INFLUENCE OF NETWORKS ON SYSTEMIC RISK WITHIN BANKING SYSTEM OF TURKEY

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**INFLUENCE OF NETWORKS ON SYSTEMIC RISK
WITHIN BANKING SYSTEM OF TURKEY**

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ABSTRACT

INFLUENCE OF NETWORKS ON SYSTEMIC RISK
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Within the Turkish banking system, systemic risk, which is defined as the propagation of a financial collapse occurred in one or more institutions to other institutions as a consequence of interconnectedness, has been examined with network analysis via the capital and liquidity channel of interbank system over the period from January 2009 to October 2014. Financial shocks of individual and multiple bank failures are simulated to measure the fragility and effectiveness of banks and peer groups. Simulation results of capital adequacy and liquidity contagion models, and network structure of the debits and credits relations among banks demonstrate the roles of banks and peer groups in the banking system. Since the effects of the global crisis in 2008 had become visible in Turkey in the early of 2009, depending on the increase in the amount of money flow among domestic banks after crisis, the number of bank failures due to the given shocks shows an increasing trend in the time span between January 2010 and October 2010. Failures of banks with higher out-degree centrality which are state-owned banks and biggest privately-owned banks lead to more bank failures and the most fragile banks belong to the peer groups with small size of share in the sector, such as fourth group of privately-owned banks and second group of development and foreign bank branches.

Keywords: Network analysis, Systemic risk, Contagion effect, Bank failure, Banking regulation

ÖZ

TÜRK BANKACILIK SİTEMİ AĞ YAPILARININ SİSTEMİK RİSKE ETKİLERİ

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Türk bankacılık sistemideki, bir ya da birden fazla kuruluşta ortaya çıkan bir finansal çöküşün bağıntılılık sebebiyle diğer kurumlara geçmesi olarak tanımlanan sistemik risk, bankalar arası sisteminin Ocak 2009 ile Ekim 2014 dönemleri arasındaki sermaye yeterliliği ve likidite kanalı üzerinden ağ analizi yöntemi ile incelenmiştir.Bankaların ve emsal gruplarının kırılganlığını ve etkililiğini ölçmek için tek bir bankanın ya da birden fazla bankanın iflas ettiği finansal şoklar simule edilmiştir. Sermaye yeterliliği ve likidite yayılma modellerinin simulasyon sonuçları ve bankalar arasındaki borç alacak ilişkisinin oluşturduğu ağ yapıları,bankaların ve emsal gruplarının bankacılık sistemi içerisindeki rollerini göstermekedir. 2008'deki global krizin etkileri Türkiye'de 2009 yılının başlarında görülmeye başlandığı için, kriz sonrasındaki yerli bankalar arasındaki para akışının artışına bağlı olarak, Ocak 2010 ve Ekim 2014 dönemleri arasında verilen şoklar sonrasında batan bankaların sayısı artış eğilimi göstermektedir. Dış derece skoru yüksek olan bankaların, kamu bankalarının ve özel bankaların en büyüklerinin, çöküşü bir çok bankanın batmasına neden olmaktadır ve kırılganlığı en yüksek olan bankalar özel bankaların dördüncü emsal grubu ve kalkınma ve yatırım bankalarının ikinci grubu gibi sektördeki payı küçük olan emsal gruplarına aittirler.

Anahtar Kelimeler: Ağ analizi, Sistemik risk, Yayılma etkisi, Banka iflası, Bankacılık düzenlemeleri

This thesis is dedicated:

To the memories of my brother Özgür Özdemir,

to the most precious person in my life, my husband Hüseyin İğde,

and

to my beloved parents

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LIST OF ABBREVIATIONS

BRSA: Banking Regulation and Supervision Agency

CAR: Capital Adequacy Ratio

ECB: European Central Bank

ESRC: European Systemic Risk Council

EU: European Union

LIQ7: Monthly Liquidity Ratio

LIQ31: Monthly Liquidity Ratio

TL: Turkish Lira

CHAPTER 1

INTRODUCTION

In this first chapter, the background, purpose and significance of the study, and the definition of the terms stated in the thesis are presented respectively.

1.1. Background of the Study

Global financial crisis that arose in the middle of 2008 and deepened by influencing world economies has changed the insight into the scope of money policies. The crisis demonstrated that classical approaches for financial stability of banks are insufficient to reduce the risks of crises. The reason is that micro-prudential approaches do not include systemic risk. (Allen & Carletti , 2013)

Contagion is one of the sources of systemic risk and it is the propagation of an individual bank failure to other banks and consequently leading to systemic risk. Financial authorities now have to detect the contagion effect level of a financial shock to the overall system and need macro-prudential policies to observe contagion risk.

In order to learn from the global crisis in 2008 and to prevent the proceeding of a crisis and coming out of new crises, in the report known as “Larosiere report” and presented to European Commission on the 25 February 2009, the necessity of macro-prudential policies are announced to the EU and international financial institutions. It is stated that regulation is required for financial intuitions which have systemic effects. Under the scope of systemic risk the suggestions are to establish the European Systemic Risk Council (ESRC) under the presidency of European Central Bank (ECB), to assess macro-economic conditions and developments in all financial institutions, and to supply data flow between ESRC and financial supervision authorities which get into action at the macro level. Additionally, an active early warning system is projected to be set up by ESRC and Economic and

Financial Council. (de Larosière, 2009)

In literature, there exist many different studies about the measurement and assessment of systemic risk by using different methods and approaches. Analysis of systemic risk over the network theory provides a new approach to elaborate the contagion effect in recent years. The linkages in the financial system indicates stability of the system against contagion and main channels of contagion.

Although the datasets of interbank markets do not exist for each country, monthly reports of banks about their relations of debits and credits with other banks and financial institutions to the Banking Regulation and Supervision Agency (BRSA) enable the financial authorities to monitor the aspect of systemic risk, which has impact on the whole financial system.

Relations of debits and credits among banks are an example of the complex network structure, similar to internet or social networks. Analyzing this network structure using the network theory, which is studied heavily in social and positive sciences, enables obtaining new information about the banks, their positions in the network, as well as the whole banking system.

1.2. Purpose of the Study

The main purpose of the study is to determine the potential systemic risk in the form of contagion in the Turkish banking system by using the datasets of debit and credit relations between individual banks. After revealing the network structure of the debit and credit relations using descriptive network metrics, positions of individual banks are elaborated. The spread of bank failures is related to the positions of the banks in the network and while investigating systemic risk, centralities indicate the potential effects of possible bank failures.

Based on the purposes mentioned above, the following aspects of the contagion are considered throughout the study:

1) Effectiveness: How failure of a bank affects other banks in the system.
2) Fragility: How a bank is affected from failures of other banks.

1.3. Significance of the Study

Systemic collapses leading to financial crises, can be exploded by collapses of markets other than the interbank market, such as the property market, as well as the failures of banks in the system. Systemic risk which is triggered by failures of banks and spread to the whole banking system is accepted as a reason to support the recovery of failed institutions by the financial authorities. Since the information on interconnectedness of banks can be obtained by network analysis, network structures can give us the opportunity to examine the aforementioned reason in detail.

Determination of the network structure of the Turkish Banking system has two main importance on the stability of the financial sector. Firstly, investigation of the characteristics of the network structure helps to predict the reactions of the financial institutions to the precautions of money policies. For example, gaining importance of interbank relations in process of the banking system and having relations of banks in order to maintain stability against liquidity shocks can be monitored from the network structure. On the other hand, the distribution of linkages between banks can affect the financial stability and contagion effect results from aftershocks. Under this scope, network analysis presents a significant tool to the authorities which are responsible from the continuity of the finance sector. In the case of not being able to perform liabilities of a bank, shocks that can propagate over the banks which are creditors from that bank can be defeated by monitoring the network structure of the banking system periodically.

The contagion effect model in this study is the first study conducted on real dataset of interbank debits and credits relation in banking system of Turkey. Also it is different from other studies in literature since it is realistic, not probabilistic and considering multiple bank failures as well as individual bank failures.

1.4. Definition of Terms

Capital adequacy ratio (CAR): It is the ratio of keeping enough equity to fulfill the credit risk, market risk and operational risk faced by banks.

Liquidity ratio: Liquidity ratio is the ability of financing demands of funds, credit needs of market and potential deposit loss, computed by dividing total assets to total liabilities.

Equity: (Capital) Equity is the residual value from the assets, after all liabilities are paid.

Risk Weighted Assets: Risk weighted assets is the sum of weighted amounts of market risk, credit risk, and operational risk.

Market Risk: Market risk is the possibility of loss exposed due to the exchange risk, specific risk and swap risk and counter party credit risk.

Credit Risk: Credit risk is the possibility of being defaulted of credits by failing to collect required payment.

Operational Risk: Operational risk is the possible risk that stems from insufficient or unsuccessful internal processes, individuals, systems or external issues.

Total Assets: All assets of an entity.

Total Liabilities: Summation of short-term and long-term liabilities of entities.

Financial Contagion: Financial contagion is a scenario in which financial shocks spread to other financial sectors.

Systemic Risk: Systemic risk is the risk of the propagation of a financial collapse occurred in one or more institutions to other institutions as a consequence of interconnectedness.

Idiosyncratic shock: The shock is specific to an individual.

Default: Default is the failure of meeting the payments of a loan which has reached maturity.

1.5. Structure of the thesis

The structure of the thesis is the following. First, approaches, regulations related to banking stability, models and model results of relevant theoretical and empirical studies dealing with the topic of systemic risk and contagion effect are discussed. It is continued with detailed explanation of the data used for the study and its collection, which is followed by an analysis of the network structure of the debits and credits relations among banks in the banking system of Turkey. The network analysis metrics of banks, groups of banks and the banking sector in general are presented with the aim of summarizing networks within time span with numerical expression and detecting important banks for the contagion. Then, capital adequacy and liquidity contagion models used to capture the contagion effect assuming idiosyncratic shocks and multiple bank failures of banks and peer groups in Turkey are described. The last part of the study summarizes the results of contagion models under two aspects; effectiveness and fragility and gives the consistency of the models.

CHAPTER 2

LITERATURE REVIEW

In this chapter, the literature review is presented. First, network theory and diffusion approach is given. Second, regulations on capital adequacy and liquidity are briefly explained. Then, different methods used to measure the propagation of systemic risk in the literature are given in the subsections.

2.1 Network Theory and Diffusion

Diffusion is described as "the process by which an innovation is communicated through certain channels over time among the members of a social system" by Rogers (2003). He also defined diffusion as a social change in the structure of the system in which new ideas or diseases are diffused, which result in apparent consequences. Rogers explained the innovation diffusion with four elements; innovation itself, communication channels, time and social system. Innovation is the perception of an idea or object as new. Communication channel is the relations among the individuals through which they communicate. For some individuals, the newness of the item is not important; if there is a channel to that individual, s/he can adopt earlier than others. The time passed between meeting the innovation and its adoption is used to compare the earliness/lateness of the adoption. Lastly, the social system of which members, individuals or organizations, are interrelated affects the diffusion. (Rogers, 2003)

Social contagion is the spread of contagion over linkages in the social system. Initially, the innovation is perceived by few individuals; then, large number of individuals adopt. Ultimately, diffusion slows than, i.e., acceleration decreases and then stops. The adoption rate, which is the rate of new adopters and an indicator of the speed of the process, can be computed from the diffusion curve. Some individuals perceive an innovation after passing a threshold. The threshold of an individual is calculated by the proportion of its neighbors who have adopted before the time of their adoption. Critical mass indicates the number of actors needed to propagate an innovation and can be obtained again from the diffusion curve by taking the first order inflection point. According to Rogers (2003) the individual can be allocated to categories in terms of their adoption times. Categories with their asymptotical percentiles can be listed as Innovators, Early adopters (First 16%), Early majority (Next 34%), Late majority (Next 34%) and Laggards (Last 16%). (Rogers, 2003)

Similar to the Rogers, Scott (1991) stated that social network theory elaborates relations of actors in the network and network structure is more important than the individuals in the network.

Diffusion of innovations has been applied to various fields, which are communications, marketing, medical sociology, development studies, health, organizational studies, knoledge management, and similar different studies. Especially in health, diffusion has gained great importance on the use of medicines, medical techniques, and health communications. (Greenhalgh et al., 2005)

In this study, the actors are the banks in Turkish banking system. Banks have debits and credits relations with other banks. Debits and credits relations are the communication channel according to the diffusion explanation of Rogers (2003) and these relations construct a social system. However, in this study, instead of the diffusion of an innovation, contagion of bankruptcies are examined. Therefore, the innovators in the Rogers (2003) terminology become failed banks. To be affected by the failures of a neighbor bank, the banks have thresholds. However, in this case, the thresholds are boundaries of capital adequacy and liquidity ratios which are recalculated due to lack of the payment collection. Since credits are important components of equity and assets of creditors, not receiving cash inflow affects their conditions in terms of capital and liquidity.

In this study, it is aimed to detect the fragile and effective banks. Fragile banks are in the category of early adopters, whereas resistant banks are in the category of laggards. The time aspect in the contagion effect is the distances of banks to other banks, rather than the actual time period.

2.2 Regulations on Capital Adequacy and Liquidity

Capital Adequacy Ratio

Global crises management mandates the supervision and inspection of the banks which are the main components of the global economy. The necessity of establishing the Basel Committee to facilitate the collaboration of the international financial institutions emerged after the oil crisis in 1974. The aim was to increase the quality of supervision in the banking sector and to increase the resilience of banks to the economic fluctuations and crises. Under the frame of these objections, Basel Committee studied the required precautions against financial shocks, and ultimately in 1988, in order to create a standard for the calculation of capital adequacy, Basel I, "Capital Adequacy Consensus" was published. (BRSA, 2008).

Basel I obligates that the capital adequacy ratio, which is the first indicator in supervision should at least be 8%. In 1996, the scope of the capital adequacy was enlarged by taking into consideration the market risk. Turkey has been applying the criteria of Basel I incrementally since 1989. As a result of the global competition environment, the financial market expanded and the banking transactions became more complicated, which led to the Basel II criteria. In Basel II, the boundary of the capital adequacy ratio was not changed, however the operational risk was included in the computation of the risks. Turkey started applying the Basel II criteria in 2006.

With global crisis in 2008, the Basel II criteria has become insufficient considering the increased number of bankruptcies in the world. Therefore Basel III criteria was published. Basel III criteria did not change the calculation of the capital requirement, however it included an additional regulation for missing inadequacies detected after the financial crisis of 2008. (BRSA, 2010)

In Turkey, the legal ratio for capital adequacy is 8%, but BRSA specified the target ratio as 12% in practice. This clarification in 2006 has become the most effective proactive precaution for the Turkish banks to avoid difficulties in capital during the period of the global crisis in 2008. In the recent global crisis, Turkey has been the only country among the OECD countries whose banking sector did not need the capital support of the public. (Aslan Külahi, Tiryaki, & Yılmaz, 2014)

In Turkey, if capital adequacy ratio of a bank is under the legal boundaries, the bank is mandated to provide legal boundaries within a period given by the Banking Regulation and Supervision Board. Additionally, after the auditions of BRSA, if the required specification for banking activities is lost, the bank should prove that the level of ratio incompliance is not important. Alternatively, the bank should present a plan for meeting the necessary condition within a given period by BRSA. Otherwise, the given official authorization is cancelled[1].

Liquidity Ratio

The first criticism made on the Base I criteria was not considering risks other than the credit risk and the market risk in the computation of the capital adequacy ratio. Risks which were not covered by the Basel I criteria, such as interest rate risk, operational risk and liquidity risk have gained importance in the changing period of the banking system. This case demonstrated that the capital ratio is not always a good indicator of the financial situation of the banks (TBB, 2000).

The most essential factor for publishing Basel III was the general conception that the existing standards are insufficient for liquidity shortages encountered in the recent global crisis. Consequently, the main innovations in the Basel III criteria are the compulsory liquidity ratios, boundaries of leverage ratios and new capital regulations (BRSA, 2010).

The first ratio related to strengthening the liquidity in Basel III, is liquidity coverage ratio. The aim of this ratio is providing the liquidity requirements in the time period of 30 days under the liquidity stress scenario specified by financial authorities. Therefore, the liquidity leverage ratio is computed by dividing the total assets of banks by the expected net cash outflow in 30 days. This ratio should be 100%.

In Turkey, in the compulsory liquidity ratio calculations, the liquidity requirements were already being performed in the basis total and foreign currency. These requirements are similar to the liquidity leverage ratio. It is why this innovation in

[1] Bankaların sermaye yeterliliğinin ölçülmesine ve değerlendirilmesine ilişkin yönetmelik. (2014). T. C. Resmi Gazete, 29111, 6/9/2014

Basel III was not a new application in the Turkish banking system. (BRSA, 2010)

In Turkey, the liquidity adequacy ratios are computed for two maturity periods, weekly (first maturity period) and monthly (second maturity period). The aim of liquidity ratios is to make banks to be able to provide a sufficient liquidity level to meet their liabilities. The legal thresholds for both liquidity ratios are 100%. In liquidity of banks for the second maturity period, incompliance should not occur twice successively in a year. Similarly, in liquidity of banks for the first maturity period, incompliance should not occur more than six times successively in a year and incompliance should be recovered in the following two weeks. If one of the liquidity adequacy ratios of a bank is under the legal boundaries, the bank should report the reasons with a time sheet to BRSA. In this case, the Banking Regulation and Supervision Board is authorized for taking necessary precautions according to the banking law.[2]

These legal boundaries for the capital adequacy and liquidity are used in the contagion models while making assumptions for failing banks.

2.3. Stress Tests for stability of banks

Stress test can be described as the process of detecting the vulnerable points of the banking system and predicting the sensitivity to various shocks. It is used for the assessment of the fragility of the banks under the circumstances of possible issues and changes in large scales in the macroeconomic environment.

Stress tests have importance in the view of determining the effects of possible negative scenarios in the financial sector on the banking system, testing the resilience of banks in case of distress and recognizing the potential issues that will be encountered. Under the scope, stress tests enable:

- To measure the fragility of banks against the risks that stem from the statement of asset-liability under the frame of banking activities.
- To clarify the risks to which banks have more sensitivity in their financial

[2] Bankaların likidite yeterliliğinin ölçülmesine ve değerlendirilmesine ilişkin yönetmelik. (2014). T. C. Resmi Gazete, 28948, 21/3/2014

structure.

- To detect the most fragile banks in comparison to other banks and the weak banks in the financial structure.
- To make clear the risk by computing possible the losses suffered from the financial crisis.
- To warn and inform the financial authorities and banks to take necessary precautions. [3]

In the stress tests studied periodically by the Banking Regulation and Supervision Agency in Turkey, the affectability of the banking system from two macro scenarios, which are the base-case scenario and the negative scenario, is tried to be predicted. The scenarios include real gross nation product, inflation, and exchange rate of dollar, short term interest rate and rate of unemployment. According to assumed scenarios, satellite models are constructed to provide the main inputs of the stress tests. These models are used to predict the rates of credit growth, non-performing loan and mortgage loan and growth rate. (Önder, Damar, & Hekimoğlu, 2014)

In the stress test study, credit risk, exchange risk, interest rate risk, revenue risk and contagion effect are taken into consideration. The impacts of the aforementioned risks on the banking system and the effect of given shocks under the scope of negative scenario on total gain/loss are computed with stress tests. Final outcomes of the stress test reach to the capital adequacy ratio. Since the legal bounds for capital adequacy ratio applied in Turkey are 8% and 12%, the banks with capital adequacy ratio under these bounds are thought to need more capital when they meet negative conditions in the financial sector. (Önder, Damar, & Hekimoğlu, 2014)

Contagion effect in the stress test is described as the effect of computed expected loss over the net amount of credits of banks by netting the debits and credits of banks between each other on capital adequacy ratio. Banks' lack of ability to collect their net debts is associated with the probability of default related to the capital adequacy ratio of debtor bank. The information of debits and credits among banks is obtained presumptively by applying "maximum entropy method" which is used for predicting

[3] Bankaların Sermaye Ve Likidite Planlamasında Kullanacakları Stres Testlerine İlişkin Rehber (2014). BDDK, 5964, 24/7/2014

the relations of debits and credits between banks. Computation of the change in capital adequacy is applied iteratively in order to get the contagion effect of insolvency in a bank on the whole banking system and contagion risk is calculated for each bank by summing the products of interbank exposure and probability of default. (Önder, Damar, & Hekimoğlu, 2014)

In this thesis, real relations of debits and credits among the banks are used to compute the contagion effect using models, not only for the capital adequacy ratio, but also for the liquidity of banks. Also, the association of lack of collecting net debts with capital adequacy is different from the calculation of new capital adequacy ratio in the contagion model in this study. Stress test computes the probability of default over the presumptively calculated relations of debits and credits, and applies this score to the capital adequacy ratio, whereas in the contagion model used in this study, the new capital adequacy ratios are obtained by omitting the net amount of debt which is assumed as not possible to be collected from the capital of banks directly and subtracting its risk weight from the risk weighted assets.

2.4. Existing Systemic Risk Models

The German sociologist Georg Simmel described money as “money is the spider that spins society’s web” in his book. At that time, Simmel stated the network aspect of money. He foresaw how a financial innovation impacts the financial system with its all entities such as institutions, society etc. (Simmel, 1907)

Global financial crisis that arose in the middle of 2008 has strikingly shown the power of interconnectedness of financial institutions. The world economy was faced with one of the biggest crises after Lehman Brothers’ default. The financial system was hit by this default and consequently for the biggest mortgage institutions, Fannie Mae and Freddie Mac, financial authorities in USA had taken the action. After that 25 banks including Merrill Lynch which is a development bank and has a branch in Turkey was brought under the control of the Department of Treasury. Then, financial crisis turned to a global crisis and automotive and retail industries received a heavy blow. The biggest companies in the automotive sector, General Motors, Chrysler and Ford, came to the point of bankruptcy. The White House prepared multi-billion dollar programs for relieving the financial sector. Nevertheless, the crisis continued to affect other countries in Europe and the Far East. The impacts of the stress period started with bankruptcy of Lehman Brothers still continue. (Coşkun, 2009). Therefore, to provide a stable financial system authorities now try not only to make policies but also to search for new tools to monitor the systemic risk. Financial network analysis recently assists on detection of shock transmissions mechanisms, i.e. channels for propagation of shocks, by modelling the links between financial institutions in the finance sector (Tumpel-Gugerell, 2010).

A financial network is described as collection of entities in financial sector which are connected by links representing a transaction or an ability to mediate a transaction (Nagurney & Ke, 2001). The main study area of the financial network analysis is for scientists and policy makers to manage and mitigate the financial crises especially caused by the systemic risk. (Minoiu & Sharma, 28 May 2014).

Systemic risk refers to the possibility of the propagation of triggering events such as financial collapse occurred in one or more institutions or market disruption, to other institutions in the financial systems as a consequence of interconnectedness as has been measured by different methods and approaches.

The network theory has been applied for analyzing systemic risk initially in Europe. Sheldon and Maurer (1998) applied network analysis on the dataset of interbank market in the Swiss banking system. Network approach to systemic risk has been studied in many countries; Wells (2002) in the United Kingdom; Furfine (2003) in the United States; Upper and Works (2004), Memmel and Stein (2008) in Germany; Elsinger et al (2006) in Austria; Degryse and Nguyen (2007) in Belgium; and Hausenblas, Kubicová and Lešanovská (2012) in Czech Republic.

Furfine (2003) described two types of systemic risk. The first one is the interception of financial shocks by financial institutions working properly at the time. The second type of systemic risk is the spread of collapses in one or more financial institutions to other institutions due to the financial connections, which is called the contagion effect. To measure the second type of the systemic risk, bilateral debit relations should be obtained. Furfine (2003) attempted a simulation study on bilateral relations of bank in the FedWire and found that the possible of the continuity of bank failures in further lags is very small. Although the study has received criticism that only the relations of banks in the FedWire were included in the study, it was conducted on real datasets.

Upper and Worms (2002) examined the contagion effect in the Germany interbank market and detected that using a safety net, which is an application of giving a guaranty for bailout of banks, reduces the effect of contagion, but not removes it. It is stated that the banking authorities can stop the initial shocks that could trigger a contagion by warning the banks about the risk. In the case of bankruptcy, before the loss in the banking system due to the contagion effect reaches to larger scales, instructions for the liquidation should be specified.

In Turkey, Saltoğlu and Yenilmez (2010) stated that distress in the financial system can be predetermined by network analysis. They used in their analysis the dataset of repo- reverse repo markets in the period of crisis. PageRank algorithm of Google was used to capture systematically the important financial institutions.

In literature, studies related to the contagion effect mostly focus on credit risk, market risk and liquidity risk or a combination of these risks. Recently, the network structure of financial institutions has been identified as an important factor of systemic risk. (Jo, 2012).

Allen and Gale (2000) assessed that the contagion effect arises from liquidity shocks in interbank markets by associating contagion effect with completeness and interconnectedness of the network structure of the market. Relativity differentiations of interbank markets affect the size of the contagion spread. It was claimed that a complete network structure of the interbank market would be resistant to financial shocks. Banks with comparative advantages of obtaining liquidity, tend towards collecting their debits from the interbank market rather than from their long term assets. As a result, contagion spreads over the whole system. In a complete market structure, contagion effect is reduced by absorption of the risk by all banks in the market, whereas in incomplete market structure, the effects of financial shocks can increase exponentially. On the other hand, in the disconnected market structure in which banks operate their activities in different groups, contagion can affect only one group and it cannot spill over the whole system. Under this scope, the contagion was elaborated over the liquidity channel by dividing the network into regions.

Lenzu and Tedeschi (2012) took a similar approach of Allen and Gale (2000) to the contagion in order to find out how systemic risk arises from interbank relations and which network structure is more resistant to systemic failures of banks. A network with 150 banks over a time span with 1000 periods was created by Monte Carlo simulations. Two scenarios were considered while giving liquidity idiosyncratic shocks. Illiquid banks without connections or connected to illiquid banks and banks connected to illiquid banks with potential contagion risk can be directly failed. Findings reveal that heterogeneity among banks makes the banking system more vulnerable to random attacks and a scale free financial network can be more fragile than a random financial network. They measured attractiveness of agents as a function of calculated threshold probability of default. On the contrary, in this thesis in place of simulating networks, the real datasets of banks are used to compose networks and measure the resilience of banks in the banking system of Turkey. Also, contagion effect is not calculated by probabilistic measurements; instead this study takes the real risks coming from interconnectedness of banks overs the debits and credits channel into consideration.

To determine the resilience of the Czech banking system to interbank contagion, an analysis was conducted on the dataset of interbank exposures between domestic banks, which was obtained from interbank loan forms. Two network analysis techniques were applied. The first one is exploration of the network structure with centrality metrics. Second technique is simulation of shocks given over credit channel, liquidity channel and asset price channel. In the benchmark model, only credit channel was taken into consideration and the new capital adequacy ratio was calculated, whereas in the extended model both liquidity and capital adequacy condition of banks were examined iteratively. It was found that eigenvector centrality mostly explains the contagion losses and after the global crisis the potential contagion has decreased. Additionally, since the liquidity of government bonds are significant, the simulations of shocks were repeated by assuming that the government bonds are no longer liquid assets. In that case, contagion losses increased in the Czech banking system. (Hausenblas, Kubicová, & Lešanovská, 2012)

In the study of Czech banking system, the dataset of interbank exposures includes only interbank loans with largest 15 loans and liabilities, whereas the dataset in this thesis spans all types of relations among financial institutions such as loans, deposits, syndication and securitization loans, receivables from reverse repo, funds from repo transactions, subordinated debts, etc.

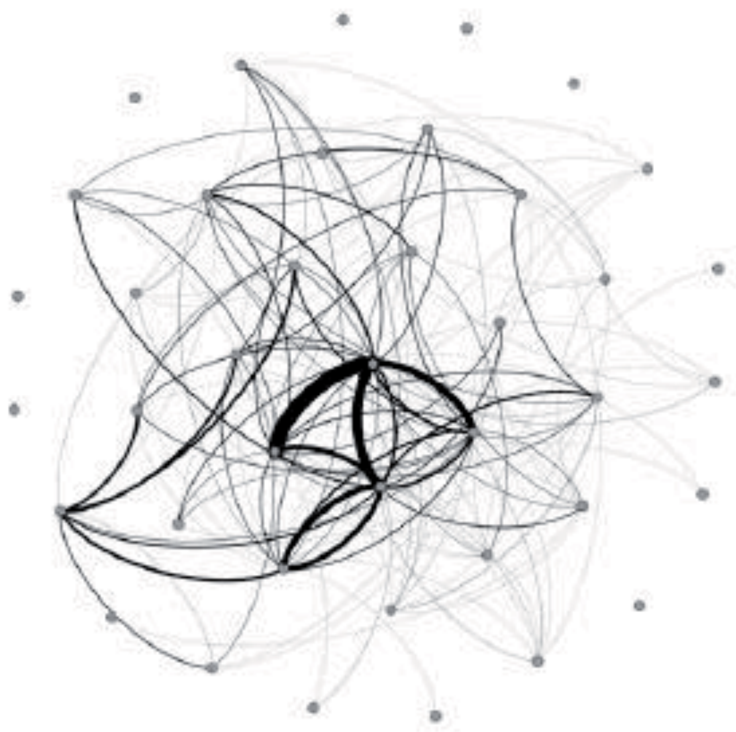


Figure 2.1. Network from Czech banking system. The thickness of the link represents the absolute value of the interbank exposure. Source: Hausenblas, Kubicová, & Lešanovská, 2012.

Figure 2.1 demonstrates a network from Czech banking system as of Q2 2012 where links represent the absolute value of the interbank exposure. In the study of Czech banking system, the direction of interbank exposures was not considered while exploring network structure of Czech banking network and interbank contagion, as it can be seen from the Figure 2.1. Contrarily, the direction of relations of debits and credits among banks is an essential point in this thesis, since directions demonstrate the money flow path on which contagion effect is monitored. In their benchmark model, they recalculated capital adequacy ratio by deducting the loss from the capital and if the new capital adequacy ratio is below the 8%, then the banks was accepted as insolvent. By adding liquidity conditions they constructed extended model. If the bank does not satisfy the liquidity condition it is considered as illiquid. Lastly they added the values of government bond to the model and recalculated the CAR for the second time. Then, they computed the contagion loss as demonstrated in Figure 2.2. They concluded that the liquidity of government bonds could be important in stress situations.

$$contagion = \frac{\sum_{i \in N} a_i - \sum_{i \in S} a_i - \sum_{i \in R} a_i}{\sum_{i \in N} a_i - \sum_{i \in S} a_i}.$$

S	as the set of banks hit by the initial shock,
R	as the set of surviving banks,
N	as all the banks in the network,
a_i	as the total assets of bank i,

Figure 2.2. Contagion loss formula in the study of Czech banking system. Source: Hausenblas, Kubicová, & Lešanovská, 2012.

CHAPTER 3

EXPLANATION AND PRELIMINARY ANALYSIS OF THE NETWORK DATA

A network is a structure consisting of a graph in which a vertex is the smallest unit and additional information on the vertices or the lines of the graph where lines are the ties between two vertices (Figure 3.1.).

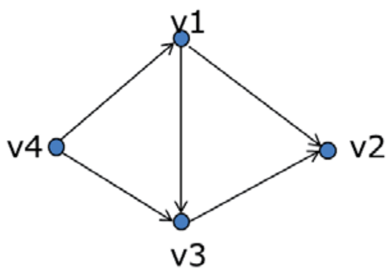


Figure 3.1. Network example

The network structure provides methods for analyzing the structure of whole network with vertices and lines and theories explaining the patterns observed in these structures. (Barnes, 1983)

In this study, the network analysis is performed with Pajek 4.01 and R version 3.0.3 is contributively used for banding matrices of results together. In Pajek, a partition tells for each vertex to which distinct class the vertex belongs, such as gender, country, city, or as in this thesis banking group, etc., and a vector tells for each vertex some numerical property (real number), such as age, weight, or as in this thesis, the capital adequacy ratio, etc.

The following subsections present the data collection and preliminary analysis of the network data. Firstly, the collection of data is explained in detail. After combining the network data, the structure of the Turkish Banking network is studied to find out the network analysis metrics of banks, groups of banks, and the banking sector in general.

3.1 Explanation of Data

Five main headings under explanation of data sub clause are interbank relation of debits and credits, capital adequacy ratio, liquidity ratios, partitions and vectors.

3.1.1 Interbank Relation of Debits and Credits

To conduct the study, monthly reports of banks to the Banking Regulation and Supervision Agency (BRSA) have been used. Banks report their relations of debits and credits with other banks and financial institutions each month in detail using forms. The reason why BRSA requires these forms from the banks is to elaborate the money flow among the financial sector. Therefore, these forms include detailed specifications about the debits and credits with classifications.

Banks should fill the following information in the forms;

- Bank Code
- Name of Institution
- Group Code of Institution:
    - Central Bank of Turkey
    - Financial Markets
    - Domestic Banks
    - Foreign Banks and Financial Institutions
    - Foreign Head Offices and Branches
    - Domestic Participation Banks
- Head Office Country Code
- Amount of Credit
- Opening Date of Credit
- Expiry Date of Credit
- Amount of Debit
- Opening Date of Debit
- Expiry Date of Debit

- Operation Codes:
    - Loan
    - Deposit
    - Loan for Financing Foreign Trade
    - Syndication Loan
    - Securitization Loan
    - Free Term Deposit
    - Fixed Term Deposit
    - Receivables from reverse repo
    - Funds from repo transactions
    - Subordinated debts
    - Demand deposit
    - Syndication loan taken over in secondary markets
    - Securitization loan taken over in secondary markets

The MS200AS form has been reported since January 2002, whereas the MS150AS form started to be reported after the Participation Banks entered the Turkish Banking Sector in 2005. Two forms are combined for 2007 and after. Therefore, in total there are 94 monthly reports on the relation of debits and credits for the period between January 2007 and October 2014, which have been included in the study of network structure.

On the other hand, capital adequacy and liquidity forms have been available in a standard format since January 2009. Therefore, the contagion analysis for the capital adequacy and liquidity are based on the data collected between January 2009 and October 2014.

Since the study has been conducted on the Turkish Banking Sector, only the Domestic Banks and Domestic Participation Banks have been used. The group codes of institutions in the forms have been used to filter out other banks and financial institutions.

The data on interbank debits and credits do not include information on the banks which were closed before 2013. Therefore, the analysis in this study is focused on the banks which have been active in the last two years to make predictions. As a result, money flow networks are comprised of 51 banks.

In the forms, the bank codes were clear, however the names of the counter parties, i.e., the Name of Institution field in the form, were not always correctly typed. As a result, the name of an institution has been typed in many different ways. For example, Ziraat Bank has 100 different names in Name of Institution field such as "T C ZIRAAT BANKASI", "ZIRAAT BANKASI", TC.ZIRAAT BANKASI AŞ., while the true name of Ziraat Bank is "T.C. ZİRAAT BANKASI A.Ş.". With a script, all different versions of the names have been transformed to a single name.

The amounts of debits and credits among the banks are aggregated by the bank code, the Name of Institution field and the period. A bank can both be the sending side of the report and the counter party in the forms, which leads to the duplicates in the data set. For example, the same amount is reported twice; as debit by one bank, and credit by the counter bank. In some cases, however, the amounts were also different. Therefore, in order to create the bidirected network for both credit and debit relations, the maximum amount of the money flow has been taken into consideration. After this preprocessing, in order to create the undirected network, the net amounts of the money flow between banks have calculated by taking the absolute value of the difference between debits and credits.

Netting of the interbank relations of debits and credits is used for capital adequacy contagion channel and for preliminary analysis of the network; on the other hand, contagion over liquidity channel is determined by the bidirected network. Netting is not necessary for simplifying the network; however, it is meaningful for detection of the contagion direction and for demonstration of the powerful side in bilateral banking relations. Netting clarifies the net amount of money flow between two banks which leads to contagion of banking failures. There may be netting agreements between banks to take into account the net exposures, however under the assumptions of the study, in case of a bank failure for capital adequacy channel, money flow that cannot be occurred and described as a loss is the medium of the contagion (Emmons, 1995). Also, netting reduces the contagion from very low levels to high levels. In this study, contagion effect level is discussed through both unidirected and bidirected networks.

3.1.2. Capital Adequacy

Capital adequacy ratio includes the following items:

1. Equity
2. Market Risk
3. Credit Risk
4. Operational Risk

The capital adequacy forms collected by the BRSA from the banks are continuously modified according to financial developments. During the periods included in this study nine different versions of these forms exist. Table 3.1 shows these forms and their validity periods,

Table 3.1 - Capital Adequacy Forms

Capital Adequacy Forms	Periods
SY410AS	March 2008 – December 2008
SY420AS	January 2009– July 2009
SY430AS	August 2009 – February 2011
SY440AS	March 2011 – May 2011
SY450AS	June 2011 – June 2012
SY500AS	July 2012 – December 2013
SY510AS	January 2013– …

Monthly capital adequacy reports have been combined with the help of script and the items have been used separately as vectors for Pajek operations.

3.1.3. Liquidity

Similar to the capital adequacy forms, liquidity forms weekly and monthly collected by the BRSA also differ from year to year. Table 3.2 shows the different versions of the liquidity forms and their validity periods.

Table 3.2 – Liquidity Forms

Liquidity Forms (Weekly-Monthly)	Periods
LY210HS – LY211HS	04.06.2008 - 01.24.2009
LY220HS – LY221HS	01.25.2009 - 02.25.2012
LY230HS – LY231HS	01.06.2012 - ...

These forms are reported weekly. Therefore, the forms which are reported on the last Friday of the months have been combined to obtain the monthly liquidity dataset. With a script, liquidity reports have been combined and their items have been used separately as vectors for Pajek operations.

3.1.4. Groups of Banks

The partitions, which have been used to elaborate the Turkish Banking Sector Network are listed below.

- Banking groups:

Table 3.3 – Banking groups

	Banking groups	Number of banks
1	State-owned banks	3
2	Privately owned banks	10
3	Foreign banks	19
4	Development and Investment Banks	13
5	Saving deposit insurance fund banks	2
6	Participation Banks (Islamic banks)	4
	Total	51

- Peer groups of banks: Beside their banking groups, banks are grouped according to their size of share in the sector.

Table 3.4 - Peer groups of banks

Peer Groups	Number of banks
EGKAMU	3
EGKYB	10
EGKYB2	3
EGOFK	4
EGOZEL1	4
EGOZEL2.1	3
EGOZEL2.2	4
EGOZEL2.3	6
EGOZEL3	4
EGTMSF	2
EGYBSUBE	6
EGYENI1	1
EGYENI2	1
Total	**51**

- Initial partition: The defaulted banks or bank groups under the assumptions are coded as 0 and the other banks are coded 1.

3.1.5. Quantifiable Values of Banks

For capital adequacy ratio

1. Equity
2. Risk Weighted Assets (Market Risk + Credit Risk + Operational Risk)
3. Capital Adequacy Ratio

For liquidity ratios

1. Total Assets
2. Total Liabilities
3. Liquidity Ratios

3.2 Structure of the Turkish Banking Network

In the literature, it is recognized that the structure of the banking network impacts the contagion of bank failures in the financial sector. Beside the network structure, balance sheet items of banks, positions of banks in the banking sector, regulations and extroversion of the banks have been identified as factors which are essential for the contagion. These factors may lead to different contagion effects in different banking sectors. (Hausenblas, Kubicová, & Lešanovská, 2012)

This study deals with two types of network structures, one directed and bidirected networks. One directed networks have been obtained after netting the relation of debits and credits. Bidirected networks are the original networks formed from the forms reported by banks to the BRSA.

The number of banks varies between 44 and 50 within the period of January 2007 to October 2014. In order to span the banks which were active on January 2013 and after, for all monthly periods 51 banks have been included in the study.

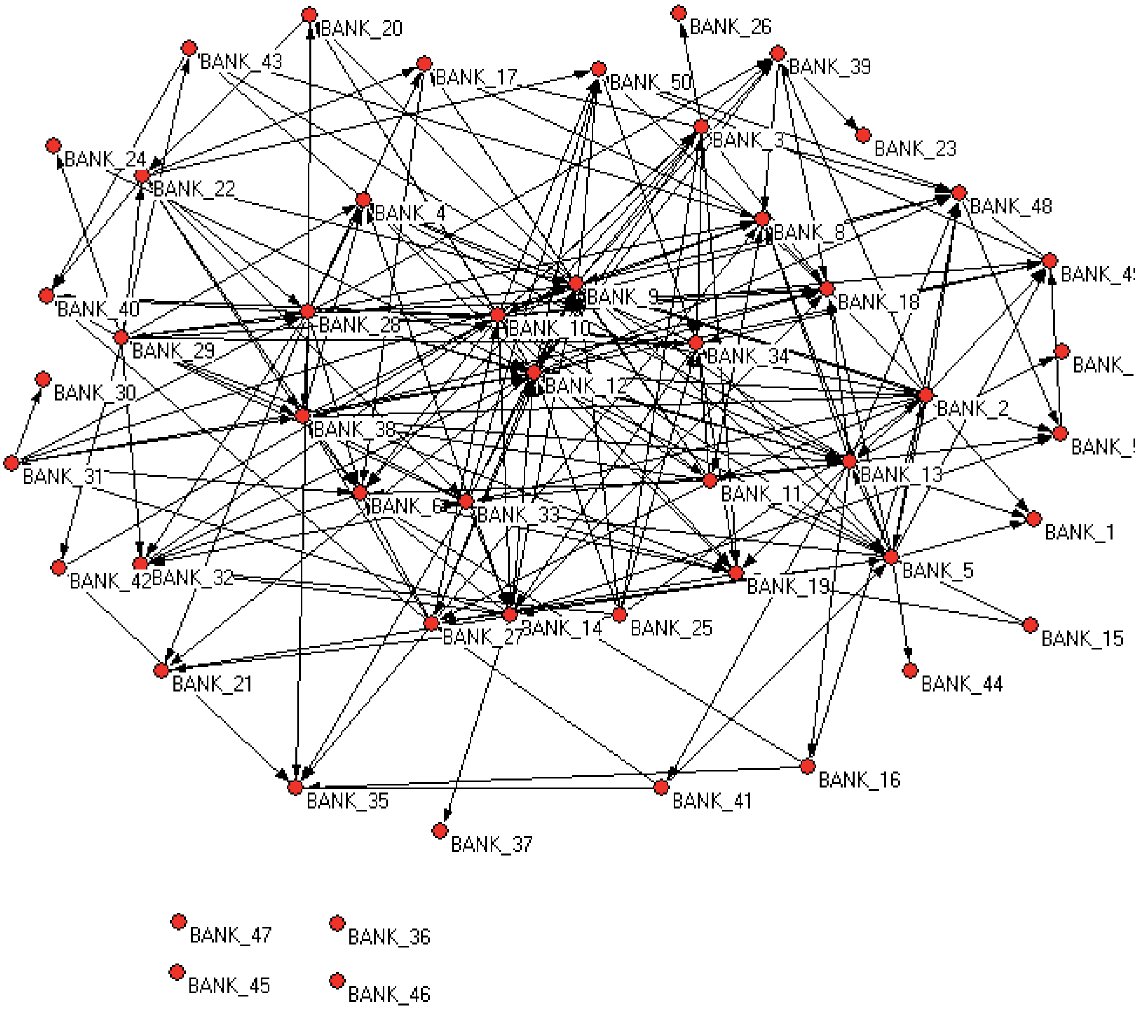


Figure 3.2. One directed network structure as of January 2007. Links represent the net amount of money flow between two banks. Isolated banks are those banks which were not active during the given period or which did not have a debit or credit relation with another bank.

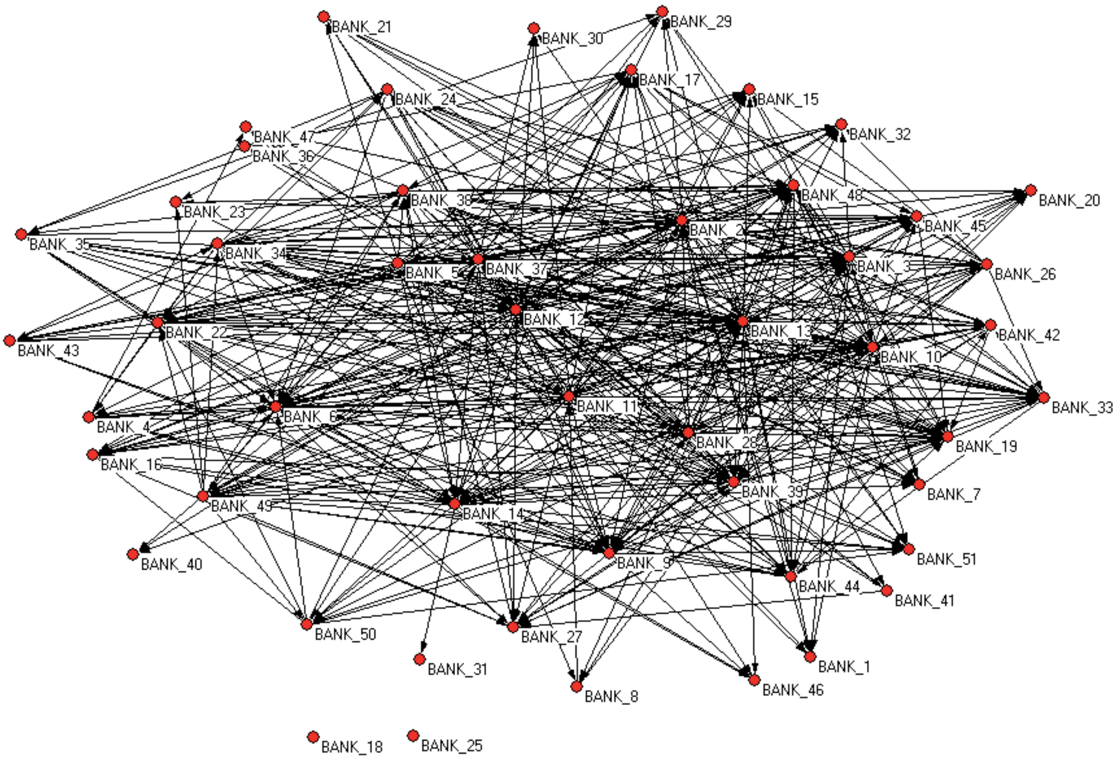


Figure 3.3. One directed network structure as of October 2014.

It can be seen from the directed networks drawn in Figure 3.2 and Figure 3.3 that the interconnectedness of the banking sector has increased over time from January 2007 to October 2014.

In this section, the overall structure of the Turkish banking network has been examined by the degree, closeness and betweenness centrality and centralization metrics. Centrality of banks refers to positions of individual banks within the network, whereas centralization characterizes network structure of the Turkish banking sector. In a highly centralized banking network, the effects of the failure of a highly central bank spreads easily and impacts the majority of the other banks.

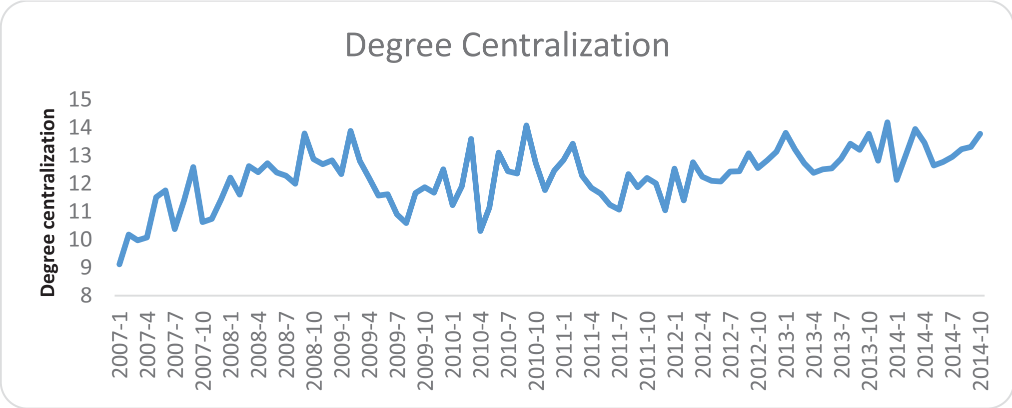
In one directed network, the number of links outgoing from the banks gives out-degree centrality, whereas the number of links incoming to the banks gives in-degree centrality. Degree centrality is the number of neighbors of banks in the undirected network. On the other hand, degree centralization of the networks in periods is the variation in the degrees of vertices divided by the maximum degree variation which is possible in a network of the same size, where variation is the sum of the absolute differences between the centrality scores of the vertices and the maximum centrality score among them (Freeman, 1979).

Table 3.5 shows the descriptive statistics of degree centralizations for the 94 monthly periods within the time span of January 2007 and October 2014.

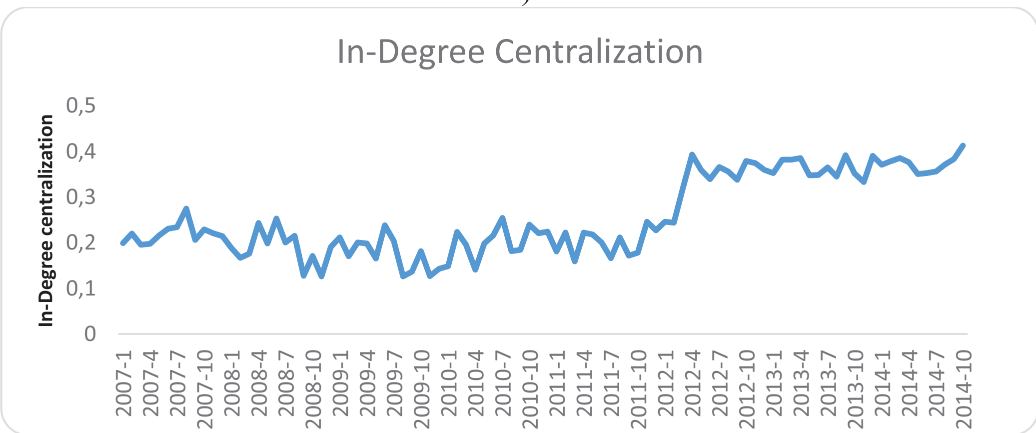
Table 3.5 - Descriptive statistics of degree centralizations within the time span of January 2007 and October 2014

Centralization	Mean	Min	Max	Median	Std. Dev.
Degree	12.270	9.122	14.194	12.403	0.996
In-degree	0.253	0.126	0.393	0.222	0.083
Out-degree	0.409	0.281	0.536	0.411	0.059

All degree centralization ranges between 9.1 and 14.2 with the mean 12.3. Since in-degree and out-degree centralizations are not very large, it can be said that the network is not highly centralized which means there is not a clear boundary between the center and the periphery.



a)



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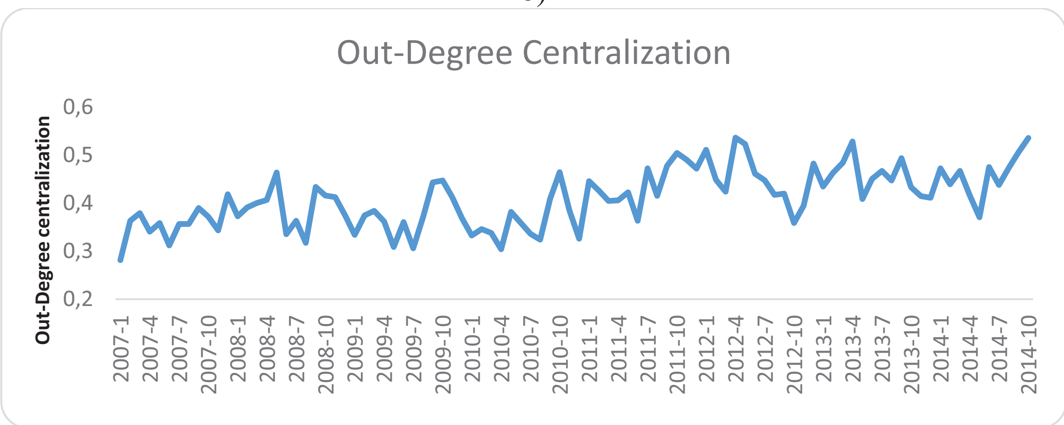
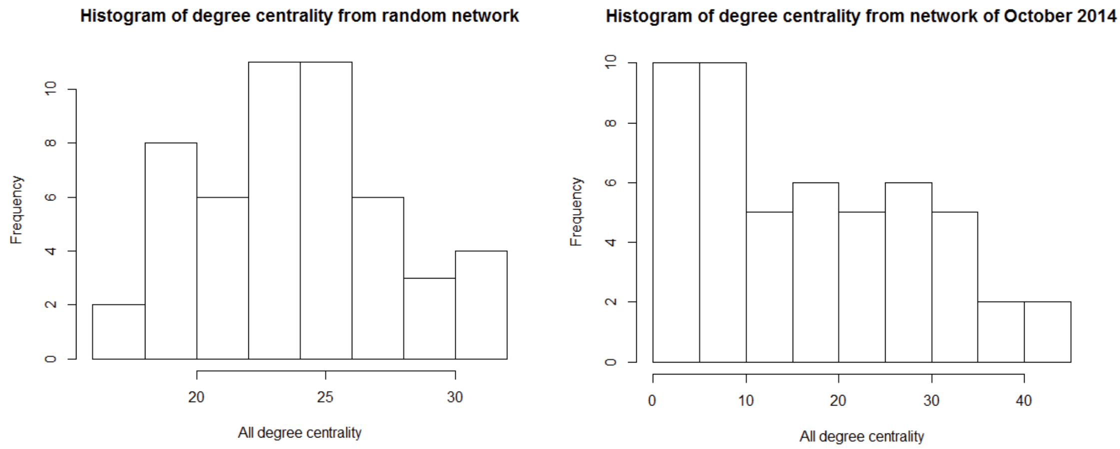


c)

Figure 3.4. Degree centralizations of Turkish Banking System within the time span January 2007- October 2014. a) Degree centralization b) In-Degree centralization c) Out-Degree centralization.

Figure 3.4 displays, the monthly change of degree, in-degree and out-degree centralization of the networks, respectively. The effects of the global crisis in 2008 is visible in Turkey in the early 2009, which explains the decrease in degree centrality after February 2009. After the second quarter of 2012, there is an increasing trend which still continues. It is more obvious in the in-degree centralization. On the other hand, overall mean of out-degree centralization is a little larger than the in-degree centralization. Some prominent banks exist according to the number of their outgoing lines. These banks are more powerful in the network. Hence if these banks are defaulted, many banks can be affected in terms of relations of debits and credits.



a) b)

Figure 3.5. Histogram of degree centrality. a) From random network. b) From network of October 2014.

Figure 3.5 demonstrates the histograms of degree centrality from created random network and from network of October 2014. The directed random network is created by Pajek according to Bernoulli/Poisson distribution. The pattern of the degree centrality from the network of real data does not match with any pattern. If the distributions of degree centrality were similar, simulation rather than real data Poisson distribution could also be appropriate. (Keeling, 1999)

The distance between two nodes in the network is the length of the geodesic which is the shortest path between two vertices. The metrics of closeness centrality and centralization are calculated by using the distances between two vertices. The closeness centrality of a bank is the number of other banks divided by the sum of all distances between the banks and all others; in other words it is 1 over Average distance. When distances are calculated in terms of the directions of lines, in and out closeness centralities are covered. Closeness centralization is the variation in the closeness centrality of vertices divided by the maximum variation in closeness centrality scores possible in a network of the same size. Variation is the sum of absolute differences between closeness centrality scores of the banks and maximum closeness centrality score in the network. The maximum possible variation in a network of size N is (N-1)(N-2)/(2N-3). (Dijkstra,1959; Freeman,1979)

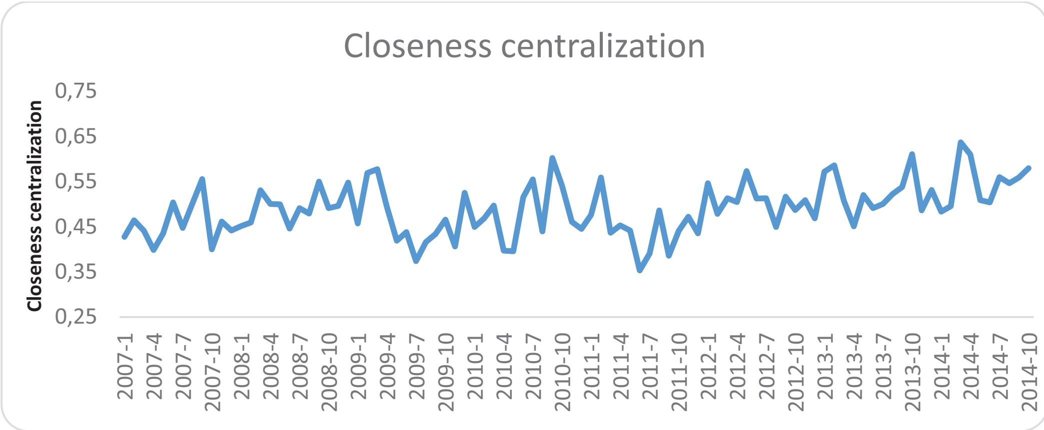
To be able to calculate the closeness centralities, the network should be connected. For this reason, the strong component of the network is extracted from the network.

Table 3.6 shows the descriptive statistics of closeness centralizations for the 94 monthly periods within the time span of January 2007 and October 2014.

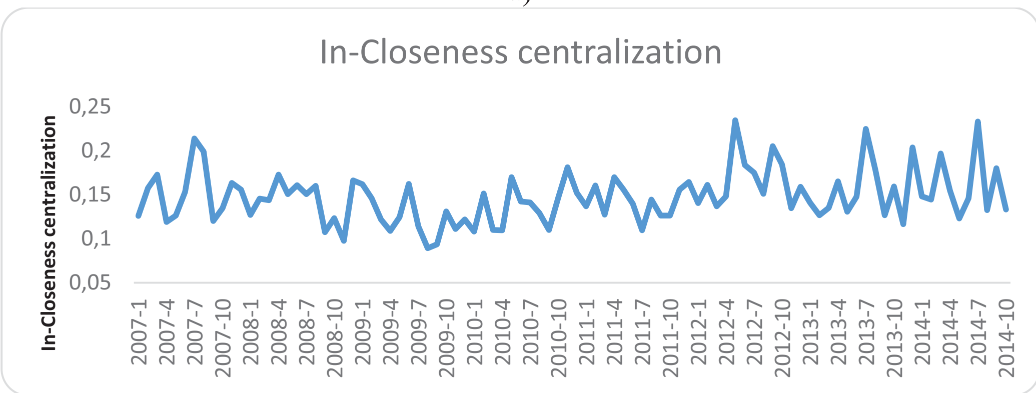
Table 3.6 - Descriptive statistics of closeness centralizations within the time span January 2007- October 2014

Centralization	Mean	Min	Max	Median	Std. Dev.
Closeness	0.489	0.353	0.637	0.491	0.058
In-closeness	0.147	0.089	0.234	0.146	0.029
Out-closeness	0.238	0.167	0.348	0.231	0.037

All closeness centralization ranges between 0.35 and 0.64 with the mean 0.49. Closeness centralization is large enough to say that on average the network is centralized according to the distances between banks. Out-closeness centralization is however a bit larger than in-closeness centralization. Hence, there exist some banks which are central according to their reachability to other banks.



a)



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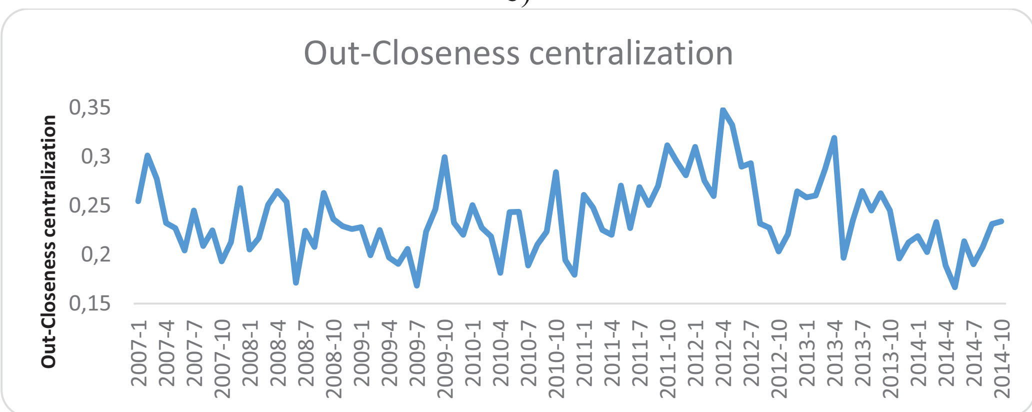


c)

Figure 3.6. Closeness centralizations of Turkish Banking System within the time span January 2007- October 2014. a) Closeness centralization b) In- Closeness centralization c) Out- Closeness centralization.

Figure 3.6 displays the monthly change of closeness, in-closeness and out-closeness centralization of the networks, respectively. The effects of the global crisis on Turkey after February 2009 are also observed from the closeness centralizations. After the second quarter of 2012, again there is an increasing trend which still continues. It is similar in the in-closeness centralization, however, it is quite stable after the beginning of 2013. Nevertheless, out-degree centralization has been steadily decreasing after May 2012.

If a bank has a high betweenness centrality score, it means that this bank is generally on the geodesics between other banks, i.e. connecting them. Betweenness centrality takes into consideration the importance of a bank for transmission of failure. The betweenness centrality of a bank is the proportion of all geodesics between pairs of other banks that include this bank, while betweenness centralization is calculated by dividing the variation in the betweenness centrality of banks by the maximum variation in betweenness centrality scores possible in a network of the same size. The variation in the betweenness centrality of banks is the sum of absolute differences between betweenness centrality scores of the banks and maximum betweenness centrality score in the network. Maximum possible variation in a network of size N is (N-1) (Freeman, 1979).

Table 3.7 shows the descriptive statistics of betweenness centralizations for the 94 monthly periods within the time span of January 2007 and October 2014.

Table 3.7 - Descriptive statistics of betweenness centralization within the time span January 2007- October 2014

Centralization	Mean	Min	Max	Median	Std. Dev.
Betweenness	0.109	0.052	0.205	0.107	0.027

Betweenness centralization ranges between 0.05 and 0.21 with the mean 0.11. Betweenness centralization is very small to say that betweenness centrality scores of the banks in the network do not vary too much, so in the network there does not exist banks which act as gatekeepers.

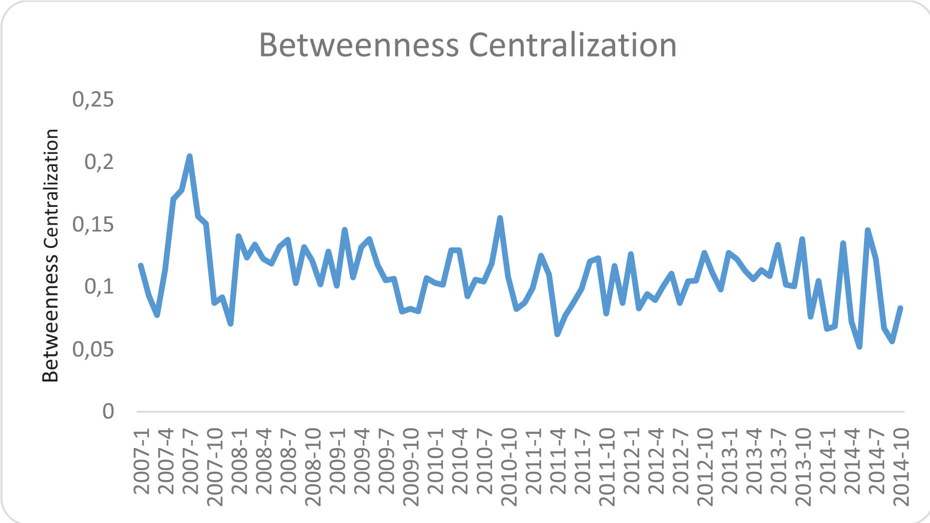


Figure 3.7. Betweenness centralization of Turkish Banking System within the time span January 2007- October 2014

Figure 3.7 displays the monthly change of betweenness centralization of the networks. Since betweenness centralization score is getting closer to zero, it can be said that almost all banks in the network have same betweennes centrality score.

The monthly change of total amount of money flow is displayed in Figure 3.8. The amount of money flow between banks in the Turkish Banking System shows an increasing trend after the end of 2010.

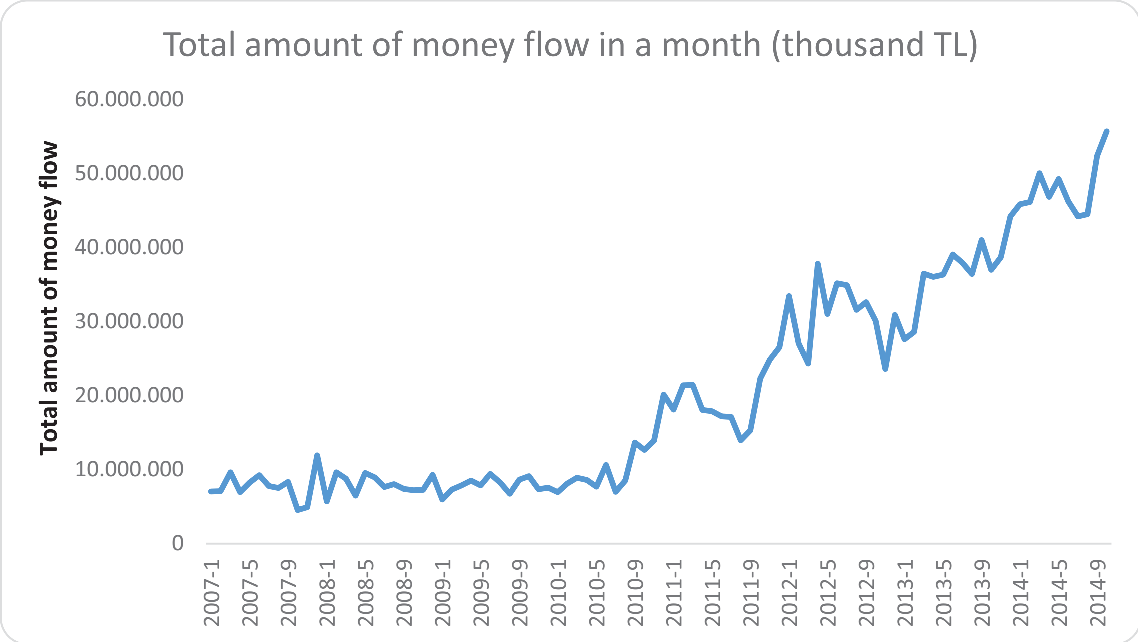


Figure 3.8. Total amount of money flow in a month (thousand TL) within the time span January 2007- October 2014

Table 3.8 shows the descriptive statistics of the monthly change of money flow for the periods 2007-2014 and 2011-2014.

Table 3.8 – Five summaries of total amount of money flow in a month

(Thousand TL)

	Mean	Min	Max	Median	Std. Dev.
Between 2007-2014	20.602.054	4.526.555	55.673.184	13.918.775	14.571.612
Between 2011-2014	33.186.074	13.939.597	55.673.184	34.173.864	10.824.113

The total amount of money flow in a month ranges between 13.940 billion TL and 55.673 billion TL with the mean 33.186 after 2011, whereas in the time period 2007 to 2014 its mean is 20.602 billion TL.

3.3 Positions of Groups of Banks in Turkish Banking Sector

In this section, instead of individual banks, the positions of their groups are evaluated. Two groupings are included in the study, banking groups and peer groups.

3.3.1 Positions of Banking Groups

Banking groups are the groups of owners, such as state, private etc. Six banking groups: State-owned banks, Privately owned banks, Foreign banks, Development and Investment Banks, Saving deposit insurance fund banks and Participation Banks (Islamic banks) exist for the time period of 2007-2014.

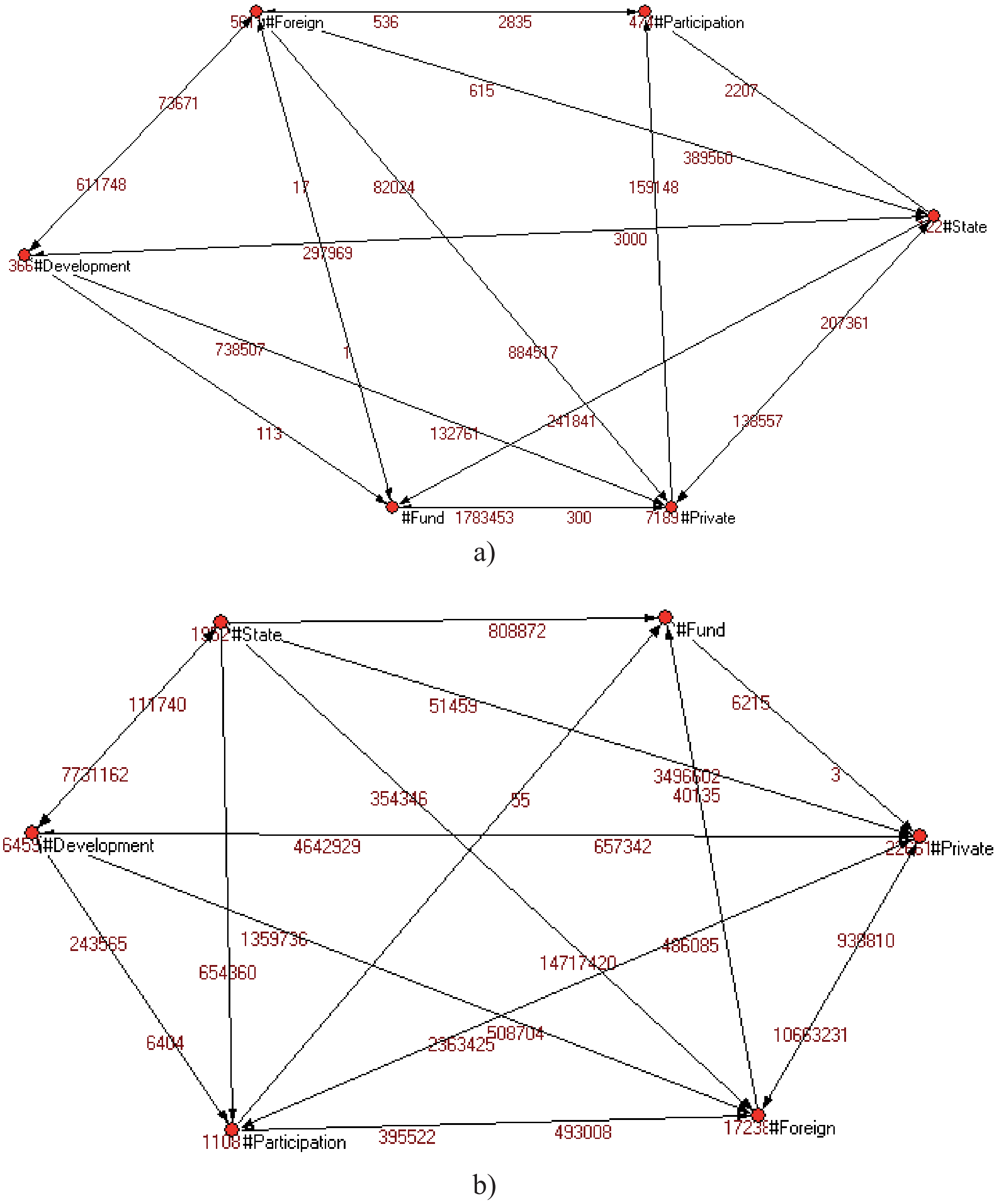


Figure 3.9. Directed network structure of banking groups. a) as of January 2007 b) as of October 2014. Links represent the net amount of money flow netween two banking groups.

The networks of banking groups include loops since banks with same banking groups have debit and credit relations among themselves (Figure 3.9).

Table 3.9 shows the descriptive statistics of amount of incoming money flow for monthly periods in 2011-2014,

Table 3.9 – Descriptive statistics of the amount of incoming money flow among banking groups within the time span of January 2011- October 2014

Banking groups	Mean	Min	Max	Median	Std. Dev.
Development and Investment Banks	10.810.565	5.652.527	15.485.116	11.465.506	3.058.176
State-owned banks	1.045.931	119.294	2.578.640	1.033.801	573.518
Saving deposit insurance fund banks	388.756	51.284	862.941	418.153	152.314
Privately owned banks	5.437.082	2.146.112	10.259.567	5.016.670	2.441.850
Foreign banks	13.617.815	3.093.413	28.106.164	13.329.439	5.750.667
Participation Banks (Islamic banks)	1.885.925	753.304	3.653.098	1.730.425	790.422

On average, foreign banks and development and investment banks have the highest incoming amount of money flow which refers to credits.

Figure 3.10 demonstrates the incoming amount of money flow in banking groups over time. In the end of the 2010, the incoming money flow starts to increase. However, definite increase is observable for foreign banks, development and investments banks and privately-owned banks.

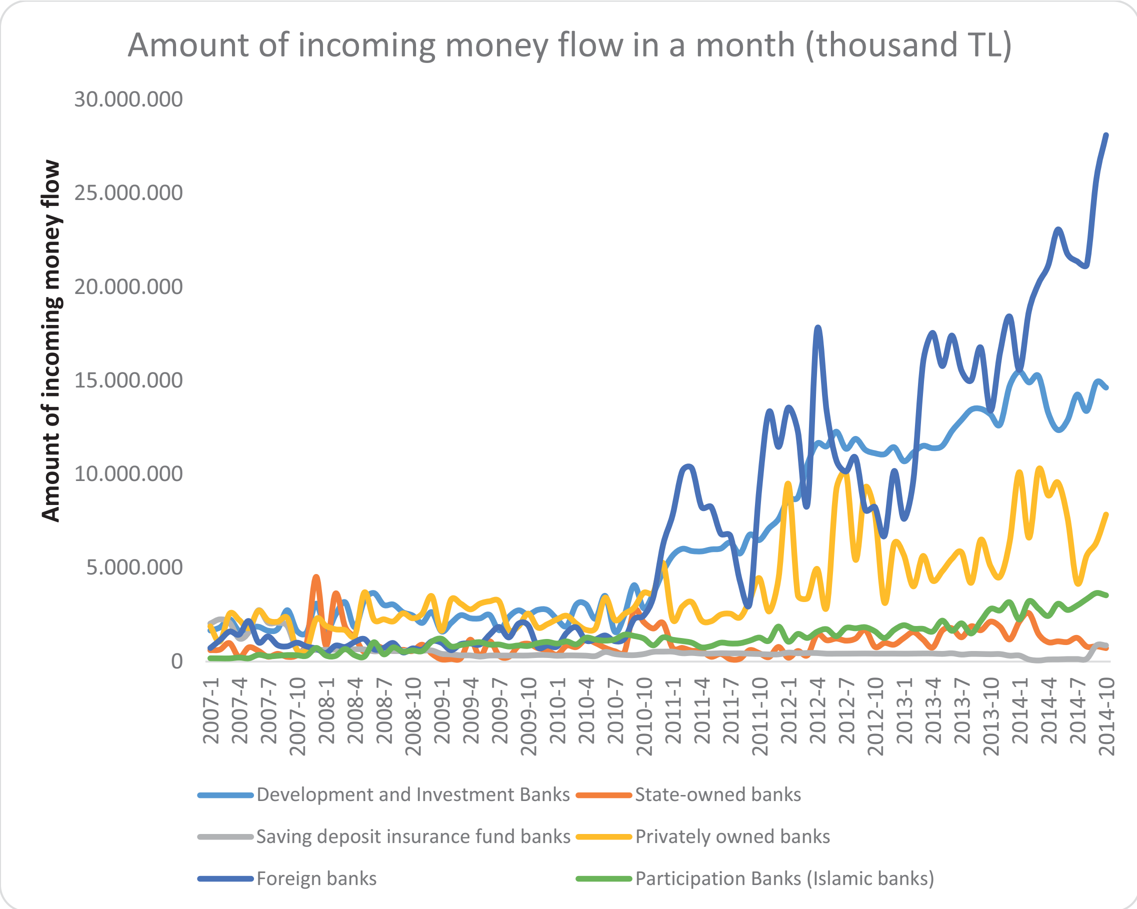


Figure 3.10. Amount of incoming money flow among banking groups in a month over time (thousand TL)

Table 3.10 shows the descriptive statistics of amount of outgoing money flow for monthly periods in 2011-2014,

Table 3.10 - Five summaries of outgoing money flow among banking groups within the time span January 2011- October 2014

Banking groups	Mean	Min	Max	Median	Std. Dev.
Development and Investment Banks	1.439.379	334.585	3.425.742	1.360.337	789.825
State-owned banks	14.120.492	6.544.467	27.603.708	12.676.004	5.624.631
Saving deposit insurance fund banks	121	1	581	110	134
Privately owned banks	13.321.995	3.002.545	23.709.748	13.977.392	5.056.639
Foreign banks	3.631.680	1.170.028	6.196.554	4.058.677	1.532.675
Participation Banks (Islamic banks)	672.407	81.773	1.912.033	376.526	628.808

On average, state-owned banks and privately-owned banks have the highest outgoing amount of money flow which refers to debits. Due to banking structure, saving deposit insurance fund banks do have almost no debits to other banks.

Figure 3.11 demonstrates the outgoing amount of money flow in banking groups over time. Similar to incoming amount of money flow, in the end of the 2010, outgoing money flow among banking groups starts to increase. The increase in the outgoing money flow is much more significant for state-owned banks and privately-owned banks. Beside to saving deposit insurance fund banks, the debits of participation banks to other banking groups is smaller than other banking groups. Also participation banks do not give so much credit to other banks. The reason is that participation banks are doing Islamic banking which is interest free banking. This banking structure isolates participation banks from other banking groups.

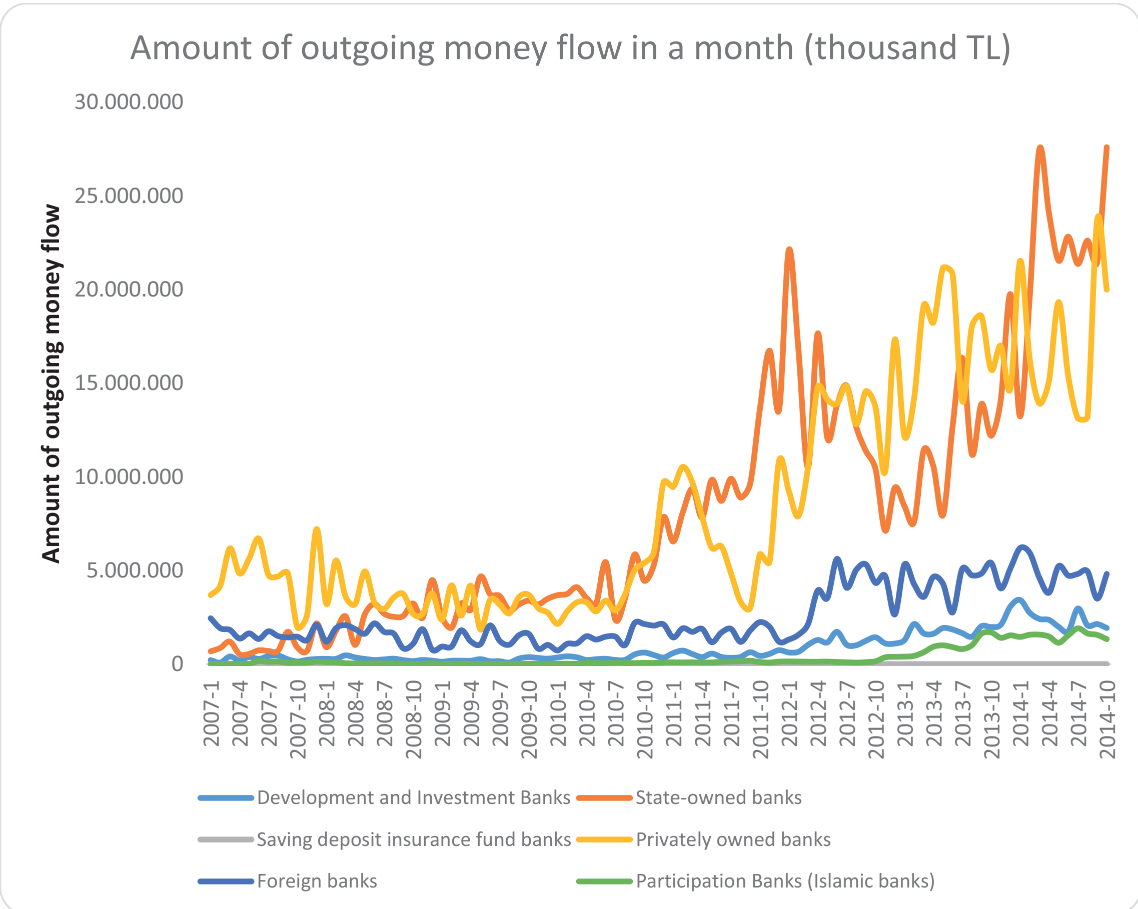
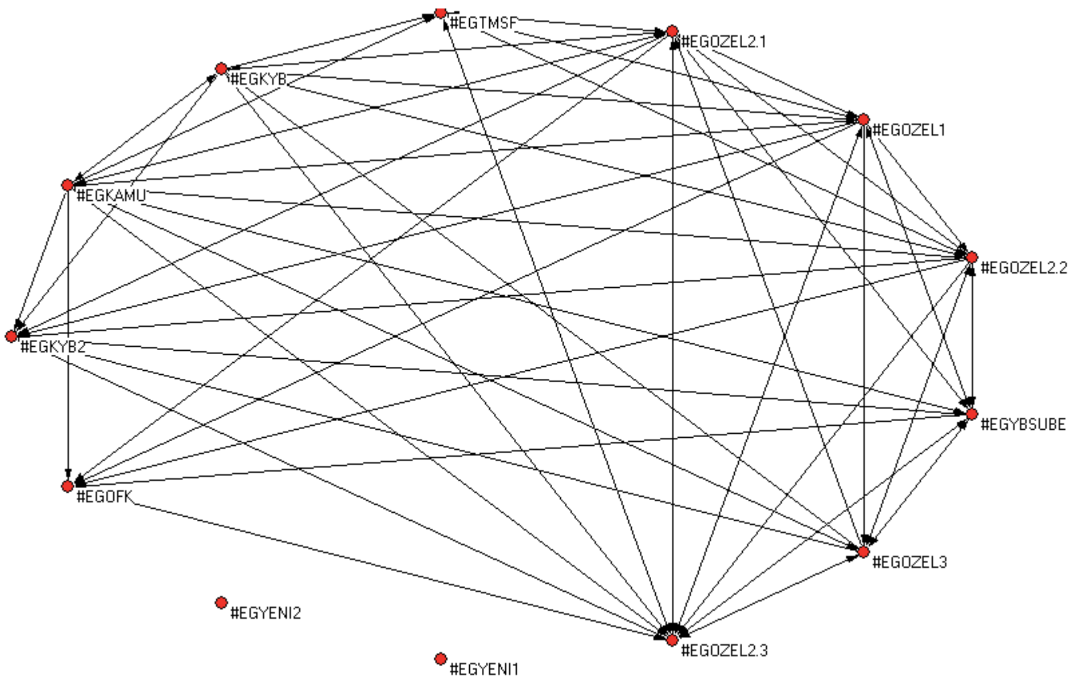


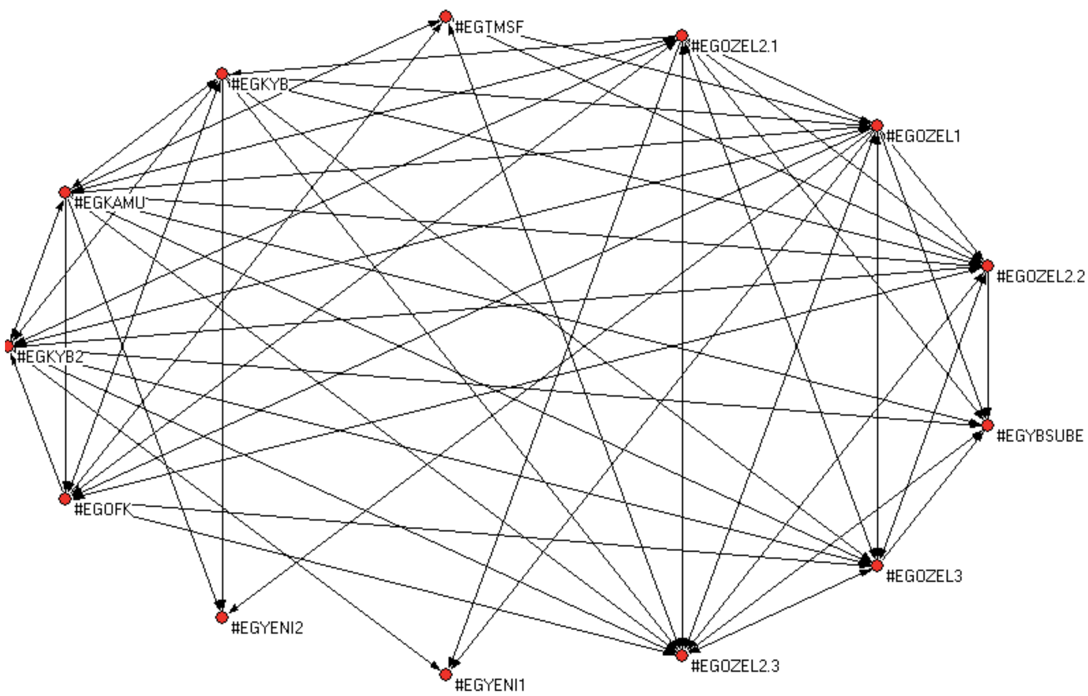
Figure 3.11. Amount of outgoing money flow among banking groups in a month (thousand TL)

3.3.2 Positions of Peer Groups

Peer groups are created by using banks' size of share in the sector beside to banking groups. For example, for the peer group "EGOZEL1", last numbers represents rankings of size and "OZEL" means privately-owned banks.



a)



b)

Figure 3.12. Directed network structure of peer groups a) as of January 2007 b) as of October 2014. Links represent the net amount of money flow between two peer groups.

The networks of peer groups include loops since banks within the same peer groups have debit and credit relations among themselves. For newly opened banks, in order to examine them closely there are special peer groups. These peer groups include only one bank; "EGYENI1" includes BANK_46, while "EGYENI2" includes BANK_47.

Table 3.11 shows the descriptive statistics of the incoming amount of money flow for monthly periods in 2011-2014.

Table 3.11 - Descriptive statistics of incoming money flow among peer groups

Peer groups	Mean	Min	Max	Median	Std. Dev.
EGKYB2	9.758.339	4.876.982	14.310.070	10.354.851	2.808.021
EGKAMU	1.045.931	119.294	2.578.640	1.033.801	573.518
EGKYB	1.052.226	347.737	1.567.026	1.139.321	317.154
EGTMSF	388.756	51.284	862.941	418.153	152.314
EGOZEL2.1	1.506.806	104.321	4.414.649	1.386.519	1.174.245
EGOZEL1	3.411.128	1.271.344	7.415.334	2.574.164	1.794.377
EGOZEL2.2	5.943.556	412.715	13.800.805	5.149.961	3.384.724
EGYBSUBE	2.332.074	138.356	5.621.791	2.215.636	1.232.853
EGOZEL3	2.743.998	1.241.284	4.535.678	2.659.289	731.355
EGOZEL2.3	2.786.969	1.122.443	4.576.563	2.729.871	859.073
EGYENI1	566.591	216	1.472.710	503.305	480.407
EGYENI2	659.682	586.909	698.985	692.828	45.708
EGOFK	1.885.925	753.304	3.653.098	1.730.425	790.422

On average, development and investment banks in the peer group of "EGKYB2" and privately-owned banks in the peer group of "EGOZEL2.2" have the highest incoming amount of money flow which refers to credits. Since these banks expect to receive payments in larger amounts from other banks, the contagion effect of a bank default on them would be higher. Newly opened banks and saving deposit insurance fund banks are the banks which are giving the least amounts of credits to other banking groups.

Figure 3.13 demonstrates the incoming amount of money flow among peer groups over time. Definite differences in incoming line values are observable for peer group of "EKYB2",second group of development and investment banks, and peer group of "EGOZEL2.2", third group of privately-owned banks, foreign banks. The graph does not span across all peer groups; it shows only the seven largest peer groups in terms of incoming money flow.

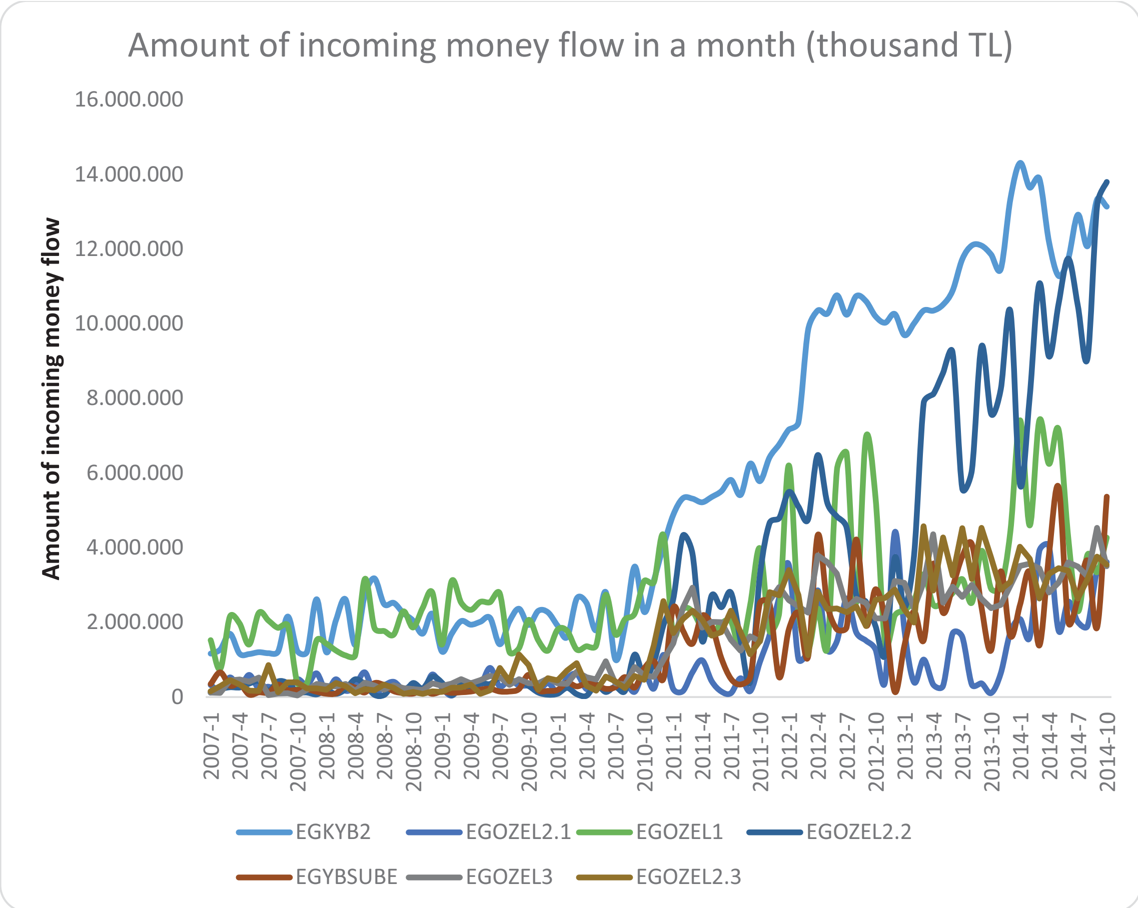


Figure 3.13. Amount of incoming money flow among peer groups in a month (thousand TL)

Table 3.12 shows the descriptive statistics of the outgoing amount of money flow for monthly periods in 2011-2014. On average, peer group of "EGKAMU", i.e., state-owned banks, and peer group of "EGOZEL1", i.e., banks that have the largest size among privately-owned banks, have the highest outgoing amount of money flow, which refers to debits. Other peer groups of privately owned banks follow these peer groups. In addition to saving deposit insurance fund banks, newly opened banks do not have debits to other banks. Because of their sizes of share in the sector, foreign bank branches do not have so much credit debt.

Table 3.12 - Descriptive statistics of outgoing money flow among peer groups within the time span January 2011- October 2014

Peer groups	Mean	Min	Max	Median	Std. Dev.
EGKYB2	849.767	116.663	2.177.536	721.371	555.564
EGKAMU	14.120.492	6.544.467	27.603.708	12.676.004	5.624.631
EGKYB	589.613	157.570	1.248.206	606.045	285.293
EGTMSF	121	1	581	110	134
EGOZEL2.1	1.818.960	245.068	3.792.039	1.903.324	930.705
EGOZEL1	11.279.213	1.914.246	20.156.610	11.669.017	4.352.981
EGOZEL2.2	1.569.244	369.200	3.305.620	1.625.839	739.656
EGYBSUBE	167.732	458	765.500	113.795	167.433
EGOZEL3	570.348	64.254	1.388.330	502.047	288.338
EGOZEL2.3	1.559.117	148.990	4.324.052	1.511.228	1.067.005
EGYENI1	0	0	0	0	0
EGYENI2	0	0	0	0	0
EGOFK	672.407	81.773	1.912.033	376.526	628.808

Figure 3.14 shows the outgoing amount of money flow in peer groups over time. Similar to incoming amount of money flow, at the end of the 2010, outgoing money flow among banking groups starts to increase. The increase in the outgoing money flow is much more significant for the peer group of “EGKAMU”, i.e., state-owned banks, and peer group of “EGOZEL1”, i.e., privately-owned banks. The banks in these peer groups are critical, since in the case of bank failure, their large amount of debits cannot be paid. As a result, their outgoing neighbors have potential for bank failure after these banks become defaulted.

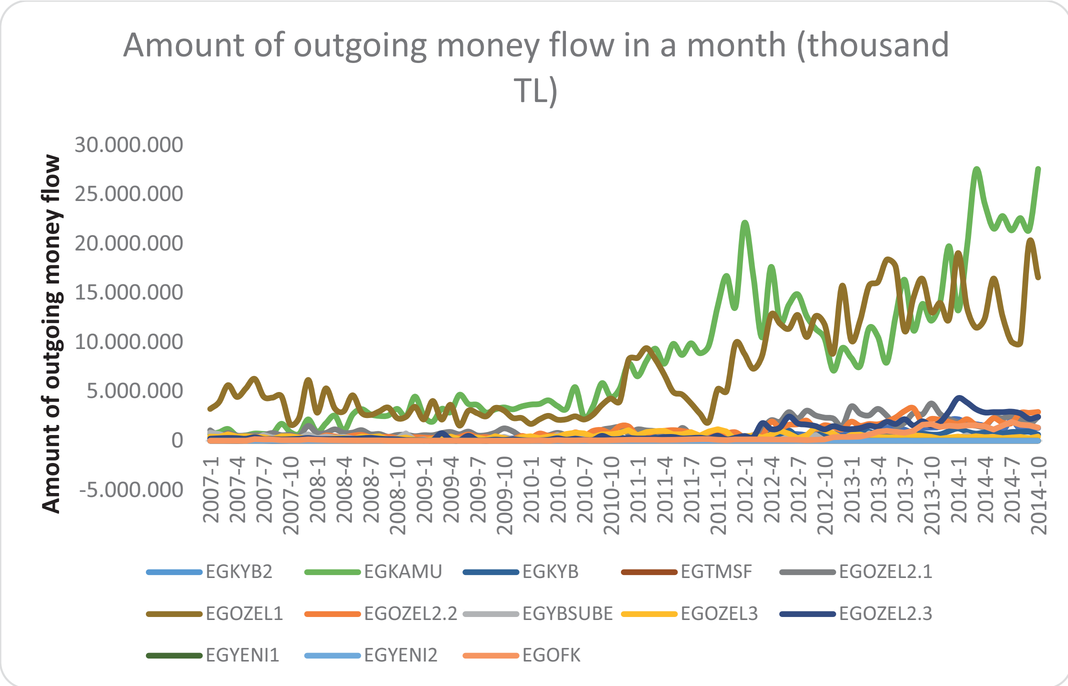


Figure 3.14. Amount of outgoing money flow among peer groups in a month (thousand TL)

3.4 Positions of Banks in Turkish Banking Sector

In social network analysis, centrality is one of the most essential and the most studied metric. It is also one of the most critical points to elaborate systemic risk, since it indicates the potential effects of possible bank failures. The spread of bank failures is highly dependent on the position of the banks in the network. (White, Boorman, & Breiger, 1976)

In order to evaluate the positions of banks in the Turkish banking system individually, a Pajek macro and an Excel macro has been created. Pajek macro exports the centrality vectors of the banks for each month separately. For each centrality, 94 vectors have been created. The Excel macro joins these 94 macros together. At the end of the transactions, a matrix has been created, whose vertical axis holds the 51 banks and horizontal axis holds the monthly periods.

First of all, to elaborate the importance of the banks in the network, in-degree and out-degree centralities have been computed according to the directed network structure of the banking system. The banks with high in-degree centralities are much more likely to be affected from failures of banks which are input neighbors of these banks, since their total assets and equities include these credits, i.e., the incoming line values. If neighbors of the banks with high in-degree centrality become insolvent, the solvencies of these banks will be under risk. As a result, decrease in the assets and equities due to failures of input neighbors lead to decrease in the capital adequacy and liquidity ratios of the banks with high in-degree centrality. On the other hand, the banks with out-degree centrality are important and risky banks in the network. When a bank failure occurs in these banks, many banks will be vulnerable to meet the effects of that failure; therefore the spread of the bank failure will be fast. These relations between input and output degree centrality and stability and fragility will also be tested with hypotheses. (Freeman, 1979)

In-weighted degree centrality gives the total incoming money flow from other banks. It is considered that banks with large amount of credits are fragile banks in terms of their affectability. Out-weighted degree centrality whereas gives the total outgoing money flow to other banks. Banks with large amount of debits are critical banks, since when these banks become defaulted, output neighbors of these banks cannot get back their credits, which are in in large amounts. In addition, these amounts depend on the size of the share in the sector. (Barnes, 1983)

Betweenness centrality measures the frequency of being on the geodesic between other banks. If a bank with high betweenness centrality score is removed from the network, number of components, i.e. unconnected networks groups may appear. Banks with high betweenness centrality score have a larger influence on the spread of bank failure. (Freeman, 1979)

Closeness centrality gives how close a bank is to other banks. It is computed as 1/ average distance path (de Nooy, Mrvar, & Batagelj, 2005). If a bank with high closeness centrality score fails, its failure spreads to the other banks swiftly, since the distance of this bank to other banks is small. This bank reaches other banks easily, which is why the banks with high closeness centrality scorers are critical in the case of bank failures. In-closeness centrality demonstrates the affectability of the banks from bank failures. If a bank has a high in-closeness centrality score, it becomes influenced by bank failures much earlier than other banks. Out-closeness centrality points the effectiveness of banks when it becomes defaulted. If the defaulted bank has a high out-closeness centrality score, since it cannot do payments to other banks, other banks will instantly be affected due to lack of liquidity. The loss in the equity and total assets results in declines in capital adequacy and liquidity ratios. (Freeman, 1979)

Table 3.13 - Descriptive statistics of the network metrics for banks over the period January 2007- October 2014.

	In-degree centrality	Out-degree centrality	In-weighted degree	Out-weighted degree	Betweenness centrality	In-closeness centrality	Out-closeness centrality	Closeness centrality
Mean	8,07	8,15	770.157	756.392	0,02	0,36	0,39	0,58
Min	1,30	0,00	60	0	0,00	0,28	0,00	0,39
Max	25,12	29,71	5.435.313	7.978.968	0,12	0,57	0,69	0,82
Median	7,94	5,32	375.683	170.662	0,01	0,35	0,42	0,56
Std.Dev.	4,51	7,92	1.160.585	1.572.676	0,02	0,05	0,19	0,09

Table 3.13 presents the descriptive statistics of calculated network metrics over the period January 2007 - October 2014. For the 94 monthly periods, in-degree and out-degree centralities have approximately the same mean of around 8. Although the average is 8.15 for out-degree centralities, there exist banks with higher degree centralities, such as 29. This indicates the existence of banks, which play key roles in the network. Similarly, in-weighted degree and out-weighted degree centralities have the same mean, which is about 760 billion TL. Betweenness centralities of banks are quite small, which means that according to the betweenness role a clear distinction cannot be made among the banks. Closeness centrality ranges between 0.39 and 0.82 with the mean 0.58.

Table 3.14 shows the network metrics calculated from the networks in monthly periods. After computing monthly metrics, their averages have been obtained for the time period 2012-2014 to be able to display the latest positions of the banks.

The betweenness centrality is very small for all banks in the network and there is not a clear difference between their scores. Only the bank with the highest betweenness centrality score has an importance.

Table 3.14 – Ranked order of network metrics for the banks in Turkish banking system based on their averages over the period 2012-2014.

RANK 2012-2014	In-degree	Out-degree	In-weighted degree	Out-weighted degree	Betweenness centrality	In-closeness centrality	Out-closeness centrality	Closeness centrality
1	25,12	29,71	5.435.313	7.978.968	0,1193	0,568	0,693	0,823
2	17,00	24,68	4.552.891	6.269.063	0,0612	0,454	0,625	0,786
3	16,03	24,00	3.592.960	4.494.240	0,0585	0,442	0,617	0,752
4	15,97	23,44	3.054.470	3.019.529	0,0510	0,441	0,611	0,737
5	13,97	20,91	2.578.519	2.760.856	0,0489	0,430	0,594	0,711
6	13,26	20,15	2.281.907	2.739.902	0,0444	0,411	0,584	0,694
7	13,12	19,38	1.582.102	1.397.624	0,0442	0,410	0,581	0,675
8	12,41	19,09	1.453.449	1.059.168	0,0336	0,406	0,572	0,674
9	11,59	17,79	1.259.407	1.052.806	0,0321	0,398	0,569	0,655
10	11,56	17,41	1.093.506	978.136	0,0307	0,395	0,569	0,653
11	10,94	17,38	959.856	876.182	0,0293	0,392	0,568	0,652
12	10,76	16,71	850.427	624.729	0,0289	0,389	0,560	0,651
13	10,18	13,88	791.702	610.486	0,0274	0,385	0,524	0,643
14	9,74	12,41	765.836	602.245	0,0256	0,377	0,503	0,638
15	9,12	10,85	743.226	316.308	0,0254	0,375	0,497	0,630
16	9,06	9,44	659.682	299.872	0,0240	0,374	0,490	0,627
17	8,91	8,70	637.169	295.797	0,0231	0,373	0,488	0,624
18	8,68	7,88	609.534	287.536	0,0222	0,368	0,485	0,599
19	8,59	7,68	606.718	271.141	0,0188	0,366	0,471	0,584
20	8,56	7,38	578.690	258.120	0,0183	0,364	0,463	0,581
21	8,50	6,74	566.591	245.652	0,0173	0,364	0,452	0,580
22	8,47	6,41	512.959	243.779	0,0151	0,362	0,448	0,570
23	8,24	6,03	483.190	212.459	0,0141	0,361	0,439	0,567
24	8,15	5,82	463.726	187.090	0,0136	0,360	0,429	0,567
25	8,06	5,32	414.190	181.530	0,0135	0,356	0,420	0,563
26	7,94	5,32	375.683	170.662	0,0131	0,354	0,418	0,560
27	7,76	5,21	364.051	160.871	0,0130	0,353	0,409	0,559
28	7,65	4,58	360.448	137.051	0,0129	0,351	0,407	0,556
29	7,47	4,47	329.388	123.758	0,0123	0,349	0,406	0,552
30	7,15	4,36	173.973	120.495	0,0112	0,348	0,405	0,548
31	6,65	4,24	168.591	86.856	0,0093	0,344	0,397	0,545
32	6,59	4,14	142.591	84.918	0,0082	0,342	0,394	0,538
33	6,21	3,09	131.141	70.212	0,0074	0,341	0,379	0,538
34	5,79	3,00	94.959	61.390	0,0060	0,341	0,373	0,534
35	5,76	2,82	79.884	60.932	0,0055	0,339	0,372	0,534
36	5,76	2,00	78.385	51.753	0,0052	0,338	0,371	0,528
37	5,60	1,90	70.140	48.415	0,0050	0,335	0,357	0,522
38	5,15	1,85	68.765	44.141	0,0043	0,329	0,350	0,516
39	4,97	1,52	51.519	43.975	0,0039	0,327	0,328	0,503
40	4,88	1,33	45.739	19.664	0,0036	0,323	0,311	0,497
41	4,76	1,32	42.294	11.844	0,0035	0,322	0,269	0,490
42	4,18	1,25	39.081	7.195	0,0035	0,321	0,269	0,489
43	4,12	1,18	37.458	4.650	0,0029	0,320	0,154	0,480
44	3,09	1,05	35.865	3.570	0,0028	0,320	0,122	0,477
45	2,65	1,00	15.969	325	0,0027	0,319	0,039	0,477
46	2,61	1,00	14.824	123	0,0017	0,313	0,039	0,475
47	2,48	0,00	11.791	0	0,0011	0,308	0,000	0,474
48	2,18	0,00	9.981	0	0,0000	0,302	0,000	0,459
49	1,65	0,00	7.085	0	0,0000	0,291	0,000	0,451
50	1,32	0,00	299	0	0,0000	0,286	0,000	0,431
51	1,30	0,00	60	0	0,0000	0,280	0,000	0,393

Table 3.15 shows the owners of the network metrics, which were listed in Table 3.14. BANK_6 and BANK_33 are the banks with the largest input degree centrality

scores and the largest amounts of credits. In other words, these banks have receivables in large amounts from many other banks. For BANK_2, BANK_12 and BANK_13, it can be said that these banks have an important influence on the Turkish Banking System, since as well as their outgoing money flow their out-degree and out closeness centrality scores are large. In the case of failures of these banks consequences of contagion would be worse and fast. Importance of the banks have been used while selecting the defaulted banks for contagion effect simulations. The network metrics are then tested according to the fragility of banks.

Table 3.15 – Ranking of banks according to their network metrics based on the averages over the period 2012-2014.

RANK 2012-2014	In-degree	Out-degree	In-weighted degree	Out-weighted degree	Betweenness centrality	In-closeness centrality	Out-closeness centrality	Closeness centrality
1	BANK_6	BANK_2	BANK_33	BANK_2	BANK_12	BANK_6	BANK_2	BANK_12
2	BANK_33	BANK_13	BANK_6	BANK_13	BANK_14	BANK_33	BANK_5	BANK_13
3	BANK_19	BANK_12	BANK_37	BANK_5	BANK_13	BANK_19	BANK_13	BANK_2
4	BANK_12	BANK_5	BANK_1	BANK_3	BANK_5	BANK_12	BANK_12	BANK_14
5	BANK_16	BANK_10	BANK_17	BANK_10	BANK_2	BANK_16	BANK_10	BANK_5
6	BANK_14	BANK_14	BANK_14	BANK_12	BANK_10	BANK_48	BANK_3	BANK_10
7	BANK_48	BANK_11	BANK_45	BANK_14	BANK_33	BANK_14	BANK_11	BANK_11
8	BANK_13	BANK_3	BANK_15	BANK_37	BANK_28	BANK_13	BANK_34	BANK_3
9	BANK_9	BANK_37	BANK_19	BANK_11	BANK_3	BANK_7	BANK_37	BANK_37
10	BANK_38	BANK_28	BANK_16	BANK_28	BANK_11	BANK_9	BANK_14	BANK_6
11	BANK_7	BANK_34	BANK_48	BANK_34	BANK_39	BANK_38	BANK_28	BANK_38
12	BANK_45	BANK_39	BANK_38	BANK_9	BANK_38	BANK_45	BANK_39	BANK_39
13	BANK_17	BANK_38	BANK_9	BANK_38	BANK_6	BANK_49	BANK_38	BANK_28
14	BANK_49	BANK_9	BANK_49	BANK_22	BANK_9	BANK_20	BANK_22	BANK_9
15	BANK_4	BANK_22	BANK_3	BANK_50	BANK_27	BANK_17	BANK_26	BANK_34
16	BANK_8	BANK_26	BANK_47	BANK_44	BANK_34	BANK_4	BANK_44	BANK_33
17	BANK_39	BANK_35	BANK_10	BANK_29	BANK_22	BANK_51	BANK_27	BANK_19
18	BANK_11	BANK_44	BANK_7	BANK_35	BANK_19	BANK_44	BANK_9	BANK_22
19	BANK_10	BANK_27	BANK_21	BANK_48	BANK_49	BANK_8	BANK_42	BANK_48
20	BANK_20	BANK_49	BANK_13	BANK_39	BANK_8	BANK_3	BANK_35	BANK_49
21	BANK_22	BANK_42	BANK_46	BANK_36	BANK_29	BANK_39	BANK_19	BANK_26
22	BANK_3	BANK_19	BANK_32	BANK_27	BANK_31	BANK_11	BANK_24	BANK_44
23	BANK_51	BANK_24	BANK_29	BANK_17	BANK_44	BANK_27	BANK_49	BANK_17
24	BANK_44	BANK_33	BANK_4	BANK_26	BANK_17	BANK_22	BANK_50	BANK_27
25	BANK_27	BANK_4	BANK_5	BANK_4	BANK_37	BANK_10	BANK_43	BANK_16
26	BANK_26	BANK_17	BANK_22	BANK_51	BANK_26	BANK_26	BANK_48	BANK_35
27	BANK_5	BANK_50	BANK_12	BANK_33	BANK_42	BANK_50	BANK_33	BANK_4
28	BANK_15	BANK_48	BANK_50	BANK_24	BANK_4	BANK_15	BANK_51	BANK_7
29	BANK_37	BANK_43	BANK_8	BANK_49	BANK_51	BANK_5	BANK_29	BANK_45
30	BANK_28	BANK_29	BANK_39	BANK_21	BANK_48	BANK_29	BANK_4	BANK_24
31	BANK_29	BANK_51	BANK_26	BANK_19	BANK_32	BANK_37	BANK_8	BANK_51
32	BANK_24	BANK_36	BANK_28	BANK_32	BANK_50	BANK_28	BANK_17	BANK_42
33	BANK_43	BANK_8	BANK_24	BANK_18	BANK_18	BANK_43	BANK_25	BANK_50
34	BANK_50	BANK_45	BANK_2	BANK_7	BANK_35	BANK_24	BANK_36	BANK_8
35	BANK_34	BANK_7	BANK_51	BANK_6	BANK_43	BANK_35	BANK_41	BANK_43
36	BANK_35	BANK_30	BANK_35	BANK_45	BANK_21	BANK_47	BANK_30	BANK_29
37	BANK_47	BANK_21	BANK_25	BANK_15	BANK_36	BANK_42	BANK_32	BANK_20
38	BANK_1	BANK_41	BANK_27	BANK_42	BANK_24	BANK_1	BANK_7	BANK_15
39	BANK_2	BANK_32	BANK_44	BANK_43	BANK_7	BANK_34	BANK_40	BANK_47
40	BANK_42	BANK_6	BANK_23	BANK_41	BANK_45	BANK_23	BANK_21	BANK_32
41	BANK_32	BANK_16	BANK_11	BANK_25	BANK_15	BANK_2	BANK_45	BANK_21
42	BANK_23	BANK_25	BANK_34	BANK_16	BANK_16	BANK_32	BANK_15	BANK_41
43	BANK_21	BANK_15	BANK_20	BANK_30	BANK_20	BANK_21	BANK_6	BANK_1
44	BANK_36	BANK_40	BANK_36	BANK_40	BANK_40	BANK_46	BANK_16	BANK_36
45	BANK_40	BANK_18	BANK_18	BANK_20	BANK_41	BANK_36	BANK_18	BANK_30
46	BANK_30	BANK_20	BANK_42	BANK_8	BANK_25	BANK_40	BANK_20	BANK_40
47	BANK_46	BANK_1	BANK_43	BANK_1	BANK_30	BANK_30	BANK_1	BANK_46
48	BANK_41	BANK_23	BANK_40	BANK_23	BANK_1	BANK_41	BANK_23	BANK_25
49	BANK_25	BANK_31	BANK_30	BANK_31	BANK_23	BANK_18	BANK_31	BANK_23
50	BANK_31	BANK_46	BANK_41	BANK_46	BANK_46	BANK_25	BANK_46	BANK_31
51	BANK_18	BANK_47	BANK_31	BANK_47	BANK_47	BANK_31	BANK_47	BANK_18

CHAPTER 4

PROPOSED CONTAGION EFFECT MODEL

In this chapter, the research methodology adopted in this thesis is presented. The design of the study, the components and calculation of contagion effect and egocentric examples are described in detail.

A bank failure can pose a risk for the banking sector by spreading, which can lead to important negative externalities to other banks. This is named as the contagion effect or domino effect. There are three types of contagion (Peydro Alcalde, 2007):

1. Financial contagion effect due to interbank linkages: The failure of a bank can lead to its creditor banks to fail.
2. Information based contagion effect: Contagion effect results from the fact that depositors and creditors take into consideration the possibility of failing of banks which have similar characteristics to failed banks.
3. Pure contagion effect: Contagion effect arises coincidently and it does not stem from interbank linkages and information commonalities.

Among the types of contagion effects, the most important threat to the stability of the banking system is the financial contagion effect due to interbank linkages. Interbank markets play a key role in providing liquidity among banks, disciplining and monitoring them. However, at the same time they are paving the way for conversion of a shock stemmed from a bank failure to a potential banking crisis, which is the systemic risk.

In this study, contagion effect, which is related to interbank linkages is investigated. This type of contagion arises from the relations of debits and credits among banks. Nevertheless, there are also debits and credits among banks by way of derivative transactions and indirect guarantees given to customers. It is not possible to extract indirect guarantees from existing datasets in the database of Banking Regulation and Supervision Agency (BRSA). On the other hand, derivative transactions impose both liability and asset to counterparties. Therefore, net derivative transactions do not lead to credit risk over nominal amounts. Net debits and credits can only exist in the amount of difference between spot price and price agreement on the date of transaction. Since transactions between domestic banks are generally short dated, variety of current values are limited. Therefore in this study, derivative transactions are not included in the study.

Effects of a bank failure and consequently not being able to fulfill its liabilities to other banks on other banks are elaborated in terms of capital adequacy and liquidity channel with interbank linkages of failed banks.

- Capital Adequacy Channel:
  Capital of a bank establishes confidence for the depositors, meets the fixed capital investments, which are compulsory for banking activities, and most importantly provides the economic stability by maintaining the continuity of the bank in the case of unexpected issues and crises. For banks with adequate capital, the risks faced due to several issues and crises can be managed and for further levels when losses are made, probability of insolvency can be in acceptable levels. On the other hand, banks without adequate capital are more vulnerable to potential risks in banking activities. These banks can fail easily and failures can spread to the whole economy and affect the economic system negatively. Banks should provide adequate capital in order to perform their banking activities healthfully by considering the quality and quantity of their activities (Büyükşalvarcı & Abdioğlu, Determinants of capital adequacy ratio in Turkish, 2011).
  In order to prevent banks from the worst case, banking authorities clarified a ratio for capital adequacy, which is simply the ratio of keeping enough equity to fulfill the credit risk, market risk and operational risk faced by banks. Failure of banks result in a decrease in the equity of banks which had provided loans to the failed banks, since failed banks cannot make payments for their loans. Therefore, their capital adequacy ratios will decrease or may be lower than the threshold specified by banking authorities. Consequently, capital adequacy ratio is an important aspect that should be included in the

contagion model (Hausenblas, Kubicová, & Lešanovská, 2012).

- Liquidity Channel:

  Liquidity is the ability of financing demands of funds, credit needs of market and potential deposit loss, and it has vital importance for financial institutions. For a bank, having liquidity deficit means not having enough ready cash for payments which is also called as bank failure. Balance of cash inflow and outflow should be provided for financial institutions. In order to avoid facing liquidity shortage, banks should allocate majority of their assets to liquid assets. Banking authorities mandate liquidity obligations in order to decrease liquidity risks of banks. If a bank provides loans to another bank, in case of a failure in the counter bank, the bank which gives loans cannot receive its credits and consequently this bank can face liquidity shortage. Therefore, liquidity is also important in assessing the contagion effect (Cifuentes, Ferrucci, & Shin, 2004).

4.1. Contagion Model

In this study, potential contagion stemming from domestic interbank relations of debits and credits has been elaborated. BRSA regularly requests data from all the banks about their debits and credits to/from other banks and their relations with the financial sector. The dataset used in this thesis has been obtained from BRSA databases. In the case of a bank failure, the defaulted bank will not be able to meet its liabilities to the other banks. The contagion model proposed in this thesis aims to present the effect of a defaulted bank on capital adequacy and liquidity of other banks.

Thresholds in Turkish Banking System:

1. Threshold for capital adequacy ratio is 12%[4].
2. Threshold for liquidity ratios is 100%[5].

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[4] Bankaların sermaye yeterliliğinin ölçülmesine ve değerlendirilmesine ilişkin yönetmelik. (2014). T. C. Resmi Gazete, 29111, 6/9/2014

[5] Bankaların likidite yeterliliğinin ölçülmesine ve değerlendirilmesine ilişkin yönetmelik. (2014).
T. C. Resmi Gazete, 28948, 21/3/2014.

It is assumed that dropping down of CAR below 12% or dropping down of monthly or weekly liquidity ratios below 100% indicates that aforementioned bank is exceeding the threshold value for classification of default.

In order to calculate new CAR of the banks which have debits and credits relations with the defaulted banks, it is assumed that the net amount of the money flow between these two banks will not occur. Therefore, the non-performing amount will be reduced from the equity of the counter bank of the defaulted bank and will be reduced from the amount subject to credit risk by multiplying the net amount with related risk weight which is 20%[6].

$$Capital\ Adequacy\ Ratio = \frac{Equity}{Risk\ Weighted\ Assets} \tag{1}$$

$$Capital\ Adequacy\ Ratio = \frac{Equity}{Credit\ Risk + Market\ Risk + Operational\ Risk} \tag{2}$$

$$New\ Capital\ Adequacy\ Ratio = \frac{Equity - Net\ Amount\ of\ Money\ Flow}{Risk\ Weighted\ Assets - 0.2 * Net\ Amount\ of\ Money\ Flow} \tag{3}$$

$$New\ Capital\ Adequacy\ Ratio = \frac{Equity - Net\ Amount\ of\ Money\ Flow}{Market\ Risk + Operational\ Risk + (Credit\ Risk - 0.2 * Net\ Amount\ of\ Money\ Flow)} \tag{4}$$

In the equation 2, it is written credit risk, market risk and operational risk. In fact the risks are weighted and they are the amounts subject to risks.

In order to calculate new monthly or weekly liquidity ratios of a bank which has debit and credit relationships with the defaulted banks, the debit balance of the bank assumed as defaulted will be reduced from total assets of the bank and the credit balance of the bank will be reduced from total liabilities.

[6] The standard risk weight applied to credit risks for loans is 20% according to the regulation, “Bankaların sermaye yeterliliğinin ölçülmesine ve değerlendirilmesine ilişkin yönetmelik”, T. C. Resmi Gazete, 29111, 6/9/2014.

$$Liquidity\ Ratio\ 7\ (Liquidity\ Ratio\ 31) = \frac{Total\ Assets}{Total\ Liabilities} \quad (5)$$

$$New\ Liquidity\ Ratio\ 7\ (Liquidity\ Ratio\ 31) = \frac{Total\ Assets - Debit\ Balance\ of\ Defaulted\ Bank}{Total\ Liabilities - Credit\ Balance\ of\ The\ Bank} \quad (6$$

$$Liquidity\ Ratio\ 7\ (Liquidity\ Ratio\ 31) = \frac{Total\ Assets}{Total\ Liabilities} \quad (7)$$

$$New\ Liquidity\ Ratio\ 7\ (Liquidity\ Ratio\ 31) = \frac{Total\ Assets - Debit\ Balance\ of\ Defaulted\ Bank}{Total\ Liabilities - Credit\ Balance\ of\ The\ Bank} \quad (8)$$

To illustrate, it is assumed that Ziraat Bank is defaulted and Ziraat Bank has debit and credit relationship with Akbank.

$$New\ Liquidity\ Ratio\ of\ Akbank = \frac{Total\ Assets - Debit\ Balance\ of\ Ziraat\ Bank\ to\ Akbank}{Total\ Liabilities - Credit\ Balance\ of\ Ziraat\ Bank\ from\ Akbank} \quad (9)$$

The proposed contagion models were negotiated with banking experts in the BRSA. They validated the formulas of ratios and steps of contagion models.

Scenarios

The diffusion of the bank failures is discussed under two different simulation aspects.

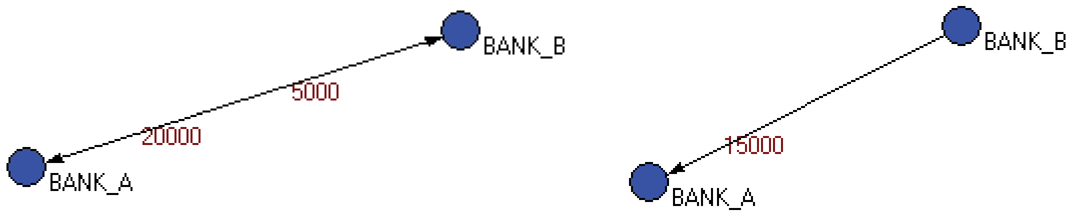
1. Idiosyncratic shocks: An individual bank failure is assumed.
2. Simulation of multiple bank failures: Diffusion starts with multiple bank failures. Failures of banking groups are assumed as multiple bank failures.

4.2. Egocentric Models

Under this subsection, the proposed contagion effect model is presented on an egocentric network. The steps of the model are described over the network.

4.2.1 Egocentric Capital Adequacy Model

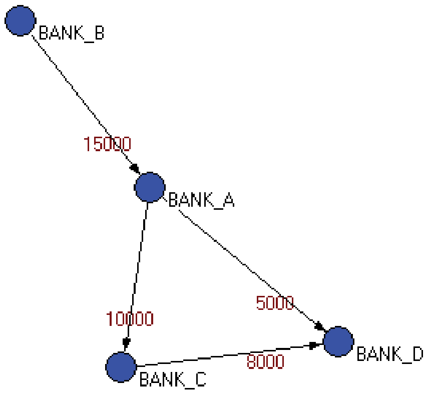
For the analysis of contagion effect on capital adequacy, directed networks of debits and credits among banks are used. Line values represent the net amount of the money flow between the two banks. Net amount of the money flow is calculated by taking the absolute value of the subtraction of credits and debits. In this way, bidirected arcs are converted to unidirected arcs, since the net amount of money flow is unidirected.



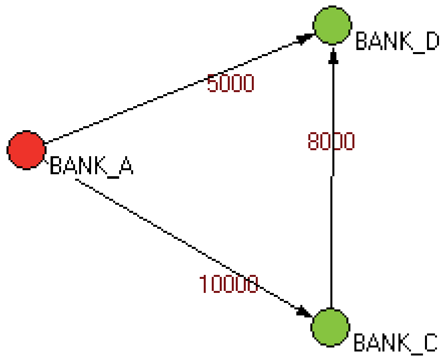
(a) (b)

Figure 4.1. Netting the amount of money flow between banks. (a) The debit of the BANK_A to BANK_B is 5.000 thousand TL, whereas the debit of the BANK_B to BANK_A is 20.000 thousand TL. (b) The net amount of the money flow between BANK_A and BANK_B is 15.000 thousand TL from BANK_B to BANK_A.

Step 1: Contagion starts with a selected bank and firstly the directly connected neighbors of the selected bank, which are detected by the distance partition, are affected from the contagion. It is assumed that when a bank is considered as defaulted, the money flow of the defaulted bank to other banks will not occur. Since outgoing money flow of the defaulted bank is assumed as unrealizable, closest output neighbors are extracted from the network to recalculate the CAR.



(a)



(b)

Figure 4.2. Network views of egocentric capital adequacy model. (a) The initial form of the undirected network. (b) View after Step 1. The BANK_A is selected to start contagion. The network is partitioned according to output distances of other banks to BANK_A.

Step 2: Line values of the network are used to recalculate the capital adequacy ratio. The net amount of the money flow is transformed to vectors. Since the neighbors are affected only by the defaulted bank, their money flow among themselves is omitted. The vector of capital adequacy ratio is included in the network.

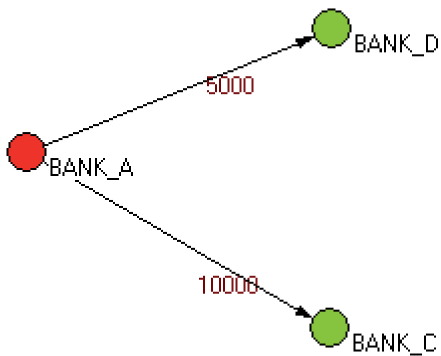
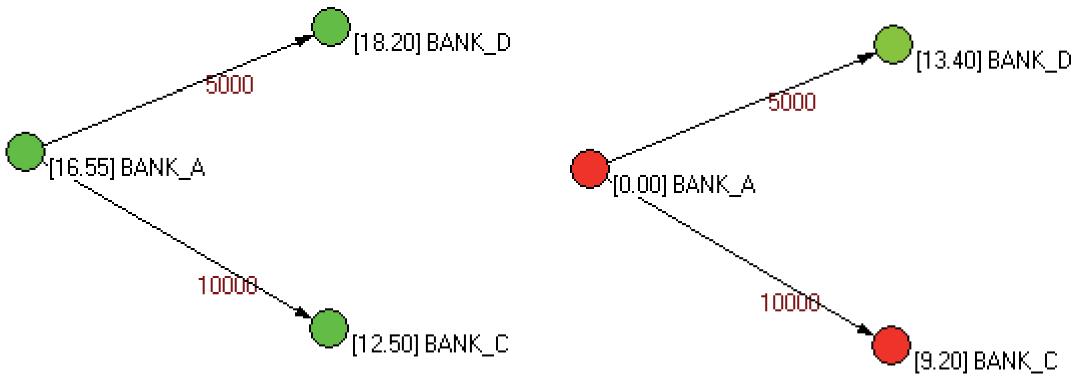


Figure 4.3. Network views of egocentric capital adequacy model. View after Step 2 in which money flow among neighbor banks is omitted.

Step 3: Beside to capital adequacy ratio, the items that are used in the calculation of capital adequacy ratio (equation 1) are stored as vectors. The net amount of money flow vector which is transformed from line values is subtracted from the equity vector, also the net amount of money flow vector multiplied by 0.2 is subtracted from risk weighted assets. New capital adequacy ratio is obtained after the dividing the new equity by new the risk weighted assets. The capital adequacy ratio of the bank which is the starting bank to be defaulted is set to 0.

Step 4: Recalculated capital adequacy ratios are partitioned into two groups according to the threshold of 12%, as explained in Section 4.1 Contagion Model. Banks with capital adequacy ratio under 12% are considered as defaulted.



(a) (b)

Figure 4.4. Network views of egocentric capital adequacy model. CAR values are shown in square brackets. (a) View after Step 3. The capital adequacy ratios of the banks are recalculated. (b) View after Step 4. The red color represents that the bank is defaulted as its CAR is under 12%.

As a result of the contagion started from BANK_A, CAR of BANK_C decreases under 12%, which is the critical threshold. This contagion continues with the defaulted BANK_C.

These steps are followed in a Pajek macro, which are repeated for each defaulted bank to analyse the contagion effect of BANK_A.

4.2.2 Egocentric Liquidity Model

In the liquidity model, the debit and credit balances of the banks separately have an impact on the liquidity level of the banks. Therefore, for the analysis of the contagion effect on liquidity, directed networks of debits and credits among the banks are used.

In Figure 4.5, incoming lines indicate credits whereas outgoing lines indicate debits. The debit of the BANK_B to BANK_A is 20.000 thousand TL, in other words BANK_A has credit of 20.000 thousand TL from BANK_B. In the same way, the debit of the BANK_A to BANK_B is 5.000 thousand TL, in other words, BANK_B has credit of 5.000 thousand TL from BANK_A.

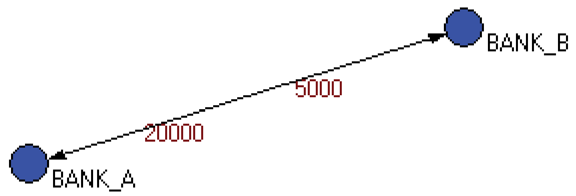
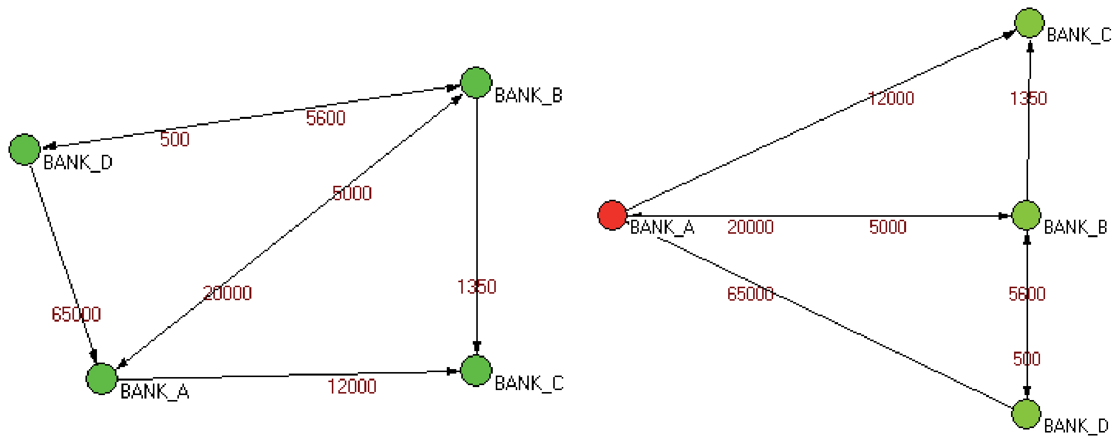


Figure 4.5. Directed network of debits and credits between BANK_A and BANK_B.

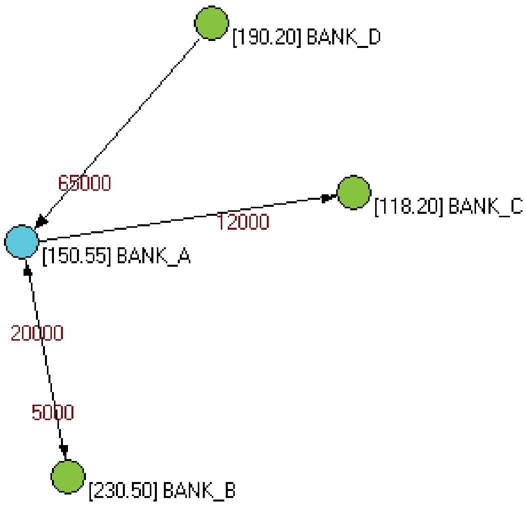
<u>**Step 1:**</u> As in the CAR model, contagion starts with a selected bank and firstly the closest neighbors of the selected bank are affected from the contagion. It is assumed that when a bank is considered as defaulted, the bank which has credit from that defaulted bank, cannot receive its assets and also the bank which has debit to the defaulted bank, does not need to send its liabilities to the defaulted bank.



(a) (b)

Figure 4.6. Network views of egocentric liquidity model. (a) The initial form of the directed network. (b) View after Step 1. The BANK_A is selected to start contagion. The network is partitioned according to distances of other banks to BANK_A.

Step 2: Since the neighbors are affected only by the defaulted bank, their money flow among themselves are omitted. Line values of the network are used to recalculate liquidity ratios. The debits and credits are transformed vectors separately. The vector of weekly liquidity ratio is included in the network.



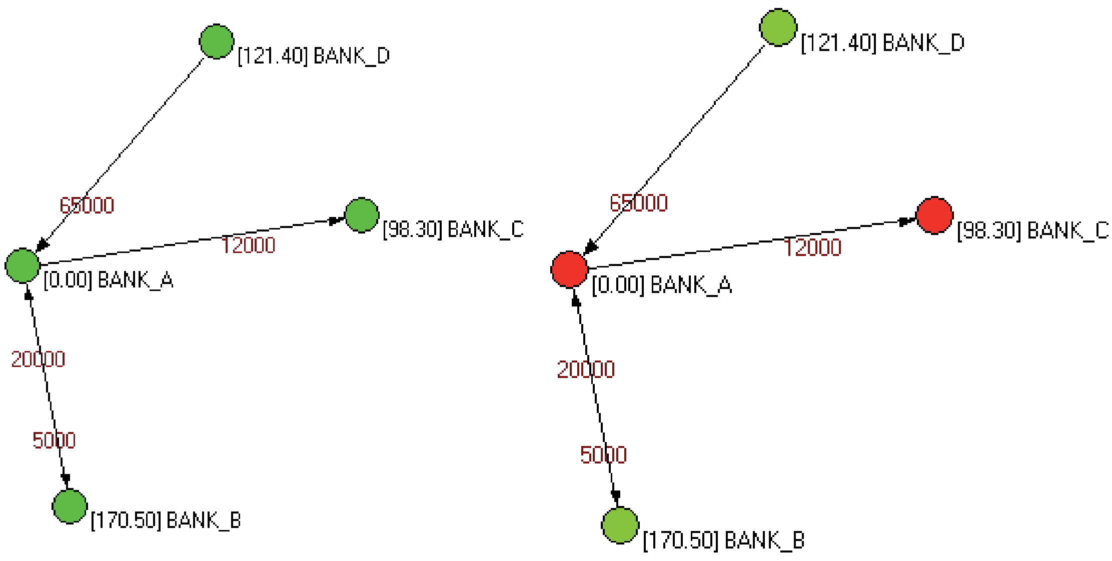
	Debits	Credits
BANK_A	17000	85000
BANK_B	20000	5000
BANK_C	0	12000
BANK_D	65000	0

(a) (b)

Figure 4.7. Network views of egocentric liquidity model. Liquidity ratios are shown in square brackets (a) View after Step 2. Vector values are liquidity ratios. (b) The table presents debits (outgoing lines) and credits (incoming lines) of each bank which are gained from directed network.

Step 3: Beside the liquidity ratios, the items that are used in the calculation of liquidity ratios (Equation 5) are stored as vectors. The amount of credits of banks from defaulted bank (BANK_A) are subtracted from their total assets and the amount of debits of banks to the BANK_A are subtracted from their total liabilities. New liquidity ratios are calculated after the division of the new total assets by the new total liabilities. The liquidity ratio of the bank which is the starting bank to be defaulted is set to 0.

Step 4: Recalculated liquidity ratios are partitioned into two groups according to threshold 100%, explained in Section 3.1 Contagion Model. Banks with liquidity ratios under 100% are accepted as defaulted.



(a) (b)

Figure 4.8. Network views of egocentric liquidity model. Liquidity ratios are shown in square brackets (a) View after Step 3. The liquidity ratios of the banks are recalculated. (b) View after Step 4. The red color represents that the bank is defaulted as its liquidity is under 100%.

Since there are two types of liquidity; weekly and monthly, these steps are repeated for monthly liquidity as well.

As a result of the contagion started from BANK_A, liquidity ratio of the BANK_C decreases under 100%, which is the critical threshold. This contagion continues with the defaulted BANK_C.

These steps are followed in a Pajek macro, which are repeated for each defaulted bank to analyze the contagion effect of BANK_A.

4.3 Egocentric Examples

In order to give an example on how the egocentric contagion models work, a monthly period has been selected. The purpose of this egocentric example is observing the small part of the main study, and taking the necessary action for the whole study.

November 2010 has been selected to monitor the diffusion which starts from one selected bank.

4.3.1 Egocentric Case of Capital Adequacy Ratio

Idiosyncratic Shock

According to the data on November 2010, Bank_22 has been selected to demonstrate the contagion effect in terms of capital adequacy ratio (CAR). Bank_22 has been assumed as defaulted, which means it is not able to fulfill its liabilities towards other banks.

First of all, from the network on November 2010, a partition which extracts Bank_22 and its nearest output neighbors have been created by using output k-neighbors function and selecting the vertex Bank_22 and maximum distance 1. Figure 4.9 shows the resulting subgroup. The geodesic distances have been used as lags in the diffusion, as used in the simple contagion model.

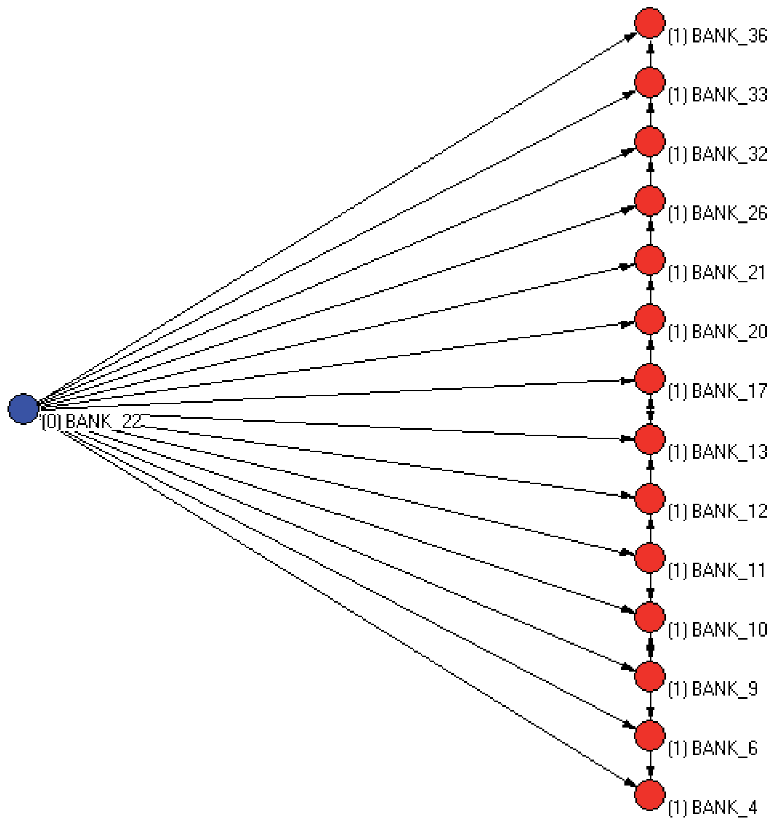


Figure 4.9. Network views of egocentric examples for capital adequacy model. Output Neighbors of Bank_22 on November 2010

In order to subtract the net amount of the debits and credits from the equity of the neighbors, the arcs between the neighbors of Bank_22 should be removed. Figure 4.10 shows the resulting network after this step.

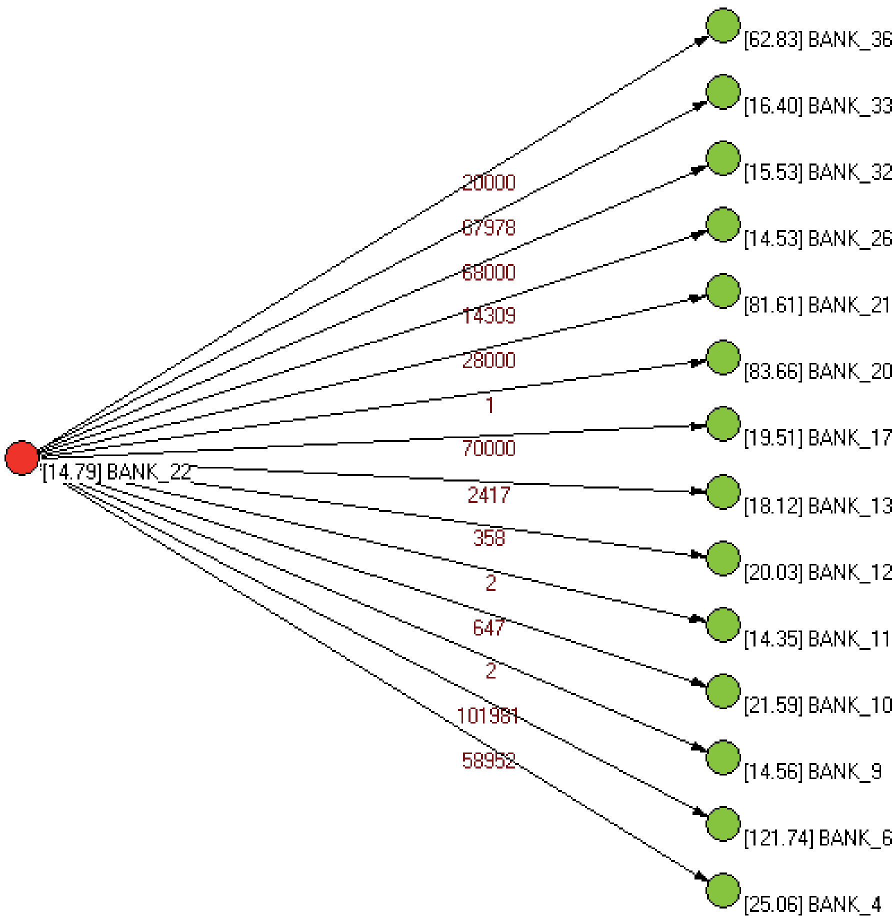


Figure 4.10. Network views of egocentric examples for capital adequacy model. Relations among neighbors of BANK_22 are omitted.

New CAR has then been calculated according to Equation 1 as explained previously. In Pajek, these calculations are applied using vector operations. After this, the CAR of BANK_22 is set to 0. Newly calculated CAR values have been transformed to partitions using 12 as the threshold, so that the banks with CAR values less than 12 form group 1, and greater or equal to 12 form group 2. Figure 4.11 shows the network after these grouping.

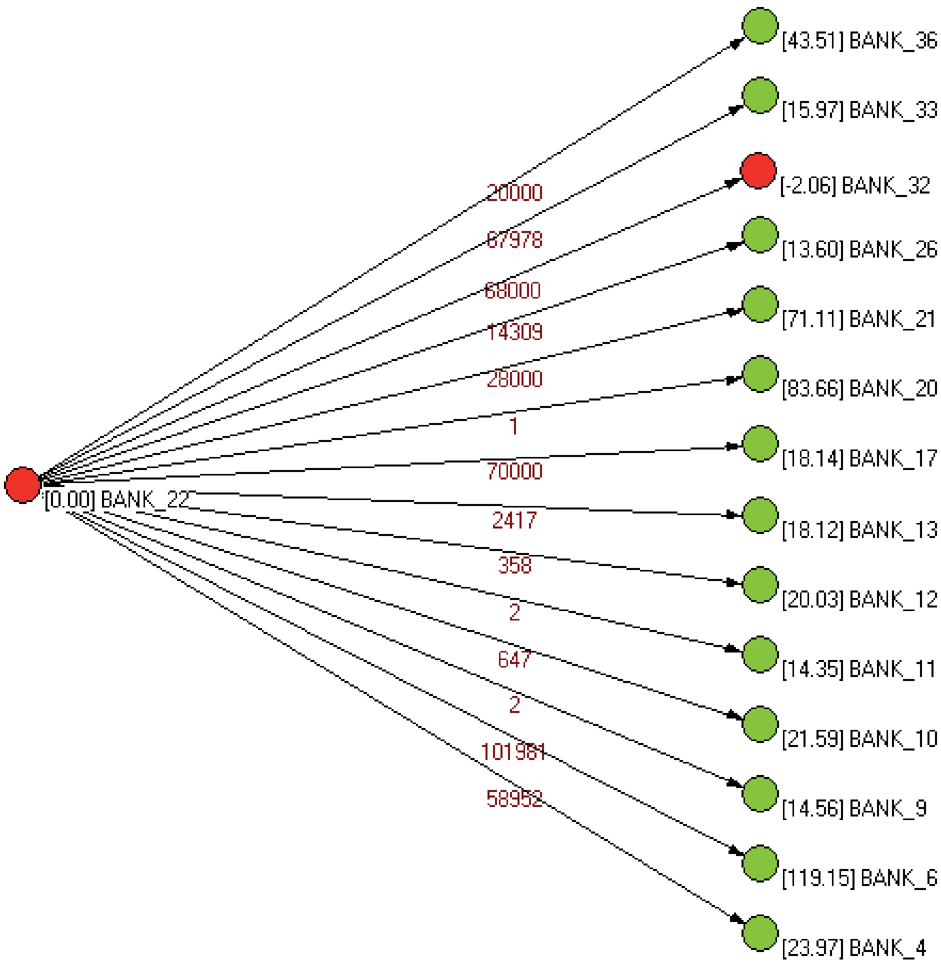


Figure 4.11. Network views of egocentric examples for capital adequacy model. Capital adequacy contagion effect of BANK_22 on BANK_32.

As shown in Figure 4.11, if BANK_22 fails, the CAR of the BANK_32 becomes -2.06, which indicates that the BANK_32 is highly dependent on the existence of the BANK_22.

Multiple Bank Failures

If more than one bank is defaulted, the contagion will be faster and two or more defaulted banks together may affect the condition of the neighbor bank. For this example, BANK_22 and BANK_4 have been considered as defaulted banks on November of 2010. Their distance vectors have been extracted separately in two partitions. These two partitions are unified under one partition by taking the minimum of the two partitions. By this way, BANK_22 and BANK_4 are in the first lag of diffusion. Again, the lines among neighbors have been omitted to transform line values to vectors accurately. Figure 4.12 shows the resulting subgroups.

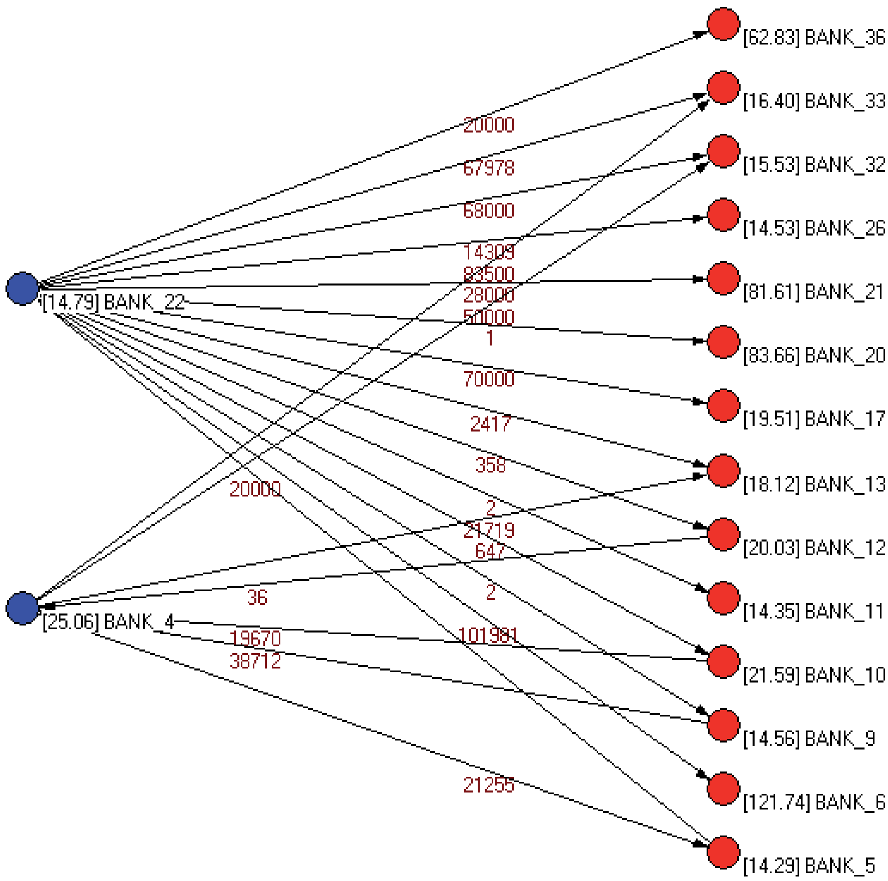


Figure 4.12. Network views of egocentric examples for capital adequacy model. Capital adequacy contagion starts with two banks, BANK_22 and BANK_4.

New CARs have been calculated by using vector operations on incoming line values as in the idiosyncratic example. The CAR of the two banks have been set to 0 and then the banks have been divided into two groups according to the CAR threshold of 12 as before. Figure 4.13 shows the network after this grouping.

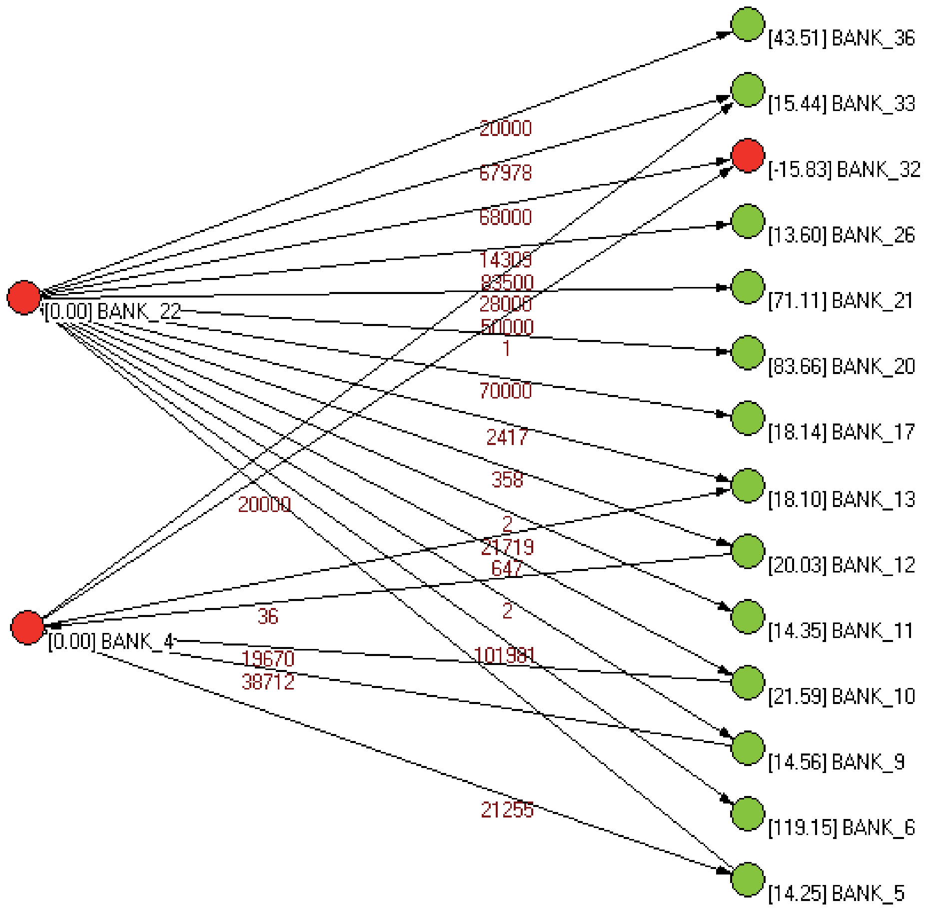


Figure 4.13. Network views of egocentric examples for capital adequacy model. Capital adequacy contagion effect of BANK_22 and BANK_4 on BANK_32.

As shown in Figure 4.13, when BANK_22 and BANK_4 fails, the CAR of the BANK_32 becomes -15.83. Note that in the previous example when only BANK_22 fails, it was- 2.06. It can be said that BANK_32 is dependent on the existence of the BANK_22 and BANK_4 and BANK_32 is a fragile bank in terms of its capital adequacy.

Egocentric Case of Liquidity

<u>Idiosyncratic Shock</u>

According to the data on November 2010, BANK_5 has been selected to demonstrate the contagion effect in terms of weekly liquidity ratio (LIQ7). Liquidity networks are directed since debit and credit balances are joined to recalculate liquidity ratios individually. BANK_5 has been assumed as defaulted, which means it is not able to fulfill its liabilities towards other banks. A partition which extracts BANK_5 and its nearest neighbors has been created by using k-neighbors function and selecting vertex Bank_5 and maximum distance 1. Figure 4.14 shows the result of this step.

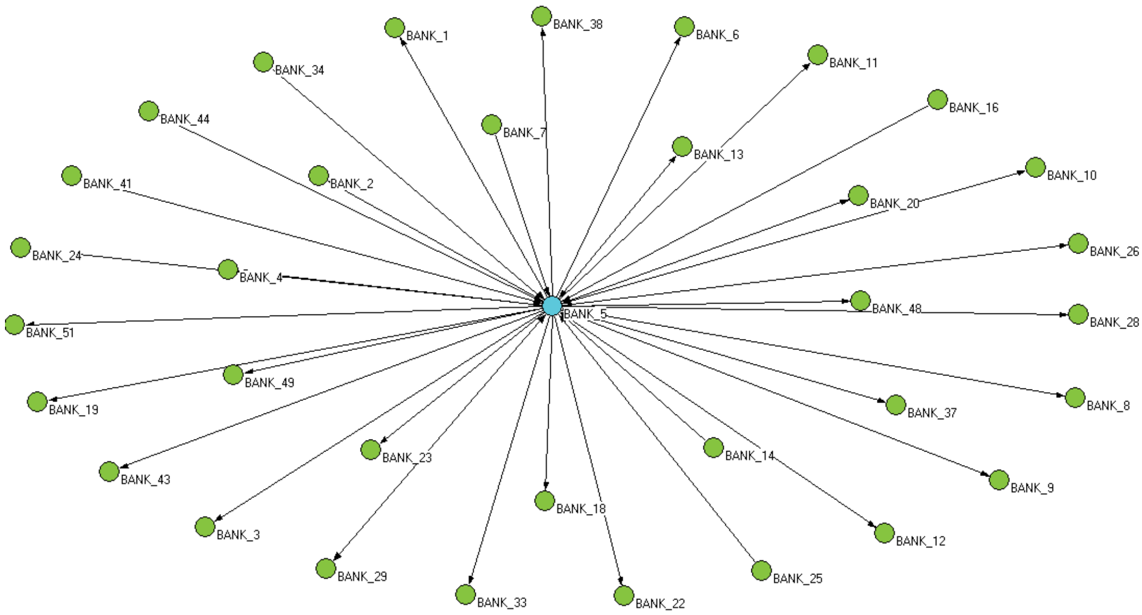


Figure 4.14. Network views of egocentric examples for liquidity model. Liquidity contagion effect starts with BANK_5.

New LIQ7 values has then been calculated according to Equation 5 as explained previously. In Pajek, these calculations are applied using vector operations. After this, the LIQ7 of BANK_5 has been set to 0. Newly calculated LIQ7 values have been transformed to partitions using 100 as the threshold, so that the banks with LIQ7 values less than 100 form group 1, and greater or equal to 100 form group 2. Figure 4.15 shows the network after these grouping.

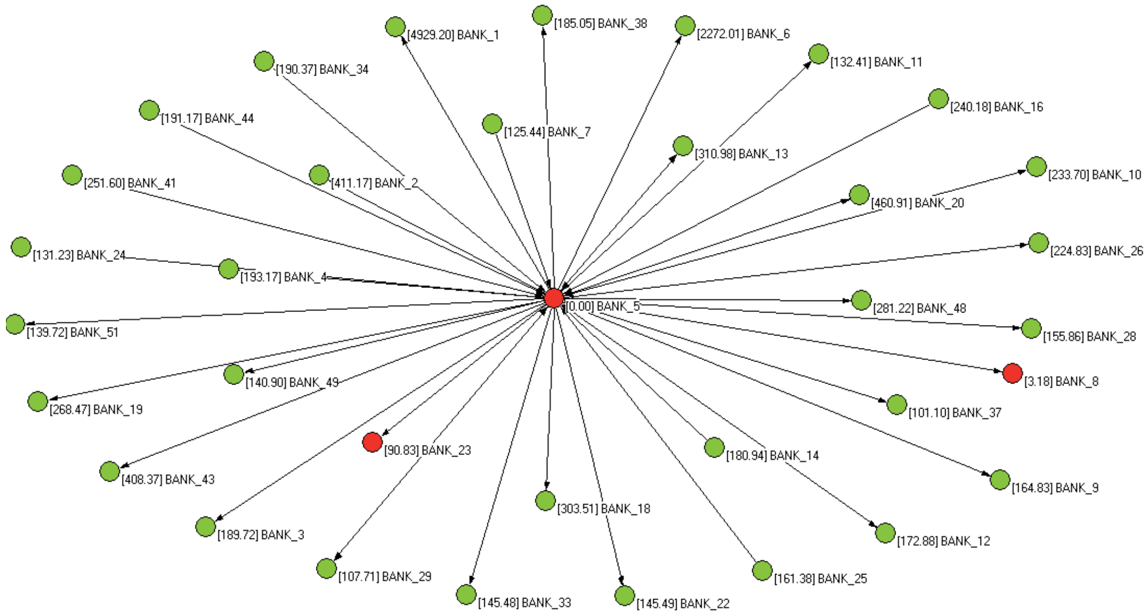


Figure 4.15. Network views of egocentric examples for liquidity model. Liquidity contagion effect of BANK_5 on BANK_8 and BANK_23.

As shown in Figure 4.15, if BANK_5 fails, the LIQ7 of the BANK_8 becomes 3.18, and LIQ7 of the BANK_23 becomes 90.83, which indicates liquidity of BANK_8 is highly dependent on the existence of the BANK_5 whereas liquidity of BANK_23 is not so much.

<u>Multiple Bank Failures after First Level of Contagion</u>

In the second level of the contagion, BANK_8 and BANK_23 have been assumed as defaulted on November of 2010, since the condition of BANK_5 affects the liquidity of these banks in the first level of contagion. Distance partitions of BANK_8 and BANK_23 are calculated separately. These two partitions are then unified under one partition by taking the minimum of the two partitions. Since the contagion continues at the second level, BANK_5 has relations with the neighbor banks of BANK_8 and BANK_23, these relations are included for the calculation of new LIQ7 values. Instead of updated values from the first level of the contagion, the LIQ7 values are recalculated under the assumption of failures of BANK_5, BANK_8 and BANK_23. Figure 4.16 shows the network after this step.

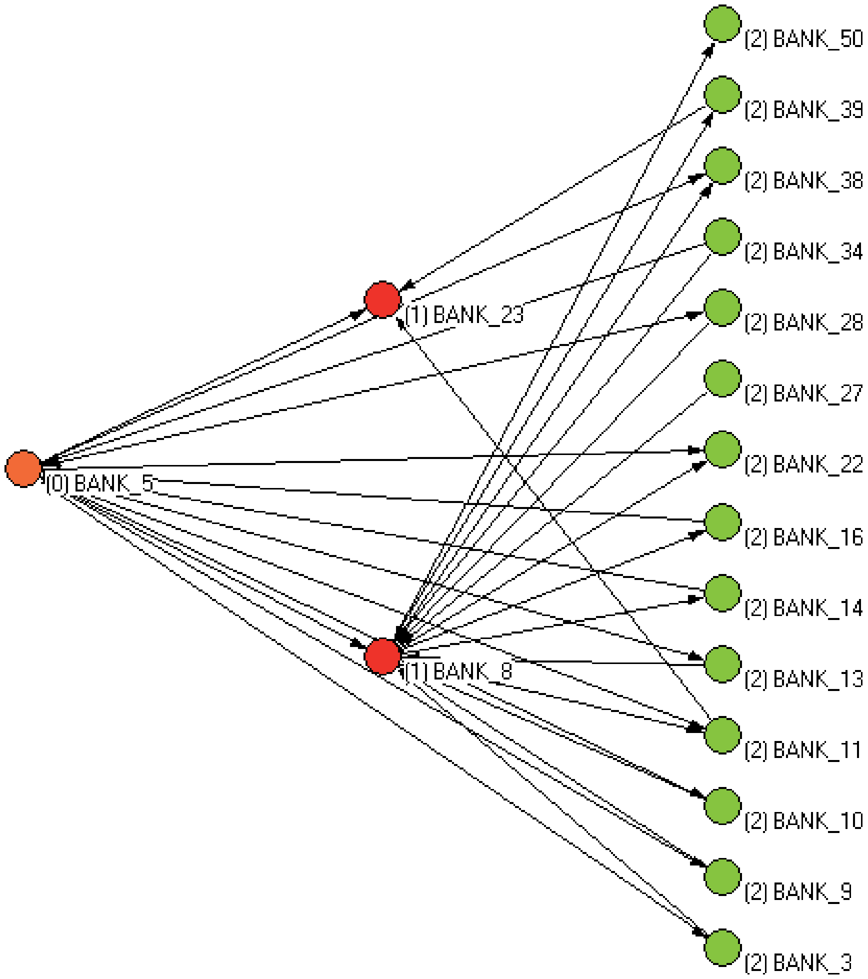


Figure 4.16. Network views of egocentric examples for liquidity model. Liquidity contagion starts with failure of BANK_5 and continues with failures of BANK_8 and BANK_23.

New LIQ7 values are calculated by using Equation 5. The LIQ7 of the banks in the first two levels of the contagion are set to 0, and the banks are divided into two groups according to the threshold of 100 on their LIQ7 values, as explained before. Figure 4.17 shows the network after this step.

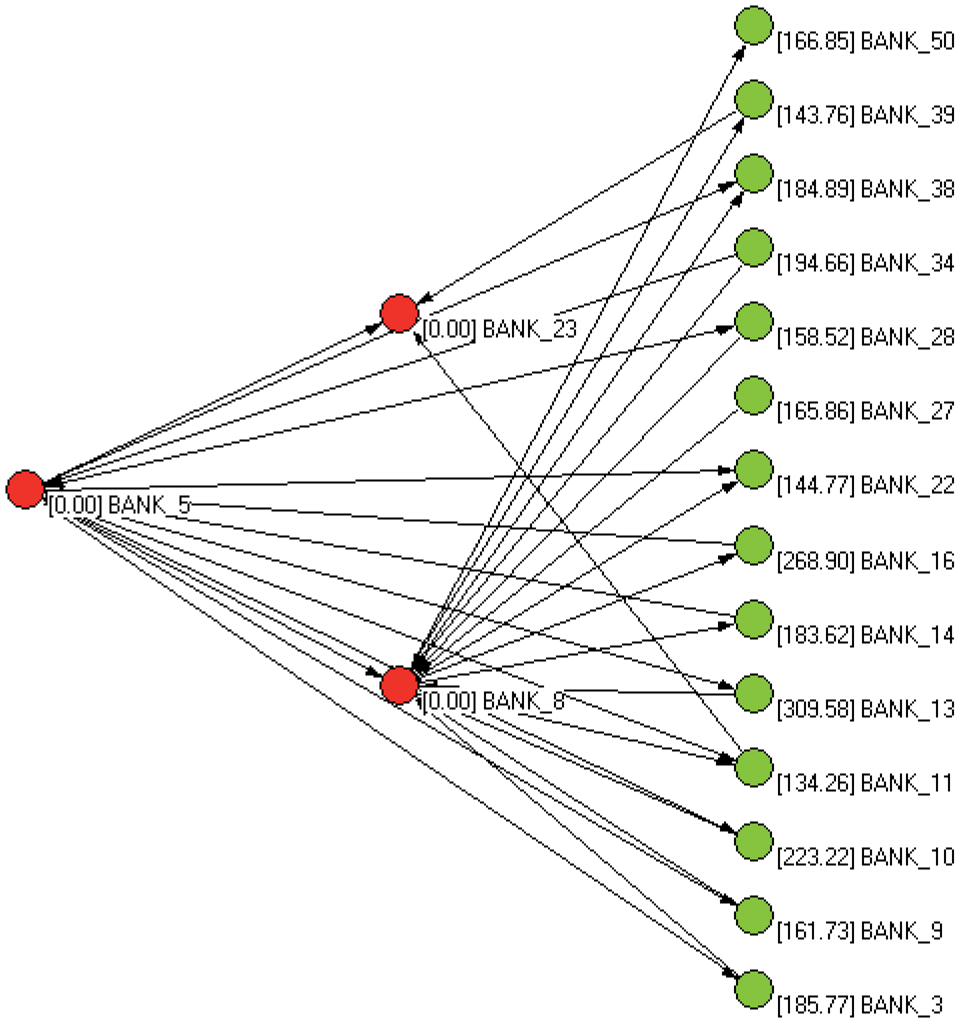


Figure 4.17. Network views of egocentric examples for liquidity model. Liquidity contagion effect of BANK_5 ends with failures of BANK_8 and BANK_23.

From this example, it can be seen that if BANK_5 fails, the LIQ7 of the BANK_8 and BANK_23 becomes insufficient and these three banks provide the condition of failure. However, the failure of these three banks does not affect the liquidity of other banks. Therefore, the contagion stops with the failures of BANK_8 and BANK_23.

4.4 Generalization of the Contagion Effect Model

The study in this thesis is conducted on 70 monthly periods and 51 banks. In each month contagion may begin with a failure of one bank or with failures of bank groups. For both starts, failures change the conditions of banks, which are neighbors of the starting banks or bank groups. These neighbors are specified by the distance vector. Distances, 0 to 50, are treated as lags in diffusion. Explained calculations for CAR, LIQ7 and LIQ31 should be repeated for all months, for all starts and for all lags. In order to facilitate the repetition of calculations, macros have been recorded. For each month, two macros have been used. The first one is for the capital adequacy ratio and the second one is for the liquidity ratio. Macros are repeated if there is an increase in the number of defaulted banks after shocks, which means the contagion effect continues, otherwise, it stops.

4.4.1. Detailed Steps of Contagion based on Capital Adequacy Ratio

Initial macro starts with an initial partition in which the defaulted banks are coded as 0 and the other banks are coded as 1. The vectors in the equation of CAR (equation 1), i.e., the equity and risk weighted assets, are also given to Pajek in the beginning. Detailed steps of the initial macro are listed below according to the Pajek 4.01 version:

1. First of all, the network which includes the relations of debits and credits of a period is given to the Pajek. The initial partition and vectors of equity and risk weighted assets are also input.
2. Network + Partition>Shrink Network: Minimum #of lines between cluster →1 and Cluster that will not be shrunk →1. Network: Initial network for one month and Partition: Initial partition. Purpose: To shrink vertices of defaulted banks.
3. Network>Create Partition>k-Neighbors>Output: Selected vertex→1 Maximum Distance (0: No limit) →1 Network: Shrinking network. Purpose: To detect the closest neighbors of defaulted bank(s) via distances.

A change may be required to the Pajek settings, which is done only once. Purpose: To set distances of vertices which are not connected to defaulted banks, from 999999998, to 51. Since there are 51 vertices, max distance can be 50. This conversion prevents the errors coming out due to missing value number, 999999998.

4. Partition>Copy to Vector: Partition: Distance to output neighbors of defaulted bank(s).

5. Partition>Copy to Vector: Partition: Shrinking partition after second step.

6. Vector>Transform>Add constant: Add constant→50. Vector: Shrinking vector after 5th step

7. Vectors>Min (First, Second): First vector: Distance to output neighbors of defaulted bank(s). Second vector: Vector created by 6th step.

8. Vector>Make Partition>Copy to Partition by Truncating (Abs)

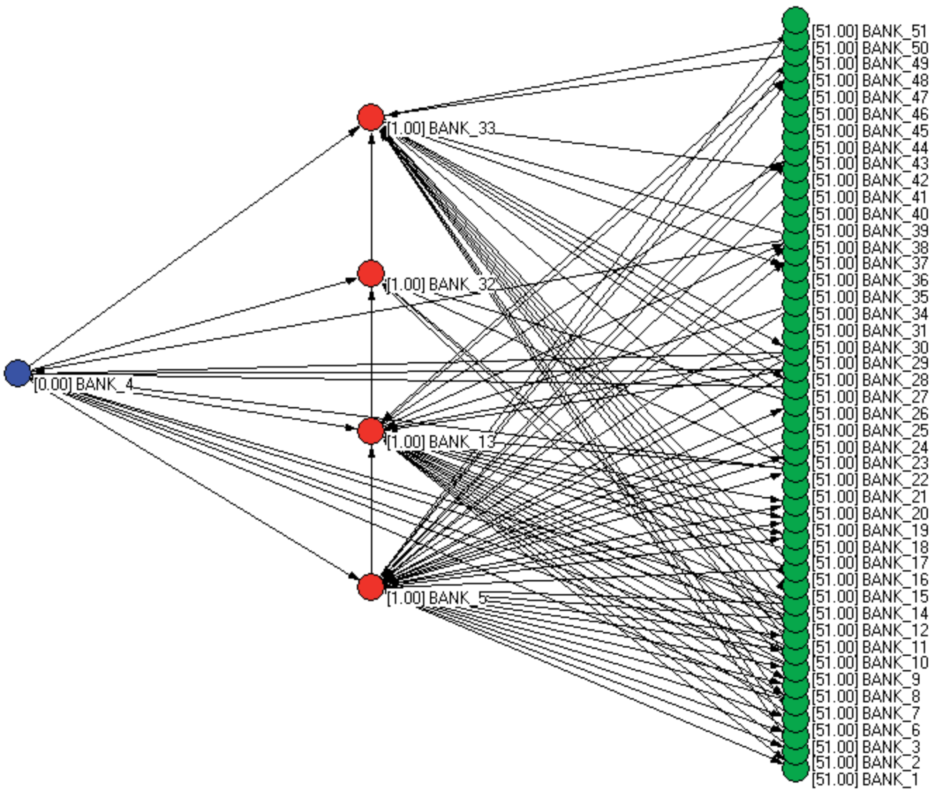


Figure 4.18. Views from steps of capital adequacy contagion. View after 8th step, defaulted bank is BANK_4.

9. Vector + Partition>Shrink Vector>Sum: Cluster that will not be shrunk →1. Vector: Equity and Partition: Initial partition. Purpose: To extract equities of banks related to the defaulted bank(s).

10. Vector + Partition>Shrink Vector>Sum: Cluster that will not be shrunk →1. Vector: Risk Weighted Assets and Partition: Initial partition. Purpose: To extract risk weighted assets of banks related to defaulted bank(s).

Purpose: To calculate the ratios of closest neighbors accurately due to incoming line values.

11. Network + Partition>Transform>Direction>Lower to Higher: Delete lines within clusters → Yes. Network: Network of defaulted bank(s) with related output neighbors and Partition: Distance to output neighbors of defaulted bank(s).

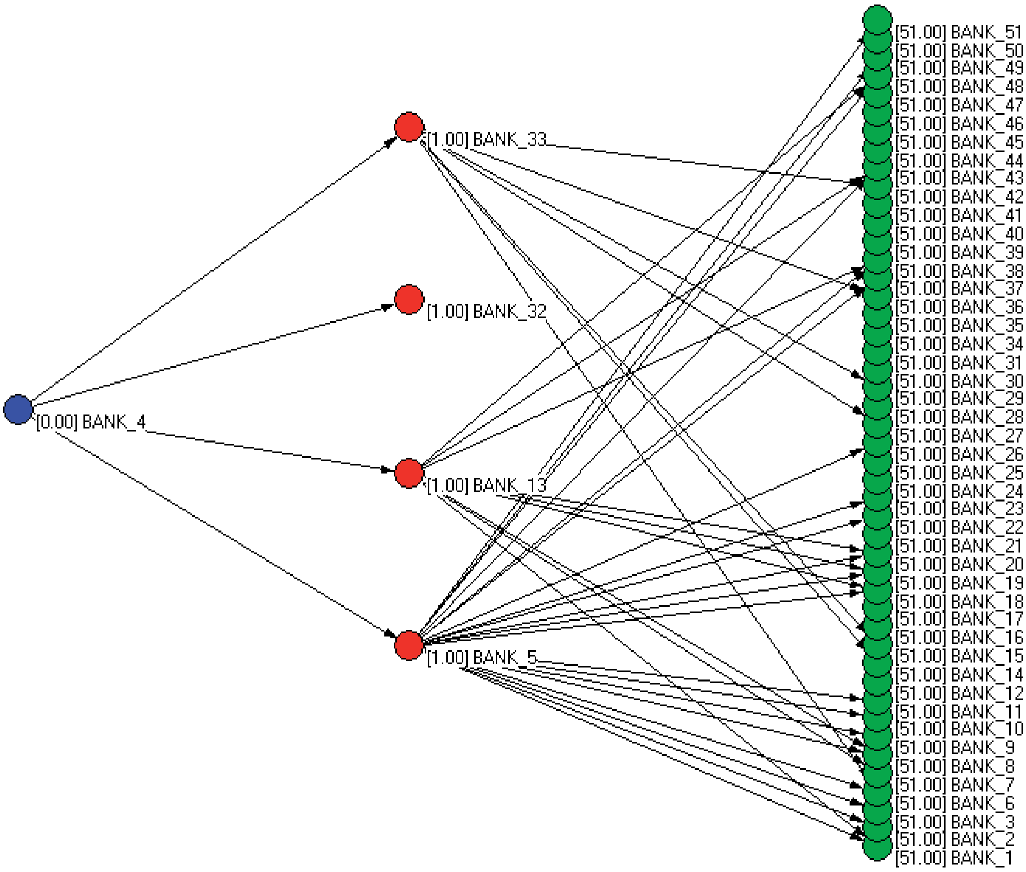


Figure 4.19. Views from steps of capital adequacy contagion. View after 11th step.

Purpose: To set the effects of banks which are not the closest banks (distance is larger than 1) to the defaulted banks to zero.

12. Partition>Binarize Partition: Select clusters→0-1 Partition: Distance to output neighbors of defaulted bank(s).

13. Partition>Copy to Vector: Partition: Partition from 12th step.

Purpose: To recalculate CAR according to equation 1.

14. Network>Create Vector>Centrality>Weighted Degree>Input: Network: Network of defaulted bank(s) with related output neighbors. Purpose: To convert incoming line values which are net amount of money flow into vector.

15. Vectors>Multiply (First*Second): First Vector: Net amount of money flow coming from 14th step. Second vector: Vector after 13th step.

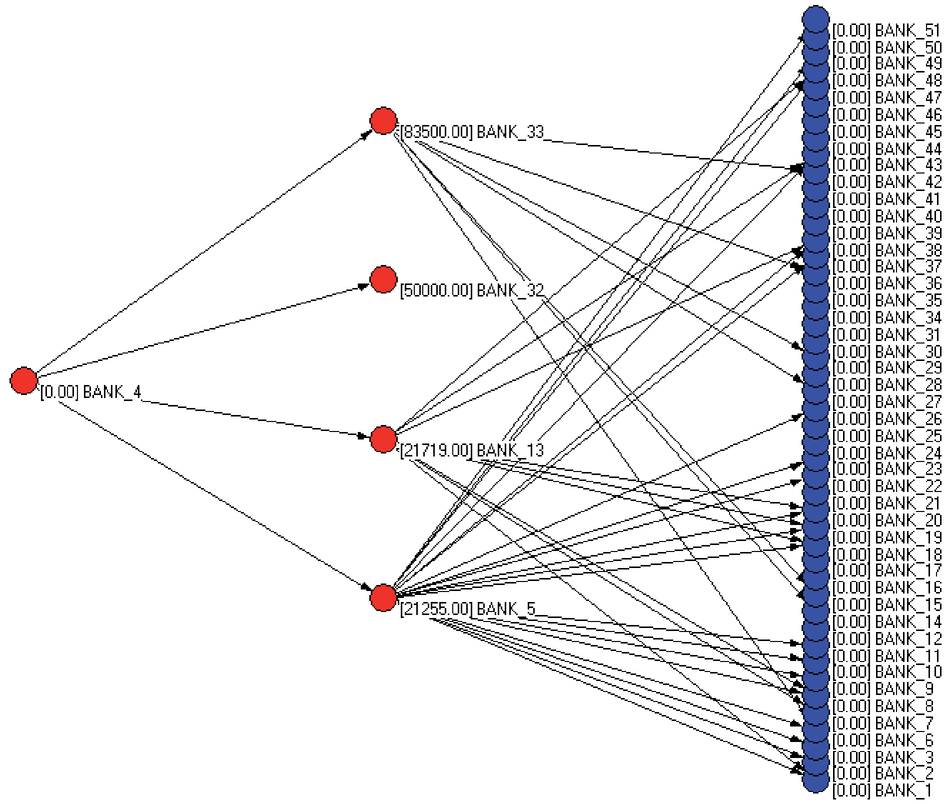


Figure 4.20. Views from steps of capital adequacy contagion. View after 15th Step. Vector values are the net amount of money flow from defaulted BANK_4 to its neighbors.

16. Vector>Transform>Multiply by: Multiply by →0.2. Vector: Vector after 15th step.

17. Vectors>Subtract (First-Second): First Vector: Shrunk equity vector in 9th step. Second vector: Vector after 15th step which is the net money flow of defaulted bank(s) to the closest banks.

18. Vectors>Subtract (First-Second): First Vector: Shrunk risk weighted assets vector in 10th step. Second vector: Vector after 16th step

19. Vectors>Divide (First/Second): First Vector: Vector after 17th step. Second vector: Vector after 18th step.

20. Vector>Transform>Multiply by: Multiply by →100. Vector: Vector after 19th step.

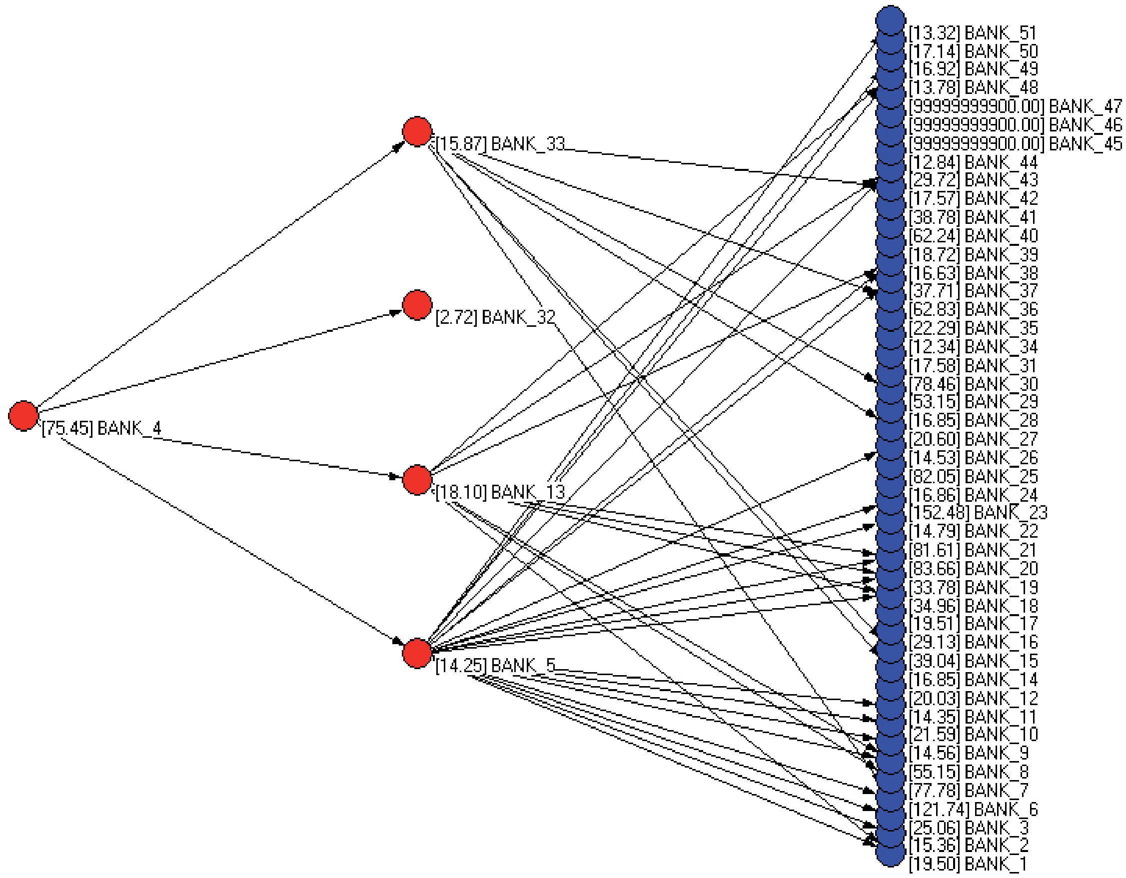


Figure 4.21. Views from steps of capital adequacy contagion. View after 20th step. Vector values represent recalculated capital adequacy ratios.

<u>Purpose:</u> To set CAR of defaulted bank(s) to zero.

21. Vectors>Multiply (First*Second): First Vector: Vector after 20th step. Second vector: Shrinking vector after 5th step.

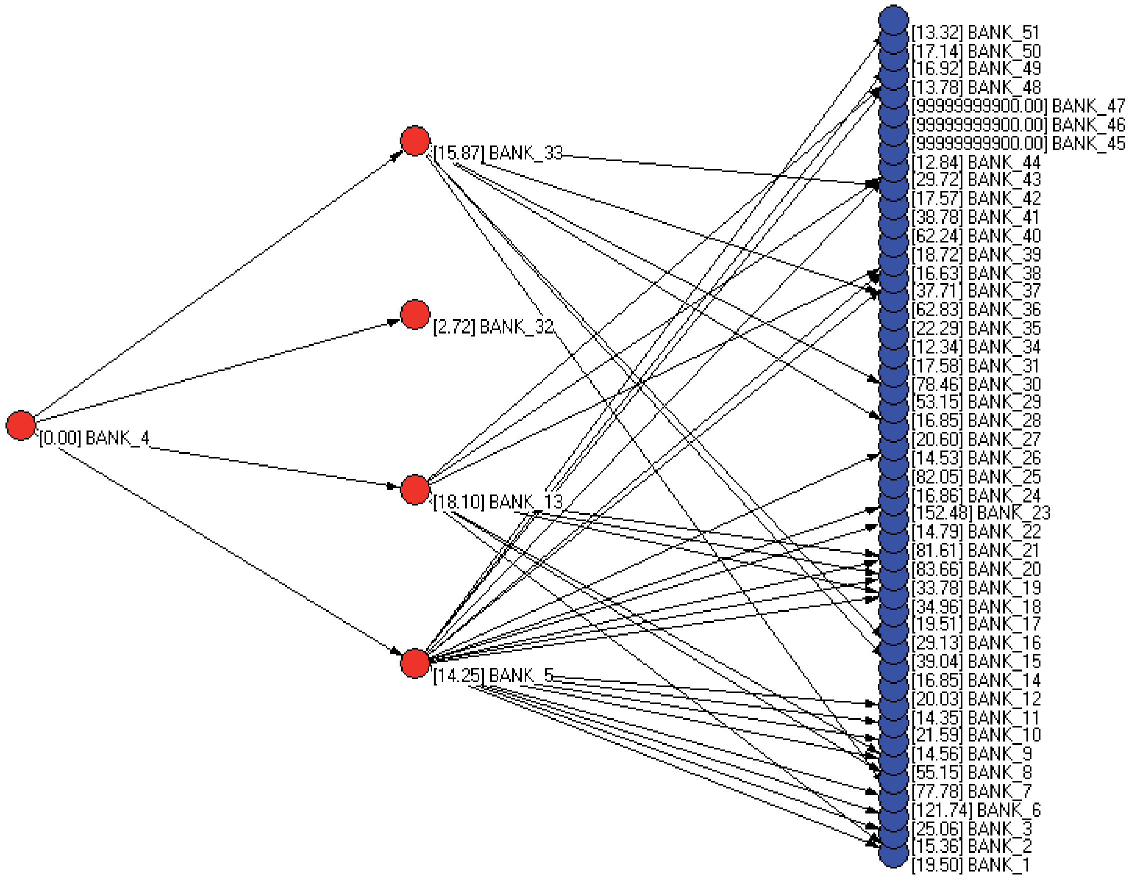


Figure 4.22. Views from steps of capital adequacy contagion. View after 21th step. The CAR of defaulted bank (BANK_4) is set to zero.

Purpose: To recreate the partition of defaulted banks according to recalculated CAR.

22. Vector>Make Partition>by Intervals>Selected Thresholds: Dividing values or #Clusters→12. Vector: Vector after 21th step which is recalculated CAR.

23. Partition>Copy to Vector: Partition: Partition from 22th step.

24. Vector>Transform>Add constant: Add constant→-1.

25. Vector>Make Partition>Copy to Partition by Truncating (Abs)

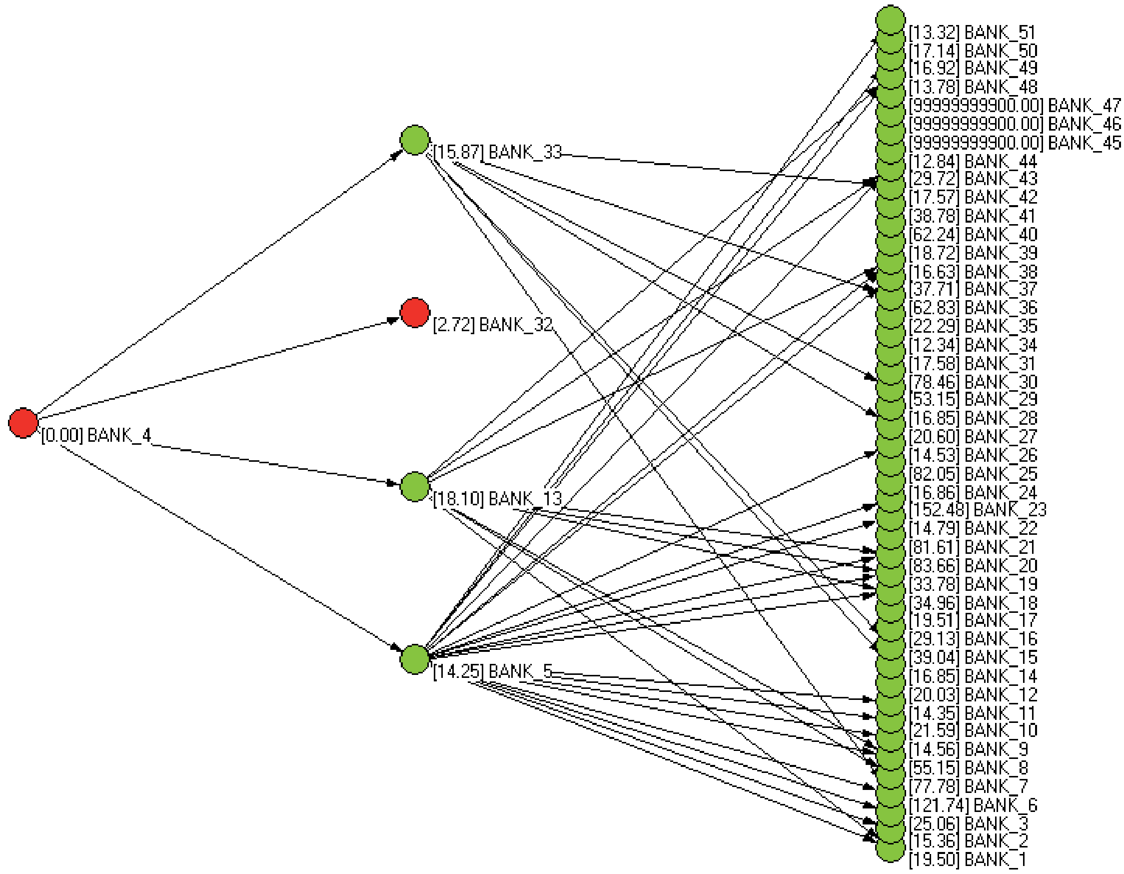


Figure 4.23. Views from steps of capital adequacy contagion. View after 25th step. The defaulted banks are displayed in red color.

Purpose: To expand shrinking partitions and vectors.

26. Partitions>Expand Partition>First according to Second (Shrink): Cluster that will not be shrunk →1. First partition: Partition from 25th step which marks defaulted banks as 0. Second partition: Initial partition which was shrunk with 2nd step.

27. Vector>Make Partition>Copy to Partition by Truncating (Abs): Vector: Vector after 21th step which is recalculated CAR.

28. Partitions>Expand Partition>First according to Second (Shrink): Cluster that will not be shrunk →1. First partition: Partition from 27th step which includes new CAR values. Second partition: Initial partition which was shrunk with 2nd step.

29. Partition>Copy to Vector: Partition: Partition from 28th step.

Purpose: To save the partition which indicates the defaulted banks and recalculated CAR values.

30. In last two steps, macro saves the partition which marks defaulted banks as 0 after 26^{th} step and the vector which includes new CAR values after 29^{th} step.

If there is not any defaulted bank after the performance of macro, the contagion stops. This Macro is presented in Appendix B.

4.4.2 Steps of Liquidity Ratio

Initial macro starts with an initial partition in which the defaulted banks are coded as 0 and the other banks are coded as 1. The vectors in the equation of liquidity ratios (equation 5), total assets and total liabilities, are also given to Pajek in the beginning. Steps of the initial macro are listed below:

1. First of all, the network which includes the relations of debits and credits of a period is given to the Pajek. The initial partition and vectors of total assets and total liabilities are also put in.

2. Network + Partition>Shrink Network: Minimum #of lines between cluster →1 and Cluster that will not be shrunk →1. Network: Initial network for one month and Partition: Initial partition. Purpose: To shrink vertices of defaulted banks.

3. Network>Create Partition>k-Neighbors>Output: Selected vertex→1 Maximum Distance (0: No limit) →1 Network: Shrinking network. Purpose: To detect the closest neighbors of defaulted bank(s) via distances.

A change may be required to the Pajek settings, which is done only once. Purpose: To set distances of vertices which are not connected to defaulted banks, from 999999998 to 51. Since there are 51 vertices, max distance can be 50. This conversion prevents the errors coming out due to missing value number, 999999998.

4. Partition>Copy to Vector: Partition: Distance to output neighbors of defaulted bank(s).

5. Partition>Copy to Vector: Partition: Shrinking partition after second step.

6. Vector>Transform>Add constant: Add constant→50. Vector: Shrinking vector after 5^{th} step

7. Vectors>Min (First, Second): First vector: Distance to output neighbors of defaulted bank(s). Second vector: Vector created by 6^{th} step.

8. Vector>Make Partition>Copy to Partition by Truncating (Abs)

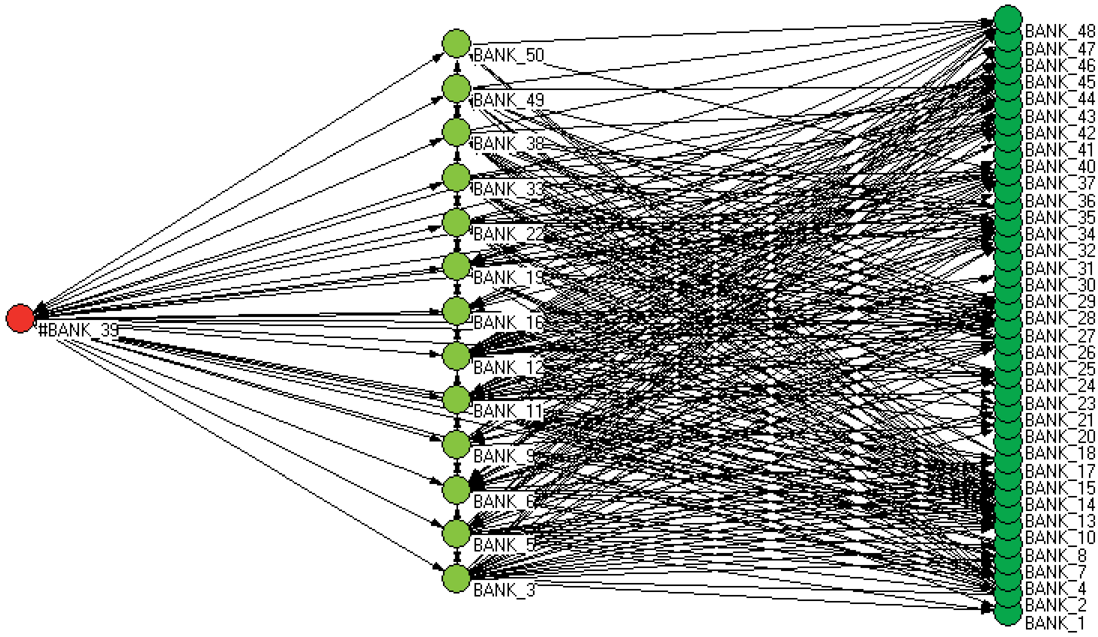


Figure 4.24. Views from steps of liquidity contagion. View after 8th step, defaulted bank is BANK_39.

9. Vector + Partition>Shrink Vector>Sum: Cluster that will not be shrunk →1. Vector: Total assets and Partition: Initial partition. Purpose: To extract equities of banks related to defaulted bank(s).

10. Vector + Partition>Shrink Vector>Sum: Cluster that will not be shrunk →1. Vector: Total liabilities and Partition: Initial partition. Purpose: To extract risk weighted assets of banks related with defaulted bank(s).

Purpose: To set the effects of banks which are not the closest banks (distance is larger than 1) to the defaulted banks to zero.

11. Network + Partition>Transform>Remove Lines>Inside Clusters: Select Clusters → [0-*]. Network: Network of defaulted bank(s) with related output neighbors and Partition: Distance to output neighbors of defaulted bank(s).

12. Partition>Binarize Partition: Select clusters→0-1 Partition: Distance to output neighbors of defaulted bank(s).

13. Partition>Copy to Vector: Partition: Partition from 11th step.

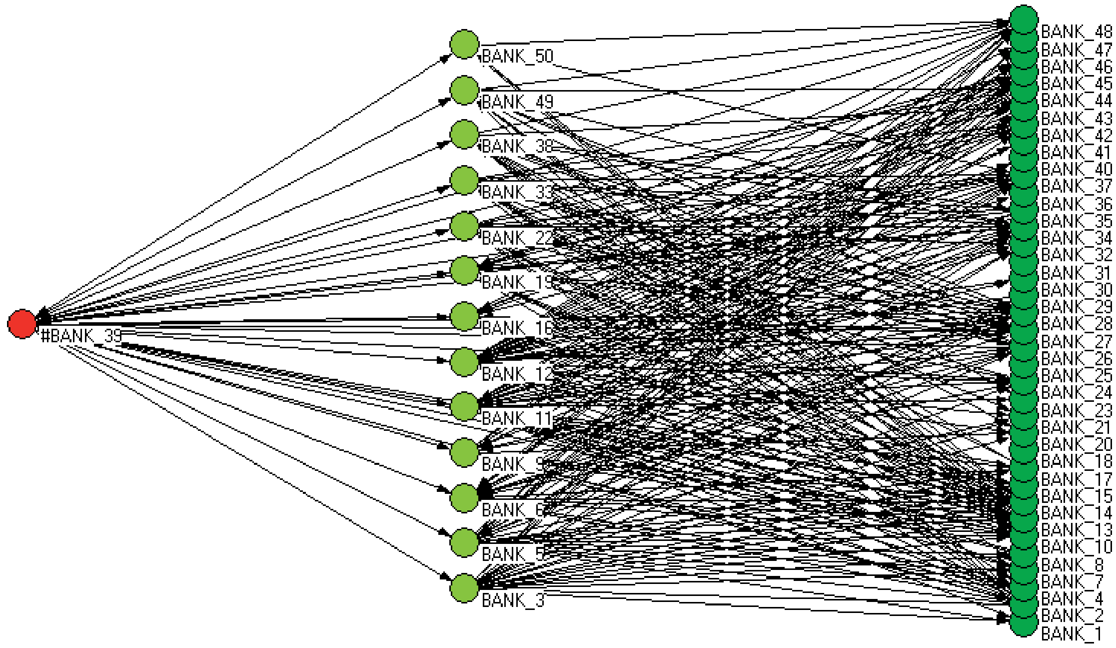


Figure 4.25. Views from steps of liquidity contagion. View after 13th step.

Purpose: To calculate the ratios of closest neighbors accurately due to incoming and outgoing line values.

14. Network + Partition>Transform>Direction>Lower to Higher: Delete lines within clusters → Yes. Network: Network of defaulted bank(s) with related output neighbors after 11th step and Partition: Distance to output neighbors of defaulted bank(s).

15. Network>Create Vector>Centrality>Weighted Degree>Input: Network: Network of defaulted bank(s) with related output neighbors after 14th step. Purpose: To convert incoming line values into vector.

16. Vectors>Multiply (First*Second): First Vector: Incoming amount of money flow coming from 15th step. Second vector: Vector after 13th step.

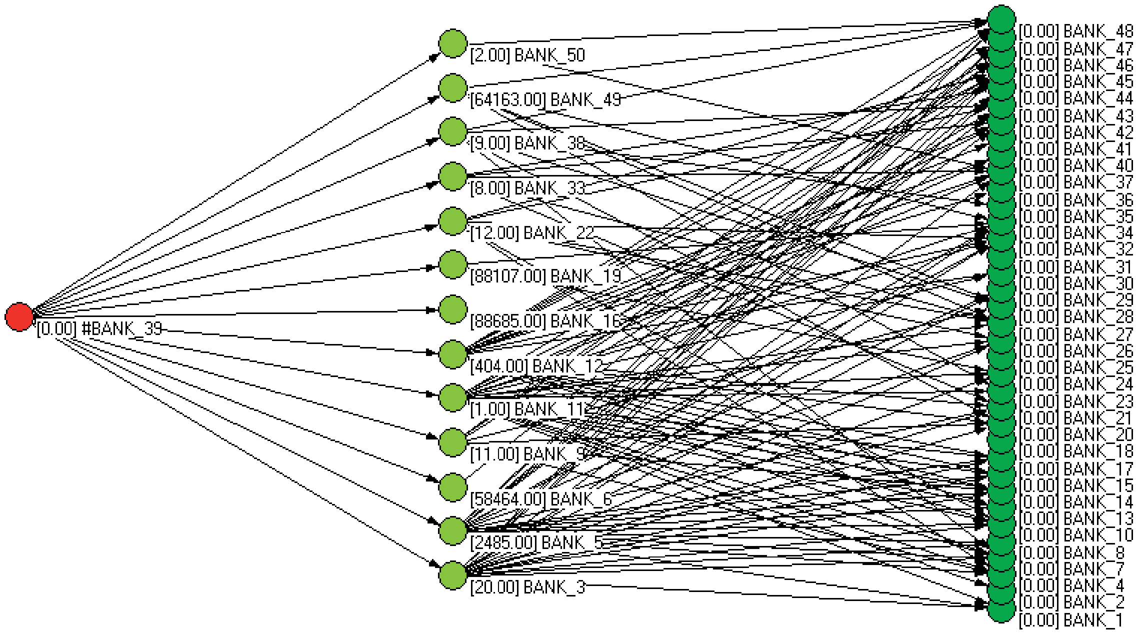


Figure 4.26. Views from steps of liquidity contagion. View after 16th step.

17. Network + Partition>Transform>Direction>Higher to Lower: Delete lines within clusters → Yes. Network: Network: Network of defaulted bank(s) with related output neighbors after 11th step and Partition: Distance to output neighbors of defaulted bank(s).

18. Network>Create Vector>Centrality>Weighted Degree>Output: Network: Network of defaulted bank(s) with related output neighbors after 17th step. Purpose: To convert outgoing line values into vector.

19. Vectors>Multiply (First*Second): First Vector: Outgoing amount of money flow coming from 18th step. Second vector: Vector after 13th step.

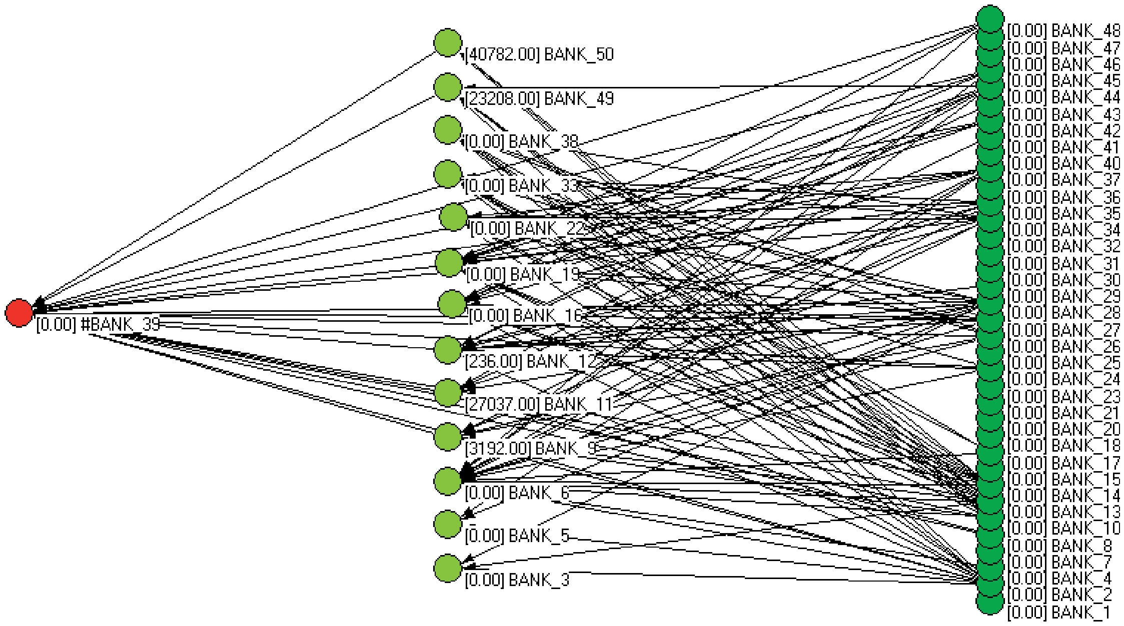


Figure 4.27. Views from steps of liquidity contagion. View after 19th step.

Purpose: To recalculate liquidity ratios according to Equation 5.

20. Vectors>Subtract (First-Second): First Vector: Shrunk equity vector in 9th step. Second vector: Vector after 16th step which is the incoming money flow of defaulted bank(s) to the closest banks.

21. Vectors>Subtract (First-Second): First Vector: Shrunk risk weighted assets vector in 10th step. Second vector: Vector after 19th step which is the outgoing money flow of neighbor bank(s) to defaulted banks.

22. Vectors>Divide (First/Second): First Vector: Vector after 20th step. Second vector: Vector after 21st step.

23. Vector>Transform>Multiply by: Multiply by →100. Vector: Vector after 22nd step.

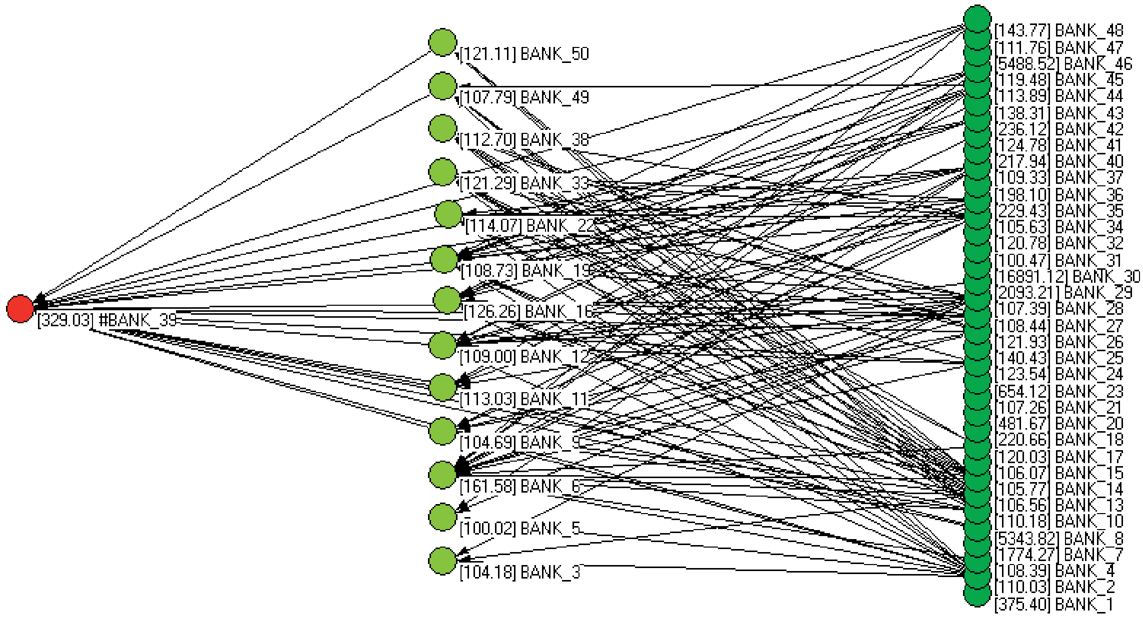


Figure 4.28. Views from steps of liquidity contagion. View after 23th step. Vector values represent recalculated liquidity ratios.

<u>Purpose:</u> To set Liquidity ratios of defaulted bank(s) to zero.

24. Vectors>Multiply (First*Second): First Vector: Vector after 23rd step. Second vector: Shrinking vector after 5th step.

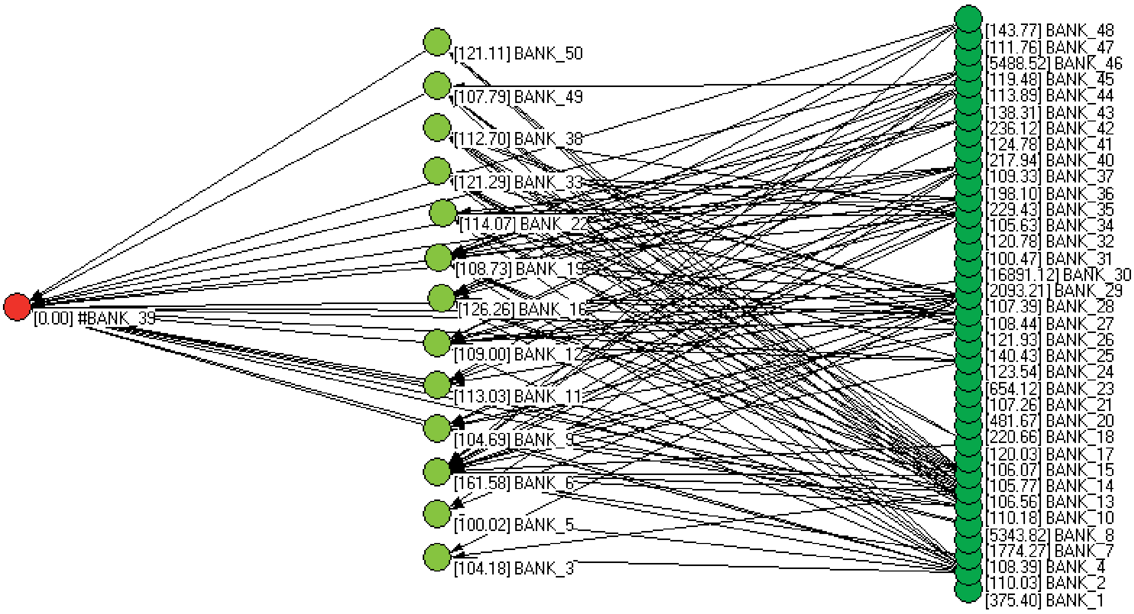


Figure 4.29. Views from steps of liquidity contagion. View after 24th step. The liquidity ratio of defaulted bank (BANK_39) is set to zero.

<u>Purpose:</u> To recreate the partition of defaulted banks according to recalculated CAR.

25. Vector>Make Partition>by Intervals>Selected Thresholds: Dividing values or #Clusters→100. Vector: Vector after 24th step which is recalculated liquidity ratio.
26. Partition>Copy to Vector: Partition: Partition from 25th step.
27. Vector>Transform>Add constant: Add constant→-1.
28. Vector>Make Partition>Copy to Partition by Truncating (Abs)

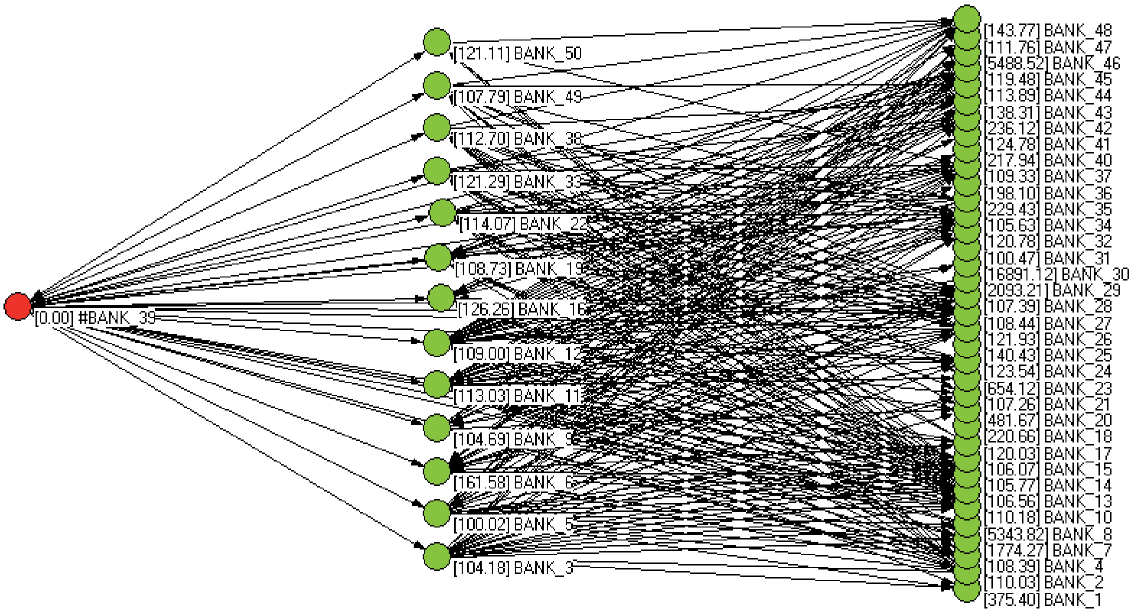


Figure 4.30. Views from steps of liquidity contagion. View after 28th step. The defaulted banks are displayed in red color.

Purpose: To expand shrinking partitions and vectors.

29. Partitions>Expand Partition>First according to Second (Shrink): Cluster that will not be shrunk →1. First partition: Partition from 29th step which marks defaulted banks as 0. Second partition: Initial partition which was shrunk with 2nd step.

30. Vector>Make Partition>Copy to Partition by Truncating (Abs): Vector: Vector after 24th step which is recalculated liquidity ratio.

31. Partitions>Expand Partition>First according to Second (Shrink): Cluster that will not be shrunk →1. First partition: Partition from 30th step which includes new liquidity ratio values. Second partition: Initial partition which was shrunk with 2nd step.

32. Partition>Copy to Vector: Partition: Partition from 31st step.

Purpose: To save the partition which indicates the defaulted banks and recalculated CAR values.

33. In last two steps, macro saves the partition, which marks defaulted banks as 0 after 29th step and the vector which includes new liquidity ratio values after 32nd step.

If there is not any defaulted bank after the completion of this macro, the contagion stops. This Macro is presented in Appendix C.

CHAPTER 5

CONTAGION MODEL RESULTS

5.1 Simulation of Idiosyncratic Shock

In this section, the contagion starts with individual bank failures, which is named as idiosyncratic shocks. These individual bank failures may lead to zero or many bank failures. Since Pajek macro is adaptable for both individual and multiple bank failures, it is performed recursively for each month over the period January 2009 – October 2014. The results of idiosyncratic shocks are saved as partitions and vectors, which include the marks of new defaulted banks and newly ratios, respectively. According to the results, after four lags the number of defaulted banks does not change; therefore, the results span four lags in 70 periods and 51 banks which are assumed as defaulted initially. These results are converted to matrices and time series lines by R, which is an open source software for statistical computing and graphics. The overall results are presented in two subsections; for capital adequacy and liquidity ratios.

In real life, ratios of banks can be under the threshold values. For such cases, banks prepare reports to explain the reasons of not achieving the required ratios, and they present their solutions to increase the ratios. When their reports are insufficient, the banks receive a warning and punishment. Since in contagion models, banks with ratios under the thresholds are assumed as defaulted, when their real ratios are under the thresholds, for model continuity their ratios are raised to the exact thresholds by increasing their assets and equities.

5.1.1. Contagion for Capital Adequacy Ratio

Contagion model for capital adequacy is applied to the data which is explained in section 3.1. First of all, equity capital and risk weighted assets are stored as vectors for each period separately. Calculations according to the Equation 4 are conducted on the data by repeating the Pajek macro explained in Section 4.4.1. Results are presented under two aspects; how failure of a bank affects other banks, i.e., effectiveness, and how a bank is affected from failures of other banks, i.e., fragility.

According to results, the total number of defaulted banks when status of a bank turns to defaulted over the period January 2009-October 2014 is presented in Table 5.1 and Figure 5.1.

Table 5.1 – Capital adequacy contagion model: Descriptive statistics of total number of defaulted banks as a result of an individual bank failure

January 2009 - October 2014

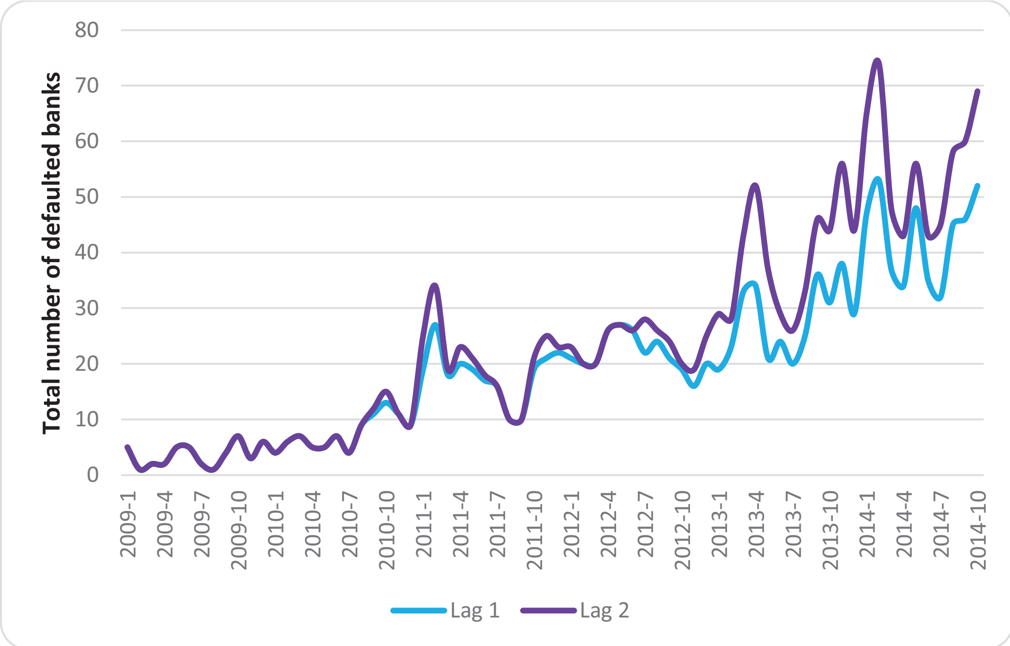
Lags	Mean	Min	Max	Median	Std. Dev.
Lag 1	19,657	1	53	19,5	13,44
Lag 2	24,200	1	74	22	18,62
Lag 3	24,714	1	75	22	19,15
Lag 4	24,729	1	75	22	19,18

January 2011 - October 2014

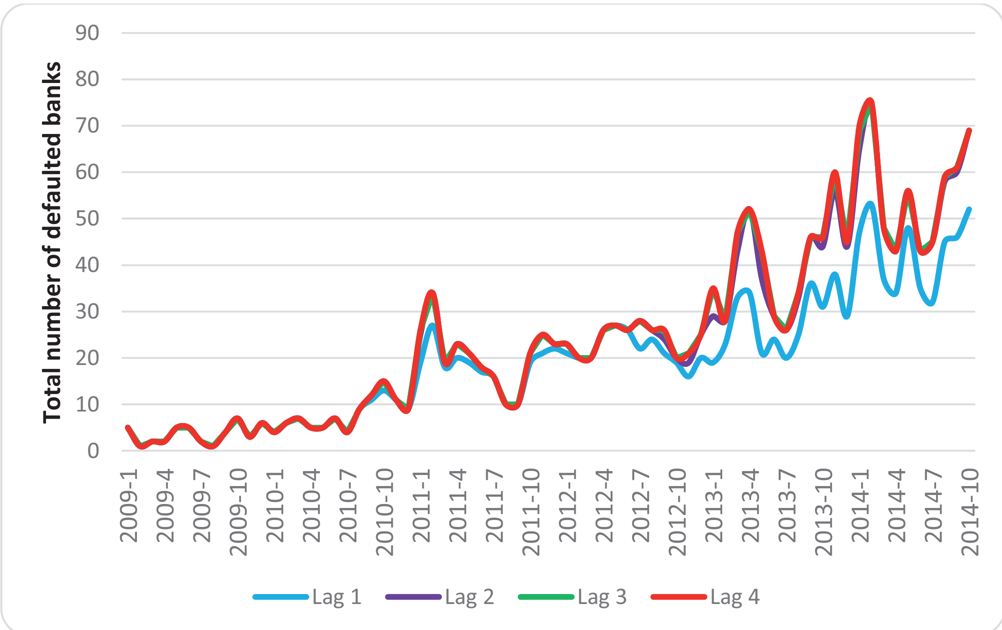
Lags	Mean	Min	Max	Median	Std. Dev.
Lag 1	27,000	10	53	23,5	10,60
Lag 2	33,848	10	74	27,5	15,80
Lag 3	34,630	10	75	27,5	16,28
Lag 4	34,652	10	75	27,5	16,33

At the first lag, the contagion starts with one bank failure. On average over the period January 2009 - October 2014, when a bank is defaulted, about 20 banks in total are affected from this failure and their CAR values decrease under threshold 12. This average number rises to 27 for monthly periods in 2011-2014 with a range between 10 and 53.

Contagion in the second lag, starts with failed banks in the first lag. After fourth lag, total number of defaulted banks reaches to its maximum. After 4th lag, total number of defaulted banks as a result of an individual bank failure ranges between 1 and 75 with the mean approximately 25, whereas its range is between 10 and 75 with an average about 35 in the period of 2011-2014.



a)



b)

Figure 5.1. Capital adequacy contagion model: Total number of defaulted banks as a result of an individual bank failure over the period January 2009 – October 2014.

The effects of the global crisis in 2008 is also observable in the contagion results. Since the total money flow among banks is getting its minimum values for the crisis period in Turkey, total number of defaulted banks after contagion gets its minimum ranges. After the crisis period, there is an increasing trend as total amount of money flow among banks and connectedness increase.

5.1.1.1 Effectiveness of banks considering capital adequacy contagion model

In this study, effectiveness of a bank is measured as the number of banks which fails when this bank is defaulted.

Table 5.2 – Capital adequacy contagion model: Number of defaulted banks when banks in the matrix failed at the first lag. Matrix is presented for the 20 banks with largest average number of defaulted banks after idiosyncratic shocks in the period January 2009 – October 2014 at the first lag

	BANK_2	BANK_13	BANK_5	BANK_12	BANK_10	BANK_14	BANK_3	BANK_37	BANK_44	BANK_11	BANK_48	BANK_50	BANK_9	BANK_38	BANK_28	BANK_51	BANK_39	BANK_27	BANK_4	BANK_22
2012-12	3	3	3	1	3	1	1	0	0	0	1	1	1	1	0	0	0	0	0	0
2013-1	1	4	3	2	1	1	0	1	0	0	1	1	1	1	1	0	0	0	0	0
2013-2	2	6	3	2	0	1	1	0	0	0	1	1	1	1	1	0	0	0	0	1
2013-3	3	6	5	3	1	1	2	1	0	1	1	1	3	1	0	0	0	0	0	0
2013-4	3	8	5	7	0	1	0	2	0	0	1	1	0	0	2	1	0	0	0	1
2013-5	1	6	3	2	1	0	1	2	1	0	1	1	0	0	0	1	0	0	0	0
2013-6	2	6	7	4	1	0	0	2	1	0	0	0	0	0	0	0	1	0	0	0
2013-7	6	5	4	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-8	5	7	4	0	0	1	0	3	1	0	0	0	0	0	2	0	0	0	0	0
2013-9	7	6	2	6	1	1	2	1	2	1	2	1	0	0	1	2	1	0	0	0
2013-10	7	4	3	2	1	1	1	3	1	1	2	1	1	0	0	2	0	0	1	0
2013-11	5	6	2	2	3	1	1	3	2	2	2	2	1	0	0	2	0	0	1	0
2013-12	4	5	5	1	0	1	1	3	3	1	2	2	0	0	0	1	0	0	0	0
2014-1	7	6	4	1	0	2	1	3	2	3	2	2	1	1	1	1	2	1	2	0
2014-2	7	4	7	2	3	0	2	3	2	3	2	3	1	1	1	1	2	2	0	0
2014-3	7	3	8	1	1	2	1	2	2	0	2	2	0	0	0	1	1	2	0	0
2014-4	5	3	5	3	0	2	3	2	1	1	2	2	0	0	0	1	1	2	0	0
2014-5	5	5	6	4	6	2	5	2	2	2	2	1	0	1	1	0	1	1	0	0
2014-6	6	6	3	3	0	2	4	2	1	1	2	2	0	0	0	0	2	1	0	0
2014-7	6	5	4	3	1	3	1	2	2	0	1	2	0	0	0	0	1	1	0	0
2014-8	7	5	5	3	1	3	4	1	2	3	2	2	0	1	1	0	1	1	1	1
2014-9	5	8	2	4	3	3	2	2	2	4	2	2	0	0	0	0	2	2	2	0
2014-10	6	10	6	6	0	2	3	1	3	3	2	2	1	1	0	0	1	1	0	1
Average 2009/01 - 2014/10	**3,2**	**3,1**	**2,5**	**1,7**	**1,4**	**1,2**	**0,9**	**0,7**	**0,5**	**0,5**	**0,5**	**0,5**	**0,4**	**0,4**	**0,3**	**0,3**	**0,3**	**0,2**	**0,2**	**0,2**

Table 5.2 is given for presenting the contagion results at the first lag. Each cell in the matrix, gives the number of defaulted banks after idiosyncratic shocks. For example, when BANK_2 is assumed as defaulted at the beginning, 6 banks become defaulted at first lag in 2014/10. Similarly, when BANK_13 is assumed as defaulted, status of

10 banks turn to default in 2014/10. Last row of the table demonstrates the average of the defaulted banks in 70 months for first lag. It is in the descending order in order to detect the most effective banks in the contagion. Only the results of periods after December 2012 are demonstrated.

Table 5.3 - Capital adequacy contagion model: Number of defaulted banks when banks in the matrix failed at the last lag. Matrix is presented for the 20 banks with largest average number of defaulted banks after idiosyncratic shocks in the period January 2009 – October 2014 at the last lag

	BANK_2	BANK_13	BANK_5	BANK_12	BANK_14	BANK_10	BANK_3	BANK_37	BANK_48	BANK_38	BANK_50	BANK_11	BANK_44	BANK_9	BANK_51	BANK_28	BANK_39	BANK_49	BANK_35	BANK_4
2012-12	3	3	3	1	2	3	2	0	1	3	1	0	0	2	0	0	0	1	0	0
2013-1	2	4	4	5	3	3	0	1	2	3	2	0	0	3	0	1	0	2	0	0
2013-2	2	7	3	3	2	0	1	0	1	2	1	0	0	2	0	1	0	1	0	0
2013-3	5	6	5	5	3	1	3	1	2	3	2	1	0	5	0	0	0	2	0	0
2013-4	5	9	5	10	4	0	0	2	3	0	3	0	0	0	3	2	0	3	0	0
2013-5	3	8	4	5	0	4	4	2	3	0	3	0	1	0	3	0	0	3	0	0
2013-6	4	8	7	4	0	1	0	2	0	0	0	0	2	0	0	0	1	0	0	0
2013-7	8	7	4	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-8	9	11	4	0	1	0	0	4	0	0	0	0	1	0	0	2	0	0	1	0
2013-9	9	9	2	6	3	1	4	1	2	0	1	1	2	0	3	1	1	0	0	0
2013-10	9	7	4	2	3	1	5	3	2	0	1	1	1	1	5	0	0	0	0	1
2013-11	9	10	3	2	3	3	5	4	2	0	2	2	2	1	5	0	0	0	1	3
2013-12	6	9	6	3	3	0	6	3	2	0	2	1	3	0	1	0	0	0	0	0
2014-1	10	10	4	3	7	0	5	4	2	1	2	3	2	1	1	1	2	1	6	2
2014-2	10	7	7	7	0	5	5	3	2	1	3	4	2	1	1	1	2	1	6	0
2014-3	8	4	8	3	5	1	3	2	2	0	2	0	2	0	1	0	1	3	1	0
2014-4	7	4	5	5	4	0	5	2	2	0	2	1	1	0	1	0	1	0	0	0
2014-5	7	6	6	5	4	6	7	2	2	1	1	2	2	0	0	1	1	0	1	0
2014-6	6	8	3	5	4	0	6	2	2	0	2	1	1	0	0	0	2	0	0	0
2014-7	8	6	4	6	6	3	3	2	1	0	2	0	2	0	0	0	1	0	0	0
2014-8	7	6	6	7	5	3	6	1	2	3	2	3	2	0	0	1	1	0	0	1
2014-9	8	11	2	8	6	3	4	2	2	0	2	4	2	0	0	0	2	0	1	2
2014-10	8	13	7	8	4	0	5	1	2	3	2	4	3	3	0	0	1	0	0	0
Average 2009/01 - 2014/10	**4,1**	**3,8**	**2,7**	**2,4**	**1,8**	**1,6**	**1,6**	**0,7**	**0,6**	**0,6**	**0,6**	**0,5**	**0,5**	**0,5**	**0,5**	**0,3**	**0,3**	**0,3**	**0,2**	**0,2**

Table 5.3 is given for presenting the contagion results at the last lag. For example, BANK_2 eventually changes conditions of 8 banks when it is failed in solvency in the period 2014/10.

For the last lag, in average for 70 months failure of BANK_2 causes 4.1 banks failures, failure of BANK_13 causes 3.8 banks failures, failure of BANK_5 causes 2.7 banks failures, and failure of BANK_12 causes 2.4 banks failures. Additionally, BANK_14, BANK_10 and BANK_3 causes many bank failures in total. After these seven banks, the average number of defaulted banks after individual failures of other banks shows a sharp decrease. Other effective banks which are less influential than these seven banks are BANK_37, BANK_48, BANK_38, BANK_50 and BANK_11.

Table 5.4 demonstrates the impacts of defaulted banks on other banks. Most effective banks are BANK_2, BANK_13, BANK_12 and BANK_5. Beside to these banks, BANK_10, BANK_14, BANK_3, BANK_37 and BANK_48 have influence on other banks. Nevertheless, BANK_1, BANK_15, BANK_20, BANK_23, BANK_30, BANK_31, BANK_32, BANK_36, BANK_40, BANK_42, BANK_43, BANK_45, BANK_46 and BANK_47 do not affect conditions of other banks.

From Table 5.4, it can also be inferred that BANK_29 lost its effectiveness after 2011, while effectiveness of BANK_33 and BANK_45 increased on average over the period 2011-2014. Also, effectiveness of BANK_29 declined for the last four years and BANK_39 affects more banks for current years. BANK_6 and BANK_21, has no more impact on conditions of other banks for the period 2011 to 2014.

BANK_46 and BANK_47 are newly opened banks. Therefore, these banks do not affect other banks as they do not have debit relations with other banks.

Table 5.4 – Results of contagion model for capital adequacy considering effectiveness of banks. a) Total number of defaulted banks after idiosyncratic shocks over 2009/01-2014/10.b) Average number of defaulted banks after idiosyncratic shocks over 2009/01-2014/10. c) Average number of defaulted banks after idiosyncratic shocks over 2011/01-2014/10

a)

Banks	Lag 1	Lag 2	Lag 3	Lag 4
BANK_2	224	280	284	284
BANK_13	215	261	265	265
BANK_5	172	187	187	187
BANK_12	122	161	169	169
BANK_14	81	119	123	124
BANK_10	99	112	115	115
BANK_3	64	107	113	113
BANK_37	48	52	52	52
BANK_48	34	40	40	40
BANK_38	25	36	39	39
BANK_50	33	39	39	39
BANK_11	34	37	37	37
BANK_44	36	37	37	37
BANK_9	27	33	35	35
BANK_51	21	31	32	32
BANK_28	21	21	21	21
BANK_39	18	18	18	18
BANK_49	10	18	18	18
BANK_35	10	16	17	17
BANK_4	12	15	15	15
BANK_27	14	14	14	14
BANK_22	12	13	13	13
BANK_34	10	11	11	11
BANK_24	5	6	6	6
BANK_26	5	6	6	6
BANK_6	5	5	5	5
BANK_29	4	4	4	4
BANK_7	2	2	2	2
BANK_16	2	2	2	2
BANK_17	2	2	2	2
BANK_21	2	2	2	2
BANK_33	2	2	2	2
BANK_45	2	2	2	2
BANK_19	1	1	1	1
BANK_32	1	1	1	1
BANK_36	1	1	1	1
BANK_1	0	0	0	0
BANK_8	0	0	0	0
BANK_15	0	0	0	0
BANK_18	0	0	0	0
BANK_20	0	0	0	0
BANK_23	0	0	0	0
BANK_25	0	0	0	0
BANK_30	0	0	0	0
BANK_31	0	0	0	0
BANK_40	0	0	0	0
BANK_41	0	0	0	0
BANK_42	0	0	0	0
BANK_43	0	0	0	0
BANK_46	0	0	0	0
BANK_47	0	0	0	0

b)

Banks	Lag 1	Lag 2	Lag 3	Lag 4
BANK_2	3,20	4,00	4,06	4,06
BANK_13	3,07	3,73	3,79	3,79
BANK_5	2,46	2,67	2,67	2,67
BANK_12	1,74	2,30	2,41	2,41
BANK_14	1,16	1,70	1,76	1,77
BANK_10	1,41	1,60	1,64	1,64
BANK_3	0,91	1,53	1,61	1,61
BANK_37	0,69	0,74	0,74	0,74
BANK_48	0,49	0,57	0,57	0,57
BANK_38	0,36	0,51	0,56	0,56
BANK_50	0,47	0,56	0,56	0,56
BANK_11	0,49	0,53	0,53	0,53
BANK_44	0,51	0,53	0,53	0,53
BANK_9	0,39	0,47	0,50	0,50
BANK_51	0,30	0,44	0,46	0,46
BANK_28	0,30	0,30	0,30	0,30
BANK_39	0,26	0,26	0,26	0,26
BANK_49	0,14	0,26	0,26	0,26
BANK_35	0,14	0,23	0,24	0,24
BANK_4	0,17	0,21	0,21	0,21
BANK_27	0,20	0,20	0,20	0,20
BANK_22	0,17	0,19	0,19	0,19
BANK_34	0,14	0,16	0,16	0,16
BANK_24	0,07	0,09	0,09	0,09
BANK_26	0,07	0,09	0,09	0,09
BANK_6	0,07	0,07	0,07	0,07
BANK_29	0,06	0,06	0,06	0,06
BANK_7	0,03	0,03	0,03	0,03
BANK_16	0,03	0,03	0,03	0,03
BANK_17	0,03	0,03	0,03	0,03
BANK_21	0,03	0,03	0,03	0,03
BANK_33	0,03	0,03	0,03	0,03
BANK_45	0,03	0,03	0,03	0,03
BANK_19	0,01	0,01	0,01	0,01
BANK_32	0,01	0,01	0,01	0,01
BANK_36	0,01	0,01	0,01	0,01
BANK_1	0,00	0,00	0,00	0,00
BANK_8	0,00	0,00	0,00	0,00
BANK_15	0,00	0,00	0,00	0,00
BANK_18	0,00	0,00	0,00	0,00
BANK_20	0,00	0,00	0,00	0,00
BANK_23	0,00	0,00	0,00	0,00
BANK_25	0,00	0,00	0,00	0,00
BANK_30	0,00	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00	0,00
BANK_41	0,00	0,00	0,00	0,00
BANK_42	0,00	0,00	0,00	0,00
BANK_43	0,00	0,00	0,00	0,00
BANK_46	0,00	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00	0,00

c)

Banks	Lag 1	Lag 2	Lag 3	Lag 4
BANK_2	4,85	6,07	6,15	6,15
BANK_13	4,24	5,24	5,33	5,33
BANK_5	3,59	3,91	3,91	3,91
BANK_12	2,20	3,02	3,20	3,20
BANK_3	1,17	2,07	2,20	2,20
BANK_14	1,20	2,02	2,11	2,13
BANK_10	1,76	2,04	2,11	2,11
BANK_37	1,04	1,13	1,13	1,13
BANK_48	0,74	0,87	0,87	0,87
BANK_50	0,72	0,85	0,85	0,85
BANK_38	0,48	0,72	0,78	0,78
BANK_11	0,70	0,76	0,76	0,76
BANK_44	0,74	0,76	0,76	0,76
BANK_51	0,46	0,67	0,70	0,70
BANK_9	0,48	0,61	0,65	0,65
BANK_39	0,39	0,39	0,39	0,39
BANK_49	0,22	0,39	0,39	0,39
BANK_28	0,37	0,37	0,37	0,37
BANK_35	0,22	0,35	0,37	0,37
BANK_4	0,24	0,30	0,30	0,30
BANK_27	0,30	0,30	0,30	0,30
BANK_34	0,22	0,24	0,24	0,24
BANK_22	0,20	0,22	0,22	0,22
BANK_24	0,11	0,13	0,13	0,13
BANK_26	0,11	0,13	0,13	0,13
BANK_7	0,04	0,04	0,04	0,04
BANK_29	0,04	0,04	0,04	0,04
BANK_33	0,04	0,04	0,04	0,04
BANK_45	0,04	0,04	0,04	0,04
BANK_16	0,02	0,02	0,02	0,02
BANK_17	0,02	0,02	0,02	0,02
BANK_19	0,02	0,02	0,02	0,02
BANK_32	0,02	0,02	0,02	0,02
BANK_36	0,02	0,02	0,02	0,02
BANK_1	0,00	0,00	0,00	0,00
BANK_6	0,00	0,00	0,00	0,00
BANK_8	0,00	0,00	0,00	0,00
BANK_15	0,00	0,00	0,00	0,00
BANK_18	0,00	0,00	0,00	0,00
BANK_20	0,00	0,00	0,00	0,00
BANK_21	0,00	0,00	0,00	0,00
BANK_23	0,00	0,00	0,00	0,00
BANK_25	0,00	0,00	0,00	0,00
BANK_30	0,00	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00	0,00
BANK_41	0,00	0,00	0,00	0,00
BANK_42	0,00	0,00	0,00	0,00
BANK_43	0,00	0,00	0,00	0,00
BANK_46	0,00	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00	0,00

5.1.1.2 Fragility of banks considering capital adequacy contagion model

In this study, fragility of a bank is measured with the number of bank failures, which affect the condition of this bank.

Table 5.5 – Capital adequacy contagion model: Number of bank failures when a bank becomes defaulted as a result. Matrix is presented for the 20 banks with largest average number of bank failures which makes banks defaulted in the period January 2009 – October 2014 at the first lag

	BANK_19	BANK_32	BANK_37	BANK_48	BANK_16	BANK_17	BANK_33	BANK_45	BANK_15	BANK_21	BANK_29	BANK_44	BANK_31	BANK_50	BANK_24	BANK_26	BANK_49	BANK_42	BANK_34	BANK_46
2012-12	3	1	6	3	2	3	0	1	0	0	0	1	0	0	0	0	0	0	0	0
2013-1	3	0	6	5	1	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0
2013-2	2	3	7	4	1	1	0	2	2	0	0	0	0	0	1	0	0	0	0	0
2013-3	3	6	6	4	1	3	1	6	0	0	0	0	0	0	0	0	1	0	0	0
2013-4	3	3	6	2	1	2	2	6	1	0	4	0	0	0	1	2	1	0	0	0
2013-5	3	2	7	0	1	1	1	1	1	0	0	0	0	0	1	0	3	0	0	0
2013-6	3	4	2	0	1	3	3	2	2	0	0	0	0	0	2	0	0	1	0	0
2013-7	2	4	3	0	1	2	1	3	2	0	1	0	0	0	0	0	0	0	0	0
2013-8	3	5	2	0	1	2	1	1	1	0	1	0	0	0	1	2	0	1	4	0
2013-9	7	3	4	1	3	2	2	3	3	0	1	1	0	0	2	2	0	1	0	0
2013-10	7	4	4	1	3	1	2	2	0	0	0	1	0	0	3	2	0	0	0	0
2013-11	7	7	4	0	8	1	3	3	1	0	0	0	0	1	0	0	0	0	2	0
2013-12	6	1	3	0	5	2	2	0	2	0	0	0	2	2	0	0	0	2	0	0
2014-1	8	5	4	1	11	3	1	0	0	1	0	0	9	2	1	1	0	0	0	0
2014-2	9	8	4	0	9	2	3	3	0	0	0	0	11	2	0	0	2	0	0	0
2014-3	10	2	4	1	8	2	3	2	1	0	0	0	0	2	0	1	0	0	0	0
2014-4	9	7	3	1	5	2	3	1	0	0	0	0	0	2	0	0	1	0	0	0
2014-5	11	10	3	1	3	2	4	1	1	6	1	0	0	2	1	0	1	0	0	1
2014-6	9	0	3	2	6	1	4	2	2	0	1	0	0	2	1	0	0	0	0	2
2014-7	7	1	3	2	3	2	3	2	2	0	1	0	0	3	0	0	0	0	0	3
2014-8	9	8	2	3	5	2	4	3	2	2	0	0	0	2	0	0	0	0	0	3
2014-9	9	0	3	2	9	3	3	4	2	0	1	0	0	2	0	1	0	4	0	3
2014-10	8	9	3	4	3	1	3	3	2	4	1	0	0	1	1	0	0	6	0	3
Average 2009/01 - 2014/10	**2,9**	**2,5**	**2,1**	**2**	**1,7**	**1,3**	**1,3**	**0,7**	**0,7**	**0,4**	**0,4**	**0,4**	**0,4**	**0,3**	**0,3**	**0,3**	**0,3**	**0,2**	**0,2**	**0,2**

Table 5.5 presents the contagion results at the first lag. Each cell in the matrix gives the number of bank failures which makes a bank defaulted. For example, BANK_32 becomes defaulted after 9 idiosyncratic shocks at first lag in 2014/10. In other words, nine individual bank failures make BANK_32 defaulted. Similarly, 8 different idiosyncratic shocks cause failure of BANK_19 in 2014/10. Last row of the table demonstrates the average of the number of the bank failures that lead to failure in that bank in 70 months for the first lag. It is in the descending order in order to detect

the most fragile banks to fail in the contagion. Only the results of periods after December 2012 are demonstrated.

Table 5.6 - Capital adequacy contagion model: Number of bank failures when a bank becomes defaulted as a result. Matrix is presented for the 20 banks with largest average number of bank failures which makes banks defaulted in the period January 2009 – October 2014 at the last lag

	BANK_19	BANK_32	BANK_16	BANK_37	BANK_48	BANK_17	BANK_33	BANK_24	BANK_45	BANK_15	BANK_22	BANK_21	BANK_44	BANK_18	BANK_31	BANK_26	BANK_49	BANK_29	BANK_42	BANK_36
2012-12	5	1	2	9	3	3	0	0	1	0	0	0	1	0	0	0	0	0	0	0
2013-1	12	0	1	11	5	2	0	0	1	1	0	0	0	0	0	1	1	0	0	0
2013-2	2	3	1	11	4	1	0	1	2	2	0	0	0	0	0	0	1	0	0	0
2013-3	12	6	1	10	4	4	1	0	6	0	0	0	0	0	0	0	1	0	0	2
2013-4	10	3	1	8	2	2	2	9	7	1	0	0	0	0	0	2	1	4	0	0
2013-5	12	2	1	10	0	1	1	11	1	1	0	0	0	0	0	0	3	0	0	0
2013-6	6	4	1	2	0	3	3	4	2	2	0	0	0	0	0	0	0	0	0	0
2013-7	5	4	1	3	0	2	1	1	3	2	0	0	0	0	0	0	0	1	0	0
2013-8	5	5	1	2	0	2	1	3	1	2	0	0	0	0	0	2	0	1	6	0
2013-9	11	3	4	4	1	2	2	3	3	3	0	0	1	0	0	2	0	1	0	0
2013-10	10	4	6	4	1	2	2	7	2	0	0	0	5	0	0	2	0	0	0	0
2013-11	12	13	11	4	0	2	3	0	3	1	0	3	0	0	0	0	0	0	6	0
2013-12	11	1	10	3	0	2	2	1	2	2	4	0	0	0	0	0	1	0	0	0
2014-1	13	5	16	5	1	3	2	6	0	0	13	1	0	0	0	1	0	0	0	0
2014-2	14	8	14	5	0	2	3	1	3	0	18	0	0	0	0	1	2	0	0	0
2014-3	14	2	13	5	1	2	3	0	2	1	1	0	0	0	0	1	0	0	0	0
2014-4	13	7	10	3	1	2	3	0	1	0	0	0	0	0	0	0	1	0	0	0
2014-5	15	10	7	3	1	2	4	1	1	1	0	6	0	0	0	0	1	1	0	0
2014-6	13	0	10	3	2	1	4	1	2	2	0	0	0	0	0	0	0	1	0	0
2014-7	12	1	9	5	2	2	3	0	2	2	0	0	0	0	0	0	0	1	0	0
2014-8	16	8	9	3	3	2	4	0	3	2	0	3	0	0	0	0	0	0	0	0
2014-9	14	0	14	5	2	3	3	0	4	2	1	0	1	0	0	1	0	1	0	0
2014-10	16	9	10	3	4	1	3	2	3	2	0	4	0	0	0	0	0	1	0	0
Average 2009/01-2014/10	**4,6**	**2,6**	**2,6**	**2,5**	**2,1**	**1,4**	**1,3**	**0,8**	**0,8**	**0,7**	**0,6**	**0,5**	**0,5**	**0,4**	**0,4**	**0,3**	**0,3**	**0,3**	**0,3**	**0,2**

Table 5.6 is given for presenting the contagion results at the last lag. For example, condition of BANK_19 is changed after 16 individual bank failures in the period 2014/10, which means BANK_19 is affected from 16 idiosyncratic shocks. Only the results of periods after December 2012 are demonstrated.

For the last lag, in average for 70 months, BANK_19 is affected from 4.6 bank failures, BANK_32 is affected from 2.6 bank failures, BANK_16 is affected from 2.6 bank failures, BANK_37 is affected from 2.5 bank failures, and BANK_48 is affected from 2.1 bank failures. Additionally, BANK_17, BANK_33, BANK_24 and

BANK_45 are influenced by many bank failures. After these nine banks, the number of individual failures that affect other banks shows a decrease. Other fragile banks which are less vulnerable than these banks are BANK_15, BANK_22 BANK_21, BANK_44 and BANK_18.

Table 5.7 demonstrates the vulnerability of banks from failures of other banks. The banks which have higher fragility are BANK_19, BANK_32, BANK_16, BANK_37, BANK_48, BANK_17, BANK_33, BANK_45, BANK_24, BANK_15 and BANK_22. Beside to these banks, BANK_21, BANK_44, BANK_29, BANK_26 and BANK_50 are affected from other banks a little more. Nevertheless, BANK_1, BANK_2, BANK_3, BANK_4, BANK_5, BANK_6, BANK_8, BANK_10, BANK_11, BANK_12, BANK_13, BANK_27, BANK_28, BANK_31, BANK_40, BANK_41, BANK_43, and BANK_47 are not affected from any bank failures.

From Table 5.7 it can also be inferred that BANK_20 and BANK_51 is more fragile before 2011, while fragility of BANK_44, BANK_29, BANK_26, BANK_42, and BANK_46, increased on average over the period 2011-2014.

Table 5.7 – Results of contagion model for capital adequacy considering fragility of banks. a) Total number of individual banks failures that cause failure of that bank over 2009/01-2014/10.b) Average number of idiosyncratic shocks that banks become defaulted after over 2009/01-2014/10. c) Average number of idiosyncratic shocks that banks become defaulted after over 2011/01-2014/10

a)

Banks	Lag 1	Lag 2	Lag 3	Lag 4
BANK_19	201	310	324	324
BANK_32	174	177	180	180
BANK_16	117	177	179	179
BANK_37	147	178	178	178
BANK_48	142	145	147	147
BANK_17	94	96	97	97
BANK_33	91	92	92	92
BANK_24	22	54	58	58
BANK_45	52	55	55	55
BANK_15	48	50	50	50
BANK_22	26	41	43	44
BANK_21	31	37	37	37
BANK_44	28	37	37	37
BANK_18	16	30	31	31
BANK_29	30	30	30	30
BANK_26	22	24	24	24
BANK_49	21	22	24	24
BANK_50	23	23	23	23
BANK_42	17	22	22	22
BANK_36	11	16	16	16
BANK_34	9	14	15	15
BANK_46	15	15	15	15
BANK_20	12	12	12	12
BANK_38	4	8	8	8
BANK_9	7	7	7	7
BANK_7	3	3	6	6
BANK_25	6	6	6	6
BANK_14	2	4	4	4
BANK_30	2	3	3	3
BANK_35	1	3	3	3
BANK_39	1	1	2	2
BANK_23	0	1	1	1
BANK_51	1	1	1	1
BANK_1	0	0	0	0
BANK_2	0	0	0	0
BANK_3	0	0	0	0
BANK_4	0	0	0	0
BANK_5	0	0	0	0
BANK_6	0	0	0	0
BANK_8	0	0	0	0
BANK_10	0	0	0	0
BANK_11	0	0	0	0
BANK_12	0	0	0	0
BANK_13	0	0	0	0
BANK_27	0	0	0	0
BANK_28	0	0	0	0
BANK_31	0	0	0	0
BANK_40	0	0	0	0
BANK_41	0	0	0	0
BANK_43	0	0	0	0
BANK_47	0	0	0	0

b)

Banks	Lag 1	Lag 2	Lag 3	Lag 4
BANK_19	2,87	4,43	4,63	4,63
BANK_32	2,49	2,53	2,57	2,57
BANK_16	1,67	2,53	2,56	2,56
BANK_37	2,10	2,54	2,54	2,54
BANK_48	2,03	2,07	2,10	2,10
BANK_17	1,34	1,37	1,39	1,39
BANK_33	1,30	1,31	1,31	1,31
BANK_24	0,31	0,77	0,83	0,83
BANK_45	0,74	0,79	0,79	0,79
BANK_15	0,69	0,71	0,71	0,71
BANK_22	0,37	0,59	0,61	0,63
BANK_21	0,44	0,53	0,53	0,53
BANK_44	0,40	0,53	0,53	0,53
BANK_18	0,23	0,43	0,44	0,44
BANK_29	0,43	0,43	0,43	0,43
BANK_26	0,31	0,34	0,34	0,34
BANK_49	0,30	0,31	0,34	0,34
BANK_50	0,33	0,33	0,33	0,33
BANK_42	0,24	0,31	0,31	0,31
BANK_36	0,16	0,23	0,23	0,23
BANK_34	0,13	0,20	0,21	0,21
BANK_46	0,21	0,21	0,21	0,21
BANK_20	0,17	0,17	0,17	0,17
BANK_38	0,06	0,11	0,11	0,11
BANK_9	0,10	0,10	0,10	0,10
BANK_7	0,04	0,04	0,09	0,09
BANK_25	0,09	0,09	0,09	0,09
BANK_14	0,03	0,06	0,06	0,06
BANK_30	0,03	0,04	0,04	0,04
BANK_35	0,01	0,04	0,04	0,04
BANK_39	0,01	0,01	0,03	0,03
BANK_23	0,00	0,01	0,01	0,01
BANK_51	0,01	0,01	0,01	0,01
BANK_1	0,00	0,00	0,00	0,00
BANK_2	0,00	0,00	0,00	0,00
BANK_3	0,00	0,00	0,00	0,00
BANK_4	0,00	0,00	0,00	0,00
BANK_5	0,00	0,00	0,00	0,00
BANK_6	0,00	0,00	0,00	0,00
BANK_8	0,00	0,00	0,00	0,00
BANK_10	0,00	0,00	0,00	0,00
BANK_11	0,00	0,00	0,00	0,00
BANK_12	0,00	0,00	0,00	0,00
BANK_13	0,00	0,00	0,00	0,00
BANK_27	0,00	0,00	0,00	0,00
BANK_28	0,00	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00	0,00
BANK_41	0,00	0,00	0,00	0,00
BANK_43	0,00	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00	0,00

c)

Banks	Lag 1	Lag 2	Lag 3	Lag 4
BANK_19	3,87	6,24	6,54	6,54
BANK_16	2,54	3,85	3,89	3,89
BANK_37	3,20	3,87	3,87	3,87
BANK_32	3,26	3,33	3,39	3,39
BANK_48	2,43	2,50	2,54	2,54
BANK_17	1,91	1,96	1,98	1,98
BANK_33	1,96	1,98	1,98	1,98
BANK_45	1,13	1,20	1,20	1,20
BANK_24	0,35	1,04	1,13	1,13
BANK_15	1,04	1,09	1,09	1,09
BANK_22	0,54	0,87	0,91	0,93
BANK_21	0,67	0,80	0,80	0,80
BANK_44	0,48	0,67	0,67	0,67
BANK_29	0,61	0,61	0,61	0,61
BANK_26	0,48	0,52	0,52	0,52
BANK_50	0,50	0,50	0,50	0,50
BANK_42	0,37	0,48	0,48	0,48
BANK_18	0,11	0,35	0,37	0,37
BANK_36	0,24	0,35	0,35	0,35
BANK_46	0,33	0,33	0,33	0,33
BANK_34	0,17	0,28	0,30	0,30
BANK_49	0,24	0,26	0,30	0,30
BANK_38	0,09	0,17	0,17	0,17
BANK_9	0,15	0,15	0,15	0,15
BANK_7	0,07	0,07	0,13	0,13
BANK_25	0,13	0,13	0,13	0,13
BANK_14	0,04	0,09	0,09	0,09
BANK_30	0,04	0,07	0,07	0,07
BANK_35	0,02	0,07	0,07	0,07
BANK_39	0,02	0,02	0,04	0,04
BANK_23	0,00	0,02	0,02	0,02
BANK_1	0,00	0,00	0,00	0,00
BANK_2	0,00	0,00	0,00	0,00
BANK_3	0,00	0,00	0,00	0,00
BANK_4	0,00	0,00	0,00	0,00
BANK_5	0,00	0,00	0,00	0,00
BANK_6	0,00	0,00	0,00	0,00
BANK_8	0,00	0,00	0,00	0,00
BANK_10	0,00	0,00	0,00	0,00
BANK_11	0,00	0,00	0,00	0,00
BANK_12	0,00	0,00	0,00	0,00
BANK_13	0,00	0,00	0,00	0,00
BANK_20	0,00	0,00	0,00	0,00
BANK_27	0,00	0,00	0,00	0,00
BANK_28	0,00	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00	0,00
BANK_41	0,00	0,00	0,00	0,00
BANK_43	0,00	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00	0,00
BANK_51	0,00	0,00	0,00	0,00

5.1.2. Contagion for Liquidity Ratio

Contagion model for liquidity is applied to the data which is explained in Section 4.3.2. First of all, total assets and total liabilities are stored as vectors for each period separately. Calculations according to Equation 6 are conducted on the data by repeating the Pajek macro explained in Section 4.4.2. As mentioned, weekly (LIQ7) and monthly (LIQ31) liquidity ratios are considered, respectively. Results are presented under two aspects; how failure of a bank affects other banks, i.e., effectiveness, and how a bank is affected from failures of other banks, i.e., fragility.

According to the results, the total number of defaulted banks when the status of a bank turns defaulted over the period January 2009-October 2014 is presented in Tables 5.8 and 5.9 and Figure 5.2.

Table 5.8 – Weekly liquidity contagion model: Descriptive statistics of total number of defaulted banks as a result of an individual bank failure

January 2009 - October 2014

Lags	Mean	Min	Max	Median	Std. Dev.
Lag 1	12,814	4	28	13	5,17
Lag 2	13,100	4	30	13	5,36
Lag 3	13,100	4	30	13	5,36

January 2011 - October 2014

Lags	Mean	Min	Max	Median	Std. Dev.
Lag 1	14,630	6	28	14,0	5,10
Lag 2	15,022	6	30	14,0	5,24
Lag 3	15,022	6	30	14,0	5,24

Table 5.9 – Monthly liquidity contagion model: Descriptive statistics of total number of defaulted banks as a result of an individual bank failure

January 2009 - October 2014

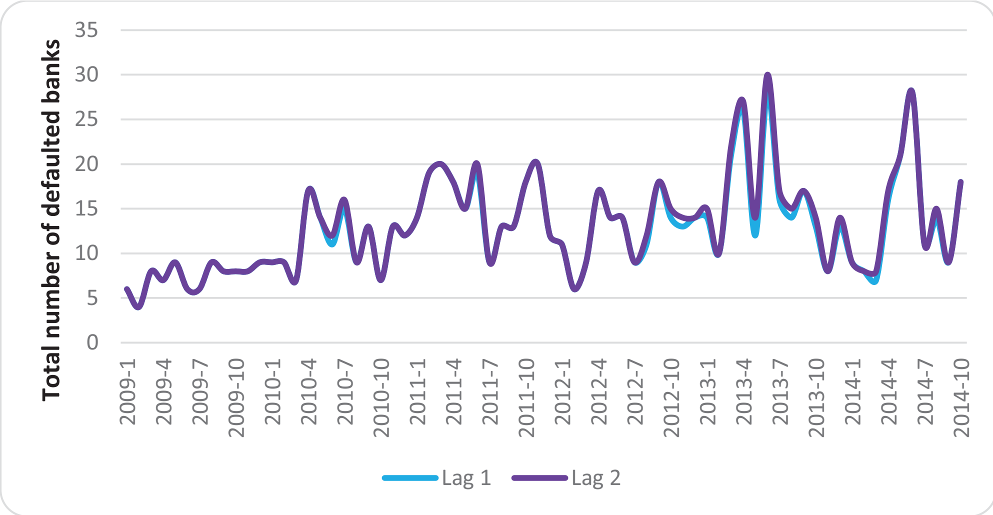
Lags	Mean	Min	Max	Median	Std. Dev.
Lag 1	10,029	1	28	9	5,91
Lag 2	10,814	1	35	9	7,09
Lag 3	10,829	1	36	9	7,14

January 2011 - October 2014

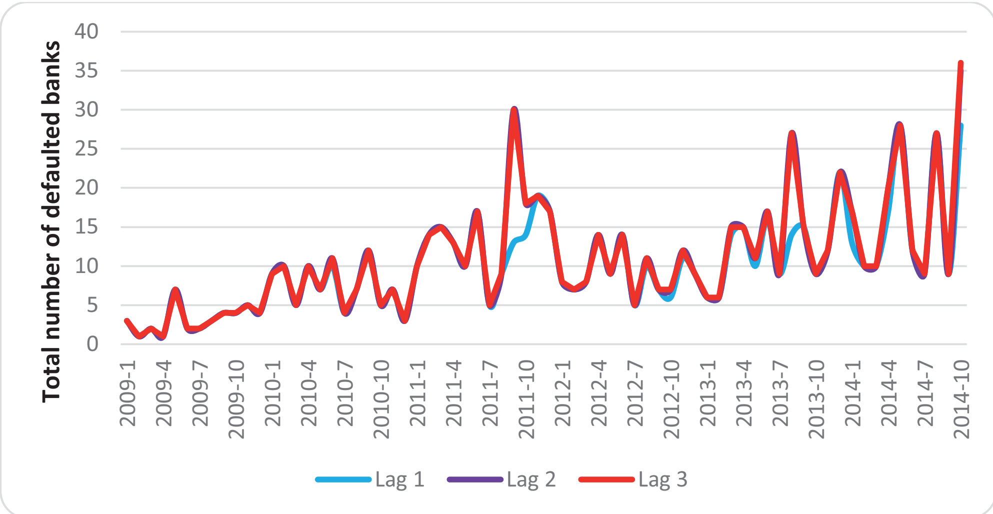
Lags	Mean	Min	Max	Median	Std. Dev.
Lag 1	12,500	5	28	11,5	5,51
Lag 2	13,674	5	35	12,0	6,89
Lag 3	13,696	5	36	12,0	6,96

At the first lag, the contagion starts with one bank failure. On average over the period January 2009-October 2014 for weekly liquidity contagion model, when a bank is defaulted, about 12.8 banks in total are affected from this failure and their LIQ7 values decrease under threshold 100. This average number rises to 14.6 for monthly periods in 2011-2014 with a range between 6 and 28. Contagion in the second lag, starts with failed banks in the first lag. After second lag, total number of defaulted banks according to weekly liquidity contagion model reaches to its maximum. After 2nd lag, total number of defaulted banks as a result of an individual bank failure ranges between 4 and 30 with the mean approximately 13.1, whereas its range is between 6 and 30 with an average about 15.0 in the period of 2011-2014.

For monthly liquidity contagion model, on average over the period January 2009-October 2014 when a bank is defaulted, about 10.0 banks in total are affected from this failure. This average number increases to 12.5 for monthly periods in 2011-2014 with a range between 5 and 28. After the third lag, total number of defaulted banks according to monthly liquidity contagion model reaches to its maximum. After the 3rd lag, total number of defaulted banks as a result of an individual bank failure ranges between 1 and 36 with the mean approximately 10.8, whereas its range is between 5 and 36 with an average about 13.7 in the period of 2011-2014.



a)



b)

Figure 5.2. Liquidity contagion models: Total number of defaulted banks as a result of an individual bank failure over the period January 2009 – October 2014. a) Weekly liquidity contagion model: b) Monthly liquidity contagion model.

Similar to the results of capital adequacy contagion model, due to effects of global crisis in 2009 total number of defaulted banks after contagion gets its minimum ranges. After the crisis period, there is an increasing trend in the number of banks failed after individual bank failures according to the liquidity contagion model. Additionally, in some monthly periods, the number of total bank failures demonstrates sudden increase. These spikes are very certain in the second quarter of

2013 for LIQ7 contagion model and in September 2011 and the last period October 2014 for LIQ31 contagion model.

5.1.2.1 Effectiveness of banks considering liquidity contagion model

In this study, effectiveness of a bank is measured with the number of banks, which fails when this bank is defaulted.

Table 5.10 – Weekly liquidity contagion model: Number of defaulted banks when banks in the matrix failed at the first lag. Matrix is presented for the 20 banks with largest total number of defaulted banks after idiosyncratic shocks in the period January 2009 – October 2014 at the first lag

	BANK_5	BANK_13	BANK_2	BANK_11	BANK_3	BANK_10	BANK_12	BANK_38	BANK_28	BANK_37	BANK_14	BANK_9	BANK_22	BANK_51	BANK_45	BANK_50	BANK_49	BANK_27	BANK_34	BANK_33
2012-12	1	2	2	2	1	1	0	1	0	0	1	0	0	1	0	1	1	0	0	0
2013-1	2	3	1	2	1	0	0	1	0	0	1	0	0	1	0	1	1	0	0	0
2013-2	1	4	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	3	5	2	2	0	0	0	1	0	1	1	1	0	1	0	1	1	0	0	0
2013-4	3	5	3	2	0	1	3	2	2	1	0	0	0	1	0	1	1	0	1	0
2013-5	2	3	2	1	0	0	0	1	1	1	0	0	0	1	0	1	0	0	0	0
2013-6	4	4	3	2	1	0	3	2	1	1	0	0	0	1	1	1	0	1	1	0
2013-7	3	1	3	2	0	0	0	2	1	1	0	0	0	1	1	1	0	0	0	0
2013-8	1	2	1	2	0	0	0	2	1	1	0	0	0	2	0	2	0	0	0	0
2013-9	1	1	3	2	0	1	3	2	1	1	0	0	0	1	0	1	0	0	0	0
2013-10	1	1	2	2	1	2	0	2	0	1	0	0	0	1	0	1	0	0	0	0
2013-11	0	2	2	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
2013-12	2	2	2	1	2	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
2014-1	1	3	1	1	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
2014-2	3	1	1	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
2014-3	2	0	2	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-4	2	2	2	2	3	0	2	0	0	0	0	0	0	0	1	0	0	1	1	0
2014-5	3	2	3	2	2	1	3	0	1	0	0	0	0	0	1	0	0	0	1	0
2014-6	3	3	1	2	2	1	2	1	1	1	0	1	1	0	1	0	0	1	1	1
2014-7	2	2	1	1	1	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0
2014-8	3	3	3	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-9	0	3	2	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-10	3	4	4	0	3	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Average 2009/01 - 2014/10	**2,3**	**2,1**	**1,8**	**1,2**	**1,1**	**1**	**0,7**	**0,4**	**0,3**	**0,2**	**0,2**	**0,2**	**0,2**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**

Table 5.10 is given for presenting the contagion results at the first lag. Each cell in the matrix gives the total number of defaulted banks after idiosyncratic shocks. For example, when BANK_5 is assumed as defaulted at the beginning, 3 banks become defaulted at first lag in 2014/10. Last row of the table demonstrates the average of the defaulted banks in 70 months for first lag. The most effective banks according to

weekly liquidity contagion model are BANK_5, BANK_13 and BANK_2. Only the results of periods after December 2012 are demonstrated.

Table 5.11 - Weekly liquidity contagion model: Number of defaulted banks when banks in the matrix failed at the last lag. Matrix is presented for the 20 banks with largest total number of defaulted banks after idiosyncratic shocks in the period January 2009 – October 2014 at the last lag

	BANK_5	BANK_13	BANK_2	BANK_11	BANK_3	BANK_10	BANK_12	BANK_38	BANK_28	BANK_37	BANK_14	BANK_9	BANK_22	BANK_51	BANK_45	BANK_50	BANK_49	BANK_27	BANK_34	BANK_33
2012-12	1	2	2	2	1	1	0	1	0	0	1	0	0	1	0	1	1	1	0	0
2013-1	2	3	2	2	1	0	0	1	0	0	1	0	0	1	0	1	1	1	0	0
2013-2	1	4	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	3	5	3	2	0	0	0	1	0	1	1	1	0	1	0	1	1	1	0	0
2013-4	3	5	4	2	0	1	3	2	2	1	1	0	0	1	0	1	1	1	1	0
2013-5	2	4	3	1	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	0
2013-6	4	6	3	2	1	0	3	2	1	1	1	0	1	1	1	1	0	0	1	0
2013-7	3	1	4	2	0	0	0	2	1	1	1	0	0	1	1	1	0	0	0	0
2013-8	1	2	2	2	0	0	0	2	1	1	1	0	1	2	0	1	0	0	0	0
2013-9	1	1	3	2	0	1	3	2	1	1	0	0	0	1	0	0	0	0	0	0
2013-10	1	1	3	2	1	2	0	2	0	1	0	0	0	1	0	0	0	0	0	0
2013-11	0	2	2	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0
2013-12	2	2	3	1	2	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0
2014-1	1	3	1	1	1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
2014-2	3	1	1	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
2014-3	2	0	3	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-4	2	2	3	2	3	0	2	0	0	0	0	0	0	0	1	0	0	0	1	0
2014-5	3	2	3	2	2	1	3	0	1	0	0	0	1	0	1	0	0	0	1	0
2014-6	3	3	1	2	2	1	2	1	1	1	0	1	0	0	1	0	0	0	1	1
2014-7	2	2	1	1	1	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0
2014-8	3	3	3	1	2	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-9	0	3	2	0	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-10	3	4	4	0	3	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Average 2009/01 - 2014/10	**2,3**	**2,1**	**1,9**	**1,2**	**1,1**	**1**	**0,7**	**0,4**	**0,3**	**0,2**	**0,2**	**0,2**	**0,2**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**

Table 5.11 is given for presenting the contagion results at the last lag. For example, BANK_5 eventually changes conditions of 3 banks when it is failed in solvency in the period 2014/10. For the last lag, in average for 70 months failure of BANK_5 causes 2.3 bank failures, failure of BANK_13 causes 2.1 bank failures, and failure of BANK_2 causes 1.9 bank failures. Additionally, BANK_11, BANK_3, BANK_10, and BANK_12 causes many bank failures in total. After these seven banks, the average number of defaulted banks after individual failures of other banks shows a decrease. Other effective banks which are less influential than these seven

banks are BANK_38, BANK_28, BANK_37, BANK_14 and BANK_9. Only the results of periods after December 2012 are demonstrated.

Table 5.12 – Monthly liquidity contagion model: Number of defaulted banks when banks in the matrix failed at the first lag. Matrix is presented for the 20 banks with largest total number of defaulted banks after idiosyncratic shocks in the period January 2009 – October 2014 at the first lag

	BANK_5	BANK_13	BANK_2	BANK_10	BANK_12	BANK_3	BANK_11	BANK_14	BANK_37	BANK_9	BANK_28	BANK_38	BANK_50	BANK_22	BANK_45	BANK_44	BANK_48	BANK_51	BANK_29	BANK_34
2012-12	1	1	1	1	0	1	1	0	0	0	0	0	1	0	0	0	0	1	0	0
2013-1	2	2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-2	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	3	3	1	0	0	0	1	0	1	1	0	0	1	0	0	0	1	1	0	0
2013-4	3	5	2	0	3	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0
2013-5	2	3	2	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0
2013-6	4	2	2	0	1	0	1	0	1	0	0	1	0	0	1	0	0	1	0	1
2013-7	3	1	2	0	0	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0
2013-8	2	3	0	0	0	1	1	0	1	0	0	0	0	1	0	1	0	0	0	1
2013-9	1	1	2	0	2	0	2	0	1	0	0	1	1	0	0	1	1	0	0	0
2013-10	1	0	1	2	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0
2013-11	1	3	3	0	2	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0
2013-12	3	1	1	1	1	1	3	1	1	1	0	1	1	0	0	2	2	0	0	0
2014-1	2	3	1	1	1	1	1	0	2	0	0	1	0	0	0	0	0	0	0	0
2014-2	3	1	1	1	0	0	2	0	1	0	0	0	0	0	0	0	0	0	0	1
2014-3	3	0	2	0	0	1	1	1	1	0	0	0	0	0	1	0	0	0	0	0
2014-4	2	1	1	0	2	2	1	1	2	0	0	0	1	0	1	0	1	1	0	1
2014-5	3	2	4	3	4	2	1	1	1	0	1	2	0	0	1	1	0	0	0	1
2014-6	1	3	1	0	2	2	0	1	1	0	0	0	0	0	1	0	0	0	0	0
2014-7	1	1	1	0	1	1	0	1	1	0	0	0	1	0	1	0	0	0	0	0
2014-8	2	4	3	0	2	1	2	3	0	1	1	0	2	1	1	0	1	0	0	0
2014-9	0	2	1	0	1	1	0	1	0	0	0	0	1	0	1	1	0	0	0	0
2014-10	3	5	4	0	2	1	2	1	2	0	1	0	1	1	1	1	1	0	0	1
Average 2009/01 - 2014/10	**1,7**	**1,6**	**1,6**	**0,7**	**0,7**	**0,6**	**0,6**	**0,3**	**0,3**	**0,2**	**0,2**	**0,2**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**

As shown in Table 5.12, the most effective banks according to monthly liquidity contagion model at the first lag are BANK_5, BANK_13 and BANK_2. Only the results of periods after December 2012 are demonstrated.

Table 5.13 - Monthly liquidity contagion model: Number of defaulted banks when banks in the matrix failed at the last lag. Matrix is presented for the 20 banks with largest total number of defaulted banks after idiosyncratic shocks in the period January 2009 – October 2014 at the last lag

	BANK_5	BANK_2	BANK_13	BANK_12	BANK_10	BANK_3	BANK_11	BANK_14	BANK_37	BANK_9	BANK_28	BANK_38	BANK_50	BANK_22	BANK_44	BANK_45	BANK_34	BANK_48	BANK_51	BANK_29
2012-12	1	1	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	1	0
2013-1	2	1	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-2	2	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	3	2	3	0	0	0	1	0	1	1	1	0	0	0	0	0	0	1	1	0
2013-4	3	2	5	3	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2013-5	2	3	3	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
2013-6	4	3	2	1	0	0	1	0	1	0	0	1	0	0	0	1	1	0	1	0
2013-7	3	2	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0
2013-8	4	0	5	0	0	2	1	0	1	0	0	0	3	2	3	0	2	0	0	0
2013-9	1	2	1	2	0	0	2	0	1	0	1	1	1	0	1	0	0	1	0	0
2013-10	1	1	0	0	2	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0
2013-11	1	3	3	2	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0
2013-12	3	1	1	1	1	1	3	1	1	1	1	1	2	0	2	0	0	2	0	0
2014-1	6	1	3	1	1	1	1	0	2	0	0	1	0	0	0	0	0	0	0	0
2014-2	3	1	1	0	1	0	2	0	1	0	0	0	0	0	0	0	1	0	0	0
2014-3	3	2	0	0	0	1	1	1	1	0	0	0	0	0	0	1	0	0	0	0
2014-4	2	1	1	3	0	3	1	2	2	0	1	0	0	0	0	1	1	1	1	0
2014-5	3	4	2	4	3	2	1	1	1	0	0	2	1	0	1	1	1	0	0	0
2014-6	1	1	3	2	0	2	0	1	1	0	0	0	0	0	0	1	0	0	0	0
2014-7	1	1	1	1	0	1	0	1	1	0	1	0	0	0	0	1	0	0	0	0
2014-8	2	3	4	2	0	1	2	3	0	1	2	0	0	1	0	1	0	1	0	0
2014-9	0	1	2	1	0	1	0	1	0	0	1	0	1	0	1	1	0	0	0	0
2014-10	3	6	5	2	0	1	2	1	5	0	1	0	1	1	1	1	1	1	0	0
Average 2009/01 - 2014/10	**1,8**	**1,7**	**1,7**	**0,8**	**0,7**	**0,7**	**0,6**	**0,4**	**0,4**	**0,2**	**0,2**	**0,2**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**

Table 5.13 is given for presenting the contagion results for monthly liquidity at the last lag. For the last lag, in average for 70 months failure of BANK_5 causes 1.8 banks failures, failure of BANK_2 causes 1.7 banks failures, and failure of BANK_13 causes 1.7 banks failures. Additionally, BANK_12, BANK_10, BANK_3, and BANK_11 causes many bank failures in total. Other effective banks which are less influential than these seven banks are BANK_14, BANK_37, BANK_9, BANK_28 and BANK_38. Only the results of periods after December 2012 are demonstrated.

Table 5.14 – Results of contagion models for liquidity considering effectiveness of banks: Average number of defaulted banks after idiosyncratic shocks over 2009/01-2014/10. a) Weekly liquidity contagion model: b) Monthly liquidity contagion model.

a)

Banks	Lag 1	Lag 2	Lag 3
BANK_5	2,31	2,34	2,34
BANK_13	2,07	2,13	2,13
BANK_2	1,76	1,94	1,94
BANK_11	1,17	1,17	1,17
BANK_3	1,09	1,10	1,10
BANK_10	1,01	1,01	1,01
BANK_12	0,74	0,74	0,74
BANK_38	0,44	0,44	0,44
BANK_28	0,29	0,29	0,29
BANK_37	0,23	0,23	0,23
BANK_14	0,21	0,21	0,21
BANK_9	0,20	0,20	0,20
BANK_22	0,17	0,17	0,17
BANK_51	0,17	0,17	0,17
BANK_45	0,14	0,14	0,14
BANK_50	0,11	0,11	0,11
BANK_49	0,10	0,10	0,10
BANK_27	0,09	0,09	0,09
BANK_34	0,07	0,07	0,07
BANK_33	0,06	0,06	0,06
BANK_44	0,06	0,06	0,06
BANK_24	0,04	0,04	0,04
BANK_35	0,04	0,04	0,04
BANK_39	0,04	0,04	0,04
BANK_48	0,04	0,04	0,04
BANK_26	0,03	0,03	0,03
BANK_29	0,03	0,03	0,03
BANK_43	0,03	0,03	0,03
BANK_7	0,01	0,01	0,01
BANK_17	0,01	0,01	0,01
BANK_19	0,01	0,01	0,01
BANK_36	0,01	0,01	0,01
BANK_1	0,00	0,00	0,00
BANK_4	0,00	0,00	0,00
BANK_6	0,00	0,00	0,00
BANK_8	0,00	0,00	0,00
BANK_15	0,00	0,00	0,00
BANK_16	0,00	0,00	0,00
BANK_18	0,00	0,00	0,00
BANK_20	0,00	0,00	0,00
BANK_21	0,00	0,00	0,00
BANK_23	0,00	0,00	0,00
BANK_25	0,00	0,00	0,00
BANK_30	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00
BANK_32	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00
BANK_41	0,00	0,00	0,00
BANK_42	0,00	0,00	0,00
BANK_46	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00

b)

Banks	Lag 1	Lag 2	Lag 3
BANK_5	1,69	1,79	1,79
BANK_2	1,56	1,71	1,73
BANK_13	1,63	1,66	1,66
BANK_12	0,74	0,76	0,76
BANK_10	0,74	0,74	0,74
BANK_3	0,60	0,70	0,70
BANK_11	0,57	0,57	0,57
BANK_14	0,33	0,40	0,40
BANK_37	0,33	0,37	0,37
BANK_9	0,17	0,23	0,23
BANK_28	0,17	0,21	0,21
BANK_38	0,16	0,21	0,21
BANK_50	0,16	0,16	0,16
BANK_22	0,13	0,14	0,14
BANK_44	0,11	0,14	0,14
BANK_45	0,13	0,13	0,13
BANK_34	0,09	0,10	0,10
BANK_48	0,10	0,10	0,10
BANK_51	0,10	0,10	0,10
BANK_29	0,09	0,09	0,09
BANK_35	0,04	0,07	0,07
BANK_49	0,07	0,07	0,07
BANK_4	0,06	0,06	0,06
BANK_33	0,06	0,06	0,06
BANK_39	0,06	0,06	0,06
BANK_7	0,03	0,04	0,04
BANK_27	0,03	0,04	0,04
BANK_26	0,03	0,03	0,03
BANK_6	0,01	0,01	0,01
BANK_17	0,01	0,01	0,01
BANK_24	0,01	0,01	0,01
BANK_36	0,01	0,01	0,01
BANK_43	0,01	0,01	0,01
BANK_1	0,00	0,00	0,00
BANK_8	0,00	0,00	0,00
BANK_15	0,00	0,00	0,00
BANK_16	0,00	0,00	0,00
BANK_18	0,00	0,00	0,00
BANK_19	0,00	0,00	0,00
BANK_20	0,00	0,00	0,00
BANK_21	0,00	0,00	0,00
BANK_23	0,00	0,00	0,00
BANK_25	0,00	0,00	0,00
BANK_30	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00
BANK_32	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00
BANK_41	0,00	0,00	0,00
BANK_42	0,00	0,00	0,00
BANK_46	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00

Table 5.14 demonstrates the impacts of defaulted banks on other banks. Most effective banks according to weekly liquidity contagion model are BANK_5,

BANK_13, BANK_2, BANK_11, BANK_3 and BANK_10, while most influential banks according to monthly liquidity contagion model are BANK_5, BANK_2, BANK_13, BANK_12, BANK_10 and BANK_3, respectively.

BANK_46 and BANK_47 are newly opened banks. Therefore, these banks do not affect other banks as they do not have debit relations with other banks.

5.1.2.2 Fragility of banks considering liquidity contagion model

In this study, fragility of a bank is measured with the number of bank failures which affect the condition of a bank.

Table 5.15 – Weekly liquidity contagion model: Number of bank failures when a bank becomes defaulted as a result. Matrix is presented for the 20 banks with largest average number of bank failures which make banks defaulted in the period January 2009 – October 2014 at the first lag.

	BANK_8	BANK_23	BANK_32	BANK_37	BANK_19	BANK_15	BANK_21	BANK_6	BANK_20	BANK_29	BANK_46	BANK_18	BANK_16	BANK_30	BANK_36	BANK_42	BANK_1	BANK_7	BANK_25	BANK_33
2012-12	4	5	1	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-1	4	5	0	1	2	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-2	4	0	1	1	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	4	5	4	1	3	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
2013-4	3	5	5	1	3	1	2	0	1	4	0	0	1	0	0	0	0	0	0	0
2013-5	4	1	0	2	2	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-6	4	5	4	2	6	2	0	2	0	0	0	0	0	2	0	0	0	1	0	0
2013-7	3	5	2	1	2	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-8	4	4	0	1	3	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2013-9	4	2	0	1	2	2	0	0	1	0	0	0	0	4	0	0	0	1	0	0
2013-10	3	2	1	1	1	1	0	1	0	0	0	0	0	2	0	0	1	0	0	0
2013-11	0	2	2	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-12	3	2	0	1	1	2	0	0	0	0	2	0	0	0	0	1	1	0	0	0
2014-1	2	2	1	0	1	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0
2014-2	0	2	3	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2014-3	0	2	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
2014-4	1	2	8	2	0	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0
2014-5	0	2	10	1	0	1	6	0	0	0	1	0	0	0	0	0	0	0	0	0
2014-6	1	2	0	0	0	2	0	19	0	0	3	0	0	0	0	0	1	0	0	0
2014-7	1	2	1	0	1	1	0	0	0	0	3	0	0	0	0	0	1	0	0	0
2014-8	1	2	3	2	0	1	2	0	0	0	3	0	0	0	0	0	0	0	0	0
2014-9	1	1	0	1	0	2	0	0	0	0	3	0	0	0	0	0	0	0	0	1
2014-10	1	2	4	2	0	3	3	0	0	0	3	0	0	0	0	0	0	0	0	0
Average 2009/01 - 2014/10	**3**	**1,8**	**1,5**	**1,4**	**1,1**	**0,6**	**0,5**	**0,5**	**0,5**	**0,3**	**0,3**	**0,3**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0**

Table 5.15 presents the contagion results at the first lag. Each cell in the matrix, gives the number of bank failures which makes a bank defaulted. For example, BANK_8 becomes defaulted after 4 idiosyncratic shocks at first lag in 2012/12. In other words, four individual banks failures make BANK_8 defaulted Last row of the table demonstrates the average of the number of the bank failures that lead to failure in that bank in 70 months for first lag. The most fragile banks according to weekly liquidity contagion model are BANK_8, BANK_23, BANK_32, BANK_37 and BANK_19. Only the results of periods after December 2012 are demonstrated.

Table 5.16 - Weekly liquidity contagion model: Number of bank failures when a bank becomes defaulted as a result. Matrix is presented for the 20 banks with largest average number of bank failures which make banks defaulted in the period January 2009 – October 2014 at the last lag.

	BANK_8	BANK_23	BANK_32	BANK_37	BANK_19	BANK_15	BANK_6	BANK_21	BANK_20	BANK_29	BANK_46	BANK_18	BANK_16	BANK_30	BANK_36	BANK_42	BANK_1	BANK_7	BANK_25	BANK_33
2012-12	4	5	1	1	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-1	4	5	0	1	3	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-2	4	0	1	1	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	4	5	4	1	4	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1
2013-4	3	5	5	1	4	1	0	2	1	4	0	0	1	0	0	0	0	0	0	0
2013-5	4	1	0	2	4	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-6	4	5	4	2	7	2	3	0	0	0	0	0	0	2	0	0	0	1	0	0
2013-7	3	5	2	1	3	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-8	4	4	0	1	4	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0
2013-9	4	2	0	1	2	2	0	0	1	0	0	0	0	4	0	0	0	1	0	0
2013-10	3	2	1	1	2	1	1	0	0	0	0	0	0	2	0	0	1	0	0	0
2013-11	0	2	2	1	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-12	3	2	0	1	2	2	0	0	0	0	2	0	0	0	0	1	1	0	0	0
2014-1	2	2	1	0	1	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0
2014-2	0	2	3	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2014-3	0	2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	1
2014-4	1	2	8	2	0	0	1	0	0	0	2	0	1	0	0	0	0	0	0	0
2014-5	0	2	10	1	0	1	0	6	0	0	1	0	0	0	0	0	0	0	0	0
2014-6	1	2	0	0	0	2	19	0	0	0	3	0	0	0	0	0	1	0	0	0
2014-7	1	2	1	0	1	1	0	0	0	0	3	0	0	0	0	0	1	0	0	0
2014-8	1	2	3	2	0	1	1	2	0	0	3	0	0	0	0	0	0	0	0	0
2014-9	1	1	0	1	0	2	0	0	0	0	3	0	0	0	0	0	0	0	0	1
2014-10	1	2	4	2	0	3	0	3	0	0	3	0	0	0	0	0	0	0	0	0
Average 2009/01 - 2014/10	**3**	**1,8**	**1,5**	**1,4**	**1,3**	**0,6**	**0,6**	**0,5**	**0,5**	**0,3**	**0,3**	**0,3**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0,1**	**0**

Table 5.16 presents the contagion results at the last lag. For example, condition of BANK_32 is changed after 10 individual bank failures in the period 2014/5. For the last lag, in average for 70 months BANK_8 is affected from 3.0 bank failures, BANK_23 is affected from 1.8 bank failures, BANK_32 is affected from 1.5 bank failures, BANK_37 is affected from 1.4 bank failures, and BANK_19 is affected from 1.3 bank failures. Additionally, BANK_15, BANK_6, BANK_21 and BANK_20 are influenced by many bank failures. Other fragile banks which are less vulnerable than these banks are BANK_29, BANK_46 BANK_18 and BANK_16. Only the results of periods after December 2012 are demonstrated.

Table 5.17 – Monthly liquidity contagion model: Number of bank failures when a bank becomes defaulted as a result. Matrix is presented for the 20 banks with largest average number of bank failures which make banks defaulted in the period January 2009 – October 2014 at the first lag.

	BANK_32	BANK_19	BANK_8	BANK_23	BANK_15	BANK_37	BANK_21	BANK_16	BANK_29	BANK_18	BANK_36	BANK_51	BANK_20	BANK_46	BANK_1	BANK_48	BANK_11	BANK_30	BANK_5	BANK_24
2012-12	0	3	1	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-1	0	1	2	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-2	0	2	0	0	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	3	3	1	5	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-4	3	3	1	0	1	0	2	1	4	0	0	0	0	0	0	0	0	0	0	0
2013-5	2	2	1	1	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-6	3	3	0	4	2	1	0	1	0	0	0	0	0	0	0	0	0	2	0	0
2013-7	3	2	0	1	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-8	0	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	9	1	0	0
2013-9	0	7	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0
2013-10	1	1	0	2	1	0	0	0	0	0	0	0	0	0	1	2	0	1	0	0
2013-11	2	2	0	2	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2013-12	1	5	2	2	2	0	0	0	0	0	0	8	0	0	1	0	0	0	0	0
2014-1	1	2	1	2	1	0	3	1	0	0	0	0	0	0	1	0	0	0	0	0
2014-2	5	2	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2014-3	1	3	0	2	1	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0
2014-4	6	1	0	2	0	0	0	5	0	0	0	0	0	0	0	3	0	0	0	0
2014-5	10	3	0	1	1	1	6	0	1	0	0	0	0	1	1	3	0	0	0	0
2014-6	0	1	0	1	2	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0
2014-7	1	2	0	1	1	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0
2014-8	8	1	0	1	1	0	2	0	0	0	0	10	0	3	1	0	0	0	0	0
2014-9	0	2	1	1	2	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0
2014-10	9	5	0	1	3	0	3	0	1	0	0	0	0	3	0	0	0	0	3	0
Average 2009/01 - 2014/10	**1,6**	**1,3**	**1,1**	**0,9**	**0,6**	**0,6**	**0,5**	**0,4**	**0,3**	**0,3**	**0,3**	**0,3**	**0,2**	**0,2**	**0,2**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**

As shown in Table 5.17, the most fragile banks according to monthly liquidity contagion model are BANK_32, BANK_19, BANK_8, BANK_23 and BANK_15. Only the results of periods after December 2012 are demonstrated.

Table 5.18 - Monthly liquidity contagion model: Number of bank failures when a bank becomes defaulted as a result. Matrix is presented for the 20 banks with largest average number of bank failures which make banks default in the period January 2009 – October 2014 at the last lag.

	BANK_32	BANK_19	BANK_8	BANK_23	BANK_15	BANK_37	BANK_21	BANK_16	BANK_29	BANK_18	BANK_36	BANK_51	BANK_1	BANK_20	BANK_46	BANK_48	BANK_11	BANK_30	BANK_5	BANK_24
2012-12	0	3	1	4	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2013-1	0	1	2	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-2	0	2	0	0	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-3	3	4	1	5	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-4	3	3	1	0	1	0	2	1	4	0	0	0	0	0	0	0	0	0	0	0
2013-5	2	3	1	1	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-6	3	4	0	4	2	1	0	1	0	0	0	0	0	0	0	0	0	2	0	0
2013-7	3	2	0	1	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2013-8	0	3	0	10	3	0	0	0	0	0	0	0	0	0	0	0	9	1	0	0
2013-9	0	7	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0
2013-10	1	1	0	2	1	0	0	0	0	0	0	0	1	0	0	2	0	1	0	0
2013-11	2	2	0	2	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2013-12	1	5	2	2	2	0	0	0	0	0	0	8	1	0	0	0	0	0	0	0
2014-1	2	2	1	2	2	0	4	1	0	0	0	0	1	0	0	0	0	0	0	0
2014-2	5	2	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
2014-3	1	3	0	2	1	0	0	1	0	0	0	0	1	0	0	1	0	0	0	0
2014-4	6	1	0	2	0	0	0	8	0	0	0	0	0	0	0	3	0	0	0	0
2014-5	10	3	0	1	1	1	6	0	1	0	0	0	1	0	1	3	0	0	0	0
2014-6	0	1	0	1	2	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0
2014-7	1	2	0	1	1	0	0	0	0	0	0	0	1	0	3	0	0	0	0	0
2014-8	8	1	0	1	1	0	2	0	0	0	0	10	1	0	3	0	0	0	0	0
2014-9	0	2	1	1	2	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0
2014-10	11	5	0	2	5	0	5	0	1	0	0	0	0	0	3	0	0	0	3	0
Average 2009/01 - 2014/10	**1,6**	**1,4**	**1,2**	**1,2**	**0,7**	**0,6**	**0,6**	**0,5**	**0,3**	**0,3**	**0,3**	**0,3**	**0,2**	**0,2**	**0,2**	**0,2**	**0,1**	**0,1**	**0,1**	**0,1**

Table 5.18 presents the contagion results at the last lag. For example, condition of BANK_32 is changed after 11 individual bank failures in the period 2014/10. For the last lag, in average for 70 months BANK_32 is affected from 1.6 bank failures, BANK_19 is affected from 1.4 bank failures, BANK_8 is affected from 1.2 bank failures, BANK_23 is affected from 1.2 bank failures, and BANK_0.7 is affected from 50 bank failures. Additionally, BANK_37, BANK_21, BANK_16 and BANK_29 are influenced by many bank failures. Other fragile banks which are less

vulnerable than these banks are BANK_18, BANK_36 BANK_51 and BANK_1. Only the results of periods after December 2012 are demonstrated.

Table 5.19 – Results of contagion models for liquidity considering fragility of banks: Average number of idiosyncratic shocks that banks become defaulted after over 2009/01-2014/10. a) Weekly liquidity contagion model: b) Monthly liquidity contagion model.

a)

Banks	Lag 1	Lag 2	Lag 3
BANK_8	3,01	3,01	3,01
BANK_23	1,80	1,80	1,80
BANK_32	1,47	1,47	1,47
BANK_37	1,39	1,39	1,39
BANK_19	1,07	1,30	1,30
BANK_15	0,64	0,64	0,64
BANK_6	0,51	0,56	0,56
BANK_21	0,53	0,53	0,53
BANK_20	0,51	0,51	0,51
BANK_29	0,30	0,30	0,30
BANK_46	0,29	0,29	0,29
BANK_18	0,26	0,26	0,26
BANK_16	0,21	0,23	0,23
BANK_30	0,14	0,14	0,14
BANK_36	0,14	0,14	0,14
BANK_42	0,11	0,11	0,11
BANK_1	0,10	0,10	0,10
BANK_7	0,10	0,10	0,10
BANK_25	0,07	0,07	0,07
BANK_33	0,04	0,04	0,04
BANK_41	0,04	0,04	0,04
BANK_31	0,03	0,03	0,03
BANK_17	0,01	0,01	0,01
BANK_47	0,01	0,01	0,01
BANK_2	0,00	0,00	0,00
BANK_3	0,00	0,00	0,00
BANK_4	0,00	0,00	0,00
BANK_5	0,00	0,00	0,00
BANK_9	0,00	0,00	0,00
BANK_10	0,00	0,00	0,00
BANK_11	0,00	0,00	0,00
BANK_12	0,00	0,00	0,00
BANK_13	0,00	0,00	0,00
BANK_14	0,00	0,00	0,00
BANK_22	0,00	0,00	0,00
BANK_24	0,00	0,00	0,00
BANK_26	0,00	0,00	0,00
BANK_27	0,00	0,00	0,00
BANK_28	0,00	0,00	0,00
BANK_34	0,00	0,00	0,00
BANK_35	0,00	0,00	0,00
BANK_38	0,00	0,00	0,00
BANK_39	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00
BANK_43	0,00	0,00	0,00
BANK_44	0,00	0,00	0,00
BANK_45	0,00	0,00	0,00
BANK_48	0,00	0,00	0,00
BANK_49	0,00	0,00	0,00
BANK_50	0,00	0,00	0,00
BANK_51	0,00	0,00	0,00

b)

Banks	Lag 1	Lag 2	Lag 3
BANK_32	1,59	1,63	1,63
BANK_19	1,30	1,41	1,41
BANK_8	1,11	1,17	1,17
BANK_23	0,94	1,14	1,16
BANK_15	0,64	0,71	0,71
BANK_37	0,59	0,64	0,64
BANK_21	0,54	0,60	0,60
BANK_16	0,40	0,51	0,51
BANK_29	0,34	0,34	0,34
BANK_18	0,31	0,31	0,31
BANK_36	0,27	0,27	0,27
BANK_51	0,27	0,27	0,27
BANK_1	0,20	0,23	0,23
BANK_20	0,23	0,23	0,23
BANK_46	0,21	0,21	0,21
BANK_48	0,19	0,19	0,19
BANK_11	0,13	0,13	0,13
BANK_30	0,13	0,13	0,13
BANK_5	0,11	0,11	0,11
BANK_24	0,10	0,10	0,10
BANK_42	0,10	0,10	0,10
BANK_25	0,09	0,09	0,09
BANK_45	0,06	0,09	0,09
BANK_6	0,07	0,07	0,07
BANK_7	0,03	0,03	0,03
BANK_17	0,01	0,03	0,03
BANK_12	0,01	0,01	0,01
BANK_13	0,01	0,01	0,01
BANK_14	0,01	0,01	0,01
BANK_41	0,01	0,01	0,01
BANK_2	0,00	0,00	0,00
BANK_3	0,00	0,00	0,00
BANK_4	0,00	0,00	0,00
BANK_9	0,00	0,00	0,00
BANK_10	0,00	0,00	0,00
BANK_22	0,00	0,00	0,00
BANK_26	0,00	0,00	0,00
BANK_27	0,00	0,00	0,00
BANK_28	0,00	0,00	0,00
BANK_31	0,00	0,00	0,00
BANK_33	0,00	0,00	0,00
BANK_34	0,00	0,00	0,00
BANK_35	0,00	0,00	0,00
BANK_38	0,00	0,00	0,00
BANK_39	0,00	0,00	0,00
BANK_40	0,00	0,00	0,00
BANK_43	0,00	0,00	0,00
BANK_44	0,00	0,00	0,00
BANK_47	0,00	0,00	0,00
BANK_49	0,00	0,00	0,00
BANK_50	0,00	0,00	0,00

Table 5.19 demonstrates the vulnerability of banks from failures of other banks. Most fragile banks according to weekly liquidity contagion model are BANK_8,

BANK_23, BANK_32, BANK_37, BANK_19 and BANK_15, while most influential banks according to monthly liquidity contagion model are BANK_32, BANK_19, BANK_8, BANK_23, BANK_15 and BANK_37, respectively.

5.2. Simulation of Multiple Bank Failures

For this analysis, instead of idiosyncratic shocks, i.e., individual bank failures, multiple bank failures are assumed to fail at the first lag. As peer groups represent the banking groups and size of share in the sector, peer groups are assumed as defaulted in the first step.

Peer groups of banks can be changed due to their size in the market, switch of banking group or new opening. There are 13 peer groups on October 2014, which is the last period of the time span in the analysis. Last peer groups of banks are used as partitions, since dynamic partitions are not allowed in Pajek. In order to prevent confusion that can stem from change in peer groups, time span of the contagion is narrowed. The period choice is now between January 2013 and October 2014. In addition to narrowing the period, 11 peer groups are included in the contagion of multiple bank failures, because peer groups of newly opened banks include only one bank.

The same steps for capital adequacy and liquidity contagion are applied to the dataset. Only difference is that the initial partitions now mark banks in the peer groups as defaulted. For example the peer group "EGKAMU" spans three banks, "T.C. ZİRAAT BANKASI A.Ş.", "TÜRKİYE HALK BANKASI A.Ş." and "TÜRKİYE VAKIFLAR BANKASI T.A.O.". Under the assumption of failure of "EGKAMU", these three banks are coded as 0 and the other banks are coded as 1 in the partition.

Results are presented under two aspects; how failures of banks in a peer group affects other banks, i.e., effectiveness of a peer group, and how banks in a peer group are affected from failures of other banks, i.e., fragility of peer groups.

5.2.1. Effectiveness of peer groups

Effectiveness of a peer group is measured with the number of banks, which fails when banks in that peer group are defaulted.

Table 5.20 – Capital adequacy contagion model: Number of defaulted banks when banks in a peer group failed at the last lag.

	EGKAMU	EGKYB	EGKYB2	EGOFK	EGOZEL1	EGOZEL2.1	EGOZEL2.2	EGOZEL2.3	EGOZEL3	EGTMSF	EGYBSUBE
2013-1	4	1	1	3	7	4	0	1	0	0	0
2013-2	4	1	0	1	11	6	1	0	0	0	0
2013-3	7	0	1	2	8	5	1	2	1	0	0
2013-4	9	0	2	3	11	2	1	1	1	0	0
2013-5	5	1	2	3	11	0	0	2	0	0	0
2013-6	9	1	2	3	12	0	0	2	0	0	0
2013-7	14	0	1	2	12	0	2	5	0	0	0
2013-8	14	1	4	5	16	2	0	3	0	0	0
2013-9	16	1	1	3	17	1	1	2	0	0	0
2013-10	11	3	3	5	13	4	1	2	0	0	0
2013-11	9	4	4	4	16	1	2	2	0	0	0
2013-12	16	2	3	4	16	1	1	1	0	0	0
2014-1	12	2	4	5	15	1	3	5	0	0	0
2014-2	14	2	3	4	14	1	3	5	2	0	1
2014-3	14	2	2	3	12	0	1	3	0	0	0
2014-4	13	1	2	3	15	0	2	3	0	0	0
2014-5	11	2	2	3	12	2	3	3	0	0	0
2014-6	8	1	2	3	11	0	2	2	0	0	0
2014-7	12	2	2	3	12	2	1	2	0	0	0
2014-8	12	3	1	3	12	4	4	2	0	0	0
2014-9	10	2	2	3	15	3	3	3	0	0	0
2014-10	16	2	1	2	18	3	4	3	1	0	0
Average 2013/01 - 2014/10	**10,9**	**1,5**	**2,0**	**3,2**	**13,0**	**1,9**	**1,6**	**2,5**	**0,2**	**0,0**	**0,0**

Table 5.20 presents the contagion results of capital adequacy model at the last lag. For example, when banks in the peer group "EGKAMU" are failed in solvency in the period 2014/10, conditions of 16 banks get worse. At the last lag for 22 months in average, failures of banks in "EGOZEL1" cause 13.0 banks failures, failures of banks in "EGKAMU" cause 10.9 banks failures, and failures of banks in "EGOFK" cause 3.2 banks failures. Most effective peer groups are "EGOZEL1" and "EGKAMU", since failures of banks in these peer groups lead to many bank failures.

Peer groups “EGTMSF” and “EGYBSUBE” do not affect other banks when there is an insolvency issue.

Table 5.21 – Weekly liquidity contagion model: Number of defaulted banks when banks in a peer group failed at the last lag.

	EGKAMU	EGKYB	EGKYB2	EGOFK	EGOZEL1	EGOZEL2.1	EGOZEL2.2	EGOZEL2.3	EGOZEL3	EGTMSF	EGYBSUBE
2013-1	5	1	0	1	4	1	2	1	0	0	0
2013-2	4	1	0	1	4	1	1	0	0	0	0
2013-3	5	0	1	1	6	2	2	0	1	0	0
2013-4	6	0	1	1	7	4	2	1	0	0	0
2013-5	4	0	1	3	5	1	1	1	0	0	0
2013-6	7	1	1	1	8	3	2	2	0	0	0
2013-7	8	0	1	2	4	2	2	1	0	0	0
2013-8	6	0	1	2	4	2	2	1	0	0	0
2013-9	7	0	1	2	6	2	2	1	1	0	0
2013-10	6	0	1	2	5	3	2	1	0	0	0
2013-11	5	1	1	1	5	2	1	0	0	0	0
2013-12	7	0	1	1	3	1	1	0	0	0	0
2014-1	6	0	1	1	5	1	1	1	0	0	0
2014-2	7	0	1	1	5	2	1	0	0	0	0
2014-3	9	0	0	0	3	0	1	0	0	0	0
2014-4	11	0	0	1	5	1	2	1	0	0	0
2014-5	6	1	0	0	4	2	2	1	0	0	0
2014-6	8	0	0	0	3	2	2	1	1	0	0
2014-7	10	0	1	1	4	1	1	0	0	0	0
2014-8	9	0	0	1	4	1	2	0	0	0	0
2014-9	5	0	0	2	4	0	1	0	0	0	0
2014-10	7	0	0	1	5	0	2	1	0	0	0
Average 2013/01 - 2014/10	**6,7**	**0**	**1**	**1**	**4,7**	**2**	**2**	**1**	**0**	**0**	**0**

Table 5.21 presents the contagion results of weekly liquidity model at the last lag. For the last lag for 22 months, in average failures of banks in “EGKAMU” cause 6.7 bank failures, failures of banks in “EGOZEL1” cause 4.7 banks failures. Most effective peer groups are “EGOZEL1” and “EGKAMU”, since failures of banks in these peer groups lead to many bank failures. Peer groups “EGOZEL2.1”, “EGOZEL2.2“and “EGOFK” have also influence on other banks. Peer groups “EGTMSF” and “EGYBSUBE” do not affect other banks when there is an insolvency issue.

Table 5.22 – Monthly liquidity contagion model: Number of defaulted banks when banks in a peer group failed at the last lag.

	EGKAMU	EGKYB	EGKYB2	EGOFK	EGOZEL1	EGOZEL2.1	EGOZEL2.2	EGOZEL2.3	EGOZEL3	EGTMSF	EGYBSUBE
2013-1	5	0	0	1	2	0	0	0	0	0	0
2013-2	4	1	0	1	3	0	0	0	0	0	0
2013-3	5	0	1	1	3	1	1	0	0	0	0
2013-4	6	0	1	1	5	1	0	0	0	0	0
2013-5	4	0	1	1	4	1	0	1	0	0	0
2013-6	8	1	1	1	6	1	1	2	0	0	0
2013-7	7	0	1	1	3	1	1	2	0	0	0
2013-8	6	3	1	0	4	0	1	1	0	0	0
2013-9	6	1	1	2	7	1	2	1	1	0	0
2013-10	4	0	1	2	5	3	2	1	0	0	0
2013-11	7	1	1	1	8	1	1	0	0	0	0
2013-12	7	1	1	1	7	3	3	1	0	0	0
2014-1	10	1	2	2	6	1	1	1	0	0	0
2014-2	8	0	1	1	6	0	1	1	0	0	0
2014-3	8	0	1	2	5	0	1	1	0	0	0
2014-4	10	0	1	2	6	0	1	2	0	0	0
2014-5	7	1	1	1	8	4	2	1	0	0	0
2014-6	6	0	1	1	4	1	2	2	0	0	0
2014-7	7	1	1	1	3	0	1	1	0	0	0
2014-8	9	2	0	1	6	1	4	2	0	0	0
2014-9	4	1	0	2	4	0	2	1	0	0	0
2014-10	8	1	1	2	7	0	3	2	1	0	0
Average 2013/01 - 2014/10	**6,6**	**1**	**1**	**1**	**5,1**	**1**	**1**	**1**	**0**	**0**	**0**

Table 5.22 presents the contagion results of monthly liquidity model at the last lag. For the last lag for 22 months, in average failures of banks in "EGKAMU" cause 6.6 banks failures, failures of banks in "EGOZEL1" cause 5.1 banks failures. Most effective peer groups are "EGOZEL1" and "EGKAMU", since failures of banks in these peer groups lead to many bank failures. Peer groups "EGOZEL2.2", "EGOFK "and "EGOZEL2.3" have also influence on other banks. Peer groups "EGTMSF" and "EGYBSUBE" do not affect other banks when there is an insolvency issue.

Also, when results of idiosyncratic shocks are grouped by peer groups, effectiveness of peer groups will be more apparent. Table 5.23 indicates that as well as in the simulation of multiple bank failures, the most influential peer groups are "EGKAMU" and "EGOZEL" in idiosyncratic shocks.

Table 5.23 – Average number of bank failures result from idiosyncratic shocks within time span between January 2009 and October 2014 grouped by peer groups

	CAR	LIQ7	LIQ31
EGKAMU	8,3	5,4	4,2
EGKYB	0,8	0,1	0,3
EGKYB2	0,8	0,2	0,4
EGOFK	1,8	0,4	0,4
EGOZEL1	9,6	4,1	3,6
EGOZEL2.1	1,4	0,9	0,7
EGOZEL2.2	0,8	1,5	0,9
EGOZEL2.3	1,0	0,3	0,3
EGOZEL3	0,2	0,1	0,1
EGTMSF	0,0	0,0	0,0
EGYBSUBE	0,0	0,0	0,0

5.2.2. Fragility of peer groups

Fragility of a peer group is measured with the number of bank failures which affect the condition of a peer group.

Table 5.24 – Capital adequacy contagion model: Number of bank failures when a peer group becomes defaulted after.

	EGKAMU	EGKYB	EGKYB2	EGOFK	EGOZEL1	EGOZEL2.1	EGOZEL2.2	EGOZEL2.3	EGOZEL3	EGTMSF	EGYBSUBE
2013-1	0	0	4	3	0	0	1	2	9	1	1
2013-2	0	0	4	4	0	0	3	3	5	0	5
2013-3	0	1	4	3	0	0	4	3	6	0	6
2013-4	0	0	3	2	0	0	6	5	11	0	3
2013-5	0	1	3	3	0	0	2	5	8	0	2
2013-6	0	2	3	2	0	0	3	6	9	0	4
2013-7	0	1	5	2	0	3	5	4	10	0	6
2013-8	0	5	5	1	0	0	4	11	11	0	8
2013-9	0	6	5	3	0	0	4	6	13	0	5
2013-10	0	6	3	3	0	0	4	6	15	0	5
2013-11	0	1	4	3	0	0	5	6	13	0	10
2013-12	0	3	5	4	0	2	9	3	14	0	3
2014-1	0	1	6	2	0	1	9	7	15	0	6
2014-2	0	1	6	4	0	2	12	1	15	0	7
2014-3	0	3	5	3	0	1	5	1	13	1	4
2014-4	0	1	5	3	0	2	5	2	13	1	6
2014-5	0	0	3	3	0	0	4	3	14	1	9
2014-6	0	1	3	2	0	0	4	2	13	1	2
2014-7	0	2	5	3	0	0	4	1	15	1	4
2014-8	0	2	3	4	0	1	4	1	16	1	8
2014-9	0	5	5	3	0	0	5	2	18	0	2
2014-10	0	5	4	4	0	1	4	4	16	2	9
Average 2013/01 - 2014/10	**0,0**	**2,1**	**4,2**	**2,9**	**0,0**	**0,6**	**4,8**	**3,8**	**12,4**	**0,4**	**5,2**

Table 5.24 presents the fragility of peer groups in terms of the results of capital adequacy contagion model at the last lag. Each cell in the matrix, gives the number of bank failures which makes a peer group defaulted. For the last lag, in average for 22 months failure of peer group "EGOZEL3" is affected from 12.4 bank failures, peer group "EGYBSUBE" is affected from 5.2 bank failures, peer group "EGOZEL2.2" is affected from 4.8 bank failures, peer group "EGKYB2" is affected from 4.2 bank failures, and peer group "EGOZEL2.3" is affected from 3.8 bank failures. These are the most fragile peer groups, respectively. Peer groups "EGKAMU" and "EGOZEL1" are not affected from failure of other banks.

Table 5.25 – Weekly liquidity contagion model: Number of bank failures when a peer group becomes defaulted after.

	EGKAMU	EGKYB	EGKYB2	EGOFK	EGOZEL1	EGOZEL2.1	EGOZEL2.2	EGOZEL2.3	EGOZEL3	EGTMSF	EGYBSUBE
2013-1	0	0	3	0	0	0	0	0	5	6	1
2013-2	0	0	1	0	0	0	0	0	2	5	4
2013-3	0	1	2	0	0	0	1	0	3	6	5
2013-4	0	0	2	0	0	0	0	0	6	6	8
2013-5	0	0	3	0	0	0	0	0	5	4	4
2013-6	0	3	4	0	0	0	1	0	6	6	5
2013-7	0	0	4	0	0	0	0	0	4	6	6
2013-8	0	1	3	0	0	0	0	0	3	6	5
2013-9	0	5	4	1	0	0	0	0	4	5	3
2013-10	0	2	5	0	0	0	1	0	4	5	3
2013-11	0	0	4	0	0	0	0	0	4	2	5
2013-12	0	0	4	0	0	0	1	0	3	3	2
2014-1	0	0	3	0	0	0	0	0	3	3	6
2014-2	0	0	4	1	0	0	0	0	5	2	4
2014-3	0	1	4	0	0	0	1	0	2	1	3
2014-4	0	0	5	1	0	0	1	1	3	2	7
2014-5	0	0	3	0	0	0	0	0	1	1	10
2014-6	0	0	8	0	0	0	1	0	2	2	3
2014-7	0	0	4	0	0	0	1	0	3	2	5
2014-8	0	1	3	0	0	0	1	1	1	2	7
2014-9	0	1	3	0	0	0	0	0	1	3	7
2014-10	0	0	4	0	0	0	1	0	2	2	2
Average 2013/01 - 2014/10	**0,0**	**0,7**	**3,6**	**0,1**	**0,0**	**0,0**	**0,5**	**0,1**	**3,3**	**3,6**	**4,8**

Table 5.25 presents the fragility of peer groups in terms of the results of weekly liquidity contagion model at the last lag. For the last lag, in average for 22 months

failure of peer group "EGYBSUBE" is affected from 4.8 bank failures, peer groups "EGKYB2" and "EGTMSF" are affected from 3.6 bank failures and peer group "EGOZEL3" is affected from 3.3 bank failures. In terms of contagion results from weekly liquidity model, these peer groups are the most fragile peer groups respectively. Peer groups "EGKAMU", "EGOZEL1" and "EGOZEL2.1" are not affected from failure of other banks.

Table 5.26 – Monthly liquidity contagion model: Number of bank failures when a peer group becomes defaulted after.

	EGKAMU	EGKYB	EGKYB2	EGOFK	EGOZEL1	EGOZEL2.1	EGOZEL2.2	EGOZEL2.3	EGOZEL3	EGTMSF	EGYBSUBE
2013-1	0	0	2	0	0	0	0	0	2	3	1
2013-2	0	0	1	0	0	0	0	0	3	1	4
2013-3	0	0	2	0	0	0	0	0	4	3	3
2013-4	0	0	1	0	0	0	0	0	6	2	5
2013-5	0	0	2	0	0	0	0	0	4	3	3
2013-6	0	3	4	0	0	0	1	0	6	3	4
2013-7	0	0	3	0	0	0	0	0	5	3	5
2013-8	0	1	3	0	0	0	1	0	4	2	5
2013-9	0	5	3	1	0	0	0	1	8	2	2
2013-10	0	1	2	2	0	0	0	0	7	3	3
2013-11	0	0	3	1	0	0	2	1	6	2	5
2013-12	0	0	4	5	0	0	0	0	8	3	3
2014-1	0	0	4	0	1	0	0	1	7	3	7
2014-2	0	0	4	2	0	0	1	0	5	1	5
2014-3	0	0	4	1	0	0	1	0	7	1	3
2014-4	0	0	4	2	0	0	0	1	7	1	6
2014-5	0	0	5	2	0	0	0	0	6	1	10
2014-6	0	0	7	1	0	0	0	0	5	1	2
2014-7	0	0	4	0	0	0	0	0	5	1	4
2014-8	0	0	4	6	0	0	0	1	5	1	7
2014-9	0	0	2	1	0	0	0	0	6	2	2
2014-10	0	0	1	1	0	0	1	0	9	3	9
Average 2013/01 - 2014/10	**0,0**	**0,5**	**3,1**	**1,1**	**0,0**	**0,0**	**0,3**	**0,2**	**5,7**	**2,0**	**4,5**

Table 5.26 presents the fragility of peer groups in terms of the results of monthly liquidity contagion model at the last lag. For the last lag, in average for 22 months failure of peer group "EGOZEL3" is affected from 5.7 bank failures, peer groups "EGYBSUBE" is affected from 4.5 bank failures and peer group "EGKYB2" is affected from 3.1 bank failures. In terms of contagion results from monthly liquidity

model, these peer groups are the most fragile peer groups respectively. Peer groups "EGKAMU" and "EGOZEL2.1" are not affected from failure of other banks.

Also, when results of idiosyncratic shocks are grouped by peer groups, fragility of peer groups will be more apparent. Table 5.27 indicates that most vulnerable peer groups for CAR contagion model are "EGOZEL3" and "EGYBSUBE" in idiosyncratic shocks, whereas for liquidity contagion models most fragile peer groups are "EGTMSF" and "EGYBSUBE.

Table 5.27 – Number of bank failures when a bank become as defaulted after within time span between January 2009 and October 2014 grouped by peer groups

	CAR	LIQ7	LIQ31
EGKAMU	0,0	0,0	0,1
EGKYB	1,2	0,6	0,5
EGKYB2	2,5	2,0	0,9
EGOFK	2,8	0,0	0,5
EGOZEL1	0,1	0,0	0,0
EGOZEL2.1	0,2	0,0	0,0
EGOZEL2.2	2,7	0,0	0,2
EGOZEL2.3	2,5	0,0	0,1
EGOZEL3	8,0	1,8	2,3
EGTMSF	0,0	4,8	2,3
EGYBSUBE	4,5	3,5	3,6

5.3. Correlations between contagion models

The contagion is evaluated over two channels, capital adequacy and liquidity channel. Since aspect of liquidity is divided into two in terms of cycle length, three contagion models are performed, CAR, LIQ7 and LIQ31. The relationship between results of these three contagion models is expected to be close. To assess the relation of contagion models, firstly the Pearson correlation between exact ratios of capital adequacy and liquidity is computed for two periods, October 2014 and December 2013. As shown in Table 5.28, between capital adequacy ratio and liquidity ratios it seems there is a strong correlation, on the other hand, weekly and monthly liquidity ratios unexpectedly are not correlated so much.

Table 5.28 – Pearson's correlation matrix of capital adequacy and liquidity ratios with p-value

2014-10

	CAR	LIQ7	LIQ31
CAR	1,000	0,633	0,560
LIQ7	0,633	1,000	0,452
LIQ31	0,560	0,452	1,000

2013-12

	CAR	LIQ7	LIQ31
CAR	1,000	0,789	0,693
LIQ7	0,789	1,000	0,269
LIQ31	0,693	0,269	1,000

P-value

	CAR	LIQ7	LIQ31
CAR	-	0,000	0,000
LIQ7	0,000	-	0,001
LIQ31	0,000	0,001	-

P-value

	CAR	LIQ7	LIQ31
CAR	-	0,000	0,000
LIQ7	0,000	-	0,057
LIQ31	0,000	0,057	-

Secondly, the correlations of results from contagion models are presented in Table 5.29 in two parts, effectiveness and fragility. For aspect of effectiveness, the results are the total number of defaulted banks as a consequence of idiosyncratic shocks at the last lag, whereas, for aspect of fragility, the results are the total number of bank failures when a bank becomes defaulted after. In general for effectiveness, all three models support each other, since they are highly correlated. Nevertheless, for fragility of banks, the only strong correlation is between LIQ7 and LIQ31 models. LIQ31 and CAR models are related to each other at 60% level. The results from CAR and LIQ7 models are not very similar.

Table 5.29 – Correlation between contagion models in terms of effectiveness and fragility of banks with p-value

effectiveness

	CAR	LIQ7	LIQ31
CAR	1,000	0,900	0,954
LIQ7	0,900	1,000	0,980
LIQ31	0,954	0,980	1,000

fragility

	CAR	LIQ7	LIQ31
CAR	1,000	0,343	0,600
LIQ7	0,343	1,000	0,859
LIQ31	0,600	0,859	1,000

P-value

	CAR	LIQ7	LIQ31
CAR	-	<0,00	<0,00
LIQ7	<0,00	-	<0,00
LIQ31	<0,00	<0,00	-

P-value

	CAR	LIQ7	LIQ31
CAR	-	0,014	0,000
LIQ7	0,014	-	0,000
LIQ31	0,000	0,000	-

Figure 5.3 and Figure 5.4 represent the scatter plots of contagion models, they demonstrate the relations of contagion models graphically.

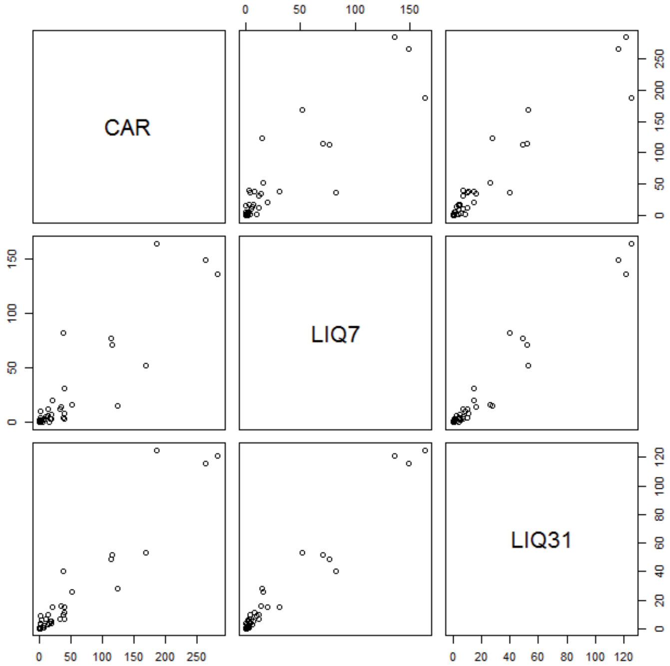


Figure 5.3. Scatter plots of contagion model results under the aspect of effectiveness.

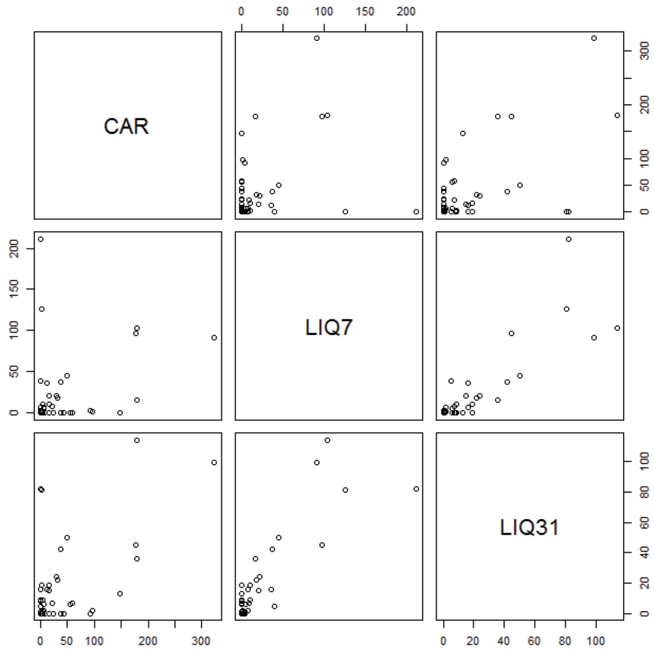


Figure 5.4. Scatter plots of contagion model results under the aspect of fragility.

CHAPTER 6

DISCUSSION AND CONCLUSION

In this last chapter, the findings at the end of the study are discussed. The conclusion, the contribution of the study and limitations and further research are presented in the following two subsections.

6.1. Discussion and Conclusion

This thesis utilized the network theory and diffusion for the contagion models based on the diffusion of innovation model determined by Rogers (2003). The regulations on the capital adequacy and liquidity and their vitality for the financial systems were presented. Banks are mandated to provide legal bounds of capital adequacy ratio (%8) and liquidity ratio (100%). Stress tests for stability of banks, studied by BRSA were also introduced. Stress tests determine the contagion effect indirectly by calculating the effect of probability of default on capital adequacy ratio. These tests use simulated datasets of debits and credits, not real datasets and do not take into account the pair-wise relationships. Existing systemic risk models and the several studies conducted to examine the systemic risk were also summarized. Each study found significant explanations of the contagion effect over the network structure and each of them has its own contribution to the investigation of the systemic risk. Similar to the existing systemic risk models, the aim in this study was to determine the potential systemic risk in the form of contagion in the Turkish banking system by using the datasets of debit and credit relations between individual banks.

With the contagion models constructed in this study, it was intended to demonstrate the effect of one or more bankruptcies on the capital adequacy and liquidity of other banks which have debit and credit relation with the failed bank. It is assumed that in the case of a bank failure, the defaulted bank will not be able to meet its liabilities to the other banks and consequently their capital adequacy and liquidity ratios will decrease. When ratios of these banks drop down below legal boundaries, they are assumed as defaulted. In a chain reaction, many banks became defaulted as a result of individual bank failures (idiosyncratic shocks) and multiple bank failures. These failure scenarios have previously been tested by Hausenblas, Kubicová, & Lešanovská (2012) for the Czech banking system. Their methods guided the assumptions made while creating the contagion models in this study.

To conduct the study, monthly reports of banks to the Banking Regulation and Supervision Agency (BRSA) in the time span of January 2007 to October 2010 were acquired. Since the study focuses on the Turkish Banking Sector, only 51 banks in Turkey and their debit and credit relations were included in the study. On the other hand, since the capital adequacy and liquidity forms have been available in a standard format since June 2008, contagion effect was determined for the time period between January 2009 and October 2014. In order to determine the contagion effect on the basis groups as well as on the basis of individual banks, banking groups and peer groups of banks were attached to the dataset.

The diffusion analysis of bankruptcies are separated into two standard techniques. First technique is the exploration of the network structure related to the interbank market and the second technique is the application of the contagion models.

Firstly, the network structure obtained from the debit credit relations of banks was investigated in terms of network analysis metrics such as degree, betweenness and closeness centralities, since the structure of the banking network impacts the contagion of bank failures in the financial sector (Hausenblas, Kubicová, & Lešanovská, 2012). The observation of the network belongs to the time period between January 2007 and October 2014.

To monitor the whole network and to capture the structure of the banking sector, in-degree, out-degree, degree, in-closeness, out-closeness, closeness and betweenness centralizations were computed for all months in the time span by using one directional network structure of debits and credits relations. It was founded that there was not a clear boundary between the center and the periphery according to in-degree and out-degree centralizations, whereas closeness centralizations indicate that there exists some banks which are more central according their reachability to other banks. The effects of the global crisis in 2008 became visible in Turkey in the early of 2009. Therefore the amount of money flow between banks in the Turkish Banking System shows an increasing trend after the end of 2010.

To explain the roles of bank groups, the network was shrunk in terms of groups of banks. On average, foreign banks and development and investment banks have the highest incoming amount of money flow which refers to credits, while state-owned banks and privately-owned banks have the highest outgoing amount of money flow which refers to debits. In terms of peer groups, peer group of “EGKAMU”, i.e., state-owned banks, and the peer group of “EGOZEL1”, i.e., the banks with the largest size among privately-owned banks, have the highest outgoing amount of money flow and definite differences in incoming line values are observable for peer group of “EKYB2”, i.e., the second group of development and investment banks, and the peer group of “EGOZEL2.2”, i.e., the third group of privately-owned banks,

In order to explore the banks which play key roles in the network, centrality metrics were used. According to results, BANK_6 and BANK_33 are the banks with the largest input degree centrality scores, the largest amount of credits and have receivables in large amounts from many banks, whereas BANK_2, BANK_12 and BANK_13 have a strong influence on the Turkish Banking System, since as well as their outgoing money flow, their out-degree and out closeness centrality scores are very large.

After this overall network and vertex characterization, in order to extract the details of the contagion model, initially egocentric cases were explained step by step. There were two channels for the propagation of bank failures: capital and liquidity channels. For the capital channel, one directional network which was created by netting the debits and credits was used, whereas for the liquidity channel bidirectional network structure of the debits and credits was used.

The contagion effect was elaborated based on two separate models for capital adequacy and liquidity. In order to initiate the contagion, idiosyncratic shocks and multiple banks failures were simulated. Macros were performed successively for all months, for all starts and for all lags. Macros were stopped if the number of defaulted banks after shocks did not increase. In this study, lags were the geodesic distances between the banks, not time.

According to the simulation results of the capital adequacy channel, after the fourth lag, number of defaulted banks reaches to its maximum. On average over the period January 2009-October 2014, when a bank is defaulted, at the last lag about 20 banks in total are affected from this failure and their CAR values decrease under threshold 12. To detect effectiveness of individual banks on other banks, the number of bank failures caused by an individual bank was computed. For the last lag, on average over the period between 2009/01 and 2014/10, failure of BANK_2 causes 4.06 banks failures, failure of BANK_13 causes 3.8 banks failures, failure of BANK_5 causes 2.7 banks failures, and failure of BANK_12 causes 2.4 banks failures. Since the total money flow among banks got to its minimum value for the crisis period in Turkey, after the crisis period, there was an increasing trend, as the total amount of money flow among the banks as well as the connectedness increase. To demonstrate the fragility of individual banks, the number of bank failures which cause a failure on an individual bank was computed. For the last lag, on average over the period between 2009/01 and 2014/10, BANK_19 is affected from 4.6 bank failures, BANK_32 is affected from 2.6 bank failures, BANK_16 is affected from 2.5 bank failures, BANK_37 is affected from 2.5 bank failures, and BANK_48 is affected from 2.1 bank failures.

According to the simulation results of the liquidity channel, after the third lag, the number of defaulted banks reaches to its maximum. Liquidity contagion model was applied both for weekly and monthly liquidity ratios. The most effective banks according to weekly liquidity contagion model are BANK_5, BANK_13, BANK_2, BANK_11 and BANK_3, while for monthly liquidity contagion model the most effective banks are BANK_5, BANK_2, BANK_13 and BANK_12. On the other hand, most fragile banks for weekly liquidity contagion model are BANK_8, BANK_23 and BANK_32, while for most fragile banks for monthly liquidity contagion model are BANK_32, BANK_19 and BANK_8.

For multiple bank failures, it was assumed that all banks in peer groups fail together. In capital adequacy and liquidity channels, most effective peer groups are "EGOZEL1" and "EGKAMU". However peer groups "EGTMSF" and "EGYBSUBE" do not affect other banks when there is an insolvency issue. For capital adequacy and liquidity contagion models, most fragile peer groups are "EGOZEL3", "EGYBSUBE", "EGOZEL2.2" and "EGKYB2".

Lastly, the correlation between the results of three contagion models, CAR, LIQ7 and LIQ31, and between the results of three contagion modes and network centrality metrics were investigated. For effectiveness, three models are highly correlated. Nevertheless, for fragility of banks, the only strong correlation is between LIQ7 and LIQ31 models, LIQ31 and CAR models are related to each other at 60% level.

Comparison of the results with other studies is not possible, since this study is the only study conducted on real dataset of interbank debits and credits relation in the banking system of Turkey. In BRSA, to measure the stability of banks, stress tests are applied, which includes credit risk, exchange risk, interest rate risk, revenue risk and contagion effect. Their contagion effect study is based on the information obtained by simulating the amounts of relations according to size of banks in the sector and their calculations are probabilistic. That is why, comparison is not rational. Also the contagion effect in the stress tests consider only individual bank failures. This study additionally takes multiple bank failures into consideration. In other aspects, the results of the study verifies individual bank situations detected by BRSA. There were some special cases for BANK_22 and BANK_51. In those months along with these special circumstances the number of their failures shows an increase, which supports the study with real life examples.

Financing authorities and banks can benefit from this study. For protection of the banks, which are vital components of the finance sector, from possible crises like Lehman and Brothers, financial authorities, BRSA, Central Bank of Turkey and Saving Deposit Insurance Fund can calculate the risks of propagation of banks failures and possible loss with this studied model. When they are scoring the stability and fragility of banks, this study can contribute to their measurements. As well as financial authorities can deal with contagion of bank failures on the bank basis, contagion can be discussed on the sector basis by investigating the network structure of interbank relations. Centrality metrics provide a facility for making predictions about contagion results without simulations. Also, in BRSA, contagion effect part of the stress tests can be changed with these results. In addition, banks can understand their positions in the sector and the importance of their position in the spread of banking failures.

6.2. Limitations and Further Research

The study has several limitations. First of all, in the forms for debits and credits relation the names of the counter banks in bilateral relation were not coded as there was only the text field for the name of institution, and the names were not correctly typed. As a result, the name of an institution was typed in many different ways. With a script, all different versions of names were transformed to one single name; however, there might have been omitted relations due to the lack of name. The information about the relations with other financial institutions including counter party name and amount is based on declaration of banks. Also the names of the banks cannot be given specifically due to privacy issues and not to defame banks.

Secondly, there are also debits and credits among banks by the way of derivative transactions and indirect guarantees given over customers, which were not included in the study. It is not possible to extract indirect guarantees from existing datasets in the database of BRSA. Derivative transactions impose both liability and asset to counterparties. Therefore, net derivative transactions do not lead to credit risk over nominal amounts. Net debits and credits can only exist in the amount of difference between spot price and price agreement on the date of transaction. Since transactions between domestic banks are generally short dated, variety of current values are limited. Therefore in this study, derivative transactions were not included.

Thirdly, relations of banks with banks abroad were not included in the study. These are reported to BRSA, but not in a standard format. The names of banks were also entered incorrectly in these forms. After putting the names of the counter party in a standard format, the study can be enlarged by including financial institutions abroad.

Fourthly, according to Base II criteria, the capital adequacy ratios of banks should be 8% minimum. However, in this study the BRSA requirement of 12% was considered. This threshold can additionally be applied to the dataset to show the worst cases of the contagion by assuming 8% as the threshold value of default.

Fifthly, results demonstrate time series lines with some patterns; therefore, seasonality and patterns in the number of bank failures as a result of contagion effect can be determined.

Sixthly, the change in the capital adequacy could have been used to explain how much a bank depends on another bank. For example, a bank failure can make capital adequacy ratio of one of its neighbor banks fall much more than that of another bank. In this study, new capital adequacy ratios has been used to determine whether it is above or below 12% only. The level of change has not been taken into account, which could have demonstrates the level of dependencies between banks.

Lastly, in this study, the datasets from previous periods were used. For further research, egocentric predictions of line values and vectors can be made for application of contagion effect model to predict future networks and their contagion effects.

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APPENDICES

Appendix A: List of Banks in the Analysis

BANK NAME	2007-3	2007-6	2007-9	2007-12	2008-3	2008-6	2008-9	2008-12	2009-3	2009-6	2009-9	2009-12	2010-3	2010-6	2010-9	2010-12	2011-3	2011-6	2011-9	2011-12	2012-3	2012-6	2012-9	2012-12	2013-3	2013-6	2013-9	2013-12	2014-3	2014-6	2014-9	2014-10
İLLER BANKASI	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
T.C. ZİRAAT BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE HALK BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE SINAİ KALKINMA BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE VAKIFLAR BANKASI T.A.O.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE İHRACAT KREDİ BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE KALKINMA BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
BİRLEŞİK FON BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRK EKONOMİ BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
AKBANK T.A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ŞEKERBANK T.A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE GARANTİ BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE İŞ BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
YAPI VE KREDİ BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
THE ROYAL BANK OF SCOTLAND PLC.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ARAP TÜRK BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
CITIBANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
BANK MELLAT	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TURKISH BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
HABİB BANK LİMİTED	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
JP MORGAN CHASE BANK NATIONAL ASSOC.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ING BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ADABANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
FİBABANKA A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
PORTIGON A.G.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■					
TURKLAND BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TEKSTİL BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
FİNANSBANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
DEUTSCHE BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TAIB YATIRIMBANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
STANDARD CHARTERED YAT. BNK. TÜRK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
SOCIETE GENERALE S.A.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
HSBC BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ALTERNATİFBANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
BURGAN BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
MERRILL LYNCH YATIRIM BANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
İSTANBUL TAKAS VE SAKLAMA BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
DENİZBANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ANADOLUBANK A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
DİLER YATIRIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
GSD YATIRIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
NUROL YATIRIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
BANKPOZİTİF KREDİ VE KALKINMA BNK. A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
AKTİF YATIRIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ODEA BANK A.Ş.																								■	■	■	■	■	■	■	■	■
BANK OF TOKYO MİTSUBİSHİ UFJ TURKEY A.Ş.																												■	■	■	■	■
INTESA SANPAOLO S.P.A.																														■	■	■
ALBARAKA TÜRK KATILIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
KUVEYT TÜRK KATILIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TÜRKİYE FİNANS KATILIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ASYA KATILIM BANKASI A.Ş.	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TOTAL NUMBER OF BANKS	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**48**	**49**	**49**	**49**	**49**	**49**	**49**	**50**	**50**	**50**

■ Active banks

Appendix B: Steps of Capital Adequacy Contagion Model

```
NETBEGIN 1
CLUBEGIN 1
PERBEGIN 1
CLSBEGIN 1
HIEBEGIN 1
VECBEGIN 1

N 1 RDN "C:\Users\ozdemiro\Desktop\CAR-idiosyncratic shocks\94\94.net" (51)
V 1 RDV "C:\Users\ozdemiro\Desktop\CAR-idiosyncratic shocks\94\ö94.vec" (51)
V 2 RDV "C:\Users\ozdemiro\Desktop\CAR-idiosyncratic shocks\94\r94.vec" (51)
C 1 RDC "C:\Users\ozdemiro\Desktop\CAR-idiosyncratic shocks\94\başlangıç\bank51.clu" (51)
Msg Shrinking
N 2 SHR 1 1 [1 ,1,1] (45)
C 3 NEIG 2 [1,1,1] (45)
V 3 MVEC 3 (45)
V 4 MVEC 2 (45)
V 5 ADDCONSTVEC 4 50.0000 (45)
V 6 MINV 3 5 (45)
C 4 MAKETRUNCPAR 6 (45)
V 7 SHRV 1 1 [1,1] (45)
V 8 SHRV 2 1 [1,1] (45)
N 3 ETOAINC 2 4 1 DEL (45)
C 5 BIN 4 [0-1] (45)
V 9 MVEC 5 (45)
V 10 LINESUM 3 [0] (45)
V 11 MULV 10 9 (45)
V 12 MUL1VEC 11 by 0.2000 (45)
V 13 SUBV 7 11 (45)
V 14 SUBV 8 12 (45)
V 15 DIVV 13 14 (45)
V 16 MUL1VEC 15 by 100.0000 (45)
V 17 MULV 16 4 (45)
C 6 MAKEVECPAR 17 [12] (45)
V 18 MVEC 6 (45)
V 19 ADDCONSTVEC 18 -1.0000 (45)
C 7 MAKETRUNCPAR 19 (45)
C 8 EXPP 7 1 1 (51)
C 9 MAKETRUNCPAR 17 (45)
C 10 EXPP 9 1 1 (51)
V 20 MVEC 10 (51)
C 8 WC "C:\Users\ozdemiro\Desktop\CAR-idiosyncratic shocks\94\başlangıç\bank51.clu" (51)
V 20 WV "C:\Users\ozdemiro\Desktop\CAR-idiosyncratic shocks\94\sonuçlar\bank51.vec" 0 (51)
```

Appendix C: Steps of Liquidity Contagion Model

```
NETBEGIN 1
CLUBEGIN 1
PERBEGIN 1
CLSBEGIN 1
HIEBEGIN 1
VECBEGIN 1

N 1 RDN "C:\Users\ozdemiro\Desktop\LIQ7-idiosyncratic shocks\94\94.net" (51)
V 1 RDV "C:\Users\ozdemiro\Desktop\LIQ7-idiosyncratic shocks\94\ta94.vec" (51)
V 2 RDV "C:\Users\ozdemiro\Desktop\LIQ7-idiosyncratic shocks\94\tl94.vec" (51)
C 1 RDC "C:\Users\ozdemiro\Desktop\LIQ7-idiosyncratic shocks\94\başlangıç\bank51.clu" (51)
Msg Shrinking
N 2 SHR 1 1 [1 ,1,1] (51)
C 3 NEIG 2 [1,1,1] (51)
V 3 MVEC 3 (51)
V 4 MVEC 2 (51)
V 5 ADDCONSTVEC 4 50.0000 (51)
V 6 MINV 3 5 (51)
C 4 MAKETRUNCPAR 6 (51)
V 7 SHRV 1 1 [1,1] (51)
V 8 SHRV 2 1 [1,1] (51)
N 3 REMLINCLU 2 4 [0-*] 1 (51)
C 5 BIN 4 [0-1] (51)
V 9 MVEC 5 (51)
N 4 ETOAINC 3 4 1 DEL (51)
V 10 LINESUM 4 [0] (51)
N 5 ETOADEC 3 4 1 DEL (51)
V 11 LINESUM 5 [1] (51)
V 12 MULV 9 10 (51)
V 13 MULV 9 11 (51)
V 14 SUBV 7 12 (51)
V 15 SUBV 8 13 (51)
V 16 DIVV 14 15 (51)
V 17 MUL1VEC 16 by 100.0000 (51)
V 18 MULV 17 4 (51)
C 6 MAKEVECPAR 18 [100] (51)
V 19 MVEC 6 (51)
V 20 ADDCONSTVEC 19 -1.0000 (51)
C 7 MAKETRUNCPAR 20 (51)
C 8 EXPP 7 1 1 (51)
C 9 MAKETRUNCPAR 18 (51)
C 10 EXPP 9 1 1 (51)
V 21 MVEC 10 (51)
C 8 WC "C:\Users\ozdemiro\Desktop\LIQ7-idiosyncratic shocks\94\başlangıç\bank51.clu" (51)
V 21 WV "C:\Users\ozdemiro\Desktop\LIQ7-idiosyncratic shocks\94\sonuçlar\bank51.vec" 0 (51)
```