Bank Avalanche Model of Systemic Risk *

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Abstract

This paper examines systemic risk and the emergence of financial contagion in bank networks. First, the paper describes the behavioral rules of an agent based model with banks and non-financial transactors. Second, the paper conducts simulations to analyze bank lifespan, profitability and bank avalanches with good and bad economic conditions in a complete network, unconnected network, circle network, and a star network. The simulation results suggest there is greater dispersion in network performance in good economic conditions than bad economic conditions and that the circle network is the most profitable and has longest bank lifespan of these financial networks.

Keywords: Systemic Risk, Financial Contagion, Agent Based Modeling
JEL Classification: D85, E37, G21, G33, G38

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1 Introduction

The modern financial system is a complex web of interactions in which market participants engage in a diverse set of transactions and relationships with other market participants. When this global financial system functions properly, financial intermediaries move capital from savers towards productive investments. The network gives the financial intermediaries access to the full set of capital and investment opportunities. This complex and interconnected financial system can also reach a critical state as systemic risk emerges undetected and serve to transmit financial shocks across the system. This paper provides a theoretical agent based model of systemic risk with banks and non-financial transactors in a complete network, unconnected network, circle network, and star network that is calibrated with good and bad economic conditions and tested for bank lifespan, profitability, and bank avalanches.

A growing body of financial stability research and a new set of regulatory policies to address systemic risk has emerged since the Global Financial Crisis.[1] Systemic risk in the financial system can be difficult to detect as it can emerge even when each individual bank appears to be stable according to traditional metrics such as bank assets, market capitalization, price to earnings ratios, and assets.[2] Stress tests such as the Dodd-Frank Act stress test mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 and the Comprehensive Capital Analysis and Review are designed to focus on

[1]Authors Daniel Friedman and Daniel McNeil in their nontechnical book *Morals and Markets: The Dangerous Balance (2nd Edition)* describe systemic risk as arising when "broken promises spread, as with excessive leverage, where node A defaulting on node B can cause B to default on nodes C and D, in turn causing defaults further along the links. Thus, a financial bankruptcy may bring innocent people down, even if they don't seem nearby, and they in turn can undermine more people. That's what happened in September and October 2008. The damage ripples outward, and it can take years to restore the network to health."

[2]Neil Kashkari, the president of the Federal Reserve Bank of Minneapolis, in a speech at the Brookings Institution on February 16, 2016 titled *"Lessons from the Crisis: Ending Too Big to Fail"* explained "A second lesson for me from the 2008 crisis is that almost by definition, we won't see the next crisis coming, and it won't look like what we might be expecting. If we, or markets, recognized an imbalance in the economy, market participants would likely take action to protect themselves. When I first went to Treasury in 2006, Treasury Secretary Henry Paulson directed his staff to work with financial regulators at the Federal Reserve and the Securities and Exchange Commission to look for what might trigger the next crisis. Based on his experience, we were due for a crisis because markets had been stable for several years. We looked at a number of scenarios, including an individual large bank running into trouble or a hedge fund suffering large losses, among others. We didn't consider a nationwide housing downturn. It seems so obvious now, but we didn't see it, and we were looking. We must assume that policymakers will not foresee future crises, either."

the capital adequacy of the largest firms and both the Financial Stability Oversight Council and the Office of Financial Research were created to monitor financial stability.[3] The Federal Reserve has also established rules for strengthening the capital positions of global systemically important bank holding companies as they pose a greater threat to financial stability of the United States.[4] Despite these research and regulatory initiatives, there is room for more research that combines complexity theory with agent based modeling to understand how systemic risk emerges through the interactions between banks and other financial market participants (Bisias et. al. (2012), Bookstaber (2014), and Battiston et. al. (2016)).

This paper investigates the ways in which financial network architecture affects financial system performance and financial stability. The first part of the paper outlines the behavioral rules of the banks, non-financial transactors, and related aspects of the agent based model. The second part of the paper analyzes the financial stability of this agent based model in a complete network, unconnected network, circle network, and star network using computer simulations. The simulations are conducted for all of the financial networks with a model calibrated for good economic conditions and for bad economic conditions. The results indicate that the circle network performs best in terms of bank lifespan and profitability among all the other networks. There is greater dispersion in profitability and financial stability when there are good economic conditions than when there are bad economic conditions.

This paper proceeds with a review of the related literature on systemic risk and financial networks in Section 2. Section 3 explains the behavioral rules of the banks and non-financial transactors. Section 4 presents and explains the model simulation results. Section 5

[3]For even more detail on bank stress-tests please refer to Bookstaber et. al. (2014), Tarullo (2014), and Fischer (2015).

[4]The Board of Governors of the Federal Reserve System approved a final rule requiring the largest and most systemically important U.S. bank holding companies to further strengthen their capital positions on June 20, 2015. Eight banks were designated GSIBs: Bank of America Corporation; The Bank of New York Mellon Corporation; Citigroup, Inc.; The Goldman Sachs Group, Inc.; JPMorgan Chase & Co.; Morgan Stanley; State Street Corporation; and Wells Fargo & Company.

concludes with suggestions for future research.

2 Related Literature

This paper uses agent based modeling to examine the financial stability of bank networks and contributes to the literature on bank stability, networks, and agent based modeling. The ideas for the agent based model in this paper draw upon the bank avalanche model by Friedman (1998 and 2012) and the concept of self-criticality from Bak et. al. (1988). Although progress has been made to better understand systemic risk since the Global Financial Crisis there is still more work to be done (Bisias et. al. (2012), Yellen (2013), Handbook on Systemic Risk (2013), IMF Guide to Stress Testing (2014), Bookstaber (2014), Freixas et. al. (2015), and Battiston et. al. (2016)).

This paper contributes to the theoretical literature on banking stability with a model in which systemic risk and financial contagion originates from the behavior of non-financial transactors and spreads through the interbank network. Early theoretical work on bank stability by Diamond and Dybvig (1983) examines how a rational and prudent actions by individual depositors to limit their own risks may be highly destabilizing to an institution designed to transform short-term liabilities into long-term assets. Allen and Gale (2002) develop a model of how financial networks influence systemic risk and in which systemic risk arises through liquidity shocks that spread from one bank to another and cause the whole system to collapse. Allen and Gale (2002) find that a complete interbank network limits the severity of a financial crisis whereas an incomplete interbank network transmits the shock more strongly across regions. In this paper, the systemic risk emerges from within the system similar to a sandpile model and self-criticality developed by Bak et. al. (1988) in which the natural dynamics of a system can lead to avalanches of bank failures.[5] This

[5]Bak et. al. (1988) describe the principle of self-criticality using a sandpile model as "To demonstrate self-organized criticality, one needs a shoebox and a cup or two of sand - sugar or salt will do in a pinch. Wet the sand with a small amount of water, mix, and gather the sand into the steepest possible pile in one corner of the box. The angle of repose (i.e., the threshold slope) is larger for wet sand, so as the water

paper, unlike Diamond and Dybvig (1983) and Allen and Gale (2002), simulates and provides analysis of the bank avalanche model of systemic risk.

This paper also contributes to a growing literature on the role of interconnectedness and financial stability by testing the behavior of different bank network architectures. Several economists have used game theory and networks to explain economic behavior (Goyal (2007) and Jackson (2010)). Caballero and Simsek (2011) build upon the interconnected bank network of Allen and Gale (2011) but limit the amount of information that banks know about their counterparties. Banks know their own counterparties but not the counterparty of their counterparties. In this context, an increase in network complexity increases payoff uncertainty and a small shock relative to agent resources leads to large fire sales. Gai, Haldane, and Capadia (2011) show that the simplest network, rather than the complex network, survives the longest. They find that contagion from shocks is less frequent and less severe for lower levels than for higher levels of interconnectedness. Acemoglu, Ozdaglar, Tahbaz-Salehi (2013) show how systemic risk in financial networks arises due to counterparty risk and find that a complete financial network is more stable than the incomplete network as long as the shocks are small. However, when the shocks reach a certain level then bank interconnectedness serves as a propagation mechanism and leads to a more fragile financial system. Glaesserman and Young (2013) develop a model of financial contagion and examine how interconnections increase expected losses, with minimal information about network architecture, under a range of shock distributions. This paper examines the degree to which different interbank network architectures change the profitability and financial stability of the system and tracks systemic risk in the form of bank avalanches.

Finally, this paper contributes to the literature by using complexity economics and agent based modeling (ABM) to examine bank avalanches and systemic risk within an interconnected financial system. This paper uses an ABM with behavioral rules for banks and

evaporates, one observes a sequence of slides - some very small, others quite large - occurring at random places on the pile. (The evaporation process can be sped up by placing the box on a warm surface, or under direct sunlight.) This experiment is also exceptionally portable, and is best done on a sunny day at the beach."

non-financial transactors as in Friedman (1998 and 2012) to analyze systemic risk in a complete network, unconnected network, circle network, and star network. The systemic risk in this ABM emerges as a critical state as a result of the system dynamics and the interactions between agents Bak et. al (1988). ABMs are well suited to examine systemic risk as they allow agents to be unique and different, interact locally, and exhibit adaptive behavior (Grimm et. al. (2010)). Furthermore, ABMs are evolving complex systems in which shocks come endogenously from the behavior and interactions of individual agents rather than coming from exogenous shocks outside of the system (Bookstaber (2012), Bookstaber et. al. (2014), Battiston et. al. (2016)). Recently, Leduc et. al. (2016) use an agent based model to examine systemic risk in financial networks with credit default swaps (CDS) and find that the CDS market improves resiliency to insolvency cascades.

3 Model Description

3.1 Overview

The purpose of this agent based model (ABM) is to examine the emergence of systemic risk in a financial network that has banks and non-financial transactors. ABMs are used for explaining systems level behavior because of their unique ability to include heterogeneity of and among agents, local interactions and learning among agents, and adaptive behavior of agents. This bank avalanche model of systemic risk has banks and non-financial transactors that follow behavioral rules from Friedman (1998) with different network architectures. The systemic risk in this model leads to bank avalanches as the failure of one bank impacts the failure of other banks in the financial system. A better understanding of these dynamics can provide insights into how the interconnected actions of bank operations leads to systemic risk, the ways in which financial network topography affect financial stability, and possibly assist in developing policies to mitigate these risks. This model description proceeds covers three main areas: overview, design concepts, and details (Grimm et. al. (2010)).

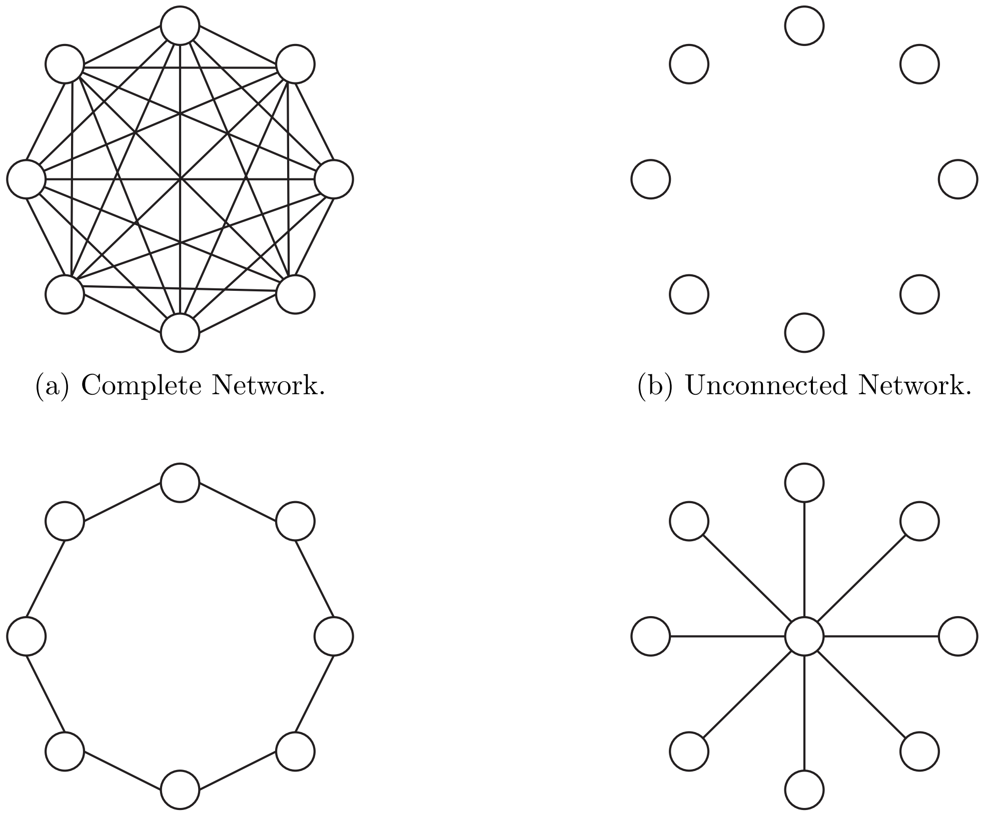
Entities

The two entities in this ABM are the banks and non-financial transactors (NFTs). Bank avalanches occur when more than one bank becomes insolvent and defaults at the same time in a simulation. The banks interact directly with NFTs and through the interbank market with other banks. Each bank maximizes their net interest revenue by taking deposits D, making loans L, and making interbank loans I_L while making sure to maintain the minimum reserve requirement R. The non-financial transactors in this ABM use the financial system to make deposits D and apply for loans L. The non-financial transactors affect the interactions and activities of the banks.

State Variables and Scales

This ABM has several system level state variables. The first state variable is the interbank network architecture through which the banks can borrow and lend to other banks. As seen in Figure 1, we consider the following architectures: complete network, unconnected network, circle network, or star network. In the complete network, each bank trades interbank deposits I_D and interbank loans I_L with all the other banks in the network. In the unconnected network, banks cannot trade interbank deposits I_D and interbank loans I_L in the network. In the circle network, each bank makes interbank deposits I_D and loans with neighboring banks. In the star network, each bank has a centrally cleared transaction of interbank deposits I_D and interbank loans I_L. The other system state variable is the total number of banks in the network.

There are state variables specific to the banks and to the NFTs. The state variables specific to the banks are the bank loan rate to the NFTs p_{loan} and the bank reserve requirement R, which is a percentage of bank assets in reserves. The state variables specific to the NFTs include: the deposit rate $p_{deposit}$ (the rate the NFT makes a deposit to the bank), the withdrawal rate $p_{withdrawal}$ (the rate the NFT withdraws a bank deposit), the repayment rate $p_{repayment}$ (the rate the NFT repays a loan), and the default rate $p_{default}$ (the rate the



(a) Complete Network. (b) Unconnected Network.

(c) Circle Network. (d) Star Network.

Figure 1: Interbank Networks of the Bank Avalanche Model of Systemic Risk.

NFT defaults on a bank loan).

This ABM operates on a daily frequency time scale where each tick in the simulation represents a day. The ABM can be setup to run any number of simulations and restarts to a new simulation once all of the banks in the network become insolvent. The simulation ends once all of them have been completed.

Process Overview and Scheduling

This ABM has several steps at each period of the simulation which are outlined in the flow diagram of the bank avalanche model in Figure 1. When the simulation begins, the NFT engages in retail activity by making a deposit or a withdrawal as well as commercial activity to engage in a loan application, loan repayment, or default on a loan. Once the NFTs have completed their actions each bank examines their level of reserves relative to the reserve requirement. If a bank has a level reserves greater than their reserve requirement then the bank can provide a loan to an NFT or an interbank loan to another bank. If the level of reserves equals the reserve requirement then the bank does not take any additional actions. When reserves are less than the reserve requirement then the bank uses its deposits to replenish its reserves, uses the interbank deposits to replenish its reserves, recalls loans from other banks, or recalls loans from NFTs. Once the bank has an appropriate level of reserves it must check to see its level of capital. When bank capital is positive the bank is solvent and continues to the next period otherwise the bank is insolvent and must be removed from the simulation.

3.2 Design Concepts

Basic principles

The basic principle for the banks in this model is to maximize their net interest revenue. Bank net worth is measured by its capital $K = R + L + I_L - D - I_D$, which is the sum of assets (reserves R, loans to NFTs L, and interbank loans I_L) less liabilities (deposits from NFTs D and interbank deposits I_D). The banks maximize net interest revenue by minimizing their reserves R by making loans to loan applicants L and to other banks I_L. In particular, each bank attempts to keep its reserves R equal to the reserve requirement R^* by using deposits D, interbank deposits I_D, and calling in loans L. A bank without sufficient deposits from NFTs to meet its requirements will access the interbank market to make this funding available from another bank in their network. When R_i falls below 0 and the number of interbank loans outstanding $I_L = 0$ then bank is illiquid. The bank i can increment reserves R by recalling loans L_i, increasing its deposits D_i and interbank deposits I_D. A bank reaches a critical state and becomes insolvent when bank capital $K < 0$ and becomes bankrupt and must be liquidated. The increased market stress as a result of this insolvency and liquidation of loans L and interbank loans I_L can affect neighboring banks that are counterparties of these transactions because of reduced overall market liquidity.

The basic principle for the NFTs is to make deposits and apply for loans at the banks which in turn affect the financial position of the banks. An NFT makes a a new deposit or loan with some positive probability $p_{deposit}$ and p_{loan} according to a Poisson distribution process. An NFT deposit leads to a deposit $D_i + 1$ and new loan $L_i + 1$ events at a bank i. Withdrawal $D_i - 1$ and repayment $L_i - 1$ events at a bank and are also initiated by NFTs randomly with probability $p_{withdrawal}$ and $p_{repayment}$ per unit of D and L every time period. There is a probability $p_{default}$ of a loan default at bank i causing $L_i - 1^*$ that induces a lower value of capital $K_i - 1$ but no change in reserves R_i.

The basic principle of the interbank market is to allow each bank to make interbank loans I_L and interbank deposits I_D with other banks in their network. At every point in time during the simulation, the ABM tracks the reserves R_i that each bank has on hand, amount of deposits D_i that each bank has from NFTs, and the number of loans L_i to NFTs. Each deposit and loan in this model have a value of 1 which makes reserves, deposits, and loans all integer values. In the model, there are interbank loans I_L and interbank deposits I_D between the banks in the network. In the real world, these connections could also represent the interbank market for CDs, credit default swaps, and FX contracts. The interbank assets for bank i are the sum of interbank loans and interbank deposits $A_i = I_{i+1} - I_i = I_L - I_D$. There is a balance so that the total bank deposits in the financial system is equal to the sum of the deposits at each individual bank $D_T = \sum_{i=1}^{N} D_i$ and the total loans by the banks in the financial system equals the sum of the loans at each individual bank $L_T = \sum_{i=1}^{N} L_i$. Although the total interbank deposits I_D and interbank loans I_L balance on the system level, the I_D and I_L may not balance at an individual bank. In this way, it is possible that an individual bank will not have the sum of its deposits equal the sum of its loans. When an individual bank does not have sufficient deposits from NFTs to meet its reserve requirement or has insufficient loans applications to satisfy the deposits then the bank will access the interbank market to request funds from another bank.

Adaptation

The banks make decisions and adapt behavior in each period to meet regulatory requirements for bank reserves, to remain competitive relative to other banks, and to respond to the market environment. The model uses a fixed Poisson distirbution process for the loan rate p_{loan} and bank reserve requirements R^* that provide baseline parameters for the bank behavior. The market environment is described by the Poisson distribution process for the deposit rate $p_{deposit}$, withdrawal rate $p_{withdrawal}$, repayment rate $p_{repayment}$, and default rate $p_{default}$. At each period every bank makes decisions about their strategy to maximize their net interest revenue through their operations with NFTs and with other banks. The banks engage in use their interbank network and through these relationships observe the strategies, profitability, and insolvency of neighboring banks. Banks can change their strategies by changing their reserve holdings. Although a bank must meet the minimum reserve requirement they can decide to increase or change their reserves so long as the amount of capital that they have is positive.

Objectives

The objective of the banks is to maximize their profits as measured by their net interest revenue. The success of the banks will depend on their profitability which is linked to the degree to which they are lending and their leverage. Profitability is the net interest revenue in each period. Recall that bank net worth is its capital K which is the sum of reserves, loans, interbank loans and less deposits and interbank deposits $K = R + L + I_L - D - I_D$. It is implicitly assumed that interest rate paid on loans L is higher than interbank loans I_L which is higher than the interest rate paid on reserves R. Furthermore, banks do not want to be illiquid or become insolvent but do not have information on the entire banking system. Throughout the simulation the banks will increasingly increase their profitability by reducing their reserves which increases the possibility of a liquidty or insolvency event in the future.

Sensing

The banks in this model sense the state of the economy and the behaviors of the other banks in their network. When the economy is doing well, the banks are receiving deposits and withdrawals as NFTs have to satisfy their retail banking needs. In addition, as the economy performs well, the banks sense an increased demand for loans, an increase in loan repayment rates, and a decrease in the loan default rates. On the other hand, when the economy is doing poorly, then the banks will sense a decreased demand for loans, a decreased demand for loans, a decrease in loan repayment rates, and an increase in loan default rates. The banks also sense the behaviors of the other banks in their network through their dealings with other banks. For example, when the economy is performing well, banks on average will have a higher rate of deposit from NFTs and a higher demand for loans. Banks can use the interbank market to either lend excess deposits or to borrow money to meet the demand from loan applicants. Because a bank can only use the interbank market if it has a connection with another bank the more connected bank networks are better able to borrow and lend excess deposits on the interbank market.

Interaction

The banks in this model interact with the non-financial transactors (NFTs) directly and interact with other banks in their network according to the behavioral rules. This ABM assumes a Poisson probability distribution of behavior that the NFTs interact with the banks to make deposits and withdrawals, apply for loans, and default with some probability and then examines how the banks react to these behaviors to make interbank loans and deposits. The banks interact with other banks in the system in order to gain competitive advantage.

The interbank transactions is a main interaction element in this ABM. When an NFT deposits or applies for a loan at a bank then this bank has the opportunity to conduct interbank transactions other banks in the network. A transaction of 1 dollar from bank i to bank j could have one of the following effects. First, $R_{i,t} - 1 \rightarrow R_{i,t+1}$ implies that a bank experiences a withdrawal in the form of a deposit or a loan with either an NFT or another bank at time t and therefore has a change in the value of reserves R_i at time $t+1$ from what it had at time t. Whenever this type of interaction occurs at bank i there is a counterparty bank j which experiences $R_{j,t}+1 \rightarrow R_{j,t+1}$ which is an increase in the level of reserves by 1 at time t to time $t+1$. The simulation keeps track of interbank loans and deposits. Therefore, if we suppose NFTs initiate deposit at bank j but then a loan at bank k, assume that $j = i-1$ and $k = i+1$, bank j reacts to this by increasing its interbank loans I_L at neighboring bank i. Note that the assets A_i is unaffected and R_i and K_i also remain unchanged.

The banks in this financial system also can experience a liquidity crisis as internal forces push the financial system to a critical state. Suppose that each bank has a target level of reserves R^*. In this financial system, when bank i has just enough deposits to meet its reserve requirement target R^* and an NFT deposit withdrawal or loan request that renders bank i illiquid. When bank i becomes illiquid the system can go into a critical state as this withdrawal from bank i goes to the neighboring bank j. This neighboring bank j can then become illiquid and this can spread the local episode to other banks in the system. Similarly, when a bank decides to have larger reserves and to change its reserve target it then can call in the loans that it has made to the other banks. Therefore, the NFTs see a critical state and rationally accelerate the crisis.

The banks in this financial system can experience a solvency crisis in the course of their every day interactions. A bank solvency crisis happens because the professional bank managers lower the capital K that they hold at the bank relative to bank assets over time. First, the banks managers lower the capital K because the banks that have higher K will lower K to be competitive with other banks. Banks with a lower K will be able, all else equal, to pay out more to shareholders and to show a higher return on equity. Banks with higher K will come under pressure to emulate the banks with the apparently lower K. Second, the bank manager compensation typically depends on relative performance. While bank managers are not penalized for poor performance in bad times they have an incentive to show the same profitability as other banks in good times. Therefore, until a state of criticality is reached the bank managers will have an incentive to reduce the K of their bank relative to the other banks. Loan default causes bank i to become insolvent. This spreads and causes other connected banks to become insolvent. Moral hazard of government intervention is not part of this model.

3.3 Design Details

Initialization

The model initialization includes calibration parameters for the banking network and system dynamics as well as a set of initial economic conditions for good economic times and bad economic times. The bank network is either a complete network, unconnnected network, circle network, or star network. The most up to date data on banks and other bank holding companies is used to initialize the ABM at 8 banks.[6] In addition, the bank reserve ratio is 30 percent, starting deposits are 100, starting reserves are 303, starting loans are 700, the loan interest rate is 5 percent, and the deposit interest rate is 1 percent. The intuition for the starting level of reserves is that all banks start the simulation just slightly above the reserve requirement. For the simulations with good economic conditions the deposit rate is 3 per period, withdrawal rate is 2 per period, loan rate is 3 per period, repayment rate is 2 per period, and the default probability is 1 percent. For the simulations with bad economic conditions the deposit rate is 3 per period, withdrawal rate is 3 per period, loan rate is 2 per period, repayment rate is 2 per period, and the default probability is 10 percent.

[6] Both the Federal Reserve Board of Governors and the Financial Stability Oversight Council (FSOC) provide public information on the following eight global systemically important bank holding companies (GSIBs): Bank of America Corporation; The Bank of New York Mellon Corporation; Citigroup, Inc.; The Goldman Sachs Group, Inc.; JPMorgan Chase & Co.; Morgan Stanley; State Street Corporation; and Wells Fargo & Company.

Input data

The current version of this ABM uses reasonable parameter values and initial conditions. Future versions could incorporate other model parameter values and initial conditions.

4 Results

The simulation results indicate that more interconnected bank networks have longer bank lifespans, are more profitable, but are also more likely to experience a bank avalanche than less interconnected bank networks. Furthermore, the profitability and the financial stability of the bank networks depends on the economic conditions. Simulations are conducted across all of the networks using a model calibration with good economic conditions and using a model calibration with bad economic conditions. The results indicate that there is greater dispersion in profitability and financial stability across the networks when there are good economic conditions than when there are bad economic conditions. Furthermore, the circle network performs best of all the networks in terms of bank lifespan, profitability, and also has less bank avalanches than the complete network.

When the model is calibrated with good economic conditions the mean simulation results indicate that the circle network performs the best of all the financial networks in terms of bank lifespan and profitability. For the simulations with good economic conditions the deposit rate is 3 per period, withdrawal rate is 2 per period, loan rate is 3 per period, repayment rate is 2 per period, and the default probability is 1 percent. As seen from Table 1, the mean bank lifespan is longest for the circle network with 9,460, for the star network is 2,668, for the complete network is 1,499, and the unconnected network is 726. The average profitability is highest for the circle network with 3,794,223 followed by the star network with 1,693,435, the complete network with 791,983, and the unconnected network with 152,019. The bank avalanche statistics indicate that they are highest for the complete network with a mean of 0.56, followed by circle network with 0.01, and no bank avalanches for the star network or the unconnected network. Appendix Table A1 provides even more detailed summary statistics on model simulations calibrated using good economic conditions.

Table 1: Mean of Simulation Results (Good Economy)

	Complete Network	Unconnected Network	Circle Network	Star Network
Bank Lifespan	1,499	726	9,460	2,668
Profitability	791,983	152,019	3,794,223	1,693,435
Bank Avalanche	0.56	0.00	0.01	0.00

The cumulative density functions of bank lifespan and profitability under good economic conditions provide additional insights into the results. Appendix Figure A2 shows that the bank lifespan for the circle network in good economic conditions is very different from the other financial networks. The bank lifespan for the unconnected network is the shortest and ends at about 2000. The bank lifespan for the complete network and the star network stabilize at 2000 with about 20 percent of the banks then continuing on until 10,000. The circle network, however, loses about 5 percent of the banks in the very beginning but then about 95 percent of the banks have a lifespan until 10,000. Appendix Figure A4 shows very different profitability cumulative density functions for the different financial networks. Almost 90 percent of the banks in the circle network make a profit over 3 million. In the complete network about 70 percent of the banks earn a profit of less than 1 million and 30 percent of the banks make a profit of over 2 million, but none over 3 million in profits. About 25 percent of the banks in the star network make less than 2 million and the other 75 percent of the banks earn a little over 2 million. Appendix Figure A6 shows that the complete network has by far the most bank avalanches of any of the other networks.

When the model is calibrated with bad economic conditions the simulation results also indicate that the circle network performs best of all the financial networks in terms of bank lifespan and profitability. As seen from Table 2, the average bank lifespan is longest for the circle network with 95 and followed by the star network with 94, the complete network with 81, and the unconnected network with 70. The average profitability is highest for the circle network with 19,004, the star network with 18,653, the complete network with 16,093, and the unconnected network with 13,796. The bank avalanche statistics indicate that the complete network has the highest amount of bank avalanches with a mean of 0.24, followed by the circle network with 0.09, the star network with 0.03, and no bank avalanches for the unconnected network.

Table 2: Mean of Simulation Results (Bad Economy)

	Complete Network	Unconnected Network	Circle Network	Star Network
Bank Lifespan	81	70	95	94
Profitability	16,093	13,796	19,004	18,653
Bank Avalanche	0.24	0.00	0.09	0.03

The cumulative density functions of bank lifespan and profitability under bad economic conditions indicate less variation across the different networks than was present under good economic conditions. Appendix Figure A3 show that cumulative density functions for bank lifespan is relatively the same across the different network. The bank lifespan for the unconnected network is the shortest and ends at about 160. However, the bank lifespans for the complete, circle, and star network converge to the same place at over 500. Appendix Figure A5 indicate that similar cumulative density functions of profitability for the different financial networks. The profitability of the unconnected network is the lowest of all the other networks and ends at 30,000. The cumulative density functions for profitability show no noticeable differences for the the complete network, circle network, and star network. The maximum profitability for the unconnected network is much lower than the other networks but only about 1 percent of banks earn more than 75,000 in the complete network, circle network, and star network. The Appendix Figure A7 shows that the complete network has by far the most bank avalanches of any of the other networks. The complete network has 176 instances with 1 bank avalanche, 31 instances with 2 bank avalanches. The circle network has 58 instances of 1 avalanche and 16 instances of 2 avalanches. The star network has 32 instances with 1 avalanche while the unconnected network, by definition because it does not have an interbank network, does not have any avalanches.

The two main results are that the circle network exhibits the best performance of all the networks and that network matters much more when there are good economic conditions than when there are bad economic conditions. One possible explanation for why the circle network does so well relative to the other networks in terms of bank lifespan, profitability, and bank avalanches is that a few of the banks become insolvent at the beginning of the simulation but because they are not connected to the entire system it does not bring down the other banks. In the complete network there is less of a change for bank failures for the bad banks to occur but then when they do the financial contagion spreads to the healthy banks too. In the unconnected and the star networks the banks are unable to take full advantage of the interbank network even if they are less likely to experience financial contagion. There is a much greater dispersion in the performance of the financial networks when there are good economic conditions than when there are bad economic conditions. More work must be done to explore the role of economic conditions on network performance.

5 Conclusion

This paper developed a model of systemic risk to examine the emergence of profitability and financial stability of different bank networks. This agent based model (ABM) introduced behavioral rules for banks and non-financial transactors with an interbank market that included a complete network, unconnected network, circle network, and a star network. Simulations were used to examine the behavior of the model using good economic conditions and bad economic conditions in the different interbank networks. These simulation results for the good economic conditions indicated that more interconnected interbank networks had longer bank lifespan and higher profitability but also a higher incidence of a bank avalanche or financial contagion. Interestingly, the circle network performed better than all of the other interbank networks, including even the complete network, suggesting that there are limits to the benefits of interconnections in good economic conditions. Whether the economic conditions were good or bad also appear to affect the bank lifespan, profitability, and incidence of bank avalanche.

This paper showed that the structure of interbank connections can affect financial contagion and the emergence of systemic risk. The results in this paper contrast with those of Allen and Gale (2002) that the complete network is the most stable and Acemoglu, Ozdaglar, Tahbaz-Salehi (2013) that incomplete networks are more stable than incomplete networks as long as shocks are small. Whereas in those models the shocks came from an external source the shocks in this model emerged through the interactions of the agents as the system reached a critical state which lead to bank avalanches. In this paper the circle network, in which the banks are not fully connected but also not unconnected either, perform the best in terms of bank lifespan and profitability. Furthermore, in this paper the performance of the various interbank networks depends also on the state of the economy and shows greater variation when there are good economic conditions than when there are bad economic conditions. In the future, the model calibration could possibly integrate real time data to monitor and stress test the global financial system. This paper also assumed that all the banks in the system faced the same set of parameters and regulatory frameworks. Future work could also explore financial stability dynamics in which the banks were not only different at the time of initialization but in which they actually faced different sets of regulations and how that would affect the system as a whole. This bank avalanche model of systemic risk can also be used to examine related issues in financial stability.

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Appendix A

Figure A1: Flowchart of Bank Avalanche Model of Systemic Risk.

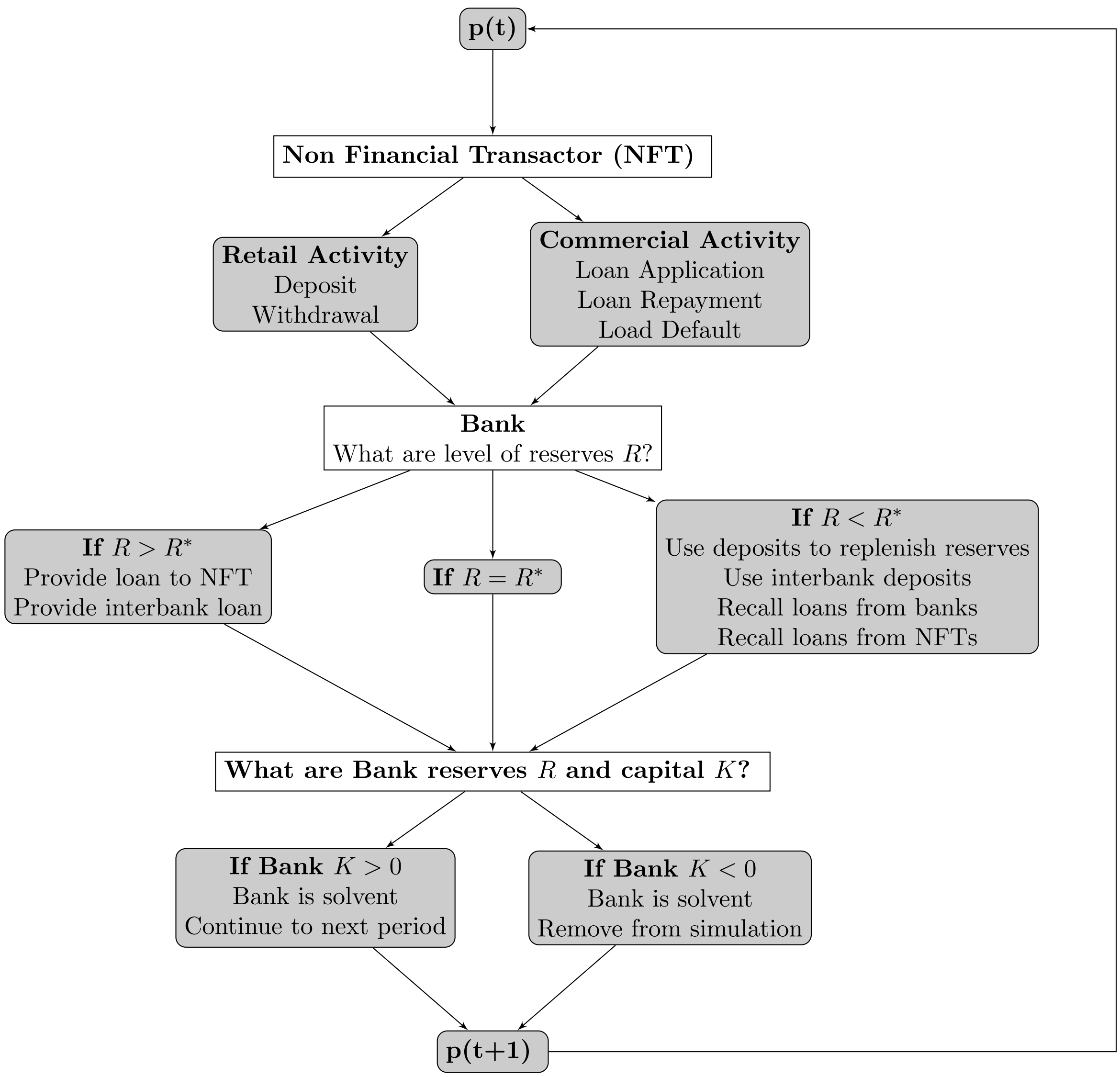

Table A1: Summary Statistics of Simulation Results (Good Economy)

		Complete Network	Unconnected Network	Circle Network	Star Network
Bank Lifespan					
	Mean	1,499	726	9,460	2,668
	Std. Dev.	2,546	291	2,198	3,665
	Min	12	15	25	35
	Max	10,080	1,938	10,101	10,093
	Obs.	1,000	1,000	1,000	1,000
Profitability					
	Mean	791,983	152,019	3,794,223	1,693,435
	Std. Dev.	912,118	36,537	786,974	712,499
	Min	14,618	64,971	8,379	63,132
	Max	4,029,960	323,740	4,191,759	2,220,368
	Obs.	1,000	1,000	1,000	1,000
Bank Avalanche					
	Mean	0.56	0.00	0.01	0.00
	Std. Dev.	0.69	0.00	0.13	0.00
	Min	0	0	0	0
	Max	3	0	3	0
	Obs.	1,000	1,000	1,000	1,000

Table A2: Summary Statistics of Simulation Results (Bad Economy)

		Complete Network	Unconnected Network	Circle Network	Star Network
Bank Lifespan					
	Mean	81	70	95	94
	Std. Dev.	91	29	116	71
	Min	2	1	3	4
	Max	2,205	188	1,834	1,649
	Obs.	1,000	1,000	1,000	1,000
Profitability					
	Mean	16,093	13,796	19,004	18,653
	Std. Dev.	9,410	3,381	20,122	6,960
	Min	3,072	5,845	3,823	3,768
	Max	127,685	29,964	358,212	92,745
	Obs.	1,000	1,000	1,000	1,000
Bank Avalanche					
	Mean	0.24	0.00	0.09	0.03
	Std. Dev.	0.49	0.00	0.34	0.18
	Min	0	0	0	0
	Max	2	0	2	1
	Obs.	1,000	1,000	1,000	1,000

Figure A2: Cumulative Density Function of Bank Lifespan (Good Economy)

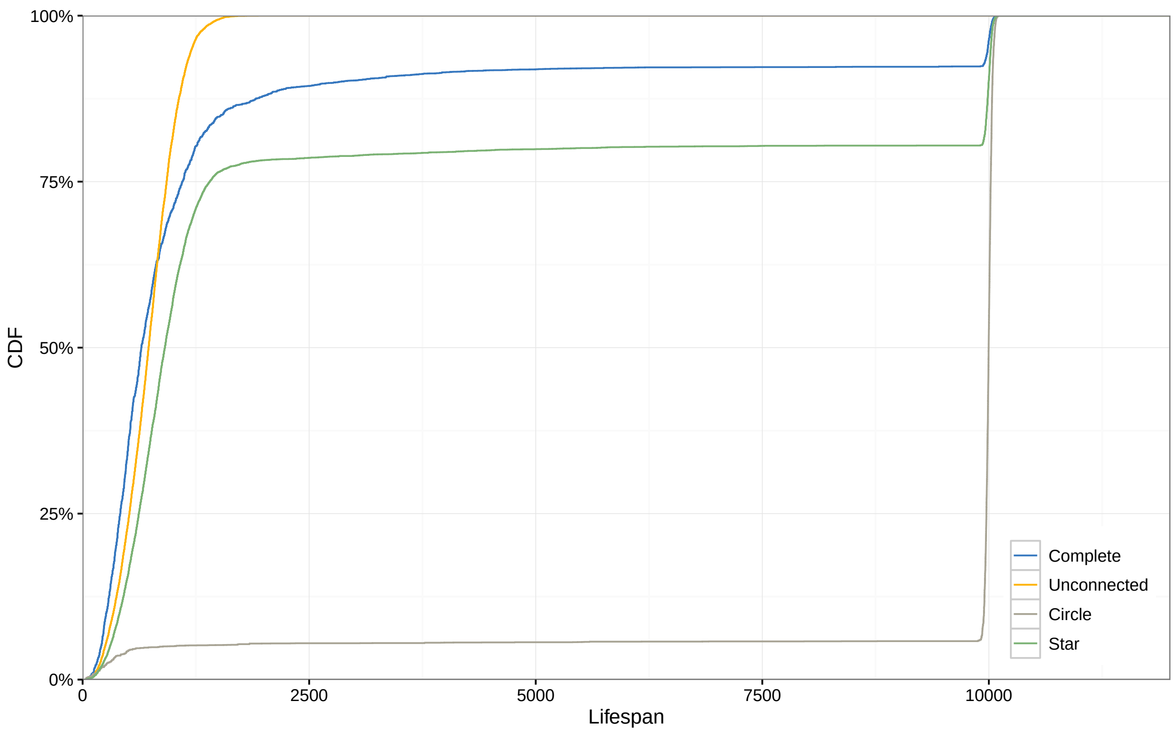

Figure A3: Cumulative Density Function of Bank Lifespan (Bad Economy)

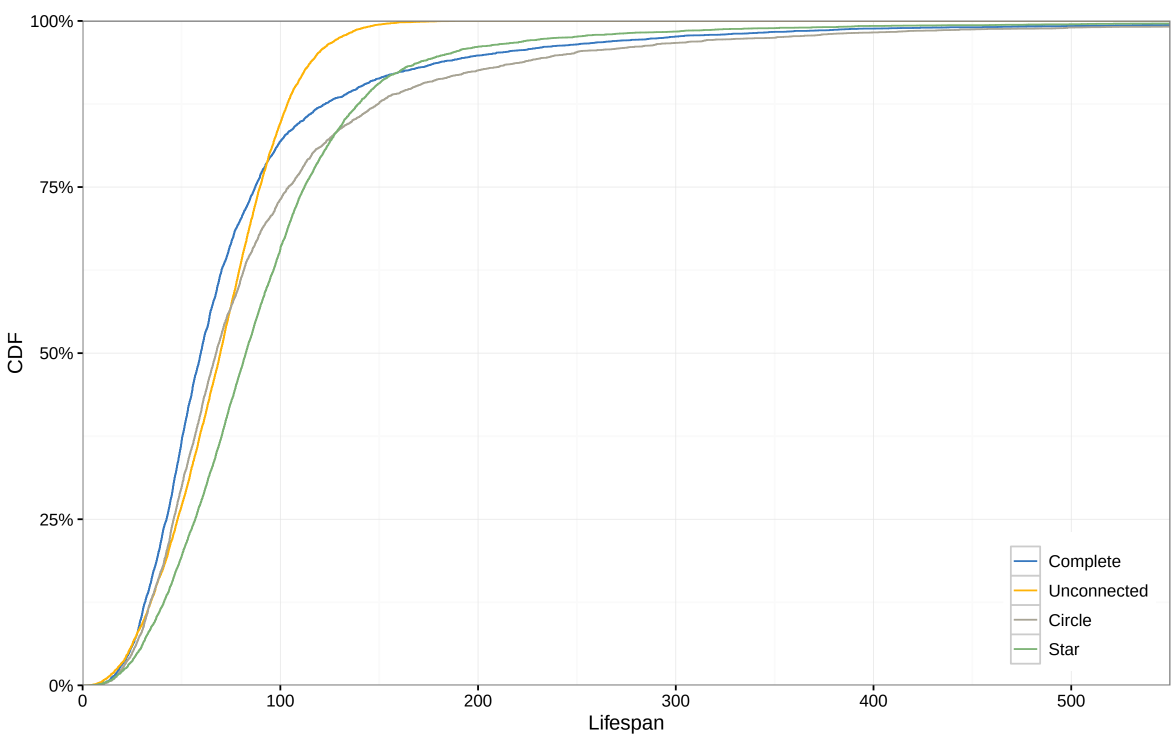

Figure A4: Cumulative Density Function of Profitability (Good Economy)

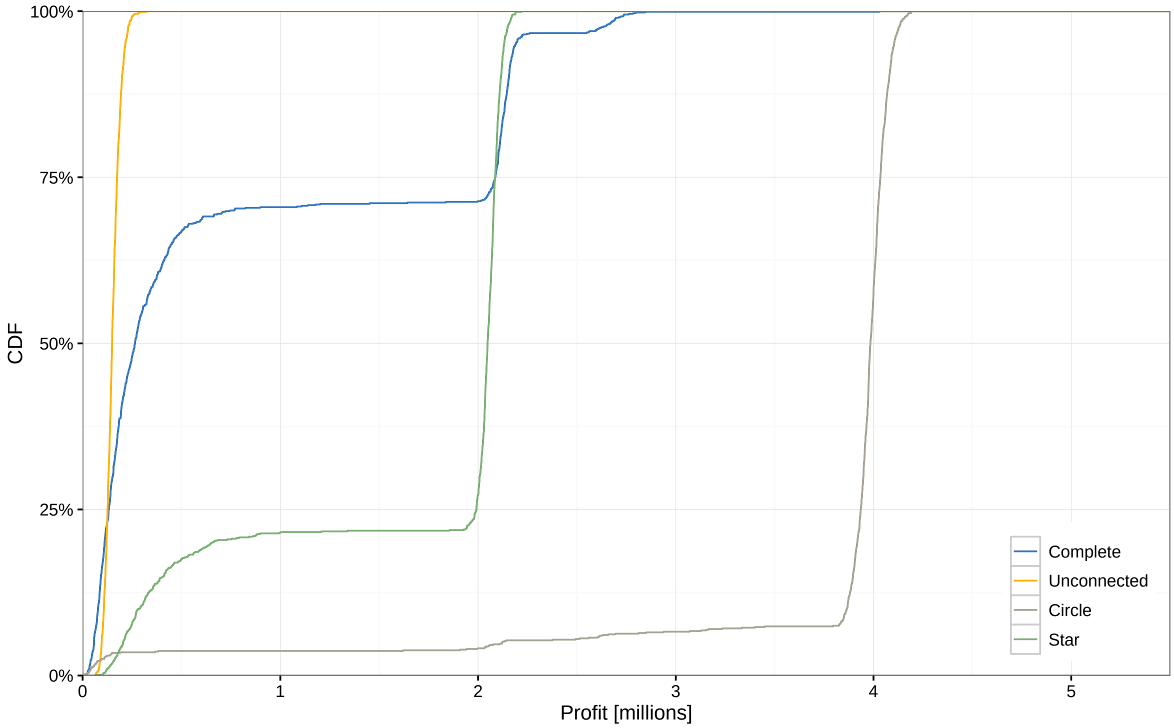

Figure A5: Cumulative Density Function of Profitability (Bad Economy)

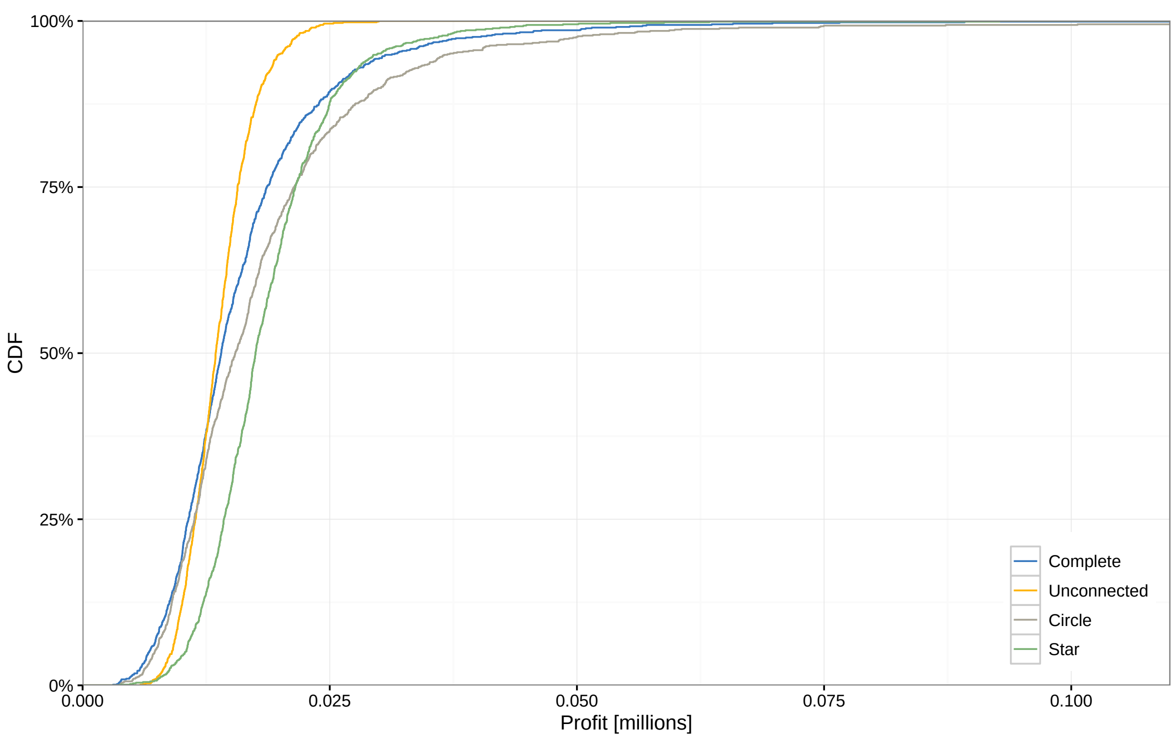

Figure A6: Summary Statistics of Bank Avalanches (Good Economy)

	Complete Network	Unconnected Network	Circle Network	Star Network
No Avalanches	547	1000	991	1000
1 Avalanche	346	0	8	0
2 Avalanches	103	0	0	0
3 Avalanches	4	0	1	0

Figure A7: Summary Statistics of Bank Avalanches (Bad Economy)

	Complete Network	Unconnected Network	Circle Network	Star Network
No Avalanches	793	1000	926	968
1 Avalanche	176	0	58	32
2 Avalanches	31	0	16	0
3 Avalanches	0	0	0	0