CONTAGION IN INTERACTING FINANCIAL NETWORKS

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Abstract

I model financial network of investors, banks and insurance company. Investors provide some investments as a debt to banks. Banks invest in an outside risky assets and they are potentially interconnected with each other via over-the-counter (OTC) contracts to diversify their portfolio. The insurance company (IC) provides credit default swap contracts (CDS) to banks. Therefore, OTC and CDS might be channels for shock propagation in the financial network. CDS were one of the main financial instruments due to which different financial institutions were interconnected with each other during the global financial crisis 2007-2008 caused severe damage for the whole financial system. I investigate whether CDS reduce or enlarge systemic risk in interacting financial networks.

Using computational model with banks hedging their asset risk via CDS, I identified that when the risk weighting on risky assets is small, banks and the whole network benefit from buying CDS since the number of defaults is less than in the case of not buying CDS. When the probability of risky project’s defaults is approximately in the interval [0.5, 0.6], we have the minimum number of bank defaults. Since financial institutions are linked with each other via OTC and CDS and a shock or default of one bank can affect multiple other banks, all banks benefit from a reduction in the number of bank defaults.
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1. Introduction

The global financial crisis 2007-2008 showed that the modern financial system is highly interconnected which creates potential channels for contagion of shocks among financial institutions. Credit default swaps (CDSs) were one of the main instruments due to which different financial institutions were interconnected with each other during the crisis caused pernicious consequences for the world economy. It raises a question addressed in this paper: do CDSs reduce or enlarge systemic risk in interacting financial networks? There are only few in depth theoretical and empirical papers of interconnectedness of banks and non-banks involved as CDS protection sellers and buyers. Therefore, using computational model with banks hedging their asset risk via CDS, I am going to identify the conditions under which CDS contracts reduce systemic risk in interacting financial networks.

In a highly interconnected financial system, where banks are linked together, a shock in one part of the system is likely to be passed to other parts of the system. An example of the importance of such links between financial institutions is the bankruptcy of the major US investment bank Lehman Brothers. The bank had relationships with many investment banks, insurance companies and other financial institutions. After bankruptcy in September 2008, their counterparties largely closed out their derivative positions where they still could make some profit. By doing so, counterparties held the collateral which Lehman had posted, which they then sold off. The simultaneous sell-off of these assets depressed market prices, many financial institutions around the world went bust and this brought huge uncertainty to the financial markets about the creditworthiness of counterparties. The collapse of Lehman in September 2008 almost brought down the world’s financial
system (Balluck, 2015). This example shows how it is important to analyze different channels of interconnectedness of financial institutions.

There are many different types of interconnectedness in financial networks. Generally speaking, financial institutions are connected to each other both directly and indirectly.

Direct interconnectedness occurs through bilateral transactions when an asset on the balance sheet of one financial institution is a liability for another. For example, if the bank A borrows money from bank B, then the two banks are directly connected. Moreover, for bank B, who has lent to bank A, borrowed money features as an asset on bank’s B balance sheet and for bank A as a liabilities (Langfield, Liu, Ota, 2014). If bank A, due to an exogenous shock, is not able to pay debts owed, bank B faces losses. This type of credit exposure between banks is a common type of direct interconnectedness.

Banks can be directly interconnected through derivatives contracts. Moreover, the size of such contracts in the real economy growths rapidly. For example, according to the Bank for International Settlements, the notional amount of outstanding over-the-counter (OTC) derivatives contracts was $630 trillion in 2014. Figure 1 shows derivatives market growth from 1998 to 2013 OTC. So a crash of the network where financial institutions are connected to each other via OTC contracts or credit default swap (CDS) contracts might cause large losses for the financial system.
Banks are also directly connected to each other via payment systems. Typically, the payment system has a small number of clearing banks and a large number of indirect participants who have access to the system through a clearing bank. According to Bank of England (Lui, Quiet, Roth, 2015) over 80% of small UK banks and building societies do not use more than one clearing bank (see Figure 2).
If a leading clearing bank were to fail, some of these indirect participants might not be able to make wholesale payments if they could not find another clearing bank within a short period. So default of the clearing bank affects other banks and might potentially force them to default as well.

Banks might also be interconnected through indirect channels. Indirect interconnectedness takes place when losses occur between financial institutions which are not counterparties. Hence, a shock or default of one bank can affect multiple other banks through mark-to-market losses, margin calls and information spillovers. For example, in the case of fire sales by distressed banks asset prices might go down which may cause mark-to-market losses for other banks. Another example of indirect interconnectedness is a lack of confidence in the credit quality of particular banks. If a bank faces a problem to pay their liabilities for any reason, then the market may revalue its liabilities. In a mark-to-market regime this reduction in value might affect other banks that have these liabilities in their portfolio. Thus, because of the possibility of a bank’s default, real defaults can happen through mark-to-market losses.
Sometimes a bank protects their investments by buying credit default swap (CDS) contracts. A CDS is a contact that provides insurance against the risk of a default by a particular company, a loan default or other credit event.¹ Credit default swaps have existed since 1994, and increased in use after 2003. According to the Bank for International Settlements by the end of 2007, the outstanding notional amount CDS contracts was $58.2 trillion, falling to $26.9 trillion by mid-year 2012 and reportedly $16.4 trillion in the second half of 2014. There are different reasons why CDS market was growing rapidly and resulting in being much larger than the markets for the underlying assets.

Main reason why CDS market was much larger than the markets for the underlying assets is that Basel II by the Basel Committee for Banking Supervision (BCBS) recognized CDS and other credit derivatives as financial instruments to mitigate credit risk. So banks used CDS for capital relief which allowed them to invest more into riskier assets with potential hedging opportunities. During the 2007-2008 financial crisis, CDS was seeing as one of the drivers of the collapse of the financial system because buying CDS contracts let banks and other financial institutions took excessive risk.

Banks and other financial institutions were linked with each other by CDS contracts so if a bank or other financial institution faced a default and insurance company couldn’t pay by its liabilities, other banks or financial institutions in a network shared these difficulties because they had contracts with failing bank. Therefore, CDS contracts were one of the channels of contagion that could propagate negative shocks and impact on financial stability. However, CDS contracts served as an instrument to mitigate risk. Through CDS contracts, a buyer of such contracts can mitigate the risk associated with an investment by shifting all or a proportion of that risk on an insurance company or other CDS seller in exchange for a periodic fee. Thus, the

¹ Usually a credit event occurs when a particular company faces a failure to make a payment as it becomes due or a bankruptcy.
buyer of CDS receives credit protection, whereas the seller of the swap promises the credit worthiness of the debt security. If the debt issuer does not default and if all goes well the CDS buyer will end up losing some money, but the buyer stands to lose a much greater proportion of their investment if the issuer defaults and if they have not bought a CDS. Therefore, CDS contracts can both enlarge risks in a financial network and mitigate them.

Basel III partly solved the problem with excessive risk taking by making tighter regulations about capital requirement. Under Basel III rules, banks have to set aside certain amount of capital based on the probability a borrower will go bust. Basel III increased the core reserves that financial institution who lends money must hold against possible losses in more than three times. But nowadays banks still trade significant amounts of CDS that might be a channel to destabilize the system and amplify shocks in the financial system to undermine financial stability.

Chains of CDS transactions may arise when different financial institutions directly or indirectly buy or sell CDS contracts between each other. For example, bank A can buy CDS contracts on a loan default from an insurance company to hedge their risks. If the condition of the reference entity worsens, the risk premium raises so bank A may sell CDSs to bank B to make money on the difference. In turn bank B can sell CDSs to bank C and etc. Therefore, indirectly bank B, bank C and other banks in the chain depend on the insurance company and if the insurance company defaults and reference entity faces a default then bank A will default on its CDSs to bank B so bank B and other banks might face losses. This means if one of the companies in the chain fails, this creates a "domino effect" of losses. In a financial system with long and complex chains of intermediation, the failure of a highly interconnected financial institution might cause problems to the financial

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system as a whole as it causes a series of other banks to default. During the 2007-2008 financial crisis the lack of transparency in this large market became a concern to regulators as a potential source of systemic risk. In order to identify whether CDS contracts reduce or enlarge systemic risk in a financial network, I intend to extend the model by Zawadowski (2013) and answer the research question: “Do CDS contracts reduce or enlarge systemic risk?” which is addressed in this paper. Zawadowski (2013) considers interbank market where banks are exposed both to asset risk and counterparty risk. In Zawadowski’s (2013) model banks can buy CDSs on other financial institutions in order to hedge their counterparty risks but in equilibrium they do not buy them because default insurance brings them less benefits than costs. So Zawadowski does not consider the financial network with banks and insurance company, limited only with interbank market. In my model I intend to consider interbank market and the market where banks interact with the insurance company that describes real-world situations and expands Zawadowski’s (2013) model.

The thesis is organized as follows. In Chapter 2 offers a literature overview about financial networks, contagion, financial stability, derivative contracts and CDS contracts, highlighting the differences between different networks and summarising their advantages and disadvantages. Chapter 3 tries to shed light on the theoretical structure of the model I am developing as well as to discuss the extensions of Zawadowski’s (2013) model which is a base model for my theoretical framework. In Chapter 4, I run numerical experiments for different scenarios to identify the relationship between various variables and provide an interpretation of the results. In the final section, particularly in Chapter 5, 6 and 7, I consider paths for a future research, some policy implications and concluding observations respectively.
An analysis of financial networks, contagion, financial stability and systemic risk is diverse and topical although most papers have their focus on understanding how the structure of financial networks can reduce or increase systemic risk (Gai and Kapadia, 2010; Gai et al., 2011; Georg, 2013; Roukny et al., 2013; Acemoglu et al., 2013; Elliott et al., 2013; Glasserman and Young, 2015; Leduc et al., 2016; Roukny et al., 2016). Let’s consider some of these papers in more details.

One of the pioneering studies about contagion in financial systems is the paper by Allen and Gale (2000). Using the framework of Diamond and Dybvig (1983) they consider a model, where a single completely connected element is always the efficient network configuration. The authors assume a network where banks are interconnected by deposits. They show that in equilibrium banks hold deposits in other banks in order to provide insurance for themselves against liquidity risk. In line with Allen and Gale (2000), Giesecke and Weber (2006), Freixas et al. (2000) show that more connections between financial institutions reduce shock propagation. In contrast, Nier et al. (2007) via different numerical simulations find out that more concentrated networks are more prone to systemic breakdown but beyond a certain level are prone less. Unlike Allen and Gale (2000), Giesecke and Weber (2006), Freixas et al. (2000) and Nier et al. (2007), Cabrales et al. (2014) consider the efficient concentration in financial networks in terms of the size of the shock. One of the main conclusions the authors make in the paper is that if a shock in the network is large then the optimal configuration of the network must have a high degree of segmentation – that is elements of the network should be of the minimum possible size. If the configuration of the network is symmetric, which means all elements are completely connected, then this configuration is optimal when the shocks are
not too large. In the case of a star structure (where there is a big central
dominant firm connected to the smaller peripheral ones) this structure is
optimal if shocks are large. The interconnectedness via cross-holdings of shares,
debt or other liabilities in a financial network is considered by Elliott et al.
(2012). Such cross-holdings, however, embody cross ownership of equity shares
among firms, rather than being the result of the securitization and exchange of
assets as in Cabrales et al. (2014).

Acemoglu et al. (2013) like Cabrales et al. (2014) consider optimality of
financial networks. As in Gai, Haldane and Kapadia (2011) in their network
model financial institutions are connected to each other by interbank lending
with unsecured claims and hence are susceptible to counterparty’s risk. One of
the main results of their paper is that, depending on whether the magnitude of
shocks is small or large, the optimal network is either complete or has
components almost isolated from the rest. When the magnitude of negative
shocks is less than a certain threshold a more diversified financial network of
interbank liabilities leads to a less fragile financial system because the losses
from default by one particular company are equally shared between other
counterparties in the network. If the network has a structure where all liabilities
of a bank are held by one financial institution, say a ring structure, then this
network is more prone to face a failure.

Continuing the topic of concentration in financial networks the study
Gai, Haldane and Kapadia (2011) also analyze the importance of the
connectivity and concentration of financial institutions in the network to
understand the way contagion happens. They illustrate both analytically and
through numerical simulations how greater complexity and concentration in
the financial network can lead to systemic liquidity crisis that threaten financial
system stability. The paper also suggests some public policy advice which
could mitigate a fragility of the financial network. These include tougher micro-
prudential liquidity regulation, countercyclical liquidity requirements, macro-
prudential policy and surcharges for systematically important financial institutions, network transparency, netting and central clearing.

Also extending Allen and Gale (2000), Freixas et al. (2000) and Georg (2013) introduce the Central bank. Freixas et al. (2000) find that by playing the role of “crisis manager” a Central bank can prevent a contagious event. One of the main findings of Freixas et al. (2000) is that on the one hand interbank connectedness can help to resist the insolvency of a particular bank whilst on the other hand despite the fact that the insolvent bank is not efficient anymore, it may operate as usual because of the implicit financial subsidy generated by the interbank’s lines of credit. Georg (2013) shows that in stable times the structure of the network does not matter and does not have a substantial effect on financial stability. In stress times concentrated under single authority networks are more stable than random networks. In times of crisis particular single bank suffers from lack of liquidity and engages in higher liquidity-driven interbank lending. This creates potential channels for shock propagation and, eventually, might cause a crash of the whole system. Although he shows that the Central bank can stabilize the financial system in the short run.

If Allen and Gale (2000) consider deposits as a channel for the spread of shocks in financial networks, then Cespa and Foucault (2014) consider the propagation of liquidity shocks between correlated assets. They show that there is a positive link between the two assets illiquidities. When one asset becomes less liquid its price becomes less informative for buyers and sellers specialized in the other assets. Thus, uncertainty increases for buyers and sellers and they require larger price reductions to absorb liquidity traders’ order imbalances. After a decrease in the liquidity of the second asset it will reduce the informativeness of the second asset price and so the initial asset also becomes less liquid.

The study by Glasserman and Young (2015) considers a broader definition of interconnectedness of different financial institutions. In their set up
they define the network as a network where elements are linked by liabilities between financial agents. They follow the framework of Eisenberg and Noe (2001) to find out the impact of network effects. Eisenberg and Noe (2001) give conditions under which “a clearing payment vector” exists and is unique. They define this vector as a vector which clears the obligations of the agents of the network – part of a complex financial system. The main result is that the chance that all financial institutions default by direct shocks is higher that the chance that default of certain financial institutions causes defaults at the rest of the financial companies.

There is a growing literature where the authors consider derivatives, particularly, CDS contracts as the way of connecting different financial institutions between each other. Zawadowski and Oehmke (2015) study the role of credit default swaps (CDSs) and motives that lead to their use. After financial crisis quite a few papers have discussed the role of CDS (Markose et al., 2010, Stulz, 2010, Bolton and Oehmke, 2011, Augustin, Subrahmanyam, Tang and Wang, 2014). Zawadowski and Oehmke use new empirical data on net notional CDS amounts and trading volumes to find out the reasons for CDSs trading. They point that CDSs are used for hedging, speculative and arbitrage reasons. In the case of hedging, the bond outstanding amount has a positive link with net notional CDS positions as well as with CDS trading volume. Firms with greater counterparty risk (due to credit guarantee services) have larger net notional CDS positions and CDS trading volume. Positive relations between different forecasts about a reference entity’s future earning outcomes and net notional CDS positions shows that investors use CDSs for a speculation. So investors try to make a profit from fluctuations in the market value of the reference entity of CDS contracts. Another motive to trade in the CDS market is arbitrage. The authors find that companies with a negative CDS-bond basis (which means that CDS is more profitable than bond) have bigger size of CDS positions. Also Zawadowski and Oehmke conclude that CDSs help
to standardize bonds market. By doing so they mean that companies which have more positions where bonds are fragmented have also larger net notional CDS amounts. In the next paper by Oehmke and Zawadowski (2015) the authors consider more precisely the relationship between non-redundant CDSs and bonds. They develop the model with two risky assets: a defaultable bond and a CDS on that bond, where CDS contracts have lower trading costs than bonds. As a result, the authors find that buying and selling CDSs reduces demand for the bond but at the same time it helps long-term investors to get easier access to the bond market and absorb more of the bond supply. The latter effect is stronger than the first one so CDSs rise up the bond price. Like Zawadowski and Oehmke (2015), Che and Sethi (2014) analyze different activities in CDS market, particularly hedging and speculation. They also conclude that the use of CDS, purchased to protect underlying asset that investors have, can rise up bond prices. But the Zawadowski and Oehmke (2015) model also shows that, first of all, CDS turnover is higher than bond turnover, second, CDS usage in bond markets decreases turnover of associated with the CDS bond and therefore reduces credit risk. Also the authors analyze the impact of CDS on welfare and possible policy regulations regarding to CDS introduction into the bond market. It turns out, the use of CDSs increases welfare because it lowers the bond’s trading costs, improves risk sharing and raises the bond price (in the case when an issuer increases positive NPV investments). Finally, Oehmke and Zawadowski (2015) conclude that a ban on naked CDSs does not help to reduce bond yields and borrowing costs.

To model a financial network we build on the framework of Zawadowski (2013). Zawadowski considers a network of investors, banks and an insurance fund which are connected to each other via hedging portfolio risks using contracts such as over-the-counter (OTC) derivatives. In the model investors give some investments as a debt to banks; they in turn invest a unit into outside risky real asset and have a possibility to diversify their portfolio.
through OTC contracts with neighboring banks and hedge their risks through default insurance on their counterparties. Thus, banks are entangled in a highly interconnected circular network of OTC contracts creating a channel for contagion and externalities which can lead to a market failure: one bank’s default negatively affects their counterparties and, as in domino, the counterparties of their counterparties etc. It is worth noting that a bank’s failure comes from the debtholder’s side: when the bank becomes more vulnerable, it is more likely that the bank faces a bankruptcy; hence lenders lose their confidence and do not roll over bank’s debt. To prevent contagion the author suggests some regulatory instruments such as taxing OTC contracts, central clearing of OTC contracts, banning OTC contracts and limiting counterparty exposures.

The literature described above offers different ways how financial networks can be constructed and whether interconnectedness helps or not to reduce the propagation of negative effects in networks. Although they all focus on only interbank market which creates a gap in the literature. However, in my thesis I offer the model which describes not only interbank market but also the market where banks interact with an insurance company, in particularly, banks buy CDS contracts from the insurance companies. Therefore, the addition of a layer of CDS contracts between banks and insurance companies on top of Zawadowski’s (2013) model of OTC contracts between banks is the main contribution of current thesis. This additional level of complexity gives a fresh look on current real-world financial networks and helps to identify the conditions under which propagation of negative effects can be prevented.
3. The Model

The model in this section aims to answer the following research question: do credit default swap contracts (CDSs) reduce systemic risk? The model is based on Zawadowski’s (2013) model where the author considers a financial system where banks are exposed both to asset risk and counterparty risk. In Zawadowski’s (2013) model banks can buy CDSs on other financial institutions in order to hedge their counterparty risks but in equilibrium they do not buy them because default insurance brings them less benefits than costs. So in equilibrium banks tend to hedge asset risk but underinsure against counterparty risk thereby Zawadowski considers only interbank market and does not answer the question: whether CDSs help to avoid shock propagation in a financial network or not. In my model banks buy CDS contracts on their own risky projects and the network consists of banks and an insurance company, thus, I am considering interbank market and the market where banks interact with the insurance company that describes real-world situations and expands Zawadowski’s model.

3.1. Model setup

The model in this section is an extension of the model by Zawadowski (2013). Consider a three-period model: \( t = 0,1,2 \), with \( N \) markets on a circle indexed by \( i = 1, \ldots, N \) and \( N > 3 \). There are three types of active agents: a continuum of investors, \( N \) banks and an insurance company. Investors, banks and the insurance company are assumed to be risk neutral. All have unlimited capital at \( t = 0 \), none of them gets additional resources at \( t = 1 \) and value payoff only in the long run, i.e. at \( t = 2 \).
Investors can only invest in debt issued by banks. Therefore, each bank \( i \) is financed by debt \( D_i \geq 0 \) provided by investors so investors can be considered as uninformed life-cycle savers.

Banker \( i \) can establish only one bank in one market \( i \), therefore, the number of banks is equal to the number of markets. The bank cannot operate in multiple markets. Moreover, after establishing the bank the banker becomes both manager and owner of the corresponding bank. Each bank can invest in a risky real project with expected return of \( R_i \). Banks are potentially interconnected with each other via over-the-counter (OTC) contracts to diversify their portfolio.

The insurance company (IC) provides credit default swaps (CDSs) to banks which may buy them to protect themselves from a default of an outside risky project (see Figure 3).

All participants in the market have full understanding of the model of the economy; know that all banks are potentially connected by over-the-counter (OTC) contracts to diversify their portfolio, know the potential existence of CDS contracts between the insurance company and banks and each lender knows the counterparties of the bank it is lending to.

### 3.2. Investors

In the spirit of Zawadowski (2013), I assume that investors provide some investments as a debt \( D_i \geq 0 \) to bank \( i \) at time \( t = 0 \). The maturity\(^3\) is fixed, i.e. it is at \( t = 2 \), while the interest rate on the debt contract (such as bonds and commercial papers) is determined endogenously such that investors break-even: the borrowing rate for bank \( i \) is \( r_{i,\text{debt}} \). The banker borrows from the market at the market interest rate. There is no revision of the debt contract between investors and banks.

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\(^3\)The maturity refers to the final payment date at which the debt contract will cease to exist and the principal (the amount borrowed) is due to be paid.
3.3. Banks

At date $t = 0$ the bank $i$ is funded by debt $D_i \geq 0$ provided by investors and equity of $1 - D_i \geq 0$ provided by bankers. Then at $t = 0$ Bank $i$ can invest some amount in the risky asset bearing in mind some amount of risk associated with this asset, and sign OTC contracts to diversify their portfolio. At $t = 1$ banks face a revaluation in the risk associated with their investment and face a decision: either liquidate an outside risky project or buy CDS contracts to protect their investments. Let $\alpha$ be a risk weighting of the risky asset, and if the revaluation happens at $t = 1$, then $\alpha$ increases from initial (at $t = 0$) $\alpha_0$ to $\alpha_1$ (at $t = 1$), so that the banks’ capital reserves are inadequate.

Bank gets the following return from their investment into the risky projects at $t = 2$:

$$R_i + \epsilon_i - \epsilon_{i+1},$$

where $R_i$ is $R_H$ if the project succeeds and $R_L(< R_H)$ if the project fails. For simplicity following Zawadowski (2013), $\epsilon_i$ are bimodally distributed independent random variables which take a positive value $+u$ with probability $\frac{1}{2}$ and negative value $-u$ with probability $\frac{1}{2}$; $\epsilon_i$ are revealed at $t = 2$.

It is worth noting that if all neighboring banks invest the same amount in the risky project and sign OTC contracts then the $\epsilon$ risks are offsetting between neighbors, for example banks $i - 1$ and $i$ have risks $-\epsilon_i$ and $+\epsilon_i$ respectively so they cancel each other out. Thus, risks $\epsilon$ are perfectly hedged away in neighboring markets and in the whole network (see Figure 3).

If banks invest different amounts of their money into the risky project then the magnitude of $\epsilon$ can vary across banks, for example banks $i - 1$ invests 0.8 and $i$ invests 0.2, they have risks $-0.2\epsilon_i$ and $+0.8\epsilon_i$ respectively so they do not wipe out each other. Hence $\epsilon$ risks are not hedged away between neighbors. This creates a propagation of endogenous shock in the financial network. Because of different amounts of investment into risky assets and

\footnote{4 I normalized the size of a bank’s balance sheet to 1.}
different amounts of cash on their balance sheets for some banks $-\epsilon$ might have high magnitude that may potentially cause a default for them. Considering that all banks are linked by OTC contracts it can create a channel for a propagation of one bank’s shock to other banks, thus collapsing the whole network of banks.

At time $t = 1$, when banks face a “shock” or revaluation in the risk associated with their investment, investors can choose to withdraw their funding and, therefore, the bank will have to liquidate the risky project. If the investment is liquidated early, at $t = 1$, it only yields a return $L$: $R_L < L < R_H$.

Banks are interconnected with each other by over-the-counter (OTC) contracts to diversify their portfolio and hedge their risks. OTC contracts are securities which are traded in some other manner rather than on a formal exchange. At $t = 0$ neighboring banks populated on the circle, say bank $i$ and bank $i - 1$, can sign contracts to share risks but all other market agents do not observe whether banks sign the contract. At $t = 2$ the final realization of $\epsilon_i$ is observable. Banks have an equal bargaining power, so they do not pay anything to each other for the contract.

Figure 3. Structure of the financial network around market $i$
A second type of interconnectedness is the existence of links between banks and the insurance company. Bank can buy credit default swaps (CDSs) on risky projects for case when the bank face shock in $\alpha$. A CDS is a contact that provides insurance against the risk of a default by a particular company, a loan default or other credit event. The CDS premia represents the cost of such insurance. Simply speaking, the bank obtains the right to sell a financial instrument for their face value (principal amount that the financial instrument will be repaid at maturity if it does not default) when a credit event occurs and the insurance company agrees to buy the financial instrument for their face value when the project of one of the banks fails at $t = 2$. The total face value of the financial instrument is known as the credit default swap’s notional principle. In our case the notional principal of the CDS is $R_H$. Therefore, the amount that the insurance company pays to the bank if a credit event occurs is $R_H - R_L$, i.e. the difference between the percentage of face value and the recovery rate of the reference entity. Suppose $s$ is a vector of CDS premium, where $s_i$ is the price at which bank $i$ purchases CDS on their own risky project. All banks simultaneously choose the size of CDS contracts which they want to buy bearing in mind the asked prices by insurance company.

### 3.3.1. Period $t = 0$

The timing of all events is summarized and presented in Figure 4 in the section 3.3.3.

At $t = 0$ each bank $i$ decides how much it wants to invest in the risky asset ($A_i$) to maximize its expected payoff:

$$\max_A E(R_i) \cdot A_i \quad s.t.$$}

---

5 Usually a credit event occurs when a particular company faces a failure to make a payment as it becomes due or a bankruptcy.
7 In our case the reference entity is a risky project.
\[ C_i \geq \frac{\alpha_0 A_i}{C_r} \] (1)

where

\( E(R_i) \) – expected return of risky asset \( A_i \);  
\( \alpha_0 \) – risk weighting associated with the risky asset;  
\( C_i \) – equity of bank i;  
\( C_r \) – capital requirement.

Condition (1) represents a regulatory capital requirement: the capital a bank has as equity is greater or equal to the amount of risk-weighted assets a bank may buy. In other words, bank cannot invest into risky assets more than it has its own equity.

Therefore, at \( t = 0 \) bank \( i \) invests \( A_i = \frac{C_i C_r}{\alpha_0} \) in the risky asset.

As a special case bank might invest one unit of investments in risky asset to maximize expected payoff (1):

So in the special case suppose that \( \alpha_0 \) is such that at \( t = 0 \) each bank invests one unit of investments in risky project bearing in mind the following condition: \( C_r = \frac{\alpha_0}{C} \).

Therefore, at \( t = 0 \) bank \( i \) invests \( A_i = 1 \) in the risky asset.

3.3.2. Period \( t = 1 \)

At \( t = 1 \) a bank might face revaluation in risk weighting \( \alpha \) caused by increasing the credit risk of bank’s investment or lowering the credit rating of this investment. This revaluation in risk weighting \( \alpha \) at \( t = 1 \), I would call as a “shock” further for a simplicity.

Suppose the credit risk of an asset increases (or credit rating is lower) so it causes that risk weighting \( \alpha \) goes up: \( \alpha_1 > \alpha_0 \), \( \alpha_{1,i} = \alpha_0 + \varepsilon_i^\alpha \), where shocks \( \varepsilon_i^\alpha \) are uniformly distributed on the interval \([0, 1]\). Each bank has two options:

---

8 If a credit risk becomes lower, it does not change portfolio.
either to liquidate the risky project or to buy a CDS contracts in order to maximize their expected payoff:

$$\max_A E(R_i) \cdot (A_i - s_i \cdot N_i^{CDS}) \text{ s.t. } C_i \geq \frac{\alpha_1(A_i - N_i^{CDS})}{C_r}$$ \hspace{1cm} (2)

where

- $E(R_i)$ – expected return of risky asset $A_i$;
- $\alpha_0$ – initial risk weighting associated with the risky asset at $t = 0$;
- $\alpha_1$ – new revaluated risk weighting associated with the risky asset;
- $C_i$ – equity of bank $i$;
- $C_r$ – capital requirement;
- $N_i^{CDS}$ - size of CDS contracts that bank $i$ chooses to buy;
- $s_i$ - cost of buying CDSs.

The problem (2) represents the maximization problem where we consider the product of expected return $E(R_i)$ and the amount of assets bank has after buying CDS contracts $A_i - s_i \cdot N_i^{CDS}$.

Condition (2) represents a regulatory capital requirement: the capital a bank has as equity is greater or equal to the amount of risk-weighted assets a bank may buy in the possibility of buying CDSs. In other words, bank cannot invest into risky assets more than it has its own equity.

Therefore, if the expected payoff is less than the return a bank gets when the risky project is liquidated, i.e. $E(R_i) \cdot (A_i - s_i \cdot N_i^{CDS}) < A_i \cdot L$, it is more reasonable for the bank to not buy CDSs and to liquidate the risky project to hold constraint (2) above. In this case the bank gets $A_i \cdot L$ and $N_i^{CDS} = 0$. It could potentially be interesting to consider the case when the bank has invested in financial assets as their risky project and liquidates them quickly via a fire sales. This situation can destabilize financial market and increase systemic risk in the network.
If the expected payoff is greater than the return a bank gets when the risky project is liquidated, i.e. \( E(R_i) \cdot (A_i - s_i \cdot N_i^{CDS}) > A_i \cdot L \), the bank will purchase CDSs, in particularly the bank will buy enough CDSs such that the constraint on risk weighted assets is an equality, so \( N_i^{CDS} = A_i - \frac{C_{CR}}{\alpha_i} \). Hence, the bank does not liquidate the risky project and at \( t = 1 \) invests the same amount of investments \( A_i \) as at \( t = 0 \). In principle, there is an option to raise more equity at \( t = 1 \) but in reality banks do it rarely and in the model it is not allowed to do.

It could be interesting to consider the following situation: when bank faces a shock such that the credit rating of a particular risky asset is downgraded, it is more likely the risky asset will default and therefore cause a default of other assets. Weaker banks suffer and more possibly they will default. Considering the fact that banks are linked to each other by OTC contracts, so a shock on asset propagates in the bank’s network, the possibility of a default of certain weak banks is increasing. If bank’s positions on risky projects are collapsing and banks bought CDSs, they will request the insurance company to pay their liabilities to banks. If the insurance company is asked to repay a lot of their CDSs, the insurance company might face some difficulties with paying their liabilities and therefore go bust which causes negative effects for other banks which are holding CDSs. As a result the whole system might fail. Details of the behavior of an insurance company are given in the section 3.4.

3.3.3. Period \( t = 2 \)

At \( t = 2 \) there are two outcomes for the return \( R_i \) (where \( i = L, H \)). The first outcome is the case when the risky project of one of the banks faces a failure so the bank gets a return in expectation \( R_L \) with the probability \( p \). The second successful outcome is the case when all projects did well and banks get
a return $R_H$. When $\theta = 1$, then it means that credit event occurred: the probability of realization at $t = 2$ is less than the probability of failure of the risky project $p$ that banks thought would be.

At $t = 2$ bank $i$ receives the following payoff:

$$(R_i + \epsilon_i - \epsilon_{i+1}) \cdot A_i + R_i^r \cdot r_i - D_i \cdot r_{i}^{\text{debt}} - s_i \cdot N_i^{\text{CDS}} + \theta \cdot (R_H - R_L) \cdot N_i^{\text{CDS}},$$

where

$$\theta = \begin{cases} 1, & \text{if credit event occurs} \\ 0, & \text{otherwise} \end{cases}$$

where

$A_i$ – amount of risky asset which bank decides to invest in;

$r_i$ – riskless asset;

$R_i^r$ – return of riskless asset;

$r_{i}^{\text{debt}}$ – debt interest rate;

$D_i$ – debt

$R_H$ – return if the risky project does not default;

$R_L$ – return if the risky project faces default;

$N_i^{\text{CDS}}$ - size of CDS contracts that bank $i$ chooses to buy;

$s_i$ - cost of buying CDSs.

Therefore, summarizing all possible realizations at each time, our three-period ($t = 0, 1, 2$) model can be expressed as in Figure 4.
Consider only one insurance company which is linked with $N$ banks by CDS contracts. At $t = 1$ insurance company sells CDS contracts to banks which decided to buy them. After considering all interconnections insurance company has the following payoff ($P$) at date $t = 2$:

$$P = \sum_{i=0}^{N-1} (s_i - (R_H - R_L) \cdot \theta),$$

with the following constraint to be sure that the insurance company is capable of making payments by its obligations:

$$C_{IC} + N_i^{CDS} \geq \sum_{i=0}^{N-1} (R_H - R_L) \cdot \theta,$$

where

$$\theta = \begin{cases} 1, & \text{if credit event occurs} \\ 0, & \text{otherwise} \end{cases}$$

$R_H$ – return if the risky project does not default;

$R_L$ – return if the risky project faces default;

$N_i^{CDS}$ - size of CDS contracts that bank $i$ chooses to buy;

Figure 4. Three-period model

3.4. Insurance company
$s_i$ - cost of buying CDSs;

$C_{IC}$ – equity of insurance company.

Payoff of insurance company (3) represents the amount insurance company gets: the difference between the benefit it gets from selling CDS and the amount it has to pay back to banks in the case of credit event happening. If banks bought CDS contracts at $t = 1$ and their risky project failed, then insurance company has to pay the buyer of CDS contracts a compensation. In order to do so, the insurance company must have enough sufficient funds. Constraint (4) represents such a requirement where the sum of equity insurance company possesses and sold CDS contracts must be greater or equal the compensation insurance company pays in the case of risky project defaults.

In section 4, I am going to consider two and many insurance companies which only provide CDS contracts to banks to identify whether systemic risk will be lower in the financial network or not. These insurance companies have payoffs as in (3) with constraint (4).
4. Numerical experiments

In order to evaluate the relationships between the parameters and the behavior of the model I run several numerical experiments.

First, I calculate a final payoff for all banks at $t = 2$ after running all other stages before. Second, I indicate that if the final equity is less than zero then bank faces default and count the number of defaults. It is important to consider bank’s defaults because it has severe consequences for the whole financial network. In my model all banks are linked to each other via OTC contracts so the failure of one bank can potentially lead to the failure of other banks causing “domino effect” – a bankruptcy of one bank may lead to a cascade of defaults. The more defaults in the system, the more fragile the system is. So I am going to find out the relationship between the number of defaults and the risk weighting of the risky assets ($\alpha$, varies such that $\alpha \in [0, 1]$), size of the shock in $\alpha$ at $t = 1$ and the probability of risky project’s failure.

All simulations use the parameter values shown in Table 1 unless otherwise stated. All parameters are chosen for a purpose to describe real world values or close to them. For example, US banking regulation has a minimum capital requirement for a bank to be capitalized of 8%. Also I set the number of banks equal to 100 as an average number of banks in many of the world’s interbank markets with some expected returns on risky investments, -10% return if project is unsuccessful at $t = 2$, also -25% return from liquidation of the risky project at $t = 1$, reflecting the numbers given in “A special report on international banking” by the Economist, May, 2013, 2015. I arrange the difference between expected return of risky asset and expected return of riskless asset as a cost of buying CDS at $t = 1$ if bank decides to buy them to insure their risky project. As stated in the model at date $t = 0$ the bank $i$ is
funded by debt $D_t \geq 0$ provided by investors and equity of $1 - D_t \geq 0$ provided by bankers so all banks get different amounts of investments and have different debt interest rates. For each bank $i$ shock $\epsilon_i^\alpha$ in $\alpha$ at $t = 1$ and shock in $p$ at $t = 2$ are uniformly distributed on the interval $[0, 1]$ while $\epsilon_i$ are bimodally distributed independent random variables which take the positive value $+u$ with probability $\frac{1}{2}$ and the negative value $-u$ with probability $\frac{1}{2}$. For simplicity, following the Zawadowski (2013) I set $u$ as 0.05. Each simulation was repeated 100000 time step run to be sure that all parameters are optimized.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N$</td>
<td>Number of banks</td>
<td>100</td>
</tr>
<tr>
<td>$Cr$</td>
<td>Capital requirement</td>
<td>8%</td>
</tr>
<tr>
<td>$p$</td>
<td>Probability of project’s failure</td>
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</tr>
<tr>
<td>$L$</td>
<td>Liquidation value</td>
<td>-25%</td>
</tr>
<tr>
<td>$R_L$</td>
<td>Return if project fails</td>
<td>-10%</td>
</tr>
<tr>
<td>$R_H$</td>
<td>Return if project is successful</td>
<td>$(ER - p R_L)/(1-p)$, $R_H \in [0, 1]$</td>
</tr>
<tr>
<td>$u$</td>
<td>Value in bimodally distribution</td>
<td>0.05</td>
</tr>
<tr>
<td>$ER$</td>
<td>Expected return</td>
<td>$p R_L + (1-p) R_H$, $ER \in [0, 1]$</td>
</tr>
<tr>
<td>$ERR$</td>
<td>Return of riskless asset</td>
<td>1</td>
</tr>
<tr>
<td>$s$</td>
<td>Cost of buying CDS</td>
<td>$ER-ERR$, $s \in [0, 1]$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Risk weighting of the risky project</td>
<td>$\alpha \in [0, 1]$</td>
</tr>
</tbody>
</table>

Table 1. Parameter values used in the simulations

4.1. Relationship between number of bank defaults and risk weighting of risky projects with no CDS

In the first simulation I consider the situation when banks do not have the possibility to buy CDS contracts. As the probability of default of the risky
project I put \( p = 0.2 \), \( p = 0.5 \) and \( p = 0.8 \), so low, medium and high level of the probability of project’s failure.

If at \( t = 1 \) banks can either liquidate the risky project or keep it so they do not have an option to buy CDS contracts at \( t = 1 \) when the shock in \( \alpha \) happened, then we can observe the higher number of defaults when \( \alpha \leq 0.501 \) (see Table 2 in Appendix). When risk weighting on risky assets is small, more banks invest in that risky assets and, therefore, after the shock happens they lose more because they thought the risk associated with asset would be same in the future. But after shock (for example, an insolvency of financial institution in the financial network caused by an increase in credit risk or lowering the credit rating of assets which this failing financial institution possesses) turned out that the risk weighting became higher than it was set before investing in particular assets, so banks have the greater number of bank defaults and we can observe negative relationship between number of banks’ defaults and risk weighting. Also different papers (Georg, 2013; Cabrales et al., 2014; Acemoglu et al., 2013) suggest that the number of bank defaults depends on the size of the shocks; therefore, it is worth considering the relationships between the size of the shock and different variables. Based on the paper by Ladley (2013) I assume that the shock is small if at \( t = 1 \) the revaluation of the risk weighting is less than 10% and that the shock is large if risk associated with the risky project increases by more than 20%.

Figure 5 shows us that if the size of the shock is large, then the greater the probability of a project’s default \( p \), the more bank defaults we might have. When \( p = 0.2 \), \( p = 0.5 \) and \( p = 0.8 \), we have 18, 46 and 74 bank defaults respectively (in the case of \( \alpha = 0.401 \)) (see Table 2 in Appendix).
Figure 5. The relationship between the number of bank defaults and risk
weighting of risky projects in the case of no CDS with various $p$ (shock is large).

Figure 6. The relationship between the number of bank defaults and risk
weighting of risky projects in the case of no CDS with various $p$ (shock is small).

Figure 6 shows that when shock is small, it does not hit banks as
significantly as when shock is large.
4.2. Relationship between number of bank defaults and risk weighting of risky projects with one insurance company

In the second numerical experiment consider the case with one insurance company which provides CDS contracts to banks. As in the first experiment I put \( p = 0.2 \), \( p = 0.5 \) and \( p = 0.8 \) so low, medium and high level of the probability of project’s failure. As a next step consider two situations with different size of shocks in \( \alpha \) at \( t = 1 \).

4.2.1. Large shock

Suppose at \( t = 1 \) the risky asset banks invested in was downgraded significantly, so risk weighting \( \alpha \) goes up: \( \alpha_1 > \alpha_0 \), \( \alpha_{1, i} = \alpha_0 + \varepsilon^i \), where shocks \( \varepsilon^i \) are large.

![Graph of the relationship between the number of bank defaults and risk weighting of risky projects in the case of one insurer with various \( p \) (shock is large)](image)

Figure 7. The relationship between the number of bank defaults and risk weighting of risky projects in the case of one insurer with various \( p \) (shock is large)
Figure 7 shows that the more banks take risk investing in the assets with high risk weighting, the less defaults banks have. Also when probability of project’s failure is 0.5 banks experience less defaults than in the case of \( p = 0.2 \) and \( p = 0.8 \) which makes \( p = 0.5 \) an “optimal” level of the probability of risky project’s default at which we can observe less bank defaults (see Table 4 in Appendix). Banks face a tradeoff between maximizing their expected payoff and taking risks and \( p = 0.5 \) provides a “balance” between these two objectives.

From Figure 5 and Figure 7 we can conclude that buying CDS contracts reduce the number of bank defaults if \( \alpha < 0.401 \). When risk weighting on risky assets is small, more banks invest in that risky assets and, therefore, after shock happening they lose more than they could lose if they bought CDS. So when the risk weighting on risky assets is small banks and the whole network benefit from buying CDS since number of defaults is less than in the case with not buying CDS (see Table 2 and Table 4 in Appendix). For example, when \( \alpha = 0.401 \) and \( p = 0.5 \) we have 46 and 4 bank defaults with not buying CDS and buying CDS respectively. Therefore, when the risk weighting is less than 0.501 and shock in \( \alpha \) is large, CDS contracts reduce systemic risk in the network. When risk is high it does not matter if banks purchase CDS contracts or not (see Figure 5 and Figure 7).

Since it is not obvious with what level of the probability of risky project’s defaults \( (p) \) we have linked, it is worth creating a picture for various \( p \) to investigate it.
Figure 8. The relationship between the number of bank defaults and risk weighting of risky projects with various $p$ (shock is large)

Figure 8 shows how the number of bank defaults depends on risk weighting and the probability $p$. In Figure 8, the scale of values of such variables as “defaults”, “alphas” and “probability” converted in another scale because of facing difficulties to create picture with proper scales in MatLab. So the scale $[0, 100]$ converted into $[0, 1]$ for variable “defaults”, $[0, 1]$ into $[0, 100]$ for “alphas” and $[0, 1]$ into $[0, 10]$ for “probability”.

The “optimal” level of the probability of risky project’s defaults is approximately in the interval $[0.5, 0.6]$. Banks face a tradeoff between maximizing their expected payoff and taking risks and $p \in [0.5, 0.6]$ provides a “balance” between these two objectives.
4.2.2. Small shock

Figure 9. The relationship between the number of bank defaults and risk weighting of risky projects in the case of one insurer with various $p$ (shock is small)

Figure 9 shows less defaults with $p = 0.2$ and small size of shock in comparison to the case when the shock is large (Figure 7). So when credit rating is going down by small amount, banks do not experience many defaults but still buying CDS help those banks to hedge their risks and reduce the number of defaults (see Table 3 and Table in Appendix).

4.3. Relationship between the number of bank defaults and risk weighting of risky projects with many insurance companies

In the third numerical experiment consider two, five, ten and twenty insurance companies to figure out how the number of bank defaults changes when risk is shared between many insurance companies. As it was found earlier that the size of the shock plays an important role, hence, I consider both large and small shocks.
4.3.1. Large shock

Consider the case when we have a large shock in $\alpha$ at $t = 1$. The shock can be any event (like Brexit in the UK in June 2016).

![Diagrams showing the relationship between the number of bank defaults and the number of insurers with various $\alpha$ and $p$ (shock is large)].

Figure 10. The relationship between the number of bank defaults and the number of insurers with various $\alpha$ and $p$ (shock is large)

In Figure 10 we can see that when we have many insurance companies CDS contracts help to share credit risk between all financial institutions resulting in the lowering of the number of bank defaults. Figure 10 shows benefits of competitive CDS market.

4.3.2. Small shock

Consider the case when we have a small shock in $\alpha$ at $t = 1$ which banks take into account when they make a decision about their investments.
As is the case when the size of the shock is large, in Figure 11 we can see that the more insurance companies in the financial network we have, the fewer defaults. Hence, financial institutions in this network share systemic risk between each other. Also the fact that insurance companies do not trade with each other explains why we do not have accumulation and propagation of the shock. When we have $\alpha \leq 0.501$, the number of defaults when a shock is small is less than when the shock is large. It seems reasonable because if the unexpected shock is large, all financial institutions potentially bear greater losses as it costs them more than in the case of the small shock.
5. Discussions

The recent financial crisis has brought many interesting research questions and one of them is the relationship between the structure of the financial networks and systemic risk. Credit default swaps (CDSs) were one of the main instruments through which different financial institutions were interconnected during the crisis. In my model I consider the simple case of what happened during the 2007-2008 financial crisis. There are possible extensions of my model.

First of all, it would be interesting to find out the relationships between CDS and other variables in the model. For example, the relationship between the size of banks and the amount of CDS banks buy and etc. Also I consider that the cost of CDS is exogenous which is a limitation of my model so I will introduce a market pricing these assets in the future.

Second, it would be beneficial for the study of financial networks and systemic risk to consider the interconnectedness of insurance companies. Insurance companies can be linked by buying and selling CDS contracts between each other. Interconnectedness amongst financial institutions creates possible channels for shock propagating, thus stress of one element of the network is likely to be transmitted to the other elements creating a future crash in the network and eventually the whole financial system. There are at least two channels for contagion in our model. First, if the insurance company faces a failure, it is not able to pay its CDS obligations, which means, in the case of default of the risky project, the bank loses their money and potentially might go the bankrupt. In fact, banks are linked with each other by OTC contracts that create a channel for propagation of defaults amongst banks and potentially might bring the whole financial network down. Second, if one bank defaults
and has quite high positions on OTC contracts with other banks then other banks might go bust.

If we consider multiple defaults of banks and many insurance companies then there are at least two channels for shock propagation in the financial network which are worth pointing out. First, if several banks in the network default because of failure of their projects at the same time, then of course debtholders lose some amount of their investments, insurance companies might not have enough liquidity to pay their CDS obligations and can potentially fail which creates shock propagation among insurance companies (although some of them can be hedged because they sell CDS to other insurance companies). Second, if one insurance company defaults, then another insurance company which has CDS contracts with this company loses their money. Since insurance companies are linked to banks by CDS contracts, it means that a failing insurance company is not able to pay its CDS obligations, which creates future difficulties for other banks because they are interconnected with each other through OTC contracts. Thereby, in the end the financial network will crash affecting the financial system as a whole.

Third, it would be interesting to consider different structures of the network, density, different size of financial institutions in the network particularly heterogeneity in the size of banks and insurance companies etc.

Finally, it would be useful to test some policy advice using our constructed financial networks to identify the most efficient one.
6. Policy implications

After the financial crisis of 2007-2008 policy makers and regulators had a big concern about the effect of credit default swaps on the shock propagation in the financial networks.

Credit default swap contracts were invented in 1994 and were primarily used only to hedge credit risk in lending activities. In 2002 assets managers and hedge funds started to use them massively making the CDS market bigger and bigger resulting from $300 billion in 1988 to $62 trillion in 2007 according to International Swaps and Derivatives Association (ISDA). Banks and other financial institutions have used them to hedge their risks, lower capital requirement and buy more risky assets. Consequences of such decisions after financial crisis 2007-2008 were harmful for the global financial system.

In section 4 I conclude that when the shock in the risk weighing \((\varepsilon_i^\alpha)\) is large and \(\alpha \leq 0.501\), then, in fact, CDS contracts help to reduce the number of bank defaults. Moreover, the more insurance companies we have in the financial network, the less defaults we can observe. When \(\alpha \geq 0.501\), then buying CDS contracts does not change the number of defaults but banks can potentially buy them to lower capital requirement and take more risks. So, a regulator can use this information to add fees for taking excessive risk by buying CDS contracts more than needed and to fill in a bailout fund. A bailout fund can be used to provide some equity to failing bank’s counterparties to avoid default cascades and a run of the investors. For example, in 2008 the United States (US) government started running $700 billion the Troubled Asset Relief Program (TARP) to stabilize the country’s financial system and prevent foreclosures in the wake of the 2007-2008 financial crises through purchasing troubled companies’ assets and equity. It was one of the biggest bailouts offered by US government to many largest financial institutions that faced severe losses.
resulting from the collapse of the subprime mortgage market. Banks, which had been providing an increasing number of mortgages to borrowers with low credit scores, experienced massive loan losses as many of these mortgages went into default.

In the situation when banks by buying CDS contracts reduced systemic risk in the financial network, the regulator can make some discounts for them in the future or lower some requirements. Bank as a commercial institution which wants to reduce their costs will have incentives to have an optimal number of CDS contracts and reduce the risks.

Another possible policy regulation is to oblige banks to monitor their counterparties or to reduce a cost of monitoring by giving additional discounts on doing so. In fact, when a bank signs a full coverage CDS contract, it has incentives to stop monitoring its counterparties especially when the cost of monitoring is too high. Although even if banks have CDS it is still recommended to monitor their counterparties to anticipate potential problems with ‘trustful’ counterparties. To do so the bank can use CDS market signals to valuate who is about to experience future downgrades, and take some actions to reduce exposure. Moreover, CDS spreads are very informative as they are determined by counterparties’ trading risks of other counterparties.

Central clearing (CCP) of CDS contracts is a key way to manage systemic risk in the financial network. When CDS contracts are traded bilaterally, they involve the risk that counterparty fails to meet their obligations under the contract. This risk can be mitigated by using a CCP to centrally clear the transaction. The CCP acts as buyer to every seller, and seller to every buyer, simplifying the network of exposures within the system. Approximately 50% of interest rate contracts and 20% of credit derivative contracts outstanding globally are now centrally cleared (Lui, Quiet, Roth, 2015). It’s necessary to increase the number of CCP. Although the regulator should bear in mind that in managing risk in the financial system, CCPs do however concentrate risk
within themselves. This will become an important point as there is likely to be further migration towards central clearing, and more concentration of activity among a small number of CCPs and their users.

As we saw in section 4, the existence of many insurance companies lowers the number of bank defaults so the regulator can limit the share bank can have with certain insurance company to ensure the existence of highly competitive CDS market.
7. Conclusions

In this research paper, I provide a theoretical framework on financial networks and run several numerical experiments to investigate whether credit default swaps reduce or enlarge systemic risk in the financial network of insurance companies, investors, and banks. There are interesting findings after conducting simulations.

First, the most remarkable result is that small shock in the risk associated should not be undervalued. When the initial risk weighting on risky assets is small and after revaluation (“shock” is happening) the risk weighting is becoming much larger than initial one, the number of bank defaults is greater in the case when they do not buy CDS contracts than in the case of buying CDS. The reason why banks face more defaults is that when the risk weighting on risky assets is small, more banks invest in that risky assets and, therefore, after the shock happens, more banks lose their investments. So when the risk weighting on risky assets is small and the shock is large, banks and the whole network benefit from buying CDS since the number of defaults is less than in the case of not buying CDS. When the risk weighting is high and a revalued increase in risk weighting (“shock”) is small, then buying CDS contracts still helps to reduce the number of bank defaults, although it does not change the number of defaults significantly. However banks can potentially buy CDS to lower capital requirement and take more risks. In the latter case, policy regulation is needed. The regulator can charge a fee from financial institutions that do not reduce systemic risk by reallocating credit exposures in a more efficient way. This fee’s collection can be used as a guarantee fund to fulfill CDS contracts obligations in the event that the insurance company was to become insolvent.
Second, the “optimal” level of the probability of risky project’s defaults is approximately in the interval \([0.5, 0.6]\). Banks face a tradeoff between maximizing their expected payoff and taking risks and \(p \in [0.5, 0.6]\) provides a “balance” between these two objectives.

Third, when we have many insurance companies CDS contracts help to restructure financial network and share credit risk between all financial institutions resulting in the lowering of the number of bank defaults.

Therefore, the existence of a credit derivative market does not always harm the financial system.
8. References


9. Appendix

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<tr>
<th>Alphas</th>
<th>Number of defaults (in average)</th>
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Table 2. The number of bank defaults with no CDS and with different \(\alpha\) and \(p\) (shock is large)

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Table 3. The number of bank defaults with no CDS and with different \(\alpha\) and \(p\) (shock is small)
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Table 4. The number of bank defaults with CDS contracts and with different $\alpha$ and $p$ (shock is large)

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Table 5. The number of bank defaults with CDS contracts and with different $\alpha$ and $p$ (shock is small)