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Modeling Risk Sharing and Impact on Systemic Risk

Walter Farkas [1,2,†] and **Patrick Lucescu** [1,*,†]

[1] Department of Finance, University of Zurich, Plattenstrasse 14, 8032 Zurich, Switzerland; walter.farkas@df.uzh.ch
[2] Department of Mathematics, ETH Zürich, Rämistrasse 101, 8092 Zürich, Switzerland
* Correspondence: patrick.lucescu@df.uzh.ch
† These authors contributed equally to this work.

Abstract: This paper develops a simplified agent-based model to investigate the dynamics of risk transfer and its implications for systemic risk within financial networks, focusing specifically on credit default swaps (CDSs) as instruments of risk allocation among banks and firms. Unlike broader models that incorporate multiple types of economic agents, our approach explicitly targets the interactions between banks and firms across three markets: credit, interbank loans, and CDSs. This model diverges from the frameworks established by prior researchers by simplifying the agent structure, which allows for more focused calibration to empirical data—specifically, a sample of Swiss banks—and enhances interpretability for regulatory use. Our analysis centers around two control variables, CDS_c and CDS_n, which control the likelihood of institutions participating in covered and naked CDS transactions, respectively. This approach allows us to explore the network's behavior under varying levels of interconnectedness and differing magnitudes of deposit shocks. Our results indicate that the network can withstand minor shocks, but higher levels of CDS engagement significantly increase variance and kurtosis in equity returns, signaling heightened instability. This effect is amplified during severe shocks, suggesting that CDSs, instead of mitigating risk, propagate systemic risk, particularly in highly interconnected networks. These findings underscore the need for regulatory oversight to manage risk concentration and ensure financial stability.

Keywords: systemic risk; agent-based modeling; financial networks; risk transfer; network interconnectedness; credit default swaps

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1. Introduction

The financial crisis of 2008 was a perfect storm of sorts. A confluence of factors led to the downfall of Lehman Brothers and the near collapse of the global financial system. While there are many factors that contributed to the crisis, credit default swaps (CDSs) played a significant role in the cascade of events that followed, with the failure of one institution having a domino effect on others. As a result, the widespread usages of CDSs created a web of interconnected risk that made the entire system vulnerable to collapse. According to Che and Sethi [1], the availability of CDSs can lead to improved borrowing conditions, but only if the buyer of the CDS has an insurable interest in the contract. In this case, the CDS contract is referred to as a covered CDS. However, if the buyer of the CDS does not have an insurable interest, the CDS is called naked. In this case, the availability of CDSs can lead to worse borrowing conditions.

When considering the financial system, it is noteworthy to mention that credit risk is not limited to the lender alone but can spread throughout the network and can lead to the collapse of the system as a whole. This phenomenon, known as systemic risk, stems from the interconnectedness of financial institutions and has been outlined by Bandt and Hartmann [2]. Systemic risk can be influenced not only by the interconnectedness of the system but also by the common portfolio exposure of financial institutions. Acharya [3] shows that when banks have similar investments, the probability of the entire system failing increases as compared to a well-diversified financial sector. Apart from these direct effects, there are also feedback channels through which systemic risk can propagate. Banks can suffer from self-fulfilling prophecies and lose access to the interbank liquidity market due to concerns of a potential default. This, in turn, can lead to an actual default. This confidence loss does not need to be limited to the interbank network only and can be extended to the bank's depositors as well. Confidence loss from the depositors side can lead to bank run scenarios, where a large number of deposits are withdrawn. This effect can strain the bank's liquidity and its ability to meet its short-term obligations. Financial networks can be seen as a complex system of interconnected actors that interact with each other via financial contracts. To study these systems, the literature has turned to network theory, which has been applied in numerous studies, such as Eisenberg and Noe [4] or Allen and Gale [5]. A more detailed discussion on modeling financial network can be found in Jackson and Pernoud [6].

Turning now to the role of CDS contracts in a financial network, we can observe two different effects, depending on how the CDSs are used. If the buyer of the CDS is exposed to the underlying entity, the CDS contract acts as a hedging mechanism that ensures the buyer is not fully exposed in the event of default of the entity. The CDS contract thus leads to a shift in credit risk within from one entity to another. If however, the buyer is not exposed to the underlying entity, the CDS can be used to speculate on the default of the underlying. Consequently, the CDS contract actually adds credit risk between the counterparts which are not directly related to the source of the credit risk. In both scenarios, the presence of CDS contracts leads to a rewiring of the financial network as illustrated by Leduc et al. [7] and Poledna and Thurner [8]. The introduction of CDS contracts within a financial network thus affects the network as a whole, having implications that go beyond the individual counterparts involved in the CDS transactions. It changes the overall risk profile of the financial system by redistributing credit risk and potentially increasing systemic risk. Acemoglu et al. [9] and Ladley [10] show that a more densely connected financial network is more resilient towards small shocks but can fail to absorb large shocks that can propagate through the system. Therefore, the presence of CDS contracts within the financial sector can lead to a more interconnected and fragile financial network, where the failure of a single entity could have far-reaching effects, amplifying the potential for systemic crises.

In the study of financial networks, particularly in the context of complex systems where institutions interact with each other to produce systemic risk, the utility of traditional predictive models, such as logistic regression, can be limited by their inability to fully capture the dynamic interactions and feedback mechanisms inherent in such a system. Agent-based models provide a robust alternative, offering a simulation framework, where individual entities, such as banks or firms, are modeled as agents with distinct behavior and interactions. This approach is particularly advantageous for analyzing the non-linear and often unpredictable behaviors that arise from the intricate interdependencies within financial markets. The relevance and effectiveness of agent-based models has been highlighted by several prior studies. For example, Gilbert [11] emphasizes the capability of ABMs to model economic processes more realistically, accounting for heterogeneity and interactions among agents. Similarly, Chen et al. [12] highlight how agent-based models integrate diverse agent strategies and learning dynamics, making them particularly effective in financial settings. Moreover, agent-based models facilitate a more in-depth analysis of how individual decisions contribute to systemic risk, which in turn can lead to more effective regulatory frameworks and risk management practices. Gatti et al. [13] explore how agent-based models can be used to simulate various economic scenarios, thus offering valuable tools to mitigate future potential systemic risk, which is in line with the conclusions of LeBaron [14].

In this paper, we study the impact of risk transfer on systemic risk by employing CDS contracts as a means to transfer credit risk across institutions. To measure the impact on systemic risk, we construct a simplified agent-based model, inspired by, yet distinctively divergent from, the frameworks presented by Leduc et al. [7] and Poledna and Thurner [8]. Our new approach can be distinguished by two key differences. First, we focus on empirical application by calibrating the model to a sample of Swiss banks, thereby ensuring the interpretability and relevance of our findings. This calibration not only ensures our model is grounded into real-world data but also provides a robust framework for assessing the nuanced impacts of credit risk transfer. Second, we introduce key exogenous shocks to understand how the financial network reacts to different scenarios. This allows us to simulate a range of plausible stress scenarios, which can stem from different exogenous shocks, and observe the reactions within the financial sector. By doing so, we can understand the resilience and robustness of the financial sector to unexpected financial stress.

The remaining of the paper is structured as follows. Section 2 puts the current paper into the context of the existing literature on systemic risk and risk transfer between financial institutions. Section 3 introduces the simulation framework used to model and study the risk transfer within the financial network. Section 4 applies the simulation framework to a sample of Swiss banks and discusses the findings, while Section 5 concludes the paper with some final remarks.

2. Related Literature

Risk sharing and systemic risk are pivotal concepts in financial risk management. They been extensively explored in the literature, particularly after the 2008 global financial crisis. Bandt and Hartmann [2] define systemic risk as the risk of the failure of the entire financial system as opposed to the failure of an individual entity. This type of risk is often the result of highly interconnected financial systems that can cause a ripple effect throughout the financial network. Acharya [3] emphasizes that systemic risk is exacerbated by the interconnectedness of financial institutions, where the failure of one institution can lead to a cascade of failures. Furthermore, Allen and Gale [5] show how local interactions can propagate systemic risk, arguing that financial institutions, in their goal to distribute risk, can also generate additional vulnerabilities due to the complex interactions created.

The literature has focused on developing new risk measures that are not only able to capture systemic risk but also each institution's contribution to it. This has led to an abundance of new measures that can identify the main contributors of systemic risk, especially in the period prior to the crisis. Tobias and Brunnermeier [15] introduce the Conditional Value at Risk (CoVaR) measure, which is computed as the Value of Risk (VaR) of the entire financial network, conditional on an institution being under distress. Two measures closely related to each other are the Systemic Expected Shortfall (SES) from Acharya et al. [16] and Systemic Risk Measure (SRISK) from Brownlees and Engle [17]. While SES measures the bank's predisposition to be undercapitalized conditional on a systemic crisis, SRISK focuses on the capital shortfall conditional on prolonged market decline.

Further contributions to systemic risk measurement incorporate network analysis to capture the interconnectedness of financial institutions. Battiston et al. [18] introduce DebtRank, which gives a measure of centrality for each bank by indicating its importance within the network. It accounts for cascading effects and is easily interpretable as the monetary amount equal to the expected loss of economic value within a financial network originating from that bank defaulting. Huang et al. [19] build on this by quantifying systemic risk through network centrality measures, which identifies the systemically important institutions within the network. Additionally, Billio et al. [20] utilize Granger causality networks to analyze the interconnectedness and the potential for contagion among financial institutions, brokers, hedge funds, and insurance companies, highlighting cross-sectoral pathways of risk.

The role of the risk transfer mechanism in financial networks has been a focal point of economic research, particularly in the context of systemic risk. A key framework for analyzing propagation of contagion across financial networks is the work of Eisenberg and Noe [4], who show how the financial distress of one entity can have an impact across the network, creating cascading effects. A large body of literature has been built on their approach, examining various aspects of financial contagion and systemic risk. For instance, Acemoglu et al. [9] provide evidence that a densely interconnected network serves as a mechanism for shock propagation, resulting in an increase of the network's fragility. Upper and Worms [21] further find that in the absence of a safety net, contagion plays a crucial role, leading to negative consequences that can affect a large number of market participants.

Further notable findings are presented by Elsinger [22], Elliott et al. [23], Rogers and Veraart [24], and Glasserman and Young [25].

There is also a literature stream focused on analyzing the impact of risk transfer through financial instruments, such as CDSs. Che and Sethi [1] argue that the availability of such products can improve borrowing conditions when properly used. Young et al. [26] focus on modeling the US CDS market and apply their newly developed contagion measure to a stress testing scenario. Their results show that a credit spread increase results in an increase in margin payments. On the other hand, Cont [27], one of the first to highlight and investigate this, emphasize the importance of adequate liquid reserves to withstand sudden shocks. Furthermore Eisenberg and Noe [4] and Allen and Gale [5] demonstrate that the network structure of financial markets can act as a mechanism through which systemic risk can propagate leading to cascading effects of defaults, where risk transfer plays a crucial role. Acharya [3] and Ladley [10] show that risk transfer can also lead to a mispricing of risk and increased likelihood of systemic failures during periods of financial stress, as risk transfer mechanisms can obscure the true risk exposure of institutions.

Various papers have also focused on artificially simulated financial network and the study of systemic risk that emerges in them. Based on the simulation framework of Gatti et al. [13], Leduc et al. [7] study how a systemic risk task at the contract level can lead to a rewiring of the financial system and a reduction in systemic risk, compared to the no-tax regime. This model is further expanded by Leduc and Thurner [28] to account for economic efficiencies, and they show the results can be achieved without lowering the total transaction volume. Teply and Klinger [29] model the European banking system and show that a single failure within the network can have negative implications for the system as a whole. Simulation studies under various conditions have also been explored by Gai and Kapadia [30], Georg [31], Caccioli et al. [32], and Nier et al. [33], among others.

The existing literature on systemic risk and risk transfer has extensively explored various mechanisms and their implications, particularly highlighting the interconnectedness of financial institutions and the role of CDSs in propagating systemic risk. However, there remains a significant gap in empirical applications of these theoretical models, particularly those calibrated to real-world data. This paper aims to fill this gap by introducing a simplified agent-based model, specifically calibrated to data from Swiss banks, to examine the impact of risk transfer via CDS contracts on systemic risk. Unlike previous models that adopt a more holistic approach, this study focuses narrowly on banks and firms, allowing for a more detailed and accurate analysis of the effects of both covered and naked CDS transactions under different stress scenarios. By incorporating exogenous shocks and observing the financial network's responses, this research provides novel insights into the resilience and robustness of the financial sector, offering valuable implications for regulatory frameworks and risk management practices.

3. Methodology

3.1. The Agent Based Model

We have developed a simulation framework which is based on the earlier research of Gatti et al. [13] and Leduc et al. [7]. This framework combines macroeconomic models with an interbank system model, which includes a multi-layer interbank loan market and a

CDS market. The model consists of two types of agents, firms and banks, who interact with each other on three distinct markets: credit, interbank loan, and CDS. Unlike Leduc et al. [7], we focus on CDS contracts issued for firms instead of interbank loans. Furthermore, we consider an open system that is vulnerable to systemic shocks in the goods market and on banks' deposits.

Limiting the model to two types of agents instead of three offers several distinct advantages. Firstly, agent-based models are often challenging to calibrate to empirical data, and each additional agent introduces more parameters that need to be calibrated. Therefore, focusing on fewer agents makes our framework more manageable to calibrate to data. Secondly, by removing unnecessary agents, we focus solely on the interbank structure of the model.

Another advantage of our framework is that it concentrates on external shocks to the system. This approach enables us to understand the behavior of the interbank system in relation to different shock scenarios, whether they come from the firm side or the deposit side. For example, the firm side shock enables us to understand the fragility of the banking system in an uncertain market, where a more significant number of firms find themselves in financial difficulty and unable to repay their loans. From the deposit side, banks can find themselves in a precarious situation when many deposits are being withdrawn. These shocks, seen as bank runs, strain the banks' liquidity and make it more difficult to meet financial obligations. By incorporating them within our framework, we can evaluate the system's robustness and resilience towards unexpected financial stress.

3.2. Firms

There are F firms producing perfectly substitutable goods. At every time step, each firm i is characterized by its internal equity $e_{f,i}(t)$, its expected goods demand $s_{f,i}(t)$, and its expected price $p_{f,i}(t)$. Following Gatti et al. [13], the expected demand and price of each given firm are computed based on the previous time step information. More specifically, $s_{f,i}(t)$ and $p_{f,i}(t)$ are a function of the excess supply and the deviation of $p_{f,i}(t-1)$ from the average price in the previous period. Additionally, each firm is characterized by a probability of default $pd_{f,i}$.

To circumvent the omission of the workers' agent within our model, we make the underlying assumption that each firm is able to hire the necessary workers to produce the desired supply. This assumption allows us to model firms without the constraints of labor availability or labor market dynamics, and analyze their interactions with the banks via credit loans. Consequently, this enables a more streamlined examination of the financial mechanisms at play, albeit at the expense of excluding real-world labor market complexities. Firms carry on production by using constant return to scale technology, with labor $l_{f,i}(t)$ as the only input:

$$S_{f,i}(t) = \alpha_{f,i} l_{f,i}(t), \tag{1}$$

where $S_{f,i}(t)$, $l_{f,i}(t)$, and $\alpha_{f,i}$ represent the supply generated, the labor hired, and a constant. While $\alpha_{f,i}$ is assumed in this model to be constant across time, it could be allowed to be time-varying in order to account for technological updates.

The contractual wage offered by firm i in period t is a function of the minimum wage $\hat{w}_t$ set by the regulator, and the wage offered by the firm in the previous period:

$$w_{f,i}(t) = \max(\hat{w}_t, w_{f,i}(t)(1 + \gamma_{f,i}(t))) \tag{2}$$

where $\gamma_{f,i}(t)$ is an idiosyncratic shock uniformly distributed on the interval $(0, h_\gamma)$. The minimum wage is revised upward in order to be in line with inflation. Thus, workers paid the minimum wage are insured against eroding purchasing power due to inflation. Using Equation (1), we can thus compute the required capital needed to create the expected goods demand $s_i(t)$:

$$W_{f,i}(t) = w_{f,i}(t)l_{f,i}(t) = \frac{w_{f,i}(t)s_{f,i}(t)}{\alpha_{f,i}}. \tag{3}$$

If $W_{f,i}(t)$ is smaller than the internal equity of the firm, the firm can directly produce the goods without the need of external capital. If, however, the firm's equity is smaller than the capital needed, i.e., $W_{f,i}(t) > e_{f,i}(t)$, the firm needs to apply for a loan to cover the remaining $c_{f,i}(t) = W_{f,i}(t) - e_{f,i}(t)$ needed to compute the desired supply of goods. Upon successfully securing a loan, a firm uses its capital to generate the desired goods. If unable to do so, the firm lowers its desired supply until no external capital is needed, i.e., $W_{f,i}(t) = e_{f,i}(t)$. We will denote by $W_f(t)$ the vector of wages that need to be paid by each individual firm.

3.3. Banks

There are B banks, each endowed with a balance sheet consisting of equity $e_{b,j}(t)$ and deposits $d_{b,j}(t)$ on the liability side and cash on the asset side (we will denote by $e_b(t)$ and $d_b(t)$ the equity and deposit vectors of the banks). Banks aim to provide liquidity to firms needing credit while ensuring they stay above their minimum capital requirements. For simplicity, we assume the risk limit of each bank is equivalent to ensuring the total notional amount of extended loans does not exceed a predefined multiple of the deposit level. One alternative to this approach would be from the perspective of the Basel III regulations, which require the tier 1 capital-to-risk-weighted assets ratio (RWA) to be above a minimum level. However, this implies another level of complexity to the model, as we would have to assign individual weights to each firm and bank.

Banks can interact with each other in two distinct markets: the interbank market and the CDS market. If a bank desires to extend a firm loan but lacks the necessary liquidity, it can approach other banks and request to borrow the necessary funds. In contrast, if a bank desires to hedge against the risk of a borrower defaulting on a loan, it can enter into a credit default swap (CDS) with another bank.

3.4. Credit Market

Each period, firms compete for loans on the credit market that need to be repaid in full at the end of the period. Given a positive credit demand $c_{f,i}(t) = W_{f,i}(t) - e_{f,i}(t)$, firm i randomly approaches K_f banks and requests an interest rate quote, where K_f is a fixed constant. This restriction ensures each firm can only approach a limited number of banks, which is in line with the real-world scenario, where firms typically have a finite set of banking relationships and limited resources to seek out new ones.

Banks asses each loan request based on a two-step procedure. In the first step, banks ensure the loan's face value is within their credit limits. If extending the new loan breaches their internal risk metrics, the banks reject the loan. Otherwise, the banks quote an interest rate which is dependent on the prevailing interest rate $r_p(t)$, the firm's financial fragility $c_{f,i}(t)/e_{f,i}(t)$, and its default probability $pd_{f,i}$. The interest rate quote of bank j towards firm i is given by:

$$r_{f,i,j}(t) = r_p(t)(1 + u_2 \tanh((1 + u_1 pd_{f,i})c_{f,i}(t)/e_{f,i}(t))). \tag{4}$$

where u_1 and u_2 are innovation terms that allow randomness to be integrated within the model. Firstly, variation in interest rates can be attributed to the banks' individual credit risk assessment. This variation is mathematically expressed as the random variable $u_1 \sim U[0, \theta]$, which controls the magnitude of firm-specific information incorporated in the interest rate calculation. Secondly, a firm's probability of default remains an unobserved event within financial markets. Consequently, this leads to divergent estimations of default probabilities by different banks. Quantitatively, this uncertainty is expressed by $u_2 \sim U[0.9, 1.1]$, which represents banks' heterogeneous perspective of a firm's probability of default. Equation (4) can be interpreted from two perspectives. The first one builds on the theory of "external finance premium" introduced by Bernanke and Gertler [34].

Conditional on ex post asymmetric information and costly state verification, the financial fragility of the borrower dictates the interest rate charged, with higher financial fragility implying higher interest rates. Alternatively, Equation (4) can be seen from the perspective of a model where banks can partially protect themselves using lending by borrowing, where the central bank acts as a lender of the last resort. In this case, the prevailing interest rate $r_p(t)$ is the interest rate the central bank charges the commercial bank.

Firms collect all interest rate quotes and order them in ascending order. Their loan preference will be dictated by the magnitude of the interest rate, with lower interest rates being more attractive.

We define the matrix $L_f(t) \in \mathbb{R}^{F\times B}$, where each individual entry $(L_f(t))_{i,j}$ represents the face value of the loan between firm i and bank j at time t if it exists and zero otherwise:

$$(L_f(t))_{i,j} = \begin{cases} \text{face value of loan if there is a loan between firm } i \text{ and bank } j \text{ at time } t, \\ 0 \quad \text{otherwise.} \end{cases} \tag{5}$$

Similarly , $r_f(t) \in \mathbb{R}^{F\times B}$ represents the interest rate of the loan between firm i and bank j at time t if it exists, and zero otherwise:

$$(r_f(t))_{i,j} = \begin{cases} \text{interest rate of loan if there is a loan between firm } i \text{ and bank } j \text{ at time } t, \\ 0 \quad \text{otherwise.} \end{cases} \tag{6}$$

3.5. Interbank Market

Each bank has limited internal liquidity used to provide loans to the firms within the system. If these funds are exhausted but the bank upholds its credit limits while extending the firm loan, the bank can apply for an interbank loan for the missing funds. Analogous to the mechanisms governing the credit market, a bank needing liquidity can randomly approach a finite number K_b of counterparts. The counterparts, adhering to an equivalent evaluation protocol, quote an interest rate that considers the bank's financial fragility, provided the prospective loan remains within their credit limits.

The quoted interest rate requested by bank j from bank k can be expressed as:

$$r_{b,j,k}(t) = r_p(t)(1 + u_2 \tanh(ff_{b,j})). \tag{7}$$

The financial fragility $ff_{b,j}$ of the bank is defined as:

$$ff_{b,j} = \frac{ms_{b,j} + a_{b,j}}{d_{b,j}}, \tag{8}$$

where $ms_{b,j}$ represent the missing funds, $a_{b,j}$ is the sum of the face value of the loans on the asset side of the book of bank j, and $d_{b,j}$ is the deposits value of bank j. Analogous to Equation (6), $u_2 \sim \mathcal{U}[0.9, 1.1]$ introduces heterogeneity in the quoted rates, thereby reflecting different banks' views on the financial fragility of the borrower.

With multiple loans between banks being possible, we define $L^1_{b,j,k}(t), \ldots L^{n_{j,k}(t)}_{b,j,k}$ as the face values of these loans, while $r^1_{b,j,k}(t), \ldots r^{n_{j,k}}_{b,j,k}(t)$ represent the associated interest rates. We then further define the matrix $L_b(t) \in \mathbb{R}^{B\times B}$, where $(L_b(t))_{j,k}$ represents the total amount owed by bank j to bank k stemming from these loans at time t:

$$(L_b(t))_{j,k} = \sum_{p=1}^{n_{j,k}} (1 + r^p_{b,j,k}(t)) L^p_{b,j,k}(t). \tag{9}$$

If there are no loans between banks j and k, $(L_b(t))_{j,k}$ is set to zero.

3.6. CDS Market

Once a bank j has extended a loan to a firm i, participants in the interbank network can engage in bilateral CDS contracts, which can be used either for hedging or speculative motives. In a standard econometric model, the decision of whether or not to purchase a CDS contract comes down to the risk–return appetite of each individual bank. This can formally be expressed via a utility function that characterizes the risk-aversion profile of a bank, with the bank's goal being to maximize its expected utility.

Characterizing each bank with its utility poses several nuanced issues that complicate the modeling and analysis of the model. These issues stem from the heterogeneous nature of banks in terms of risk tolerance and the complexity involved in capturing systemic interconnections. The accurate characterization of each bank in terms of risk tolerance demands extensive data on the banks' preferences and behavior, which would further complicate the calibration procedure of the model. Furthermore, to capture the impact of risk sharing on systemic risk, it is necessary to understand how changes in utility affect the level of interconnectedness.

To overcome this cumbersome approach, we propose a novel idea that allows us to easily control the level of interconnectedness between banks and study the network under different shocks. We define by $CDS_c \in [0,1]$ the probability that a bank wants to buy a covered CDS contract on its loan. As such, an increase in CDS_c could be associated with a higher risk aversion within each bank, generating a more interconnected network. Similarly, we define $CDS_n \in [0,1]$ as the probability that a bank wants to buy a naked CDS on a loan that is not on its balance sheet, with an increase in CDS_n implying that banks engage in more speculative business. By allowing CDS_c and CDS_n to vary between zero and one, we can study the network under different levels of interconnectedness that can stem either from a risk or speculative perspective.

Consider bank k wants to buy a CDS contract on the loan given by bank j to firm i at time t, where k is not necessarily different from j. This loan is characterized by its face value $(L_f(t))_{i,j}$ and the associated interest rate $(r_f(t))_{i,j}$. Bank k chooses a certain probability (CDS_c if $k = j$ else CDS_n) to buy a CDS contract on said loan and approaches K_c banks within the network to request a spread. The spread represents a percentage of the notional value that needs to be insured, which for simplicity we choose to be $(L_f(t))_{i,j}$. Each counterpart computes the spread based on Hull and White [35] assuming no counterpart risk but some uncertainty on the underlying's default probability. Bank k then chooses the CDS with the most attractive spread.

As a firm can acquire a maximum of one loan within our framework, we can aggregate the information from the CDS market on the loan of firm i at time t with two matrices $C_n^i(t), C_s^i(t) \in \mathbb{R}^{B\times B}$. $C_n^i(t)$ holds information regarding the notional amount of the CDS contracts on the loan of firm i and is defined as:

$$(C_n^i(t))_{j,k} = \begin{cases} \text{notional amount of the CDS between } j \text{ and } k \text{ on the loan of firm } i \text{ at time } t, \\ 0 \quad \text{otherwise,} \end{cases} \tag{10}$$

where j represents the buyer of the CDS, while k represents the seller. Similarly, $C_s^i(t)$ holds information on the spread of the CDS contracts on the loan of firm i:

$$(C_s^i(t))_{j,k} = \begin{cases} \text{spread of the CDS between } j \text{ and } k \text{ on the loan of firm } i \text{ at time } t, \\ 0 \quad \text{otherwise.} \end{cases} \tag{11}$$

In the case of firm default, the amount the CDS seller needs to pay to the CDS buyer is a function of the notional amount and the recovery rate:

$$\text{Payment} = (1 - \text{Recovery Rate}) \times \text{Notional Value}, \tag{12}$$

where the recovery rate is the percentage of the loan the firm was able to pay back.

3.7. Goods Market

The goods market is simulated via an exogenous shock applied to the consumption of each firm. By varying the magnitude of the shock, we can control the level of firms in financial distress, which can generate a spillover effect within the interbank system via the bank-to-firm loans.

We define $\xi_{f,i}(t)$ as the relative consumption for each firm i for period t. Once the desired supply $s_{f,i}(t)$ has been produced, each firm can sell $\xi_{f,i}(t)s_{f,i}(t)$ of its supply and receive $p_{f,i}(t)$ per supply sold, with the remaining supply assumed perishable. The relative consumptions are assumed to be independent and identically distributed realization drawn from $\mathcal{N}(\mu_{goods}, \sigma^2_{goods})$, with the underlying constraint that $0 < \xi_{f,i}(t) < 1$. The mean μ_{goods} of relative consumptions thus controls the supply level sold, while the standard deviation σ_{goods} allows for variability across firms. A higher μ_{goods} implies firms can sell more of their supply, which ensures their liquidity, while with a lower μ_{goods}, firms can find themselves in financial difficulty and unable to repay their loans.

Once the goods market is finished, we can write the balance sheet of each firm. On the asset side, firm i will have $p_{f,i}(t)\xi_{f,i}(t)s_{f,i}(t)$, while on the liability side, firm i will have the equity $e_{f,i}(t)$ and potentially a loan that needs to be repaid.

We let $p_f(t)$, $\xi_f(t)$, $s_f(t) \in \mathbb{R}^{F\times 1}$ represent the price vector of goods, the relative consumption of goods, and the supply generated by each firm. Each entry i within each vector represents information related to the i^{th} firm.

3.8. Deposit Shock

The bank deposit shock is modeled similarly to the goods market one. We assume each bank receives a shock proportional to its deposit level. Let $D_{shock} \sim \mathcal{N}(\mu_{deposit}, \sigma^2_{deposit})$ represent a random variable from which we draw B independent samples denoted by $d^{shock}(t) = (d_1^{shock}(t), \ldots d_B^{shock}(t))^T \in \mathbb{R}^{B\times 1}$. Each bank will thus incur a shock $d_j^{shock}(t)d_{b,j}(t)$ to their deposits. These deposit outflows (or inflows) must be processed before the market clearing. They can have an impact on the liquidity of the bank, as they can strain a bank's liquidity, making it difficult to meet its obligations.

3.9. End of Period Clearing

At the end of each period, each market participant must clear their obligations. This entitles firms to make sure they can repay any outstanding loans. If they can do that, the firms stay solvent. Otherwise, the firms default and use all available capital to repay the loan partially. For banks, clearing obligations is more complex, as one bank's default can influence the liquidity of another bank. To that end, we employ the clearing mechanism of Eisenberg and Noe [4] to identify the defaulting banks and clear all obligations. We will denote with t_+ the end of period t.

By equalizing each firm's balance sheet, we can identify the defaulting firms. In the case of no loan on the balance sheet of firm i, its equity at the end of period t is given by:

$$e_{f,i}(t_+) = e_{f,i}(t) - W_{f,i}(t) + p_{f,i}(t)\xi_{f,i}(t)s_{f,i}(t), \tag{13}$$

which is the value of the asset side of the balance sheet. In contrast, if firm i has a loan with bank j with a face value of $(L_f(t))_{i,j}$ and interest rate $(r_f(t))_{i,j}$, the loan must be repaid. The firm can repay the loan if the value of the asset side of the books is larger than the loan's value. Specifically, the firm is not defaulting on the bond if $p_{f,i}(t)\xi_{f,i}(t)s_{f,i}(t) > (1 + (r_f(t))_{i,j})(L_f(t))_{i,j}$. In such a case, the equity of firm i and the end of period t is given by:

$$e_{f,i}(t_+) = p_{f,i}(t)\xi_{f,i}(t)s_{f,i}(t) - (1 + (r_f(t))_{i,j})(L_f(t))_{i,j}, \tag{14}$$

as the face value of the loan plus the initial equity is equal to the funds necessary to produce the supply. If the firm cannot repay the loan in full, it uses all available funds to repay a portion of the loan, specifically $p_{f,i}(t)\xi_{f,i}(t)s_{f,i}(t)$. In this case, the end-of-period equity is zero, and the firm defaults.

The end-of-period equity of the firms can be written in vectorized format as:

$$e_f(t_+) = (e_f(t) + L_f(t)\mathbb{1}_B - W_f(t) + p_f(t) \circ \xi_f(t) \circ s_f(t) - ((J_B + r_f(t)) \circ L_f(t))\mathbb{1}_B)^+, \tag{15}$$

where $\mathbb{1}_B \in \mathbb{R}^{B\times 1}$ represents a one-dimensional vector full of ones, $\circ$ is the Hadamard product (for two matrices A and B of the same dimension $m \times n$, the Hadamard product $A \circ B$ is a matrix of the same dimension as the operands, with elements given by $(A \circ B)_{i,j} = A_{i,j}B_{i,j}$), $J_B \in \mathbb{R}^{B\times B}$ is a matrix full of ones, and A^+ is the positive part of matrix A with $(A^+)_{i,j} = \max(0, A_{i,j})$. The defaulting firms can then be easily identified as the set:

$$\text{defaulting firms} = \{i \mid i \in \{1, \dots, n\} \text{ and } e_f(t_+)_i = 0\}. \tag{16}$$

To employ the clearing mechanism of Eisenberg and Noe [4], we need to compute the wealth vector, denoted by $\omega(t_+) \in \mathbb{R}^B$, and the liability matrix $L(t_+) \in \mathbb{R}^{B\times B}$. The wealth vector represents each bank's available funds to repay its counterparts in the interbank network. At the same time, the liability matrix contains information on the amount each bank owes to each other, with $L_{i,j}(t_+)$ representing the funds owed by bank i to bank j at the end of period t.

The wealth of bank j can be computed as the bank's initial equity plus the funds received from firm loans. As deposit shocks must be processed before market clearing, we need to subtract any deposits that must be paid out from the wealth.

The funds received by each bank from each firm can be written as a matrix $V(t_+) \in \mathbb{R}^{F\times B}$:

$$V(t_+) = \min((J_B + r_f(t)) \circ L_f(t), \mathbb{1}_B^T \otimes (p_f(t) \circ \xi_f(t) \circ s_f(t))), \tag{17}$$

where the max operator is taken element-wise, and $\otimes$ represents the Kronecker product (For two matrices A and B of dimensions $m \times n$ and $p \times q$ the Kronecker product $A \otimes B$ is a matrix of dimensions $pm \times qn$ with elements given by $(A \otimes B)_{i,j} = A_{\lceil i/p\rceil,\lceil j/q\rceil} B_{(i-1)\%p+1,(j-1)\%q+1}$). The total funds received by each bank from all firms can then be expressed as $V_f(t_+) \in \mathbb{R}^{B\times 1}$:

$$V_f(t_+) = V(t_+)^T \mathbb{1}_F. \tag{18}$$

Finally, we can write the wealth vector as:

$$\omega(t_+) = e_b(t) + V_f(t_+) + \min(d^{shock}(t) \circ d_b(t), 0), \tag{19}$$

where the min operator is taken element-wise, and the final term in Equation (19) ensures we only deduct negative deposit shocks.

To construct the liability matrix, we need to compute the outcome from the interbank and CDS markets. For the interbank market, each bank needs to repay the face value of the loans and the accrued interest, which we conveniently denote by $L_b(t)$. For the CDS market, each CDS buyer needs to pay the spread of the CDS and receive protection from the seller if the firm defaults. The payment of CDS spreads is captured by the matrix $C_s(t) \in \mathbb{R}^{B\times B}$:

$$C_s(t) = \sum_{i=1}^{F} (C_s^i(t) \circ C_n^i(t)). \tag{20}$$

In the case of firm default, the CDS seller only needs to pay back a fraction of the notional value of the CDS as described by Equation (12), with the recovery rate being expressed as a function of the value of the loan that needs to be paid back and what the firm pays back. Using our matrix notation, the recovery rate vector $R(t_+) \in \mathbb{R}^{F\times 1}$ can be expressed as:

$$R(t_+) = (V(t_+)\mathbb{1}_B) \oslash (((J_B + r_f(t)) \circ L_f(t))\mathbb{1}_B), \tag{21}$$

where the operator $\oslash$ is the modified Hadamard division which returns 1 if the denominator is equal to zero (for two matrices A and B of the same dimension $m \times n$, the modified Hadamard division $A \oslash B$ is a matrix of the same dimension as the operands, with elements given by $(A \oslash B)_{i,j} = \mathbb{1}_{\{B_{i,j}=0\}} + \mathbb{1}_{\{B_{i,j}\neq 0\}} A_{i,j}/B_{i,j}$). Using this modified operator, the recovery rate is 1 if the firm fully repays the loan or does not have a loan with a bank. The payment of CDS insurance can then be quantified using the matrix $C(t_+) \in \mathbb{R}^{B\times B}$:

$$C(t_+) = \Big(\sum_{i=1}^{F} (1 - R(t_+)_i) C_n^i(t)\Big)^T, \tag{22}$$

where the transpose ensures entry $C(t_+)_{i,j}$ represents the amount bank i owes to bank j.

The liability matrix $L(t_+)$ can then be expressed as:

$$L(t_+) = L_b(t) + C_s(t) + C(t_+) \tag{23}$$

$$= L_b(t) + \sum_{i=1}^{F} (C_s^i(t) \circ C_n^i(t)) + \Big(\sum_{i=1}^{F} (1 - R(t_+)_i) C_n^i(t)\Big)^T. \tag{24}$$

The clearing mechanism of Eisenberg and Noe [4] takes the liability matrix and the wealth vector and defines the outstanding liabilities vector $\overline{L}(t_+)$, and the relative liability matrix $\Pi(t_+)$:

$$\overline{L}(t_+) = L(t_+)\mathbb{1}_B \tag{25}$$

$$\Pi(t_+)_{ik} = \frac{L(t_+)_{ik}}{\overline{L}(t_+)_i}, \text{ if } \overline{L}(t_+)_i > 0, \text{ and } \Pi(t_+)_{ik} = 0 \text{ else.} \tag{26}$$

The clearing mechanism then computes the payment vector $p(t_+)$, which establishes the total amount each bank has to pay to its counterparts, which is the solution to:

$$p(t_+)_i = \min\Big\{\overline{L}(t_+)_i, \omega(t_+)_i + \sum_{i=1}^{B} \Pi(t_+)_{ik} p(t_+)_k\Big\},\ i \in \{1, \dots, B\}. \tag{27}$$

Once the market is cleared, we can identify the defaulting banks which can arise from two scenarios. Either the bank was unable to pay all outstanding debt to market participants, or it was unable to equalize the balance sheet to ensure deposits are covered. In both of these situations, the bank is considered to be defaulting.

The defaulting firms and banks are removed from the network, and we replace them with new ones, which are constructed as the averages of the remaining market participants.

4. Simulation Study

We apply our agent-based model for a network consisting of $B = 80$ banks and $F = 10{,}000$ which is calibrated to empirical data of the Swiss interbank market.

We consider a one-period model, and study the dynamics of the network under different CDS appetite regimes as well as different shocks scenarios. As discussed in Section 3, the model can incur shocks stemming from the goods market clearance and changes to the deposits held by the banks. For every model specification, results will be averaged over 10,000 independent simulations.

We collected bank data from Fitch Connect at the end of December 2022 for the Swiss interbank market. After cleaning the data, we ended up with 80 unique banks that reported their equity, total deposits, and total loans. For each bank within our sample, we initialize an agent within our framework that inherits the equity and total deposits of the actual bank.

The firms within the system are generated through a stochastic process, where the parameters of each agent are drawn from predefined probability distributions. This approach ensures that the generated agents exhibit heterogeneity, observed in a sample of real-world firms. In selecting the parameter sampling distributions, we rely on methodological choices inspired by precedents in existing literature. Distinctively, we innovate by adopting a joint bounded Pareto normal distribution to determine the agents' equity and supply levels. This novel approach allows us to capture the complex relationship between these two often interlinked parameters.

4.1. Model Calibration

To ensure interpretability of the model results, we calibrate the model to the retrieved empirical data. Additionally, we calibrate the goods market to account for a small fraction of firm defaults, which will later serve as a baseline for the goods market exogenous shocks.

The initial phase of the calibration process prioritizes ensuring that the system generates a suitable level of firm loans across independent simulations. For this purpose, let $\theta \in \mathbb{R}^M$ denote the parameter vector characterizing the firms' initialization, while *seed* represents the initial seed of the simulation. In an ideal scenario, the model would be calibrated to the empirical data across a wide range of seed values to ensure variation in the inherent randomness of the agent model is captured. However, such a procedure is extremely demanding. Given the high dimensionality of the parameter space, the highly nonlinear structure of the minimization problem, and the extremely demanding simulation procedure, this approach would result in an exponential number of simulation runs.

Our calibration approach overcomes this by splitting the process into two distinct phases. In a first step, we run the minimization problem under a predefined seed value. This ensures that the calibration procedure converges to the optimal parameters within a reasonable time frame. In the second step, given the optimal parameter set, we run many independent simulations, each with a different random seed, to ensure little variability across them.

Given the simulated and empirical loan-to-equity ratios $LE_{1,\theta,seed}, \ldots, LE_{B,\theta,seed}$ and $\widehat{LE}_1, \ldots, \widehat{LE}_B$, our objective is to determine the parameter vector $\widehat{\theta}$ that minimizes the $\mathcal{L}_2$ loss function. (We have considered three different loss functions: $\mathcal{L}_1$, $\mathcal{L}_2$, and $\mathcal{L}_{max}$. Among these three, $\mathcal{L}_1$ and $\mathcal{L}_2$ perform the best, with $\mathcal{L}_2$ slightly winning in terms of maximum absolute deviation from the true observations.) As mentioned before, our approach will initially calibrate the model over a single random seed value *seed*. The optimal parameter vector $\widehat{\theta}$ is then the solution to the following minimization problem:

$$\widehat{\theta} = \min_{\theta} \big(\frac{1}{B} \sum_{i=1}^{B} (LE_{i,\theta,seed} - \widehat{LE}_i)^2 \big). \tag{28}$$

Figure 1 presents the simulated loan-to-equity ratios against the empirical loan-to-equity ratio, with the red dotted line indicating the 45° degree line. The comparison reveals a high degree of similarity indicating the calibrated model can capture the structure imposed by the empirical data. This is further confirmed by running a linear regression of the empirical ratios against the simulated ones, which gives us a slope coefficient of 1.01 with a t-statistic of 33.49. These results emphasize the effectiveness of the calibration process, demonstrating that the simulation model can accurately replicate the distributional characteristics of the loan-to-equity ratio observed in real-world data.

Under the optimal parameter vector $\widehat{\theta}$, we run 10,000 independent simulations, each with a different random seed, and compute the Mean-Squared Error (MSE) and Mean-Absolute Error (MAE) for each of them. Table 1 presents the median MSE and MAE error rates across the simulations and the 99% confidence intervals. Overall, the results suggest minor variation across simulations, confirming the calibration's robustness.

Finally, we fine-tune the goods market to account for a small fraction of firm defaulting, corresponding to a stable market period. Given the optimal parameter vector $\widehat{\theta}$ and the desired consumption mean μ_{goods}, we run 1000 simulations and calculate the median value of defaulting firms along with 99% confidence intervals, which are displayed in Figure 2. We select μ_{goods} as the baseline good market period, where only 2% of firms default.

Table 1. Median and 99% confidence intervals of the Mean-Squared Error (MSE) and Mean-Absolute Error (MAE) across 10,000 simulations under the optimal parameter vector $\widehat{\theta}$.

	Median	**99% Confidence Interval**
MSE	0.20	(0.14, 0.54)
MAE	0.29	(0.23, 0.37)

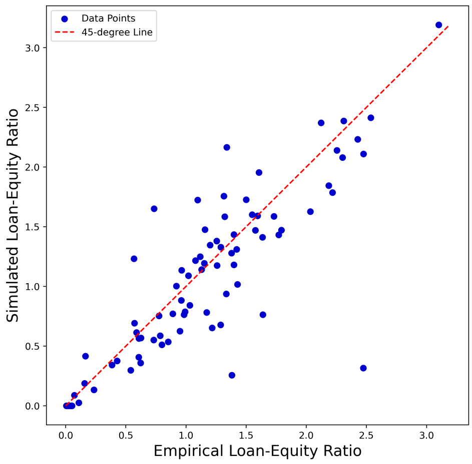

Figure 1. The figure displays the simulated loan-to-equity ratios against the empirical loan-to-equity ratio. In red, we display the 45° degree line.

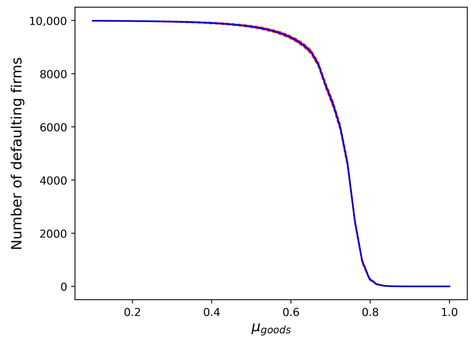

Figure 2. The plot presents the median number of defaulting firms (in blue) and the associated 99% confidence interval (in red) as a function of the relative consumption mean μ_{goods}.

4.2. Scenarios

We test the interbank network's resilience towards exogenous shocks, depending on its interconnectedness via CDS contracts, by considering several scenarios under which banks find themselves in financial distress. As previously outlined in Section 3, exogenous shocks can arise from the goods market or bank's deposit outflows.

The goods market is cleared via exogenous goods consumption for each firm as drawn from a random distribution characterized by location and scale parameters. By decreasing the location parameter, we achieve a lower average goods demand, while an increase in the scale parameter increases the variance in consumed goods across firms. Consequently, firms experiencing lower goods demand may encounter financial distress, impeding their ability to fulfill loan obligations. This economic perturbation can propagate to the interbank network through the credit market, potentially leading to numerous firms defaulting on their debts and placing banks at risk. To capture this effect, we consider an average goods demand decrease of $\Delta\mu_{goods} = 5\%$ in all subsequent scenarios.

The exogenous deposit shock generates deposit outflows (or inflows) with seniority over fulfilling banks' obligations within the interbank network. This can leave banks with less capital to cover their debts within the network and increase each bank's probability of default. We will consider three negative deposit shock levels, varying in severity from 0.5% up to 10%.

To accurately capture the impact of CDS contracts on the distress network, the model is simulated across a grid of CDS probabilities, ranging from 0% to 50% for CDS_c and from 0% to 5% for CDS_n. The robustness and reliability of the results are ensured by running 10,000 simulation for each parameter set.

Finally, our aim is to understand how the shock scenarios impact the differently specified financial networks. To do this, we look at the total equity change of the system. For each simulation run, we calculate the total equity change between the start and end of the period. By analyzing these distributions, we can gain insights into how differently specified networks react to the three shock scenarios.

4.3. Results

As previously discussed in Section 4.2, we will consider several regimes. Each regime will be characterized by a decrease of 7.5% in goods demand and by varying deposit shocks. The network's initialization is the same across all regimes, which is achieved by using the same seed values.

Figure 3 presents a snapshot of the simulated interbanking system relationships for the largest seven banks under different levels of CDS probabilities. The nodes symbolize the banks within the system which are colored according to their internal equity, from large equity reserves (red) to small equity reserves (green). The edges represent the different contractual obligations between banks, with the arrow pointing to the bank that needs to receive the funds. The width and color of the edges represent the size of the obligations, from large (in red and thicker) to small (in green and thinner).

Clearly, the largest banks are the ones that engage the most in CDS contracts, by acting as counterparts in the CDS market. This characteristic is persistent across all three subplots. However, as the desire for securing investments increases, the value of their obligations increases as well. As such, the two largest banks within the system find themselves in a precarious situation if the underlying firm market exhibits a negative shock. If unable to meet their obligations, their default will ripple through the financial network, impacting the stability of the other banks.

We compare different model specifications by analyzing the total equity return distribution of the financial system. Given the goods demands and deposit shock, we run 10,000 simulations and compute the total equity return for each, calculated as the percentage change in the total equity of the network. In Figure 4, we show the histogram of total equity returns for a deposit shock of 0.5%. In all three subfigures, the blue distribution represents the model with no CDSs present, while the red and green ones allow for a degree of covered and naked CDS within the system. Subfigure (a) presents the results where only covered CDS are allowed, while Subfigure (b) allows only naked CDSs. Finally, Subfigure (c) allows a mix of both covered and naked CDSs. Similarly, Figures 5 and 6 present the results for a deposit shock of 5% and 10%, respectively.

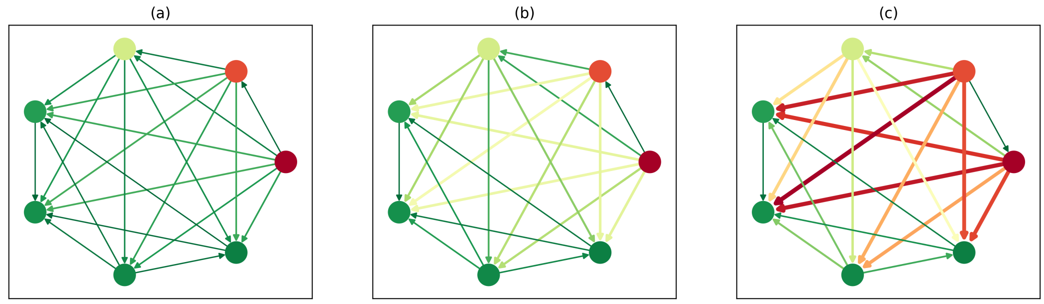

Figure 3. The plot presents the simulated interbanking interactions among the five largest banks by equity under different CDS_c probabilities. Subplot (**a**) represents the results for $CDS_c = 10\%$. Subplot (**b**) represents the results for $CDS_c = 25\%$. Subplot (**c**) represents the results for $CDS_c = 50\%$. The color of the nodes represents the size of the individual equity of the banks, from small (green) to large (red). The color and width of the edges represent the size of the liabilities between banks, from small (in green and thin) to large (in red and thick).

All networks demonstrate resilience to minor deposit shock, with no significant total equity losses observed. This indicates that the financial networks are robust to small losses, even when CDSs are transactioned. In the cases where banks are allowed to buy or sell CDS contracts, we observe higher variance and kurtosis in the equity return distribution. This indicates that while CDSs can provide useful hedging options, their presence introduces greater variability and instability within the network. Under medium and large deposit shocks, the effect generated by covered CDSs is pronounced. Instead of containing losses, covered CDSs act as a channel for systemic risk propagation across the financial network as indicated by the prominent left fat tail in the returns distribution. These left tails represent more frequent negative outcomes, which are less extreme in the absence of CDSs. Similarly, naked CDSs exacerbate systemic risk, leading to even larger potential equity losses.

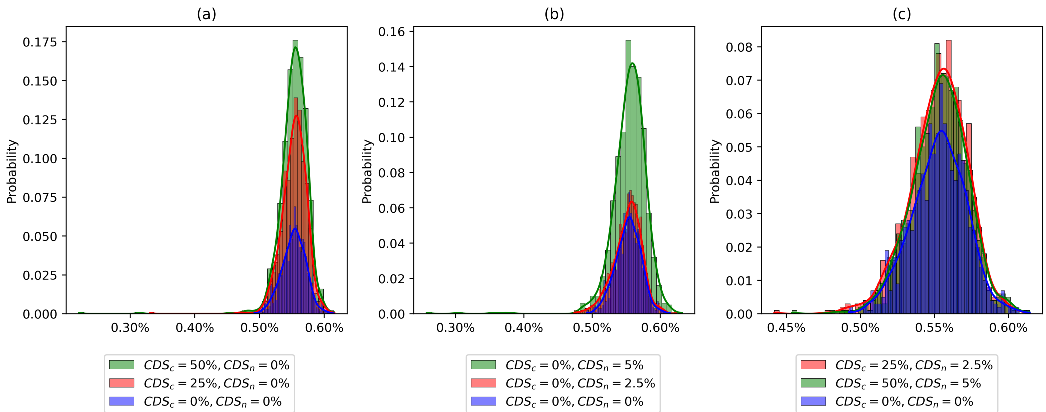

Figure 4. Histogram of total equity returns distributions under different model specifications and a deposit shock of 0.5%. The x-axis represents the total equity return, while the y-axis represent the normalized bars that bar heights sum to 1. Histogram (**a**) compares the results between no CDSs within the system (blue) with networks, where only covered CDSs are allowed (red and green). Histogram (**b**) allows only naked CDSs (red and green), while histogram (**c**) allows a mix of both naked and covered CDSs.

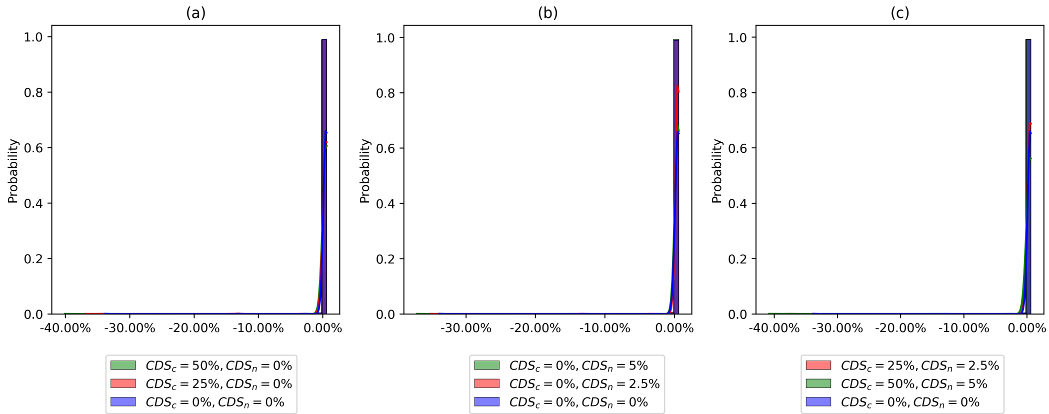

Figure 5. Histogram of total equity returns distributions under different model specifications and a deposit shock of 5%. The x-axis represents the total equity return while the y-axis represent the normalized bars that bar heights sum to 1. Histogram (**a**) compares the results between no CDSs within the system (blue) with networks where only covered CDSs are allowed (red and green). Histogram (**b**) allows only naked CDSs (red and green), while histogram (**c**) allows a mix of both naked and covered CDSs.

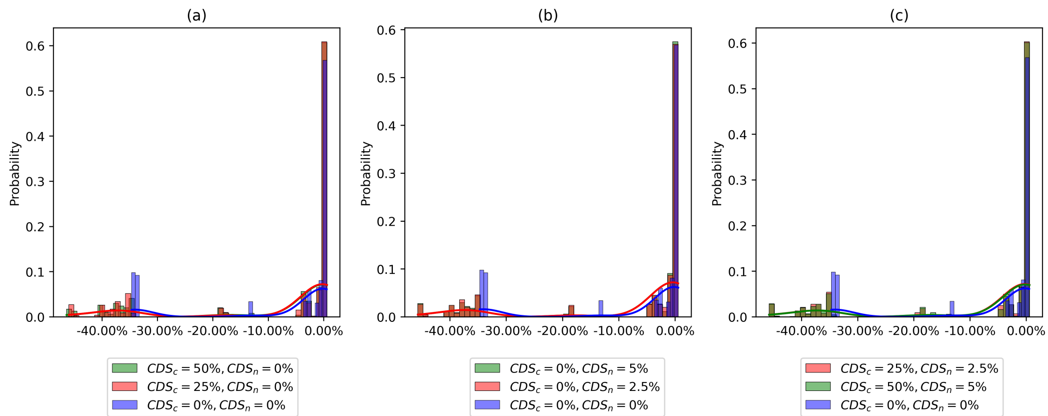

Figure 6. Histogram of total equity returns distributions under different model specifications and a deposit shock of 10%. The x-axis represents the total equity return, while the y-axis represent the normalized bars that bar heights sum to 1. Histogram (**a**) compares the results between no CDSs within the system (blue) with networks where only covered CDSs are allowed (red and green). Histogram (**b**) allows only naked CDSs (red and green), while histogram (**c**) allows a mix of both naked and covered CDSs.

5. Conclusions

We construct a simplified agent-based model to study the impact of risk transfer on systemic risk using CDS contracts as a means to transfer risk across financial institutions. Our model is inspired by, yet distinctively divergent from, the framework of Leduc et al. [7] and Poledna and Thurner [8]. We consider two types of agents, firms and banks, which interact in three distinct markets: credit, interbank loans, and CDSs. This contrasts with the previous literature, which has focused on a holistic approach, modeling each prominent economic actor.

This study contributes to the existing literature by providing empirical evidence from simulations based on real-world data of Swiss banks, highlighting how variations in risk-sharing mechanism can impact financial stability. Unlike previous models, this study specifically examines the effect of both covered and naked CDS transactions under different stress scenarios, thus offering a more detailed understanding of systemic risk propagation.

The advantage of including only banks and firms within our framework is twofold. Firstly, agent-based models are notorious for being challenging to calibrate to empirical data, with each additional agent generating more parameters that need to be calibrated. Secondly, we can focus solely on the interbank structure of the model. Central to our framework is the empirical application by carefully calibrating the agent-based model to a sample of Swiss banks. By doing so, we ensure our results are interpretable and relevant. Furthermore, the developed framework can thus be used by regulators to assess the nuanced impacts of credit risk transfer on the financial system. Finally, we introduce exogenous shocks to understand how the financial network reacts to different risk scenarios. This approach enables us to simulate a range of plausible stress scenarios, which can stem from different exogenous shocks, and observe the behavior of the financial network.

To control the level of CDS contracts between banks, and thus the level of interconnectedness within the financial network, we introduce two variables $CDS_c, CDS_n \in [0,1]$, which control the probability that a financial institution wants to buy a covered CDS or a naked CDS, respectively. By allowing these two variables to vary between zero and one, we can study the financial network under different levels of connectivity that can stem from a risk or speculative perspective. Coupled with varying deposit shocks, we can analyze how a tightly connected financial system behaves in the presence of systemic risk. Our results show that the financial networks demonstrate resilience under minor deposit shocks, with no significant total equity losses observed. However, when CDSs are allowed to be traded, the total equity returns distributions exhibit larger variance and kurtosis, indicative of instability added to the system. When medium and large exogenous deposit shocks are applied to the system, the effect generated by CDS is pronounced, acting as a channel for systemic risk propagation across the network rather than as a hedging mechanism, with results in line with Acemoglu et al. [9]. Consequently, rather than acting as a hedging mechanism, the presence of covered CDSs generates prominent left fat tails in the total equity returns distribution, which are representative of heightened systemic risk during periods of financial distress. Similar results are observed for naked CDSs, exhibiting the same characteristic as in the case covered CDSs. Therefore, the increase in CDS demand, which can be attributed to higher demand from the banks' side to safeguard their investment, leads to a tightly interconnected network that is unable to withstand sudden systemic shocks.

By focusing on CDSs, our findings extend the work of Poledna and Thurner [8], which were focused on the effects of derivatives without delving into the nuances of covered versus naked CDS impact. Furthermore, while Acemoglu et al. [9] demonstrates how network interconnectedness could influence systemic risk, our study quantifies how specific risk-sharing mechanisms via CDS transactions contribute to systemic risk, particularly under different stress scenarios. This responds to the broader call by Eisenberg and Noe [4] for more detailed analysis of financial instruments within systemic risk framework. Our results also contrast those of Gai and Kapadia [30], who found that interconnectivity could sometimes lead to resilience in financial networks. In contrast, we observe that interconnectivity via CDS contracts lead to an increase in systemic risk, particularly during market downturns. Furthermore, our analysis aligns with insights from Glasserman and Young [36], who studies how shocks can propagate across financial networks, showing that CDS transactions can act as a propagation of systemic risk.

The implications of this research extend to both financial regulators and institutions engaged in risk management. The findings suggest that in highly interconnected networks, instruments such as CDSs fail to act as a hedging mechanism and act as a conduit for systemic risk propagation. This leads to scenarios where stability is compromised in times of financial distress. Regulatory bodies can use these insights to formulate policies that might include stricter control of derivative instruments and enhanced monitoring of interbank exposures. Lastly, the study's primary limitation lies in its reliance on simplified agents, which might not capture the full complexity of the financial markets. Future studies could extend this research by considering more generalized agents that allow for different risk transmissions.

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Abbreviations

The following abbreviation is used in this manuscript:

CDS Credit Default Swap

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