Systemic Liquidity Crisis with Dynamic Haircuts

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Systemic Liquidity Crisis in a Banking System with Dynamic Haircuts

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Abstract

In this paper, using network tools, I analyse systemic impacts of liquidity shocks in interbank market in case of endogenous haircuts. Gai, Haldane and Kapadia (2011) introduce a benchmark for liquidity crisis following haircut shocks, and Gorton and Metrick (2010) reveal the evidence from 2007-09 crisis for increasing haircuts with banking panic. In the benchmark model, I endogenize and update haircuts dynamically during the period of stress. The results significantly differ from static haircut case. I show that the gap in the impacts of haircut shocks between dynamic and static haircuts is persistent for different experiments. I analyse the effects of connectivity, balance sheet and network positions of banks, and liquidity level and distribution on crisis. As well as aggregate and idiosyncratic shocks, by considering possible correlations on the asset sides of banks, I also introduce a shock hitting several banks at the same time. This study may be useful for policy makers to predict the consequences of liquidity shocks more accurately. The findings are also related to microprudential regulation on liquidity surcharge for systemically important financial institutions (SIFI's) and produce policy recommendations on minimum liquidity requirements.

Keywords: systemic risk, liquidity risk, liquidity crisis, liquidity hoarding, random network, geometric network, dynamic haircut, liquidity surcharge, systemically important financial institution (SIFI)
JEL Classification Numbers:

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1 Introduction

In recent years, especially after 2008 crisis, more effort has been directed by both policy makers and academia in order to investigate and understand the nature and dynamics of systemic risk in financial systems, since its social and economic costs are significant[1]. The literature on systemic risk has different approaches. One approach is market indicators as a measure of risk. Huang *et al.* (2011) study individual contributions of banks to system-wide risk with default probability, institution size and asset correlation, and recommend surcharge policy for systemically important financial institutions (SIFI's). Acharya (2009) models systemic risk as correlation of returns on assets that are held by banks by considering the market level impact of investment choices of individual banks. The level of market liquidity is also a key parameter for systemic crisis. Acharya *et al.* (2010) provide an example of liquidation costs in the market. Acharya and Merrouche (2010) analyse bank demand for liquidity and its effects in the interbank market during the period of crisis. They conclude how liquidity hoarding ends in a decreased volume of interbank market by using 2007-08 crisis data. Acharya and Skeie (2011) relate financial crises to decreased volume of transactions, and explain it by modelling precautionary hoarding of banks. They conclude that illiquidity of assets gives rise to low volumes in stress periods and finally markets can completely freeze. Gai, Haldane and Kapadia (2011) provide a model of liquidity crisis with hoarding and haircuts. As a benchmark, in the context of 2007-08 crisis, they show how the complexity and concentration affect the contagious process. Another strand of literature focuses on the role of leverage on systemic risk. Acharya *et al.* (2010) focus on the conflicting effects of leverage: improving liquidation of the market and potential risks inherited to the system. Another type of studies on the effect of liquidity on crisis includes haircuts. Gorton and Metrick (2010) reveal the evidence for increased haircuts during the 2007-09 crisis, with the banking panic, which increases borrowing costs and makes access to credit harder. It is not a financial shock which gives rise to a one jump in haircuts, but it is a cycle through which haircut values increase. They argue that first stage shock and bad news following it may start the cycle and a loss of confidence makes market liquidity dry and market freeze. Moro (2013) is another study focusing on this fact. During the ongoing financial crisis, depositors even apply greater haircuts on collaterals to allay their concerns about the default of their counterparties. Chapman *et al.* (2011) present a model of central bank collateralized lending and get optimal haircut settings. Ghosal *et al.* (2010) is on sovereign debt restructuring and size of haircuts. Their analysis suggest that there is a correlation between delay length and size of haircut. Longworth (2010) argue about the the market failure in the setting of haircuts has led to an deterioration of both the financial boom of the last decade and the financial bust. He mentions about over-fluctuations that haircuts had been squeezed in the boom and then rose dramatically during the period of crisis. He explains the spiral triggered by a lower market liquidity and higher volatility. The cycle results in higher haircuts, which, at the end, gives rise to much lower liquidity in the market. Since the trend of haircuts follows the financial cycle, they have procyclical characteristics, and when market has liquidity losses, it makes the liquidity even lower.

Another approach is to use network measures to identify SIFI's. Hu *et al.* (2010) and Soramäki and Cook (2013) develop different algorithms for the purpose. Simulation based network studies investigate the role of interbank network as absorber or amplifier of the risk. Kuzubaş *et al.* (2014), in a balance sheet based network model, investigate systemic impacts of network connectivity for heterogeneously levered banks in the context of Nier *et al.* (2007). Iori *et al.* (2003) and Montagna and Lux (2012) construct balance sheet based models in order to investigate the relation between network topology and systemic risk. Iori *et al.* (2006) study banking systems with both homogeneous and heterogeneous banks.

[1] See Hoggarth, Reis and Saporta (2002), Kapp and Vega (2012), Dijk and Mathijs (2013) and Goodman and Mance (2011) for detailed analyses of costs of systemic financial crises.

Gai *et al.* (2012) produce policy recommendations on the architecture of network. Jo (2012) extends to the network analysis in Chan-Lau (2010) linking liquidity risk and solvency risk and infers policy recommendations for Basel requirements. Haldane *et al.* (2009) discuss the role of complexity and concentration, concluding the interconnections among institutions may act as amplifier or absorber for the risk depending on the level of connectivity. Eisenberg and Noe (2001) and Diamond and Dybvig (1983) include market dynamics in model based studies. Gleeson *et al.* (2011) propose a method for calculating the expected size of contagion in the contexts of Nier *et al.* and Gai and Kapadia (2010). Ex-post descriptive analysis of interbank networks is also useful to explore the feature of real-world financial systems[2]. Most of the studies using real-world networks of financial systems concludes that a few institutions have relatively large number of linkages, thus financial networks, rather than being uniform, have scale-free characteristics.

In an interbank money market, in which financial institutions establish lending and borrowing relations, an idiosyncratic or/and systematic haircut shock hitting a bank in the system may be amplified and spread over the entire system via liquidity hoarding of banks based on their balance sheet positions. Even if an idiosyncratic shock may put only a bank in stress in its liquidity position in the first stage, hoarding of the stressed bank may cause other banks to have shortages in liquidity, and they may be forced to hoard their interbank assets, too. Thus, interbank lending linkages are an important channel in a systemic liquidity crisis, which spreads from lender to borrower through the system. Moreover, a first shock hitting a bank (or more) may cause a loss in confidence, start a banking panic and give rise to the cycle of increases in haircuts, which ends in further loss of interbank funding of banks. As well as hoarding, this may be the second channel of the risk inherited to the system. Resilience of the system is measured by the amount of the systemic impacts of liquidity shock, that is, the contagion of liquidity shortages. Balance sheet and network positions of banks, endogenous level of panic and perceived risk in the system, and the topology and concentration of the network are both crucial aspects of financial stability in liquidity crises. Therefore a model for banking system should take these features into account.

In this paper, I introduce endogenously dynamic haircuts into a balance sheet based network model of systemic liquidity crisis, which is missing in the previous literature. In the context of Gai, Haldane and Kapadia (2011(, I endogenize haircuts for the period of crisis by considering Gorton and Metrick (2010). They give the evidence about the haircuts that haircuts increase in the period of stress. They show the trend how they increase during the recent 2007-09 crisis. Their findings suggest that 2007-09 financial crisis was a banking panic. Since repo haircuts are determined by agents in the market and open to change, when participants are not ignorant, there may be increases in haircut levels, especially followed by bad news, and financial institutions cannot finance themselves after a threshold. I try to mimic time varying and procyclical characteristics of haircuts for the period of crisis. I incorporate this type of endogenous and dynamic modelling of haircuts into the benchmark model. By considering the evidence, my extension makes the benchmark model in Gai, Haldane and Kapadia (2011) more realistic. I use same parameter values and as in the benchmark case in order to be comparable with their results. The benchmark article interpret an event as "systemic liquidity crisis" if 10% or more of banks have to withdraw their interbank assets. To be more complete and comprehensible, I use number of banks that have to hoard as the systemic risk measure. This new measure illustrates the exact difference between dynamic and static haircuts. Following the benchmark article, both random and geometric networks are analysed. By performing simulations in Monte Carlo framework, I compare my findings with the static haircut case for each experiment, and I extend policy experiments on liquidity requirements. I

[2]See Kuzubaş *et al.* (2013) for a descriptive analysis of Turkish 2001 banking crisis, Arnold *et al.* (2006) for the US market, Benitez *et al.* (2012) for Mexican banking system, Puhr *et al.* (2012) for Austrian interbank market and Caldarelli *et al.* (2007) for an analysis of Italian overnight money market

change the minimum requirements and amount of surcharge by keeping overall level of liquidity constant in order to see the effect of liquidity distribution and bank characteristics on liquidity crisis. As in Gai, Haldane and Kapadia (2011), I focus on both the idiosyncratic haircut shocks to a randomly chosen bank, and a combined shock with a systematic haircut increase, and explore the change on the tipping points of network, that is, the role of network complexity and concentration in the resilience of the system against a liquidity crisis. Another question in the article is what if, instead random shocks, the most interconnected lender bank is hit by a targeted shock. I extend benchmark experiment by adding also least connected lender in order to see the effect of network positions of shocked bank more clearly. The systemic impact of shocks for different asset and liability compositions and volume of interbank market are also investigated. Since there may be correlations of returns on assets of some banks in the system, I also apply a multiple shock procedure arising from high correlation of assets of several banks which invest closely correlated assets[3]. This type of shock hitting several banks at a time is between system-wide and idiosyncratic shocks. I give shock to 10% of banks at the same time, and detect the results, which is ignored in the previous simulation based studies. The policy experiment on liquidity suggests some to-the-point policy recommendations for higher minimum requirements with lower liquidity surcharge for the same system-wide liquidity level. I observe how a constant haircut framework underestimates the systemic impacts of haircut shocks and how results significantly differ from a constant haircut framework for each experiment.

In section 2, I introduce the model and define environment. In section 3, simulation, experiments and following policy implications are illustrated and discussed. Finally Section 4 concludes.

2 Theoretical Framework

In this study, I have extended Gai, Haldane, Kapadia (2011) by introducing dynamic and endogenous haircuts into the period of crisis. They construct an interbank money market network model with N institutions with balance sheets given as in Table 1:

Balance Sheet of Bank i	
Total Assets(A_i)	Total Liabilities(L_i)
Fixed Assets (${A_i}^F$) Collateral Assets (${A_i}^C$) Reverse Repo (${A_i}^{RR}$) Unsecured Interbank Assets (${A_i}^{IB}$) Liquid Assets(${A_i}^L$)	Retail Deposits (${L_i}^D$) Capital (K_i) Unsecured Interbank Liabilities (${L_i}^{IB}$) Repo (${L_i}^R$)

Balance sheet identity of bank i is given by $L_i = A_i \quad \forall i = 1...N$. In the model, fully liquid assets are assumed to be used as collateral to obtain repo funding without any haircut, or sold without any discount in price, whereas fixed assets and unsecured interbank assets cannot be used as collateral for repo financing. Aggregate haircut, $h \in [0, 1]$, is associated with using collateral assets to get repo funding. It reflects perceived risk of lender of the bank for the collateral of the borrower and protects the lender against losses arising from counterparty default. They also use bank specific haircut, $h_i \in [0, 1]$, which is associated with the specific risk of any bank in the system. As a result, maximum repo funding can be

[3]See Acharya (2009).

obtained from collateral assets is $(1-h-h_i){A_i}^C$. In addition, amount of collateral by reverse repo assets is ${A_i}^{RR}/(1-h)$, thus maximum repo funding by rehypothecating collateral is $(1-h-h_i){A_i}^{RR}/(1-h)$. A bank is liquid if total amount of its collateral assets for repo funding plus its new unsecured borrowing from interbank market, ${L_i}^N$, exceeds existing repo funding and a liquidity shock e_i or possible interbank fund losses arising from hoarding behavior of its lenders. Hoarding makes the network effect on liquidity crisis central. If μ_i fraction of the lenders of bank i withdraws λ portion of their interbank lendings from the bank, bank i may face an interbank funding loss in the amount of $\mu_i \lambda L_i^{IB}$. Thus, the liquidity constraint is[4]

$$ {A_i}^L + (1-h-h_i){A_i}^C + \frac{(1-h-h_i){A_i}^{RR}}{(1-h)} + {L_i}^N - {L_i}^R - \lambda_i \mu_i {L_i}^{IB} - e_i \geq 0 \tag{1} $$

where ${L_i}^N$ is new unsecured borrowing[5].

2.1 Balance Sheet Construction and Shock Transmission

The liability side of balance sheets are given homogeneously for all banks. Asset size is given exogenously except ${A_i}^{IB}$ and ${A_i}^F$. After network is constructed, ${L_i}^{IB}$ for banks are distributed evenly among their lenders. Through this way, interbank assets are drawn endogenously via network. Finally, according the ${A_i}^{IB}$, ${A_i}^F$ values are determined. At the end, total interbank liabilities are equal to total interbank borrowing in the interbank money market[6]. That is,

$$ \sum_{i=1}^{N} L_i^{IB} = \sum_{i=1}^{N} A_i^{IB} \tag{2} $$

As in the benchmark article, I introduce a liquidity shock which measn an increase in idiosyncratic haircut (h_i) and it wipes out some amount of repo funding of bank i. In some experiments, it is given to a randomly chosen bank, whereas, for geometric network I also shock the bank which has the maximum and numbers of lending links in the system. I also incorporate aggregate haircut shock, an increase in h with idiosyncratic shock. All banks at initial state use all of their collateral assets to get repo funding. That is, at the initial state,

$$ {L_i}^R = (1-h-h_i){A_i}^C + \frac{(1-h-h_i){A_i}^{RR}}{(1-h)} \tag{3} $$

At the first step, after an idiosyncratic haircut shock hits a bank (or a system-wide haircut shock hits all banks), it losses some percentage of its repo funding with existing collaterals. If its repo financing (including liquid assets) cannot meet its repo borrowing[7], ${L_i}^R$, as a defensive action, it is forced to withdraw its interbank assets from its borrowers. Thus its borrowers lose interbank funding by hoarding of their lender. If one or more of these borrowers face a liquidity shortage in their liquidity constraint, it also has to hoard its interbank assets from its own borrowers. This domino effects spreads from lender to

[4]To be comparable with benchmark case, I also assume that $\lambda = 1$ for each experiment, which means full withdrawing.
[5]As in Gai, Haldane, Kapadia (2011), it is assumed to be 0.
[6]Since my aim is to introduce the dynamic haircut, I use same benchmark values as in Gai, Haldane and Kapadia (2011) for balance sheet components.
[7]That is, if liquidity constraint falls below zero.

borrower[8]. The procedure ends when either all banks have to hoard money or liquidity shock is absorbed by the liquidity of the banks in some stage[9].

The haircuts are given exogenously in the benchmark case. I endogenize them using the extent of systemic impacts of the shock and time dimension of shock spread process. Following the shock, haircuts increase as more banks have to hoard money. Gorton and Metrick (2010) argue about the bad news which triggered the 2007-09 crisis by giving rise to increases in repo haircuts during the period. They started the panic and worsened as more news arrive. The panic ended in increasing repo haircuts which amplifies the first stage impact of the shock and has severe effects. Hence, it was not an only first stage shock which lead one jump in haircuts, but it is a persistent process of increases in haircuts. The first and relatively less effective shock creates a loss in confidence and starts the cycle through which liquidity in the system dries up. In the procedure, period 1 starts when an exogenous and systematic and/or idiosyncratic haircut shock hits the system, and ends when banks that have to hoard withdraw their interbank assets from their borrowers. At the beginning of period 2, some lending links may be broken by hoarding. Since participants are not ignorant and banking panic starts, they realise the systemic risk in the system and measure the risk according to the number of banks which face liquidity shortage up to now[10]. In other words, I model the level of panic according to the number of banks that face liquidity shortage up to that time period. By considering the evidence, I try to mimic the procyclicality and time-varying features of haircuts in the model. I update haircuts endogenously, using same initial level as in benchmark plus the endogenous level of perceived panic for the system. After a shock hits the system at $t = 0$, the period of stress starts if some banks have to hoard money, and the haircut t time t,

$$h_t = 0.1 + \frac{S_t}{N} \tag{4}$$

where S_t represents the number of banks that had to hoard money up to period t. Haircut increases through the rounds if more banks have to hoard as time passes. As bad news arrive about the banks, haircuts increase in a cycle of panic. Moreover, I update initial bank specific haircut according to the liquidity position of banks. Instead of a zero bank specific haircut, I endogenize banks specific haircut, too. If a bank is near to have liquidity shortage[11], its counterparties perceive it more risky and its h_i increases to 0.05. In other words, after news about a specific bank that it has less liquidity and may be in stress with the next shock, its depositors perceive it as riskier than other banks. As h or h_i increases in a cycle triggered by an initial shock, same amount of collateral gets less funding, i.e. cost of borrowing increases, since counterparties want to protect themselves more strictly with panic.

2.2 Simulation Procedure

In this section, I describe the simulation procedure. Given the $L_i^{IB}, L_i^R, L_i^D, K_i, A_i^C, A_i^{RR}$ and A_i^L values in the balance sheets, I create realisations of directed and unweighted random and geometric networks. One source of randomness in the model stems from this network structure. It maps the randomness of asset sides of balance sheets via interbank assets. In order to eliminate noise and differences in realisations, I create a Monte Carlo framework over 1000 runs of the system with 1000 network realisations, and I take average values of degree (connectivity) for nodes across realizations of graphs. In the procedure, the lending links are dynamically updated because of hoarding behavior. In other words,

[8] Through the procedure I count number of banks which have to hoard

[9] For model and procedure details, I refer the reader to Gai, Haldane, Kapadia (2011).

[10] Benchmark article use aggregate haircut as 0.1 for all experiments

[11] I assume if its overall liquidity goes below 1% of its balance sheet, it is perceived to have greater default probability, and its lenders may increase its haircut to provide extra protection.

lenders have the priority to break thier lending links to their borrowers and withdraw their interbank assets if they face shortages in liquidity. This leads to a decrease in the volume of interbank transactions during the period of crisis[12]. Links are not netted [13].

In some experiments, a randomly chosen bank (or 10% of banks) faces an idiosyncratic haircut shock for each specific realisation of network. This is the second source of randomness. In order to eliminate this, for each realisation of networks, I choose and shock random banks for 50 times, and I take average number of hoarding banks[14].

If bank j borrows from bank i in the network realisation, and if it also borrows k other banks in the interbank market, the amount that bank i lends to bank j is $L_j^{IB}/(k+1)$. That is, I follow the procedure of benchmark study which distribute the interbank borrowing for each bank evenly among its interbank lenders. In this way, having constructed the network, A_i^{IB} (thus A_i^F) values are determined endogenously. Benchmark parameter values are represented in the Table 1:

Summary of benchmark parameters of the model			
Parameter	Description	Benchmark value	Range
N	Number of banks in the system	50	Fixed
L_i^{IB}	Unsecured interbank liabilities	15%	15% and 25%
L_i^R	Repo liabilities	20%	Fixed
A_i^{IB}	Unsecured interbank assets assets	Endogenous by network	-
K_i	Capital	4%	Fixed
L_i^N	New unsecured interbank borrowing after shock	0	Fixed
A_i^C	Collateral assets	10%	Fixed
A_i^F	Fixed assets	Endogenous by A_i^{IB}	-
A_i^{RR}	Reverse repo assets	11%	Fixed
h	Aggregate haircut	Endogenous by systematic liquidity shortage	0.1-0.9
h_i	Bank specific haircut	0	0-0.15
λ	Proportion of deposits withdrawn by hoarding	1	Fixed

Table 1: Benchmark parameter values

3 Simulations and Results

In this section, I illustrate and discuss my results based on simulations.

I observe, the framework for liquidity crisis which assumes constant haircuts in the period of stress may underestimate the systemic impacts of liquidity shocks. The gap between dynamic and constant haircut cases are persistent for most levels of connectivity and different balance sheet and network positions of banks.

Since some banks invest same (or highly correlated) assets, a shock may hit several banks in the system at the same time. In the multiple shock experiment, the system is affected severely for both dynamic and constant haircut cases. Even less banks are affected for very high level of connectivities

[12]For evidence to this decrease, see Gorton and Metrick (2010).

[13]I allow for both lender and borrower linkage for any two banks in the system. Both ij and ji elements of the adjacency matrix can be 1 at the same realisation of the network. If bank i both lends to bank j and borrows money to bank j, they are both lender and borrower for each others. They both may hoard their lending from each others and shock may propagate both form j to i and i to j. Note that in the network, ji element means j lends to i, as a convention for simulations.

[14]I take averages first for 50 of randomly chosen banks, and 1000 realisation for each of this random bank choice. The average value of number of banks that hoard over 1000 realisations is taken after the average of 50 shock spread process for randomly chosen banks.

for static haircuts, network topology and connectivity do not make the system more resilient when I update haircuts. Since the effect of shock is multiplied by the cycle of increasing haircuts in the dynamic case, the network effect on absorbing the inherited liquidity shortage is not strong enough even for high connectivity levels.

If a shock (combined with a systematic haircut shock) hits the most or least connected lender in the system, for static haircut case, the role of network in absorbing or amplifying the shock changes significantly according to the connectivity level. On the other side, when haircuts are dynamically changed, no turning point for connectivity is observed, system collapses for most levels of connectivity.

In the case of targeted shocks, since the effect of a combined shock is too high to see the tipping points of connectivity in the case of dynamic haircuts, I also introduce specific haircut shocks to the most and least connected lenders. If only a bank specific shock hits the most and the least connected lenders, the role of network on liquidity crisis gains importance for the dynamic case, too. The trend of systemic impact with connectivity level is similar for both versions, but there is again a persistent gap in the number of banks affected. If the least connected lender faces with an idiosyncratic haircut increase, its effect to the system is significantly lower for low and high level of connectivities when compared with the case of most connected lender.

Keeping the total amount of liquid assets same for the whole system, a policy which decreases the minimum required individual level of liquidity and compensates it by applying a tough surcharge according to the volume of individual interbank transactions, changing only the distribution of liquidity with individual surcharges, may impair the resilience of the system against liquidity shocks. Additionally, no matter how it is distributed, a higher level of system-wide liquidity makes system more resilient for both dynamic and static cases.

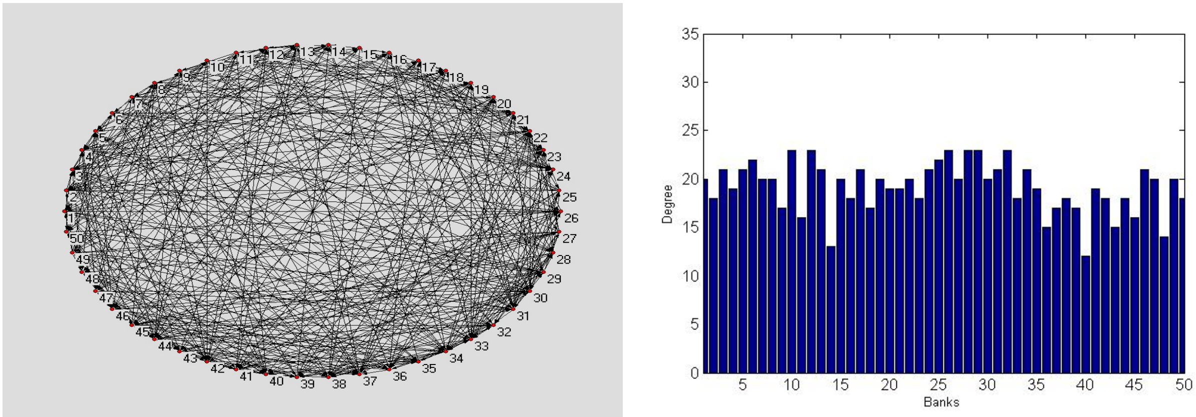
3.1 Examples from Network Realisations

Gai, Haldane and Kapadia (2011) state that real-world financial networks do not have a uniform degree distribution, instead they have fail tail distributions with a small number of players that have large number of links[15]. The simulations for uniformly distributed network are interpreted as benchmark, whereas fat-tailed geometric network is more suitable for real-world networks. Following Figure 1 and 2 illustrate examples from both of realisations of the two[16] and corresponding degrees[17] of nodes.

[15]Boss *et al. (2004), Arnold et al. (2007), Caldarelli et al. (2008), Benitez et al. (2012) reveal the evidence from different interbank markets.*

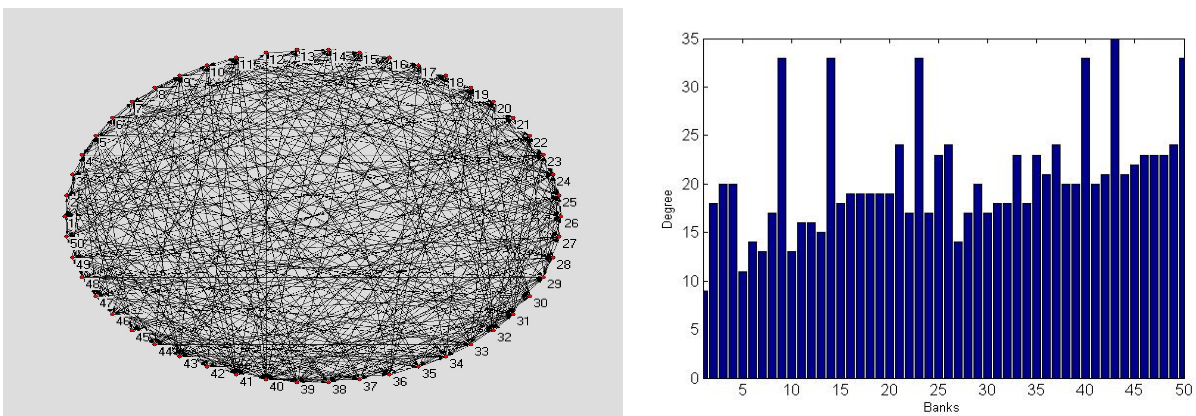
[16]p=0.2

[17]The degree of any bank represents its total number of interbank relations including borrowing and lending links.



((a)) ((b))

Figure 1: Interbank random network



((a)) ((b))

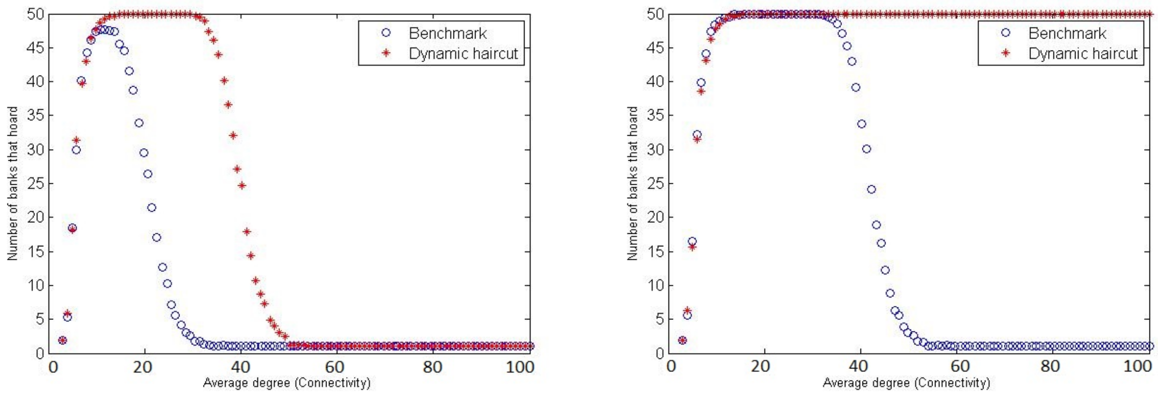
Figure 2: Interbank geometric network

As can be seen, in a geometric network, the links are not distributed evenly, and a few banks have a large number of links which mean that they are highly connected when compared to other banks. On the other side, in a random network, there are no such outliers[18]. Geometric network also gives the chance to select differently connected lenders in the experiments.

[18]No node with a degree greater than 30 for this specific realisation.

3.2 Random Network

3.2.1 Idiosyncratic and Combined Shocks



((a)) The effect of idiosyncratic shock

((b)) The effect of combined shock

Figure 3: Effects of shocks

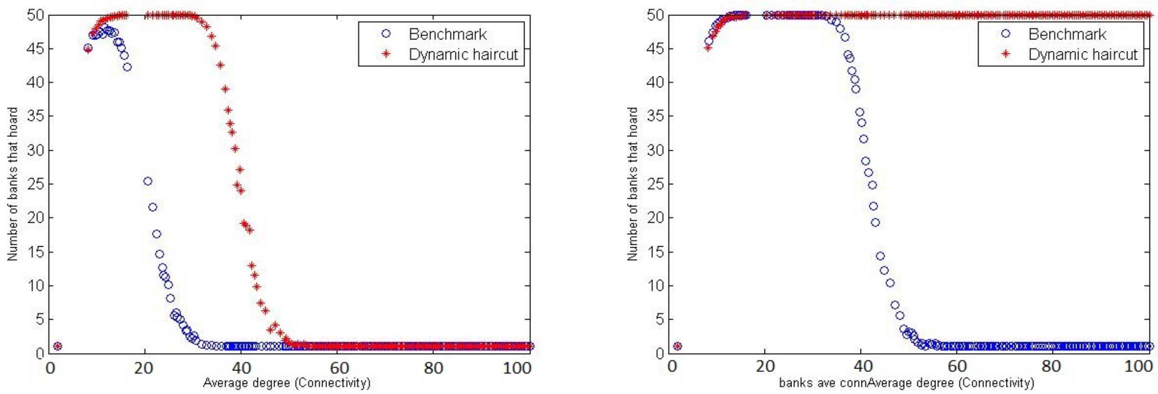
In Figure 3(a), a randomly chosen bank faces with a haircut increase, I observe the difference in the number of banks that have to hoard between benchmark and dynamic haircut cases in each connectivity levels. For low connectivity levels, the level of crisis does not show much difference, but after a level of connectivity around 10, dynamic haircuts cause more banks to face liquidity shortage. Approximately all the banks face liquidity shortage and hoard interbank assets for a large range of connectivity. This means that volume of interbank market is close to zero because of broken lending links, i.e. interbank market freezes. In case case of static haircuts, on the other side, shock does not effect all banks in the system for even the worst situation, and number of banks that hoard goes down earlier. For high level of connectivity, since I distribute the amount borrowed for a bank among its creditor, all banks enough many borrowing and lending links to absorb the hoarding behavior some of their lenders. As a result, systemic impacts of liquidity shock decreases and system becomes more resilient for both dynamic and static cases[19]. In Figure 3(b), an idiosyncratic shock that hits a random bank is combined with a systematic haircut increase. The results worsen for both cases. The number of banks that have to withdraw their interbank assets increase and very high for a larger range of connectivity for benchmark case; but it is devastating for dynamic case. No matter in with level the system is connected, systematic plus idiosyncratic haircut shock case, system collapses for endogenous haircuts. In this case, increasing level of connectivity is not enough to absorb the systemic effect of individual liquidity shortages, since bad news and panic followed by it pulls the haircuts to higher levels and since initial level of aggregate haircut is already high.

[19]The result on the role of connectivity on systemic risk is consistent with Kuzubaş, Saltoğlu and Sever (2014).

3.3 Geometric Network

In this section, the links in the system are not distributed evenly, instead, geometric distribution i chosen and some banks are expected to have higher number of links[20].

3.3.1 Idiosyncratic and Combined Shocks



((a)) The effect of idiosyncratic shock

((b)) The effect of combined shock

Figure 4: Effects of shocks

In Figure 4(a), a random bank is by an idiosyncratic shock, whereas in Figure 4(b), an idiosyncratic shock to a randomly chosen bank is combined with a systematic haircut shock, I observe similar results as in random network for both cases. Even the trends for the role of connectivity in absorbing or amplifying the shock are similar for both types of networks, the main distinction is that geometric network acts as a stronger absorber of the shock with a decrease in the number of banks that have to hoard.

3.3.2 Multiple Shock

In this experiment, I introduce a series of multiple idiosyncratic shock to randomly chosen banks. A systematic shock is modelled as system-wide haircut increase in the model, whereas idiosyncratic shocks are represented as an increase in bank specific haircuts. Between the two types of shocks, because of close characteristics of asset sides of banks, there may be shock that hit several, but not all, banks in the network. I choose 10% of banks randomly and hit them by shock. In this case, for connectivity levels up to 60, we do not observe a difference between dynamic and static haircut cases, for both all banks have liquidity shortages and system collapse. After this turning point, the network connectivity starts to absorb the risk inherited to the system for static case, whereas it does not have such a strong effect for dynamic case which still gives rise to the collapse of all system. For the most connected case, where connectivity is 100, the levels of crisis is highly different between 2 cases. As mentioned in Acharya (2009), this multiple shock may mimic the fact that banks may invest same (or highly correlated) assets, thus a shock that hits these of kind of assets may harm several banks at a time in the system. This may be a comprehensive analysis to foresee the systemic effects of real-world shocks.

[20]Gai, Haldane and Kapadia (2011) use random network as benchmark, and since geometric network is better to mimic real world financial systems, they conduct experiments with geometric networks. I follow the same pattern.

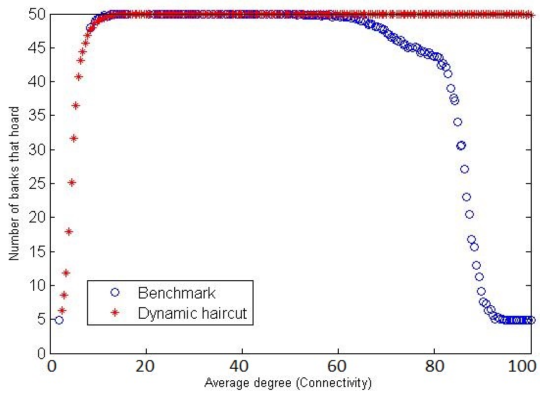


Figure 5: Effect of multiple shock

3.3.3 Volume of Interbank Market

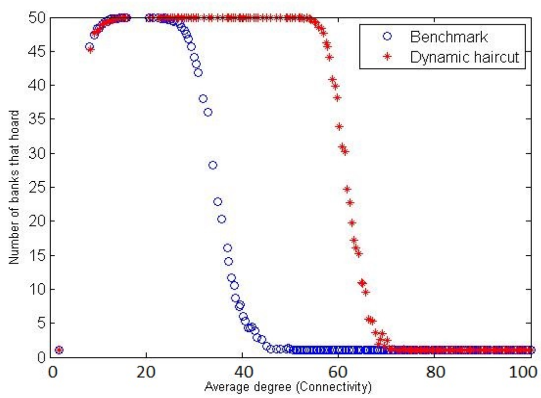


Figure 6: Effect of L_i^{IB}

Figure 8 represents the results for a different liability[21] composition of banks in the case of an idiosyncratic haircut increase for a randomly chosen bank. Following the benchmark article, I increase the average volume of interbank transaction to 25% in the balance sheets of banks[22]. In this case, I have applied only an idiosyncratic haircut shock to a randomly chosen bank, thus the result is comparable with Figure 5. By comparing the two, I observe that the increase in the size of interbank money market makes the system more fragile for a wider range of connectivity level for both dynamic and static cases. When banks borrow and lend higher amounts in interbank money market, the borrowers will be affected severely when a creditor hoards its money from them, since the amount of their losses are greater. Thus,

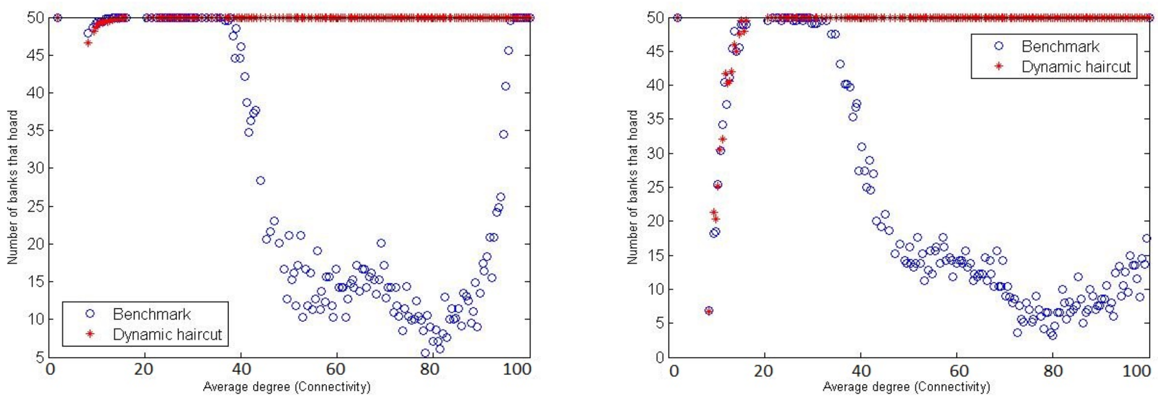
[21]Since interbank assets of banks are determined endogenously via network, higher interbank liability for all banks maps to higher interbank assets for whole system.

[22]When I increase interbank liabilities to this level, since $\sum_{i=1}^{N} A_i^{IB} = \sum_{i=1}^{N} L_i^{IB}$, even if interbank assets are distributed heterogeneously, average value of interbank assets will increase 25% for the system.

for a larger range of connectivity, the banks are more vulnerable to the losses of their interbank funding. On the other hand, for very high level of connectivities, it is still resilient against liquidity shocks. In this case, th connectivity threshold where liquidity shortage can be absorbed by the network is higher, since the shortage inherited to the system by any bank is larger and it loses its effects when a borrower borrows money from many lenders, which is higher than Figure 5.

3.3.4 Combined Shocks to Target Banks

For following two experiments, an idiosyncratic shock given to a random banks is combined with an aggregate haircut increase.



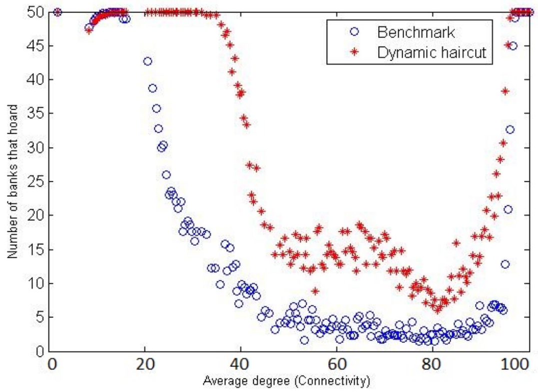
((a)) The most connected lender ((b)) The least connected lender

Figure 7: Effect of a combined shock to target banks

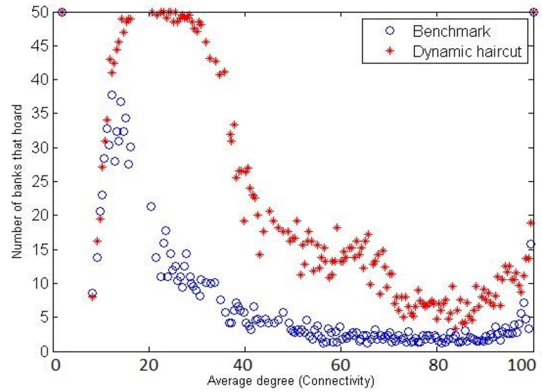
In Figure 7(a), for each realisation of geometric network, following the benchmark article, I choose the bank which has highest number of lending relationships and hit it by an idiosyncratic shock with a combined aggregate haircut shock. Since it is the bank which may potentially pass liquidity crisis to the largest number of banks in the system, the shock has severe effects. It is comparable with Figure 4(b), and I see that the absorbing effect of increasing connectivity levels are not that clear in this case for static haircuts. It first decreases then fluctuates, but amplifies the shock sharply for very high level of connectivity. Figure 7(b) illustrates the results when I hit the bank with lowest lending links. Although I observe same pattern for both cases, for Figure 7(b) in static framework, after connectivity level of 80, we do not observe such an increase in number of banks that hoard. Even in high levels of connectivity, since it is the bank with lowest number of borrowers and its borrowers has lent money from many other lenders, a shock spreading from it may be absorbed in highly connected networks. Since the level of shock is too high for dynamic case, in order to observe tipping points of the network for dynamic case too, next section illustrates the results when only idiosyncratic shock hits the system.

3.3.5 Idiosyncratic Shocks to Target Banks

Figure 8 represents the results for an idiosyncratic shock hitting the lenders with most and least number of lending links in the system.



((a)) The most connected lender



((b)) The least connected lender

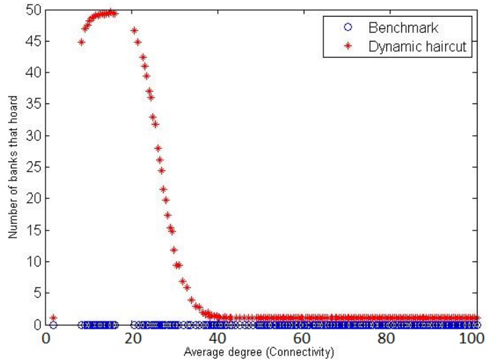
Figure 8: Effect of an idiosyncratic shock to target banks

Figure 8 is comparable with Figure 4(a) which represents the results when a bank randomly chosen and hit by an idiosyncratic shock. In both 8(a) and 8(b), the role of network on systemic crisis follows the similar pattern for both dynamic and static cases. The main difference is in the higher and lower levels of connectivity. A shock to the most connected lender create severe results when compared with a shock to the least connected one, especially for these connectivities. The gap for the dynamic and static frameworks is again persistent and static haircut model may underestimate the number of banks that have to hoard.

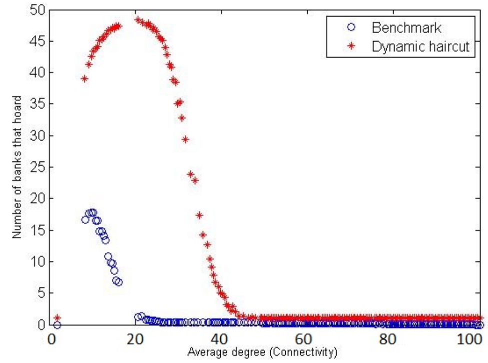
3.3.6 Policy Recommendations on Liquidity Requirements

In this section, the system is by an increase in aggregate haircut and a randomly chosen bank receives a haircut shock. In the first figure, a strict minimum liquidity requirement, 3.5%, is applied for all banks. For the second experiment, minimum requirement is decreased to 2% of balance sheet for liquid assets, but a liquidity surcharge policy is conducted in order to keep the overall liquidity level in the system constant for all cases. All banks have to keep an additional amount of 10% of their interbank assets as liquid, in the form of ${A_i}^L$. Thirdly, minimum liquidity rule is even reduced to 1%, but again with the same purpose, 16.3% of the interbank assets are required to be kept as liquid. Finally the values are 1% and 20%[23]. I extend the experiment in the benchmark article to see the effect of minimum requirement more clearly. The reason why I conduct experiments even with more reduced minimum requirements up to 0.5% is to analyse the effect of liquidity distribution over banks in the case of same levels for system-wide liquidity. Lower minimum requirements with tough surcharge policies according to the volume of individual transactions in interbank market versus higher minimum requirements with softer (or no) surcharge policies are analysed. The following four experiments show the implications of these two patterns in policy making.

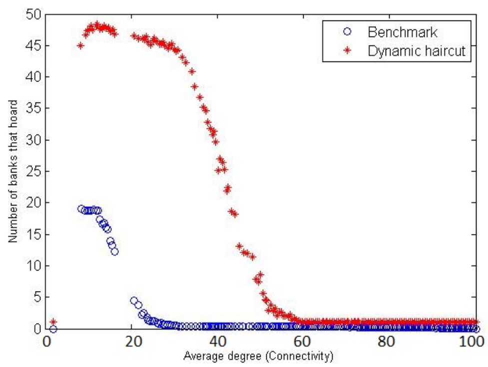
[23] A strict minimum liquidity require the 3.5% of total assets to be liquid for all banks, whereas other three experiments changes the distribution of liquidity and creates differently liquid banks. Note that all four experiments keep the overall level of liquidity same for the system. Since A_i^{IB} is 15% for the system, for both cases, 3.5% of total assets are liquid.



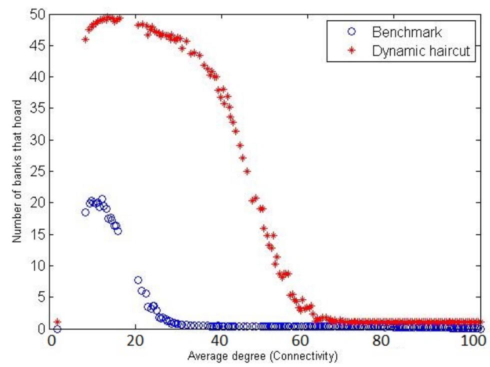
(a) Minimum requirement: 3.5%



(b) Minimum requirement: 2%



(c) Minimum requirement: 1%



(d) Minimum requirement: 0.5%

Figure 9: Policy experiments on liquidity requirements

In Figure 9, from first to fourth policy experiment, I observe, for both dynamic and static cases, the extent of crisis increases as the distribution of liquidity becomes more asymmetric among banks. Although system-w,de level of liquidity is same, as minimum requirement is decreased and a surcharge policy is applied, there are banks with low and high individual liquidity levels, and ystemic impact of liquidity shock worsens. It becomes harder to absorb the shock. That is because, when minimum requirement is low, there are some vulnerable banks which may face liquidity shortage easily and starts the cycle of stress by hoarding. Their hoarding behavior first makes other banks lose their interbank funds, and secondly for dynamic case, gives rise the cycle of increases in haircuts. I also note that even the lower minimum liquidity requirement makes system more vulnerable for both cases, the effect of minimum requirement is more clear for dynamic case, since the vulnerable banks may easily give rise to the cycle of increasing haircuts as a second channel of crisis. The lowest minimum level, despite the fact that total liquid assets are same in the system on average, gives rise to worse results. I conclude that a tough and uniform level of liquidity requirement may be more useful when compared with low minimum liquidity requirement with aggressive surcharge policy. In addition, when compared with Figure 4(b), if overall level of liquidity is higher in the system, even if it is distributed asymmetrically among banks, system is more resilient. A tough macroprudential regulation improves the strength of the financial network.

4 Conclusion

In recent years, systemic risk, meaning contagious threat on liquidity shortages for whole financial system triggered from lenders to borrowers has drawn significant attention from the literature. Introducing time varying and procyclical trend of haircuts in crisis periods, I try to construct a more realistic framework of liquidity crisis. To the best of my knowledge, this study is the first attempt to endogenize haircuts in a balance sheet based network model of liquidity crisis. It gives a room for more accurate predictions of the extent of crisis and to see the effect of dynamic haircuts by comparing with the static case. I repeat all the experiments of benchmark case in also dynamic contexts. I also extend the experiments of benchmark article. Firstly, target shock is also given the least connected lender, as well as the most connected one, in order to see the effect of the network position of the shocked bank more clearly. As a measure, I count number of banks that have to hoard, instead of count "systemic liquidity crisis" events. This measure is more complete and allows me to see the gap between dynamic and static cases. I broaden the policy experiments on liquidity requirements in order to observe the effect of tough minimum requirement and surcharge policies on liquidity crisis more clearly. By considering Acharya (2009), I conduct an experiment in which several banks are hit by the shock at the same time. This is also an attempt to get more realistic results. Since evidence suggest that the assumption of constant haircuts during the crisis is unrealistic, a model using static haircuts may underestimate the impacts of all types of haircut shocks. Through the experiments, I observe that the gap between dynamic and constant haircut cases are persistent different network connectivities and topologies, as well as for different balance sheet and network positions of banks. My extension on haircuts is an attempt to model the banking panic endogenously and the results mimic the reduction of the volume of interbank market and decreasing interbank lending relationships for the crisis. Moreover, the experiment by multiple shocks for 10% of banks may help to predict the effect of shocks that hit potentially correlated assets of banks. For both dynamic and constant haircut cases, a multiple shock affects the system severely. I observe, less banks are affected for very high level of connectivities for static case, since the systemic impacts of shock is too large to absorb, network topology and connectivity do not have significant effects for dynamic case. In order to see the effect of connectedness of the lender that is hit by the shock, other than randomly chosen banks, I give a combined (aggregate plus idiosyncratic) and idiosyncratic shocks to the most and least connected lenders in the system. If an idiosyncratic shock hits these lenders, for static case, the role of network in absorbing or amplifying the systemic risk changes significantly by the connectivity. On the other hand, when haircuts are procyclical, no turning point in the role of connectivity is observed, system collapses for most connectivity levels, since the consequences of shock is too high for dynamic case to absorb. Secondly, an idiosyncratic shock is given to same banks in order to see the effect of connectivity for the dynamic case, too. Since the amount of shock is less, it is possible to track the tipping points for dynamic haircut case also. If the most connected lender receives the shock, the role of network on crisis changes significantly, with connectivity, for both dynamic and static cases. The trend of systemic impact with connectivity level is similar for both versions of haircuts, but there is again a persistent gap in banks affected. If the least connected lender faces a bank specific haircut increase, especially for low and high levels of connectivity, its effect to the system is significantly low, when compared with the most connected lender case. The aim for policy experiments is to measure the effect of bank and system-wide liquidity policies on the systemic liquidity crisis. Keeping the total amount of liquid assets same for banking system, a tough policy with high liquidity requirement for all banks makes system more resilient. The microprudential policy which decreases the minimum required level of liquidity, and compensates it by applying a tough surcharge related to interbank assets of banks, may impair the resilience of the system. In addition, a macroprudential policy of high level system-wide liquidity, no matter what is the microprudential regulation, makes system more resilient, when compared with the low level of overall liquidity. This study, as a attempt for the combination of time varying haircuts into a liquidity crisis framework, can be taken as a benchmark. The results may also produce policy recommendations for BASEL III.

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