_{it}^C dr_t^l + \frac{1}{2} C_i^c L_{it}^C \left(dr_t^l\right)^2. \tag{12}$$

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,

$$A_{it}^B = \sum_{j=1}^{N} w_{ij} L_{jt}^B. \tag{13}$$

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 each industrial sector index by its own unique stochastic 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.

$$dI_{jt} = \alpha(I_{j\mu} - I_{jt})dt + \sigma_j I_{jt} dW_{jt} + I_{jt} dJ_{jt}, \tag{14}$$

where W_{jt}, $\{j \in 1, \ldots, M\}$, 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,

$$dA_{it}^{I} = \sum_{j=1}^{M} s_{ij} dI_{jt}. \tag{15}$$

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

$$E_{it} = C_{it} + G_{it} + M_{it}^{C} + A_{it}^{B} + A_{it}^{I} - D_{it} - L_{it}^{B} - L_{it}^{C}. \tag{16}$$

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) [7] 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,

$$Z - Score = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E, \tag{17}$$

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,

$$Z - Score_r = 1.2A + 0.6D. \tag{18}$$

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 the stress scenarios, we include sharp declines in either the value of industrial loans or the cash & cash equivalent holdings of the banks. The first type of stress shock arises in the real economy and is experienced by the banking sector via one (or more) of its industrial sectors exposures. 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 levels 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 of simulation.
2. -10% shocks to a randomly chosen set of industrial sectors at days 20 and 200 of a year's duration of simulation.
3. -10% shocks to randomly chosen industrial sectors and -15% cash shock to a randomly chosen set of large banks, both applied at 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. 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. During the financial crisis, after the financial sector suffered the shock, the stress quickly spread to the domestic and overseas real economies. 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 in our model, the bank is considered bankrupt. Other banks holding debt of a failing bank recover 60% of its market value. Financial distress can also spread through possible fire-sale of assets when a stressed bank becomes insolvent. 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 in the single tranche design 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 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 [39],

$$\frac{E_{it}}{TA_{it}} \leq \alpha_i, \tag{19}$$

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

Under the single trigger design, there is only one bank-level trigger that controls the conversion of CoCo debt. In contrast, a dual trigger design adds a systemic trigger to monitor the health of the whole banking system. The systemic trigger is defined in terms of the total asset, $TA_{it} = C_{it} + G_{it} + M_{it}^C + A_{it}^B + A_{it}^I$, as follows,

$$\frac{1}{N}\sum_{i=1}^{N}\frac{E_{it}}{TA_{it}} \leq \beta, \tag{20}$$

where β is the threshold value and N is the number of banks in the system. Under the dual trigger design, bank i's CoCo debt will not convert unless the systemic trigger is also activated, even if the bank-level trigger is already activated. Thus, the two designs of trigger indicate a trade-off between the protection of individual bank failures and their contribution to the stability of the entire banking system.

2.4 Systemic Risk Measures

The primary purpose of CoCo debt is to mitigate systemic risk of the banking system. Therefore, it is crucial to adopt an appropriate measure for systemic risk. One straightforward way is to count the actual number of bank failures after a stress event, however this is an ex-post measure. Among the prominent market-based measures for systemic risk, we use the Delta-CoVaR measure [3][2], which is based on the concept of value-at-risk. Delta-CoVaR serves as a base measure of negative externality or spillover cost imposed by banks on the system.

In this paper, we use average number of bank failures and the Delta-CoVaR measure, with the latter widely used in the banking and network science literature. $CoVaR_q$, is defined as the q-th percentile of the value of an asset conditional on a given shock experienced by a set of assets or firms. 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,

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

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 $CoVaR_q$, $\Delta CoVaR_q$ (Delta-CoVaR), defined as follows is used to measure systemic risk:

$$\Delta CoVaR_q = VaR_q - CoVaR_q^{Shock}. \tag{22}$$

Therefore, $\Delta CoVaR_q$ (Delta-CoVaR) is the difference between the value-at-risk, VaR_q, and the co-movement value-at-risk, $CoVaR_q^{Shock}$, which eliminates the reference to a baseline. The larger the $\Delta CoVaR_q$, the higher the systemic risk.

3 Theoretical Simulation Analysis

A theoretical analysis of the model developed in the previous section requires a reasonable choice of model parameters. We obtain several key statistics, i.e., key financial and accounting ratios, from publicly available data sources for banks of different sizes. The model is implemented to conduct a simulation analysis of a theoretically defined banking system. In dearth of relevant, comprehensive data, simulation analysis is an ideal tool to explore the efficacy of CoCo debt, given no CoCo debt currently exists in the US market and none of the CoCo debt issued in Europe have ever triggered.

[2]Other systemic risk measures include those proposed in [18],[5],[28], [51], [38], [30], [24] and [17], and surveyed in [16].

Table 1: Key Statistics for several key financial and accounting ratios from actual banks' financial statements to generate a realistic reduced-form balance sheet theoretical model for each bank. The data are obtained from Federal Deposit Insurance Corporation (FDIC).

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%

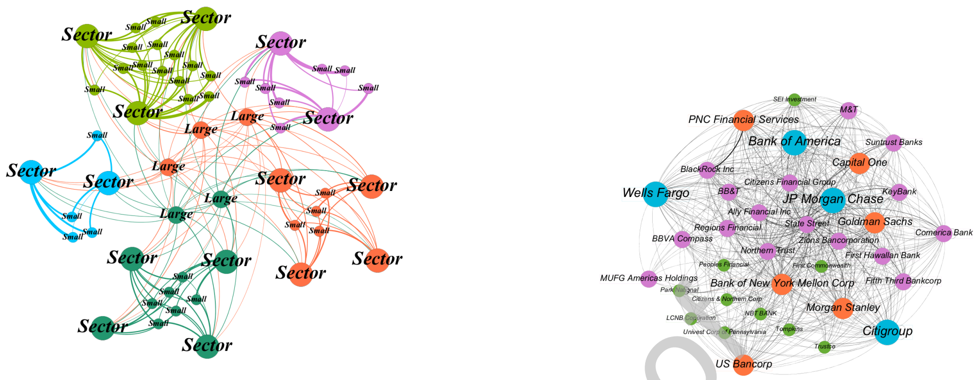
3.1 Topology of Theoretical Network

Our theoretical banking network consists of 40 banks, of which there are 5 large banks and 35 medium/small banks. Although a banking system consisting of 40 banks is not nearly as large as the banking system of large economies, it is large enough to allow for incorporation of essential interconnectedness attributes without making the model too cumbersome to implement and simulate. As stated above, 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. To illustrate the clustering in banks' investments, large banks are assumed to have diversified industrial debt holdings, while medium/small banks hold debt from a subset of industrial sectors.

The chosen 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 40 total bank nodes, implies that the network is complete without self-loops. Closeness centrality of a node, as reported in the table, measures the 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 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 suggest that all banks are equally highly connected with others in the network. These properties are summarized without accounting for the edge weights of the network, and even as a non-weighted network, they serve as a reference for the empirically calibrated network studied later in the paper.

Table 2: Network Properties for the theoretical reduced-form balance sheet bank network.

	Avg. Degree	Diameter	Avg. Path	Closeness	Betweenness	Cluster Coef.	Component	Modularity
Network	39	1	1	1	0	1	1 weak ; 1 strong	0.101



(a) 40 Bank Theoretical Industry Common Exposures

(b) Empirical 36 Bank Network

Figure 2: In Figure 2(a), connections between banks and the industrial sectors denote the industrial loans made by the banks to the sectors. Large banks are highly diversified across sectors, while small banks remain concentrated in specific sectors shown in a color. Figure 2(b) visualizes the empirical inter-bank equity holdings of 36 US BHCs based on the data of 13F filings. It is a weighted, directed network of 36 nodes and 627 edges with size of node represents BHC size and thickness of edge represents the fraction of equity holdings.

Figure 2(a) illustrates the connections between banks and the industrial sectors through the industrial loans made by the banks to the sectors. 15 largest nodes represent the 15 industrial sectors, while large and small banks are denoted by labeled smaller nodes. Industrial sectors are grouped into five sub-clusters, with large banks diversified in their loans to almost all sectors, while medium/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 scenario described in Section 2.2, we generate 10,000 runs of simulation of the banking system under each of the following three cases: banks issue no CoCo debt, banks issue only single trigger CoCo debt, and banks utilize the dual trigger design of CoCo debt. The two systemic risk measures described in Section 2.4, namely the average number of bank failures and the $\Delta CoVaR_q$ for equity value at 5% confidence level, are estimated for each case. Table 3 reports key statistics for the simulation under the first stress test scenario of only one industrial shock. The

Table 3: The number of bank failures and the equity $\Delta CoVaR_{0.05}$ for a -10% shock randomly applied to 15 industrial sectors indexes at day 20 of one year's daily simulation. The equity $\Delta CoVaR_{0.05}$ is normalized by initial equity value. Columns (1) - (3) report the statistics of the whole banking system, Columns (4) - (6) for large banks, and Columns (7) - (9) for medium/small banks. Panel A shows mean of the two statistics with no CoCo, with a single trigger CoCo, and with a dual trigger CoCo under 10,000 simulations. Panel B shows difference between the statistics under different scenarios, along with the statistical significance. For instance, -1.7073 in column (1) of Panel B is the difference between 0.1743 and 1.8817 in Column (2) and Column (1) of Panel A. The Bootstrap t-statistics are reported in parentheses. Signs ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

A: Systemic Risk Measures	Banking System			Large Banks			Medium/Small Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single Trigger	Dual Trigger	None	Single Trigger	Dual Trigger	None	Single Trigger	Dual Trigger
Mean of bank failures	1.8817	0.1743	0.6076	0.0001	0	0	1.8816	0.1743	0.6076
Equity $\Delta CoVaR_{0.05}$	0.1629	0.0848	0.0801	0.1218	0.1045	0.1039	0.1948	0.0742	0.0748

B: Significance Test	Banking System			Large Banks			Medium/Small 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	-1.7073***	-1.2740***	0.4333***	-0.0001	-0.0001	0.0000	-1.7072***	-1.2739***	0.4333***
	(-46.56)	(-33.80)	(27.26)	(-1.00)	(-1.00)	(.)	(-46.56)	(-33.80)	(27.26)
Equity $\Delta CoVaR_{0.05}$	-0.0781***	-0.0828***	-0.0047	-0.0173***	-0.0179***	-0.0006	-0.1206***	-0.1200***	0.0005
	(-10.37)	(-10.97)	(-0.81)	(-2.59)	(-2.71)	(-0.09)	(-12.85)	(-13.24)	(0.08)

average number of bank failures and the equity $\Delta CoVaR_q$ for the banking system are shown in Panel A of Table 3 for the three cases: no CoCo debt issuance, single trigger CoCo debt, and dual trigger CoCo debt. Panel B of the table compares the three cases by reporting the differences in bank failures and $\Delta CoVaR_q$ for the three cases, along with their statistical significance. Compared with the case of no CoCo debt issuance, both single trigger and dual trigger CoCo debt conversion significantly reduce the average number of bank failures and decrease the $\Delta CoVaR_q$. Thus, CoCo debt of either trigger design mitigates the systemic risk of the banking system.

As shown in columns (1) and (2) of Panel B in Table 3, introducing single trigger and dual trigger CoCo debt to the banking system reduces the average number of bank failures by 1.7073 and 1.2740, respectively. Equity $\Delta CoVaR_q$ decreases by 7.81% and 8.28%, respectively, for the single trigger and the dual trigger CoCo debt. All coefficients are significant at the 1% level. We further decompose the results for large banks and medium/small banks. The statistical difference in results is attributed to the medium/small banks. We do not observe a decrease in average bank failures for the large banks, as no large banks are observed to fail. However, there is a decrease in large banks' equity $\Delta CoVaR_q$. Therefore, both trigger designs of CoCo debt protect the large

Table 4: The number of bank failures and the equity $\Delta CoVaR_{0.05}$ for a -10% shock randomly applied to 15 industrial sectors indexes at day 20 and day 200 of one year's daily simulation. Other details are as for Table 3.

A: Systemic Risk Measures	Banking System			Large Banks			Medium/Small Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single Trigger	Dual Trigger	None	Single Trigger	Dual Trigger	None	Single Trigger	Dual Trigger
Mean of bank failures	4.6103	0.6935	1.3799	0	0	0	4.6103	0.6935	1.3799
Equity $\Delta CoVaR_{0.05}$	0.3138	0.1990	0.1747	0.2574	0.2067	0.2058	0.3660	0.1939	0.1499
B: Significance Test	Banking System			Large Banks			Medium/Small 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	-3.9168***	-3.2304***	0.6864***	0.0000	0.0000	0.0000	-3.9168***	-3.2304***	0.6864***
	(-68.98)	(-56.06)	(23.63)	(.)	(.)	(.)	(-68.98)	(-56.06)	(23.63)
Equity $\Delta CoVaR_{0.05}$	-0.1147***	-0.1391***	-0.0244***	-0.0506***	-0.0516***	-0.0010	-0.1721***	-0.2161***	-0.0440***
	(-15.16)	(-18.89)	(-3.93)	(-8.31)	(-8.50)	(-0.18)	(-19.87)	(-25.52)	(-6.90)

banks from systemic risk, as measured by $\Delta CoVaR_q$.

Although both single and dual trigger CoCo debt issuance protects the banking system, their effectiveness is not the same. We compare the effectiveness of two trigger designs in columns (3), (6) and (9) of Panel B in Table 3. Column (3) shows that single trigger CoCo debt protects the banking system better in terms of average bank failures. The single trigger design reduces the average bank failures by 0.4333 more than does the dual trigger. However, although not statistically significant, the dual trigger CoCo debt outperforms in terms of the equity $\Delta CoVaR_q$, by an improvement of 0.47%. Separating the results for the large and medium/small banks, the difference in the average number of bank failures between single and dual trigger CoCo debt once again arises due to the medium/small banks.

Results remain consistent when we apply the more severe stress scenario of two industrial shocks, described in Section 2.2. Table 4 provides the corresponding results, which are similar to the results in Table 3, but with greater economic magnitude and higher statistical significance. It is important to note that the difference in the equity $\Delta CoVaR_q$ for the single and the dual trigger CoCo debt cases under this more extreme stress scenario is both statistically significant and of higher economic magnitude. Therefore, the more severe the industrial shock, the better the protective effect of the dual trigger CoCo debt in terms of equity $\Delta CoVaR_q$.

Financial shocks can arise both in the industrial sectors and through banks' other investment activities. In the reduced-form balance sheets for the banks, all the impacts arising from banks'

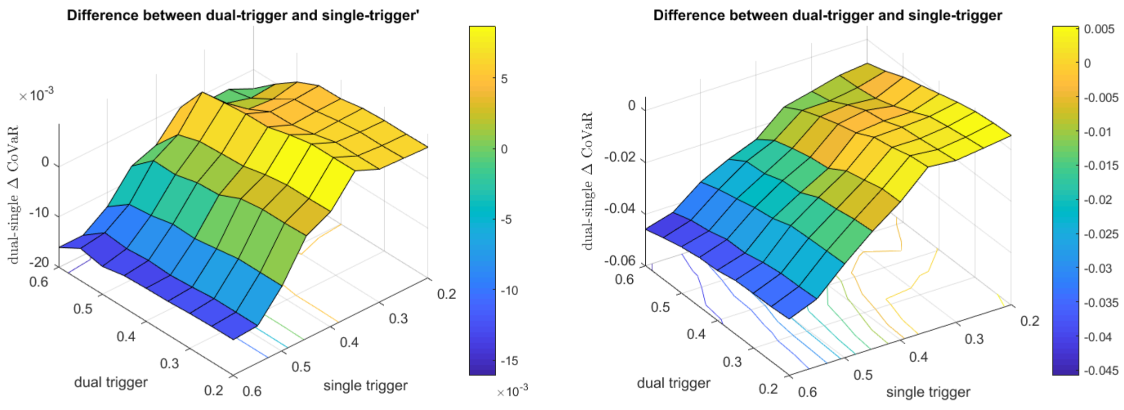
Table 5: The number of bank failures and the equity $\Delta CoVaR_{0.05}$ for a -10% shocks to a randomly chosen set of industrial sectors and a -15% cash shocks to 5 randomly chosen large banks, both applied at day 20 of one year's daily simulation. Other details are as for Table 3.

A: Systemic Risk Measures	Banking System			Large Banks			Medium/Small Banks		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CoCo design	None	Single Trigger	Dual Trigger	None	Single Trigger	Dual Trigger	None	Single Trigger	Dual Trigger
Mean of bank failures	2.0508	0.1895	0.5729	0.1840	0.0007	0.0076	1.8668	0.1888	0.5653
Equity $\Delta CoVaR_{0.05}$	0.3447	0.1668	0.1852	0.5645	0.2931	0.3907	0.2008	0.0763	0.0679
B: Significance Test	Banking System			Large Banks			Medium/Small 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	-1.8612***	-1.4779***	0.3833***	-0.1833***	-0.1765***	0.0068***	-1.6779***	-1.3014***	0.3765***
	(-46.25)	(-35.97)	(23.50)	(-25.89)	(-24.70)	(6.56)	(-45.92)	(-34.74)	(23.22)
Equity $\Delta CoVaR_{0.05}$	-0.1779***	-0.1595***	0.0184***	-0.2714***	-0.1738***	0.0976***	-0.1245***	-0.1329***	-0.0083
	(-21.61)	(-19.71)	(3.27)	(-35.04)	(-21.34)	(13.87)	(-13.58)	(-15.26)	(-1.43)

other investments and financing activities must be reflected through the "cash & cash equivalents" component of the balance sheet. To address this channel of stress, we implement the third stress scenario discussed in Section 2.2, where we simultaneously apply an exogenous industrial shock and an endogenous cash shock. The cash shock is applied to the large banks, since they form the core of the banking system. The results are shown in Table 5.

Conversion of CoCo debt increases the stability of the banking system and the medium/small banks, in terms of both the number of bank failures and equity $\Delta CoVaR_q$. Since large banks suffer the cash shock in this scenario, they benefit from the protective role of CoCo debt conversion. However, compared with the first industrial shock scenario, the difference in $\Delta CoVaR_q$ for the two designs of CoCo debt triggers has changed. In column (3) of Panel B in Table 5, the single trigger now outperforms the dual trigger design. The large banks in the system contribute the most to the flipped sign. Dual trigger CoCo debt still performs 0.83% better in reducing $\Delta CoVaR_q$ for medium/small banks. But single trigger CoCo debt performs even better for large banks, beating the dual trigger case by 9.76%. As a result, the single trigger design beats the dual trigger one in terms of the equity $\Delta CoVaR_q$ for the whole banking system.

A plausible explanation for the results of the third stress scenario is that, since large banks are directly affected by cash shocks and industrial shocks, they are more likely to be the first ones to experience financial distress. Even when bank level triggers for large banks may activate, CoCo debt cannot convert unless the system-level trigger also activates. Therefore, the dual trigger CoCo



(a) One Industrial Shock

(b) Two industrial Shocks

Figure 3: Difference in the $\Delta CoVaR_{0.05}$ for dual versus trigger CoCo (z-axis) corresponding to different trigger levels for both bank-level and systemic triggers, ranging from 20% to 60% of the equity ratio. The baseline level is 60% for the systemic trigger and 40% for the bank-level trigger.

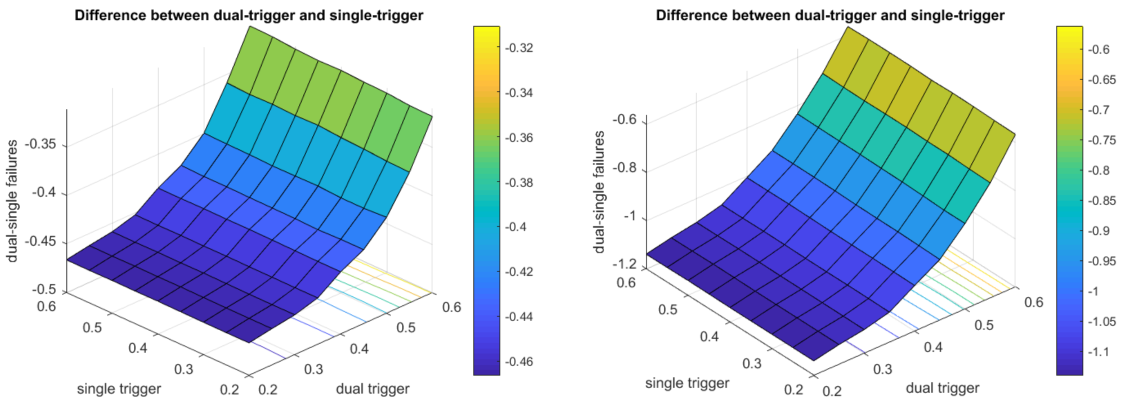
debt would fail to protect large banks, compared with the single-trigger CoCo design, which allows for CoCo debt conversion as long as its bank-level trigger is activated. In conclusion, the single trigger CoCo design is better at protecting individual banks or banks that initially suffer distress, while the dual trigger CoCo design outperforms in terms of banking system resilience.

3.3 Sensitivity of Simulation Results

In this section, we consider variations from the baseline model set up of Section 3.2 for evaluating the robustness of the results. Since the choice of trigger levels is most crucial for the definition of CoCo debt design, we first assess the implication of different trigger levels, followed by evaluating a two-tranche design of CoCo debt. A two-tranche design of CoCo debt is essentially a mixture of two CoCo debt issuances in the financing structure of a bank, each issuance defined by the properties of the two trigger types of single tranche CoCo debt.

3.3.1 Trigger Level

Trigger levels of CoCo debt design are perhaps the most complicated and controversial feature of the instrument. Currently there is no universally accepted CoCo trigger level, either in academic research or in the financial markets. In Europe, all CoCo instruments have triggers based on capital adequacy ratio, varying in terms of ratio type and level [56]. In order to obtain insights on the "optimal" choice of trigger, we explore different trigger levels for both bank-level trigger and systemic trigger, ranging from 20% to 60% of the equity ratio. The baseline levels in the earlier



(a) One Industrial Shock

(b) Two industrial Shocks

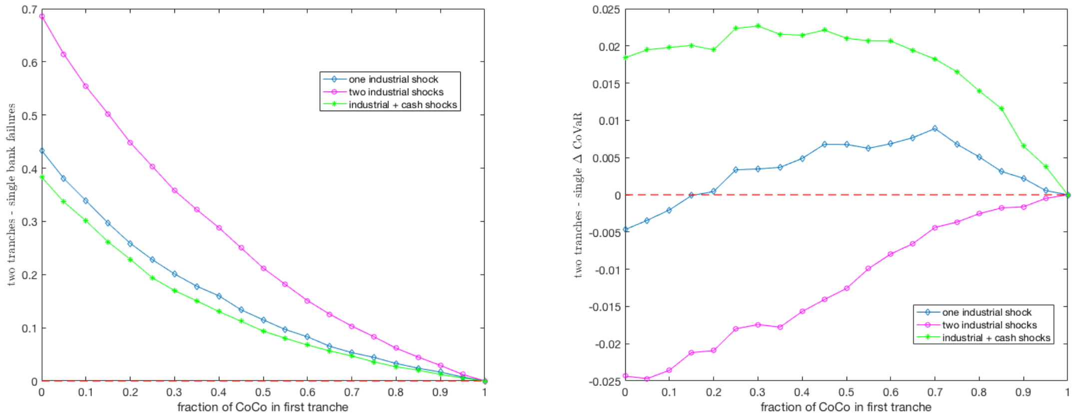
Figure 4: Difference in number of bank failures under dual versus single trigger CoCo debt (z-axis), for same trigger levels as in Figure 3.

section were 60% for the systemic trigger and 40% for the bank-level trigger. Figure 3 shows the sensitivity with the z-axis representing the difference of $\Delta CoVaR_q$ estimated under dual and single triggers.

Under either one or two industrial shocks, the difference (with sign) in $\Delta CoVaR_q$ is negatively correlated with the level of individual trigger in the dual trigger design. In other words, the $\Delta CoVaR_q$ from dual trigger becomes much lower than that from single trigger, implying an improved mitigation of systemic risk. Intuitively, with the same level of systemic trigger, a higher bank-level trigger makes it easier for CoCo debt to convert. In the dual-trigger design, the systemic trigger does not affect the result that much. Interestingly, instead of an "optimal" trigger level, we find the system-level trigger to be an "insensitive" trigger level. Figure 4 shows the change in number of bank failures in response to the change in trigger levels. The difference between average bank failures under dual trigger and single trigger designs is negatively correlated with the choice of system-level trigger in the dual trigger design. This is reasonable because a lower systemic trigger hinders the conversion of CoCo debt.

3.3.2 Two-Tranches CoCo

In Section 3.2, we find that single and dual trigger CoCo debt designs have different advantages. A well-designed CoCo debt instrument should function effectively irrespective of the structure of the banking system and the shock type suffered by the banking system. A natural extension combining the advantages of the single and the dual trigger design of CoCo debt is to consider a CoCo debt



(a) Number of Bank Failure (b) $\Delta CoVaR$

Figure 5: Performance of Two-Tranches CoCo with single trigger CoCo in terms of the bank failures and $\Delta CoVaR_{0.05}$. We compare two-tranches CoCo with $\gamma \in [0, 1]$ against the single trigger CoCo in terms of difference in $\Delta CoVaR_{0.05}$ and the number of bank failures.

structure with multiple tranches. A two-tranche CoCo debt structure is one such combination, where like the dual trigger CoCo, one of the tranches has a bank-level trigger and a systemic trigger, while another tranche gets triggered by bank-level conditions. A fraction, γ, of the CoCo debt first converts when the bank-level trigger is activated. The rest does not convert unless both the triggers are activated. Clearly, γ is an important parameter in the design of a two-tranche CoCo debt. In two special cases, the two-tranche CoCo debt reduces to a single trigger CoCo debt when $\gamma = 1$, and to a dual trigger CoCo debt when $\gamma = 0$. We compare results for different levels of γ against the single trigger CoCo debt case, i.e. $\gamma = 1$.

As shown in Figure 5, the number of bank failures monotonically decreases with respect to γ in case of all three stress scenarios, reaching a minimal point for $\gamma = 1$. This is precisely the level of γ when the two-tranche CoCo debt becomes a single trigger CoCo debt. The equity $\Delta CoVaR_q$ shows no clear optimal level for γ between 0 and 1 that works for all the stress scenarios. The best choice of γ for $\Delta CoVaR_q$ is either 0 or 1, depending on the stress scenario considered. If the shocks are all exogenous (from the industrial sectors), the larger the shock, the more the dual trigger component benefits the bank. This is consistent with the findings of Section 3.2.

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 for each bank in the model. In fact, data for systemic risk assessment are either not comprehensively collected or not released for research purposes [26]. 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 13F filings with the US Securities and Exchange Commission (SEC). 13F filings provide long positions in equity securities, with unique identifiers for the equity issuers. Therefore, to use these data for inter-bank exposures and common exposures information, we must slightly modify the reduced-form balance sheet model developed in Section 2, 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. The appendix in supplementary material includes a flowchart for data extraction from 13F filings, call reports and other data resources.

4.1 Reduced-form Balance Sheet Model Modification

The balance sheet identity of Equation (16) is modified for the total assets 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 inter-bank exposures and common exposures, respectively. Total liabilities of each BHC include deposits, D_{it}, common debt, L^B_{it}, and CoCo debt, L^C_{it}, 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,

$$E_{it} = C_{it} + G_{it} + M_{it} + E^B_{it} + E^F_{it} - D_{it} - L^B_{it} - L^C_{it}, \tag{23}$$

where E^F_{it} and E^B_{it} denote BHC i's holdings of equity securities against other BHCs and against non-financial firms, respectively. The weights, $w_{ij}, \{i, j \in 1, \ldots, N\}$ and $s_{ij}, \{i, j \in 1, \ldots, N\}$ in Equations (3) and (4) now 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,

$$dI_{jt} = u_j I_{jt} dt + \sigma_j I_{jt} dW_t, \quad \forall j = 1 \ to \ M. \tag{24}$$

Since 13F filings are made by bank holding companies (BHCs) rather than commercial banks, we must approximate banks by BHCs, and thus use "BHC" and "bank" interchangeably going forward. Top-tier BHCs, also known as the ultimate domestic parent organizations, hold three types of entities, namely, bank holding companies, nonbank holding companies, and commercial banks. Avraham et al. (2012) [11] document that most assets of a BHC are generally held in a small number (between one to five) of domestic commercial banks, even though the BHC additionally controls a large number of nonbank subsidiaries. For example, in 2012, JP Morgan Chase & Co., the largest BHC by total assets, controlled 3,391 subsidiaries and only four domestic commercial banks. These four commercial banks and their subsidiaries held 86% of the BHC's total assets[3]. We address the lack of observability of inter-bank holdings at the commercial bank level by approximating commercial banks with BHCs in our empirical validation analysis.

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 13F 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: 4 super large, 6 large, 16 medium and 10 small banks, consistent with the Mid-size Bank Coalition of America Research Report bank-size definition [53].

Besides the 13F data obtained from SEC EDGAR system, data required for our model calibration are obtained from Federal Financial Institutions Examination Council (FFIEC), Capital IQ and the Bloomberg Terminal. The FFIEC quarterly call report data for the 36 banks are collected for

[3]A detailed look at the structure of US bank holding companies and related regulatory files can be found in [11]. The organizational structure of each BHC is reported annually as part of the *FR Y-6 Annual Report of Bank Holding Companies*; BHCs are required to file an organizational chart, intercompany ownership and control relationships, and data on domestic branches, among other information. Top-tier BHCs also report any changes to the firm's worldwide organizational structure including mergers, acquisitions, or transfers of interests in other entities, internal reorganizations, commencements of new activities, and openings, closings or relocations of branches or subsidiaries to *FR Y-10 Report of Changes in Organizational Structure*. Data of these two reports can be obtained from the National Information Center repository. Each domestic commercial bank files a detailed set of quarterly financial reports commonly known as "Call Reports" (FFIEC 031, if the bank has both foreign and domestic offices, or FFIEC 041, if it has only domestic offices). Call Reports are prepared on a consolidated basis at the bank level, not for the BHC.

the past 10 years, from 2007Q1 to 2016Q4. These data are used to estimate balance sheets' specific parameters. We obtain Moody's credit ratings of the 36 BHCs from the Bloomberg Terminal, where ignoring the rating adjustments for simplicity, 21 BHCs have a rating of A, 14 have Baa, and 1 bank has Ba rating. 25 of the 36 BHCs participate in the Fed's Stress Tests program[4].

We aggregate the non-financial firms' equity securities reported in the banks' 13F 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 [41]. 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.

The potential data bias between 13F filings made by BHCs and call reports filed by commercial banks is addressed as follows. We collect call reports for each representative commercial bank that shares the same headquarter location as its holding company's headquarter. Additionally, 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 13F filings. We then scale down the total liabilities, $TL_{i,t}$, and deposits, D_{it}, with the ratio of total liabilities to total assets and the ratio of deposits to total assets, respectively, obtained from call reports.

$$\hat{TL}_{it} = \left(\frac{TL_{it}}{TA_{it}}\right)(C_{it} + G_{it} + A^L_{it} + E^f_{it} + E^b_{it}), \tag{25}$$

$$\hat{D}_{it} = \left(\frac{D_{it}}{TA_{it}}\right)(C_{it} + G_{it} + A^L_{it} + E^f_{it} + E^b_{it}), \tag{26}$$

where $\frac{TL_{it}}{TA_{it}}$ is the ratio of total liabilities to total assets and $\frac{D_{it}}{TA_{it}}$ 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, say $(\hat{TL}_{it} - \hat{D}_{it})$.

5 Empirical Simulation Analysis

We conduct a validation study using simulation analysis of the model calibrated in Section 4. A detailed network analysis of the empirically defined bank network is provided in an appendix as

[4]Dodd-Frank Act Stress Tests: `https://www.federalreserve.gov/supervisionreg/dfa-stress-tests.htm`

Table 6: The number of bank failures and the equity $\Delta CoVaR_{0.05}$ for a -10% shock to 11 randomly chosen industrial sectors indexes at day 20 and day 200 of one year's daily simulation based the real-world network calibrated from 13F filings. Other details are as for Table 3.

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)

supplementary material. 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 calibrated, reduced-form balance sheet 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 both endogenous and exogenous shocks are directly applied to only large & super large BHCs, it makes more sense to apply the system-level trigger of the dual trigger CoCo debt design to a firm-size weighted equity ratio[5]. This is because the medium and small banks in our chosen sample are calibrated to have on average a high equity ratio. In such a setting, a uniformly weighted system-level equity ratio is biased to result in no system-level trigger activation, even when the large & super large banks are in serious distress. Therefore, we consider the following size-weighted

[5]Size effect is non-trivial in the 13F calibrated empirical network. Four super large BHCs, JP Morgan Chase & Co, Bank of America Corp, Wells Fargo, and Citigroup, account for 61% of total assets of the empirical banking system. The top 10 largest BHCs hold more than 80% of the total assets. The 16 medium and small BHCs hold much less than 20% of the total assets.

systemic trigger for the entire banking system,

$$\frac{\sum_{i=1}^{N} E_{it}}{\sum_{i=1}^{N} TA_{it}} \leq \beta, \tag{27}$$

An industrial shock to a sector transmits to its connected sectors at 60% of the original shock, while a liquidity shock to BHCs transmits to their connected BHCs at 80% of the intensity of the original shock. The bank-level trigger of CoCo debt is set at 40% of the bank's initial equity-to-asset ratio, while the systemic trigger 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% levels to allow the systemic trigger to activate more readily. A low systemic trigger may never be invoked, as seen in Section 3.3.1, until the entire banking system reaches a severely distressed condition. This could end up being too late for corrective actions.

Table 6 shows key statistics for the empirical analysis when the banking system experiences only industrial shocks. Panel A of Table 6 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 6 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 $\Delta CoVaR_q$ from CoCo debt conversion is significant only for the large & super large BHC groups, but not so for the medium & small BHC groups. We find that the dual trigger CoCo debt does not effectively reduce bank failures for the medium & small BHCs, as the coefficient of -0.0380 in column (8) of Panel B is not statistically significant.

Columns (3), (6) and (9) in Panel B of Table 6 report the comparisons for the two designs of CoCo trigger for the entire banking system and for the two subgroups. Considering the entire banking system, CoCo debt with a single trigger is better at saving individual banks by an average of 0.9886. In contrast, CoCo debt of dual trigger outperforms single trigger by 1.08%, which is

Table 7: The number of bank failures and the equity $\Delta CoVaR_{0.05}$ for a -10% shocks to 11 randomly chosen industrial sectors indexes and -10% cash shocks to 10 randomly chosen large & super large BHCs, at day 20 and day 200 of one year's daily simulation based on the real-world network calibrated from 13F filings. Other details are as for Table 3.

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)

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 unclear, since the coefficient of -0.05% is not statistically significant.

Table 7 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 6, except that dual trigger CoCo debt starts to become 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 the banking system integrity, especially for the large & 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 & small BHCs.

We find that the balance sheet evolution characteristics of the large BHCs in the empirically calibrated banking network to be more vulnerable than that of the medium & small BHCs, resulting in the large & super large BHCs hitting the CoCo trigger more frequently, and thus, activating CoCo debt conversion. Moreover, an all-or-nothing CoCo debt conversion also causes limited conversion of CoCo debt for the medium & small BHCs. We evaluated the two-tranche CoCo debt design in the theoretical analysis, where a specific choice of γ could be chosen to benefit the medium & small BHCs. The optimal level of CoCo debt issuance for a specific size of BHC and the exact partial levels of CoCo debt conversion in a two-tranche design, once activated, remain questions that need further investigation. Additional design issue regarding callability of CoCo debt and inter-bank holding of CoCo debt can be investigated in further investigation, both of which will benefit from policy guidance to maintain efficacy of CoCo debt in mitigating systemic risk [10]. In a recent study, it is found that under specific network settings, replacing unsecured inter-bank debt by standardized versions of CoCo inter-bank debt can help reduce systemic risk [37]. Thus, further highlighting the importance of policy guidance for standardized CoCo debt design and usage.

6 Conclusion and Discussion

The 2008 global financial crisis illustrated the challenge of contagion in bank failures. Contingent convertible (CoCo) debt is 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 studied 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 created a network model based on reduced-form balance sheets of the banks, where network nodes depict the banks and network edges represent the inter-bank debt holdings.

The banking system network model is implemented and analyzed using simulation analysis. Systemic risk analysis is undermined by the unavailability of detailed bank-specific data. Appropriately detailed data to enable systemic risk assessment are either not collected or not released for research purposes [26]. Real world bank holding companies and present day banking system are very complex systems [20]. In presence of limited data, simulation analysis tools are ideal to study the behavior of complex systems, especially when the actual system is not available to experiment with.

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 13F calibrated networks with several financial stress scenarios. We find that while CoCo debt with a single trigger results in lowering the average bank failures, it is the dual trigger design that outperforms in controlling systemic risk in terms of the $\Delta CoVaR_q$ risk measure when external shocks spread through the banking network. Difference in efficacy of the different designs of CoCo debt trigger is essentially a trade-off in addressing systemic risk. While a two-tranche CoCo debt design combines the benefits of a single trigger and a dual trigger, a fixed tranche depth may not work for all banks and stress scenario types. Consistent findings between the theoretical model, where inter-bank and common exposures are due to debt instruments, and the empirical model, where inter-bank and common exposures are due to equity instruments, suggests that a mix of debt and equity instruments making the inter-bank and common exposures would result in a behavior of the network consistent with what we find in our analysis.

While we investigate trigger designs for CoCo debt for super 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, as in the two-tranche CoCo debt design, and a guideline may also be needed for new CoCo issuance, once all the CoCo debt of a bank depletes. Our sensitivity analysis highlights 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 a need for caution regarding the self-saving properties of CoCo debt once it is triggered. For instance, how will the market react when the very first CoCo debt gets triggered for conversion, and any deleterious feedback effects that generates. Callability of CoCo debt is another important design feature that should be guided by policy. For enabling the instrument's purpose to address financial stability concerns, the instrument cannot be considered at par with other types of debt a firm issues, therefore the callability aspect of CoCo design should be evaluated in a future study.

Skeptics of CoCo instruments have argued that CoCo debt instruments are excessively complex and unlikely to provide the adequate loss-absorbing capacity to banks [2]. Deutsche Bundesbank and Axiom Alternative Investments (2018) [32] argue that these 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. Koziol and Lawrenz (2012) [50] show that under specific conditions, CoCo debt may even destabilize the whole banking system. Concerns also exist regarding bank regulators having to call back coupons for the CoCo debt due to new regulations that restrict banks' ability to pay out coupons, dividends, and other bonuses [45]. Since data for these effects is not available to researchers, and in some cases may be available only at the event of the next crisis, it is difficult to assess the full spectrum of risks and costs implications of CoCo debt issuance and conversion. These issues must be investigated in future research.

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