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Analyzing Systemic Risk with Financial Networks: An Application During a Financial Crash[1]

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ABSTRACT

A financial network model, where the coded identity of the counterparties of every trade is known, is applied to both stable and crisis periods in a large and liquid overnight repo market in an emerging market economy. We have analyzed the financial crisis by using various network investigation tools such as links, interconnectivity, and reciprocity. In addition, we proposed a centrality measure to monitor and detect the 'systemically important financial institution' in the financial system. We have shown that our measure gives strong signals much before the crisis.

JEL: F3, G1, D8. Keywords: systemic risk, financial regulation, financial crisis, BASEL III, systemically important financial institution, Turkey, IMF.

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1. Introduction

The financial Crisis hit the global economy between 2007–2009 has demonstrated the importance of systemic risk, a concept which can cause breakdown in the financial system. This crisis also led the financial authorities to rethink the effectiveness of financial regulation with the existing tools.

Thus, as pointed out by Lo (2010), starting point for regulatory reform is to develop formal measures of systemic risk measures that capture the linkages of the system. Moreover, in a recent study commissioned by the G-20, the IMF determined that systemically important institutions are not limited to those that are the largest, but also includes others that are interconnected and that can impair the normal functioning of financial markets

But the increased complexity and connectedness of financial markets is a relatively new phenomenon that requires a fundamental shift in our linear mode of thinking with respect to risk measurement. However, while many tools exist for measuring systemic risk, these measures have, at best, yielded indirect indications of the build-up of systemic risk over the last few years because regulators lack the necessary data to generate definitive, timely, and actionable measures.

More importantly, recent financial regulation discussions on "Systemically Important Institutions" (SIFI) focus on two main issues. First, how to choose the most important institutions is a very challenging task. There are various potential criteria to be used to define a metric. For instance, is it the total asset size of the bank, or is it the connectedness (or potential to destroy the banking system) see Thornton (2009). In addition, on the basis of this choice, banks are expected to leave a certain capital buffer (see Mendosa et al (2010). All these recent discussions boil down to propose a metric to measure the systemic importance of a given institution.

In this paper we wanted address these critical regulatory questions by using some network tools on a real financial crash data set. More particularly, we wanted to answer the following questions. How can we detect and monitor the stress on a financial system? Which network tools can be used? Second, we wanted to propose a financial network tool to detect the most interconnected institution in a system. Our analyses are based on an overnight money market network during the Turkish financial crash in 2000. As is known, Turkish economy suffered from twin financial crises in November 2000 and February 2001. Annual interest rates reached 2000% overnight in the former and 7500% in the latter. It was observed that the structure of the market was changed by a Systemically Important Institution (SIFI) and November crisis destroyed the centralized network around this player. This episode was very similar to the one occurred in US during September 2008 so we claim our results can be used to draw conclusions for a general crisis. By using some network tools we aimed to propose some answers to the very important and challenging regulatory questions. First, we proposed the two network tools namely the number of links in a network and the connectivity of a given network. By using these tools one can monitor the network system's distress level. In addition we wanted analyze whether a network metric can be used to detect and monitor the heavily interconnected institutions. For this purpose we have modified the Google's Page rank algorithm and have observed that the most interconnected (or SIFI) can be successfully detected five months before the crisis occurs. As our paper is one of the first application of a financial network during an actual crash our results can be useful in drawing policy recommendations.

The organization of our paper is as follows section 2 summarizes the literature on systemic risk and its network applications. Section 3 describes Turkish financial crisis of 2000. Section 4 presents empirical results and Section 5 concludes.

2. Literature Review

The notion of systemic risk has gained great importance for the world financial system during the last decade. The financial crises in many countries can be considered as realizations of the systemic risk in the financial system.

The last global financial turmoil provoked debates about controlling systemic risk with financial monitoring and regulation and network approach is having a bigger part in these debates. Lo (2008) proposes a set of measures for systemic risk which are leverage, liquidity, correlation, concentration, sensivities and connectedness. He emphasizes that deriving the network-map of the financial system is beneficial to analyse these systemic risk measure. Brunnermeier (2009) shows network risk as an example of Bear Sterns crisis of March 2008.

Systemic risk is defined as the risk of experiencing systemic events in the strong sense (De Bandt and Hartmann 2000). Systemic events, contagion and systemic crisis must be well-defined to understand the concept of systemic risk. A systemic event is caused by an initial shock which can be either idiosyncratic or systematic. If the initial shock does not generate a failure or a crash in the system in the second round effect then the systemic event is weak. On the contrary, a failure or a crash means that the systemic event is strong. Contagion is the mechanism which transmits the initial shock to the failure or crash of institutions or markets. We can talk about a systemic crisis if the strong systemic event makes many failures of many institutions or crashes of many markets. The systemic risk studies have generally focused on interbank markets since exposures among different banks have the strong potential for contagion in the case of a banking failure. There are seminal papers which construct microeconomic foundations for systemic risk and contagion (Rochet and Tirole 1996), (Allen and Gale 2000).

There is a new channel of research which combines networks and systemic risk. The common characteristics of real-world networks were uncovered by physicians (Albert and Barabasi 2002) and the discovery has been benefited by different branches of science. The real-life networks were different from the random and homogenous networks of the Erdös-Renyi model. Many real-life networks such as internet and citation networks were scale-free which means that their nodes were following a power-law distribution.

New opportunities provided by network theory have been benefited by researchers of finance in a growing sense. Interbank markets were investigated in the light of network theory. Banks (nodes) established a network where the transactions were considered as directed links. Since the information of all transactions are necessary to establish a network, in case of missing data balance sheets of banks were used to construct the exposure matrices (Upper and Worms 2004). On the other hand, when interbank payments/market data is available it is directly possible to have the network topology. The exploitation of detailed data led to conclusions about interbank networks. The most significant result is that financial networks share the same main characteristics with other real-world networks. It was found that the interbank payments over the Fedwire Funds Service formed a scale-free network. Moreover, the topological properties of this network had changed significantly just after the September 11, 2001 attacks (Soramaki, et al. 2007). Austrian large-value payment system was compared with Fedwire and it was found that distance measures are independent of size similar to other small-world networks (Boss, et al. 2008). Another study found a monthly pattern and a structural change over years for the Italian segment of the European overnight market with the help of network analysis (Iori *et al* 2008).

Recent global financial crisis motivated the ideas that linking the systemic risk with network topology. Researchers have been trying to define the elements of network topology in terms of their impact on risk, institutional failures and crises. Particularly the impact of connectivity on systemic risk is a hot topic of research in this sense. Haldane (2009) claims that interconnected networks exhibit a knife-edge or tipping point property. Connectivity serves as a shock-absorber within a certain range; but beyond the range connections cause risk-spreading and fragility.

Below studies also approve the two-sided impact of connectivity on systemic risk. Iori, Jafarey, & Padilla (2006) constructed an interbank market model in which fluctuations in deposits constitute the risk of default. The simulation results showed that when banks are homogenous, connectivity in interbank market reduces the number of defaults. On the other hand, when banks are heterogeneous with respect to liquidity and size, connectivity became a channel of contagion. Moreover the homogeneity itself was found to be a source of contagion.

Another study investigated systemic risk and contagion by using network theory (Nier, et al. 2007). Banks were modeled as nodes of a network and they have two types of assets which were interbank assets and external assets. A shock was given to the external assets of one bank and the effects of this shock were observed by simulation. The first part of the article in which banks are homogeneous show that a higher net worth decreases the number of defaults and a higher percentage of interbank assets increases the default ratio. On the other hand the effect of connectivity is not monotonic. For very low levels of connectivity an increase reduces the robustness of the system. For medium levels its effect is unambiguous. Connectivity strictly reduces number of defaults for very high levels. This effect of connectivity is described as an M-shaped curve. The model was extended to a tiered banking system and in addition to above characteristics default situation of large and small banks were observed. If a large bank is connected to many small banks, its shock can be absorbed by these banks.

Interbank credit lines are introduced as a channel of contagion other than interbank exposures (Müller 2006). A bank's failure creates contagion not only through its liabilities but also through the dry up of credit lines of the failed bank to other banks. Interbank exposures and credit lines channels are modeled distinctly. Models are simulated through a creation of a fictitious default on the Swiss interbank market. According to the simulation results higher capital buffer and liquidity improve resilience of the market; homogenous and dense interbank networks turn out to be more stable. On the other hand there is an ambiguity for the effect of credit lines. They increase resilience during normal times but they have a reverse impact under financial stress.

Recent global financial crisis raised new questions. Finding reasons of the failure of economic and financial theory to foresee such a big turmoil have been one of the hottest debates in the field. New methods on financial modeling and systemic risk calculation have been searched to increase the foresight of academic work. Applications of the network theory on systemic risk are getting more popular since it can solve some problems of the theory. Network models consider financial institutions as interconnected and heterogeneous entities. Heterogeneity is due to not only difference in volume but also in connectivity. Role of central nodes in contagion and risk dispersion can be very beneficial for systemic risk studies.

Some recent studies have drawn attention on the potential of network theory to understand and prevent financial crisis. Lo (2008) states that developments in network theory made detecting vulnerable areas possible. His systemic risk measures needs applications of network theory to financial data but he also mentions difficulties to reach necessary data in shadow banking systems.

Moreover central banks have been becoming more interested in network analysis since they have the responsibility to monitor and prevent systemic risks. European Central Bank organized a workshop named "Recent Advances in Modelling Systemis Risk Using Network Analysis" to bring together researchers working in the field and to promote further research. Gertrude Tumpell-Gugerell, member of the Executive Board of the ECB, explains the importance of the network analysis for modelling systemic risk in the introductory remarks of the workshop (Tumpell-Gugerell 2010). Tumpell-Gugerell mentions that recent financial crisis reminded the importance of links and connections in a financial system. She counts two main areas that network theory can help: measuring resiliency of financial systems, showing major triggers and channels of contagion. Another important point is that Tumpell-Gugerell claims that interconnections will serve as shock amplifiers rather than absorbers. Finally, she states that system is highly vulnerable if a highly connected player is disrupted. In this case even if the initial shock is not strong, it might lead to a systemic crisis.

Another recent study investigates Credit Default Swaps network in the United States during the fourth quarter of 2008 (Markose, et al. 2010). They observe that CDS market is clustered around 6 players and they try to find the impact of these highly interconnected agents on financial contagion. They implement Agent-Based Computational Economics (ACE) approach for the market to control for random networks. They reach the result that random networks have more contagion and more bank failures than the empirical network which is clustered around some players.

It can be seen that recent debate on systemic risk analysis using network theory is focused on the effect of connectivity. Connections whether being shock absorbers or shock amplifiers is a very important question. This study is a contribution on this field in this respect. Network analysis of a financial market which is highly centralized around a player during the crisis year is a very special empirical case for this discussion. The role of Demirbank on network structure is central for this study. Network structure before and during crisis period is analyzed to answer the question whether interconnections serve as shock absorbers or shock amplifiers.

Another important contribution of this study is taking network measures in a time-series perspective. Network measures are important to describe a market but it is more important to observe how the market changes. Observing time-series behaviour of network measures are crucial in that respect. Especially if a financial crisis period is investigated evolution of network structure should be identified. Results of this study is interesting because they are derived from time-series behaviour of network parameters which shows the dramatic structure change before and after the crisis.

3. Turkish Financial Crisis of 2000

In Turkey, financial instability has been significant a problem for a long time. To control inflation level which was close to 100% throughout the 1990's, Turkey signed its sixteenth stand-by agreement with the IMF in 1999. The agreement led to a crawling peg exchange rate regime and floating interest rates. Thus this agreement prevented the government to intervene in the overnight market during the November crisis.

The program limited the short foreign currency positions of Turkish banks to 20% of their total assets. However, this ceiling was exceeded by using "off-balance sheet" transactions and derivative instruments such as local bonds or Eurobonds as collaterals. The increase in domestic interest rates in the second part of 2000, dropped the value of these collaterals and banks faced margin calls as a results. Banks facing a margin call demanded on the overnight market and these demands increased interest rated more. At the end the system went to a vicious loop between interest rates increases, drops on collateral values and demand on overnight market.

Yield curve inversion caused serious difficulties for several large financial institutions including the largest borrower in the overnight market, Demirbank. These difficulties are the main factor behind the increasing demand for liquidity towards the end of 2000. Liquidity starving banks including Demirbank started to sell their assets and caused a sharp stock market drop. The efforts of government and the support signal of the IMF could not succeed and rumors about the failure of some banks started to spread in late November. Meanwhile, solvent local banks to limit their lending to those rumored to be in trouble. In addition, many foreign creditors cut their lines towards the end of trouble. A rapid capital outflow was triggered on November 22 since foreign and solvent domestic investors sold Turkish lira. The liquidity provided by the Central Bank (CB) creating additional demand for foreign currency since CB did not intervene in the overnight market. Turkish Central bank did not support the liquidity needs of Demirbank because of a mandate between IMF. A limit on Net Domestic Asset in Turkey IMF did not allow Central Bank to assist the needs of Demirbank. As a result, CB cut providing liquidity on November 30 and the cut increased overnight interest rate 2000%. Capital valued at USD 6 billion left the country and the outflow eroded 25% of the CB reserves. IMF emergency loan on December 5 stabilized the economy for a short period. [2]

4. Empirical Findings

4.1 Descriptive Statistics

In this section some descriptive statistics of the network will be presented. We have studied the overnight money market data between 11 January 2000 and 21 December 2000. There were altogether 240 daily networks in which these institutions are considered (in network jargon institutions are they are known as nodes) and their transactions (known as links in the network literature). There are 136 institutions participating the Istanbul Stock Exchange overnight money market during the data studied. These institutions have different codes in the data and only Demirbank was distinguished due to its heavy activity level during the period.

There are 3 ± 2.6 nodes in GSCC on average. For a significant number of days GSCC does not exist. It means that directed links are very limited in our network. That is if a bank borrows from another one, that bank does not lend to the other one during the same day.

[2] To find the detailed story of Turkish financial crises of 2000-2001, see (Van Rijckeghem and Üçer 2005).

Almost all node pairs are connected only in one direction in Turkish overnight money market network. It makes GSCC not appropriate for the analysis.

Consequently, GWCC is analyzed in this study. The average number of nodes in GWCC (n) is 103 ± 3.3. When we consider that there are 136 institutions in total 75% of institutions participated in the market on average. As the standard deviation is 3.3, it can be concluded that participation is stable in the overnight market. In addition, 50 institutions took place in the network during all of 240 days which supports the argument that network participation is stable. For Fedwire interbank payment network the average size of the GSCC was found to be 5086 ± 128 and for Austrian interbank payment network the average of GSCC is 133 (Soramaki, et al. 2007) (Boss, et al. 2008). On the other hand the number of participating banks was 215 in 1999, 196 in 2000, 183 in 2001 and 177 in 2002 (Iori *et al*(2008)). Turkish overnight money market network is comparable to Austrian interbank payment network and Italian overnight market network in terms of network size while US interbank payment network has a significantly higher size.

The average daily volume of Turkish money market was $(2 \pm 0.33) \times 10^{15} TL$ which is approximately 3.3 billion US dollars whereas this value is 1.3 trillion dollars for the Fedwire, 1.1 billion Euros for Austrian network (Soramaki, et al. 2007) (Boss, et al. 2008). Thus, it is clear that Turkish overnight money market is a very small network compared to Fedwire interbank payment network in the US but it is bigger than a small European network such as Austria.

There are 431 ± 47 directed links (m) in the network on average. The average connectivity of Turkish money market is 4.1 ± 0.42 %. In other words 4.1% of network capacity is used on average. The connectivity value is 0.3% on Fedwire network and 0.3 in Austrian network. This difference can be explained by the different type of networks. In interbank payment systems different banks make transfers with their counterparties that they can see. An institution can choose the institution to make transaction. Therefore institutions that have stronger financial ties, similar market powers or similar risk levels are more likely to make transaction with each other.

The reciprocity value is 0.99 ± 1 % on average in Turkish overnight money market network while Fedwire network has 21.5% reciprocity on average. It shows that almost all links are one sided in the Turkish overnight market network during the period studied in the article. It implies that in a given day, if institution A borrows from B, B does not borrow from A during the same day. This leads to a market which is separated between borrowers and lenders. To check this conclusion top ten borrowers and lenders were listed. As can be seen, the top borrowers list is totally different than that of top lenders. We have also observed a high degree of concentration in the borrowing side. Institutions with code number 5 and 3 both have a very large share borrowing side while the lending side is more balanced. This is the first diagnostics of Systemic Risk proposed by Lo(2010). Another evidence for this argument is maximum in and out degree measures. Institution with the highest in-degree for a given day borrowed from 63 different institutions on average. On the other hand institution with the highest out-degree for a given day lent to 17.7 different institutions on average. It is clearly seen that the strongest hub of borrowers has much more links than that of lenders. Saltoglu and Danielsson (2003) also showed that borrowing side of the overnight market has a monopolistic structure while lending side is more equally distributed.

Code	Average Borrowing Volume	Code	Average Lending Volume
5	0.58255625	31	0.27286875
3	0.419885417	25	0.271627083
13	0.142254167	28	0.176372917
9	0.117970833	49	0.081472917
8	0.10435	107	0.074672917
23	0.10068125	43	0.073891667
25	0.090235417	30	0.05859375
11	0.081760417	57	0.054925
96	0.057325	12	0.049752083
16	0.03800625	47	0.04695625

Table 1: Average Volume of Top 10 Borrowers and Lenders

	Mean	Median	Min	Max	SD
n	103	103	103	113	3.3
m	431	424	339	588	47
p(%)	4.1	4	3.06	5.23	0.42
r(%)	0.99	0.81	0.00	7.00	1
Degree					
max k(in)	63	64	40	91	9.7
max k(out)	17.7	17	11	27	3.2

Table 2: Descriptive Statistics for Turkish overnight money market network

4.2 Representation of the Network

Below graphs are representations of the Turkish overnight market network on selected days. Graphs are obtained by using Pajek software. Thickness of a line represents the amount of flow on that day. Backbone induction method was applied to show significant links of the network (Serrano, Boguna and Vespignani 2007). This method eliminates links that are statistically insignificant. If probability of a given link is above 99% this link is significant and included in the backbone. In this method two sided links are converted to one sided net links. If there is a link from node A to node B with a value of 5, and from node B to node A with a value of 3 then we have the link from node A to node B with a value of 2. Therefore there are at most one link between two nodes. *P* value of a given link is calculated by the following formula:

$$\alpha_{ij} = 1 - (k-1)\int_{0}^{p_{ij}} (1-x)^{k-2}\, dx$$

In this formula k is the total number of in and out links from node i, and p_{ij} is the weight of given link divided by total weight of in and out links of node i. For a given link between node i and node j, this *p* value is calculated for both nodes and if it is below the chosen significance level then the link enters the backbone. This method eliminates links but not nodes thus it can derive the backbone without eliminating nodes.

This method is necessary to have a clearer picture of the network since insignificant links prevents the observer to focus on the backbone. In other words these graphs do not show all links in the network but they represent only some statistically significant links.

5 days were selected from different periods of Turkish overnight market during year 2000. These days are 1 March, 30 October, 22 November, 1 December and 5 December. These days were selected to represent different periods throughout year 2000. 1 March belong to the pre-Demirbank domination period. 30 October is before the crisis and one of the days in which Demirbank was a massive borrower. 22 November is the beginning of the financial turmoil while 1 December is the day of collapse and 5 December is the day in which Demirbank was taken over.

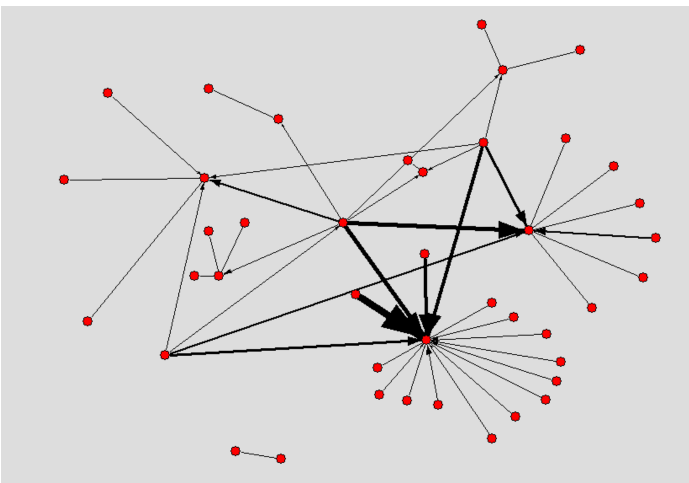
A multi-centered network is observed in 1 March. Since overnight market forms a real-world network which is not random, there are some central nodes. In other words there is heterogeneity among financial institutions. Two borrowing centers can be observed from the graph. But these centers are not the only concentration points of the backbone since there are other local centers. This can be explained by the fact that at this point of time Demirbank had not started its “bet” which led to the domination of the market. Although it is one of the leading players, it is not the unique center. This structure is a representation of the backbone before the full domination of Demirbank.

Centralization of the network can be fully observed by 30 October. The backbone is almost fully constructed around Demirbank. The network can be interpreted as Demirbank borrows from everyone and everyone lends to Demirbank. In other words while Demirbank occurs as the unique significant borrower, lending market has a multi-player structure. Second graph clearly shows how actions of a player change the structure of the whole market. It is a clear picture of Turkish overnight money market before the crisis.

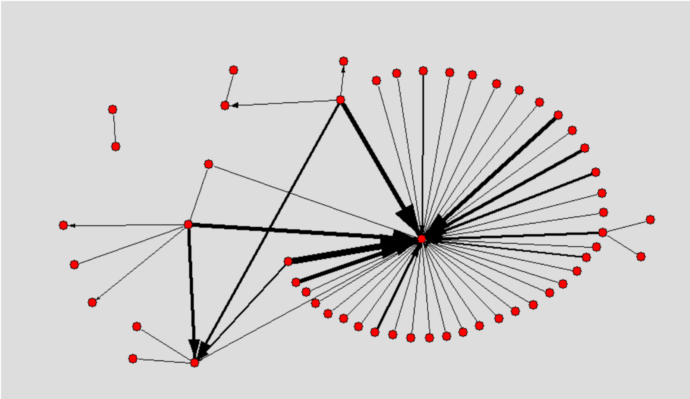
Third graph takes the picture of the first day of the financial downturn. The fully centralized structure was demolished with the turmoil and the backbone was weakened by 22 November. There are still two borrowing centers but these centers are weaker due to the start of crisis. Demirbank still borrows but the backbone is not around Demirbank. This graph represents the limitation in lending behavior at the beginning of the crisis very well. From the first day "good day" structure around Demirbank does not exist and backbone is damaged. One can observe lines are thinner which shows a decrease in market volume.

The destruction can be observed better by 1 December, the day that market volume was at its bottom. The third and fourth graphs show the impact of financial crisis. In these days financial institutions stopped lending since borrowing by Demirbank was considered too risky. The structure which was formed around Demirbank's borrowing collapsed due to the dramatic decrease in risk appetite.

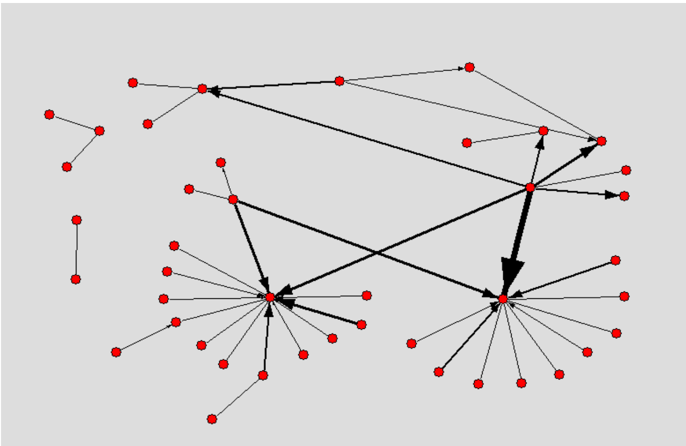
Fifth graph shows a multi-centered structure by the end of the crisis, 5 December. The takeover of Demirbank changed the picture, and backbone got a bit stronger with the normalization of the market. This picture shows the beginning of recovery from the crisis.



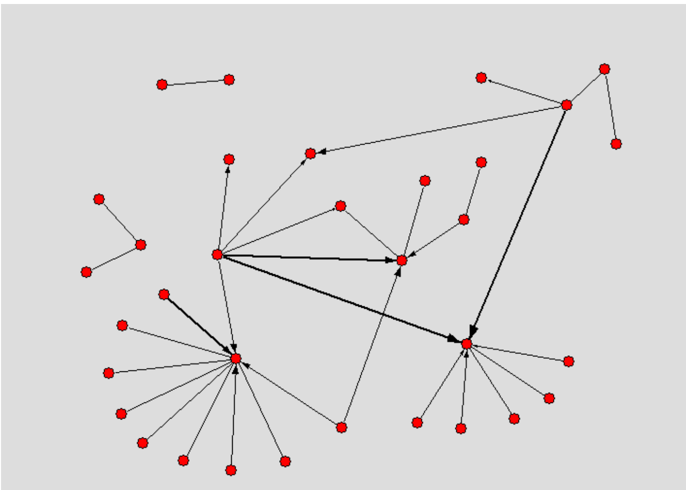
1 March 2000



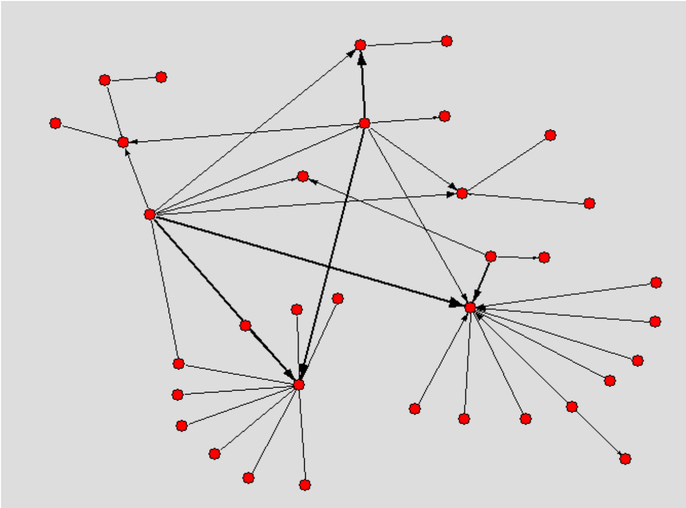
30 October 2000



22 November 2000



1 December 2000



5 December 2000

Figure 2- Backbone of the network for selected days, 0.01 significance

4.3 Volume

The volume of the Turkish overnight money market during 2000 can be seen from Figure 3. The market volume had a decrease during summer months and by the end of the August it shifted upward. The increase continued from September to November. It is clear that this upward shift was due to the dramatic increase in Demirbank's overnight borrowing. Figure 4 shows that Demirbank's borrowings increased nearly three times from the late August to the mid-November. "Demirbank's bet" was based on huge amount of T-bill purchases and funding these assets through overnight borrowing (Van Rijckeghem and Üçer 2005). Since domination of the interbank market by a small number of debtors or creditor is an indicator of centralization (Müller 2006), Demirbank's strategy made the network much more centralized.

Volume	Mean	Std
Pre-Crisis	2.42	1.79
Crisis	2.12	3.46
t value	**5.20	

Table 3: Volume in pre-crisis and crisis periods (in quadrillion TL). t value tests the significance of difference between two periods. * means 95% significance, ** means 99% significance.

The behavior of market volume during the crisis period is as it is expected. As the panic started on 22 November, volume decreased dramatically and reached its bottom on 1 December. It can be considered as a market downturn which is one of the main aspects of crises periods.

But there is another point in the trend of volume during the crisis period. As it can be observed from the figure the bottom level of volume is close to the level before the huge borrowings of Demirbank. In other words, the volume loss in the crisis period is due to the decrease in Demirbank's borrowing.

Demirbank volume of borrowing	Mean	Std
Pre-Crisis	9.96	2.47
Crisis	7.55	3.05
t value	**3.70	

Table 4: Demirbank's borrowing volume in pre-crisis and crisis periods (in quadrillion TL). t value tests the significance of difference between two periods. ** means 99% significance.

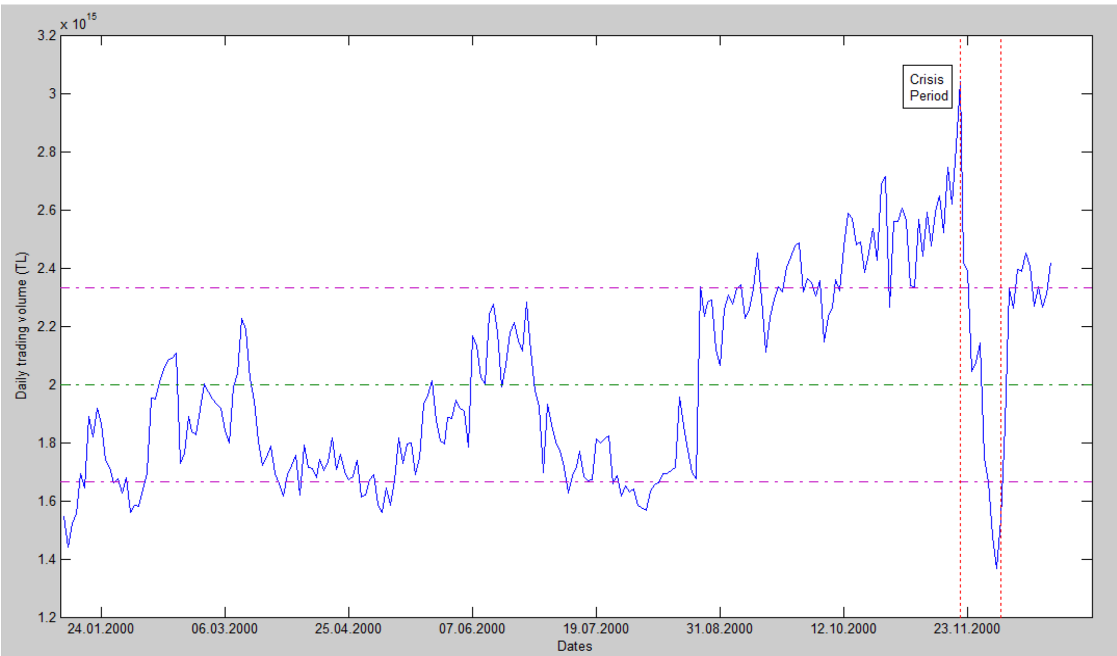


Figure 3- Daily volume of Turkish money market

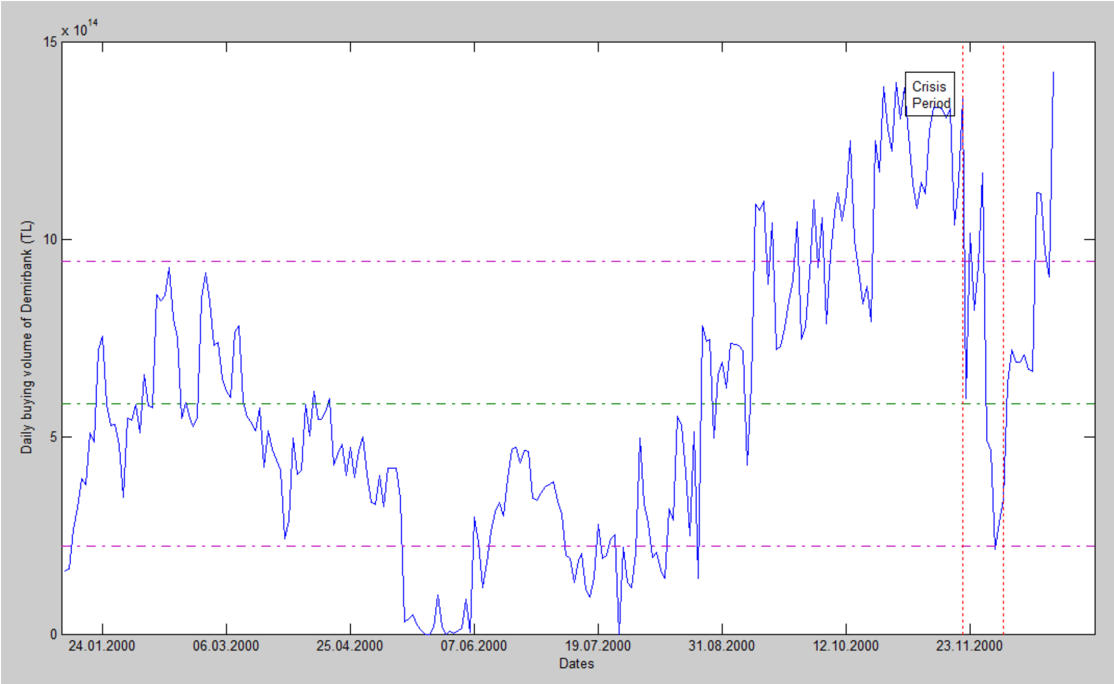


Figure 4- Daily borrowing volume of Demirbank

4.4 Connectivity

Figure 5 shows the time path of number of links (m) for the sample period. The most interesting observation is that volume and m follow different paths before the November crisis. During three months before the November crisis number of links follows a decreasing path while daily trading volume increases significantly.

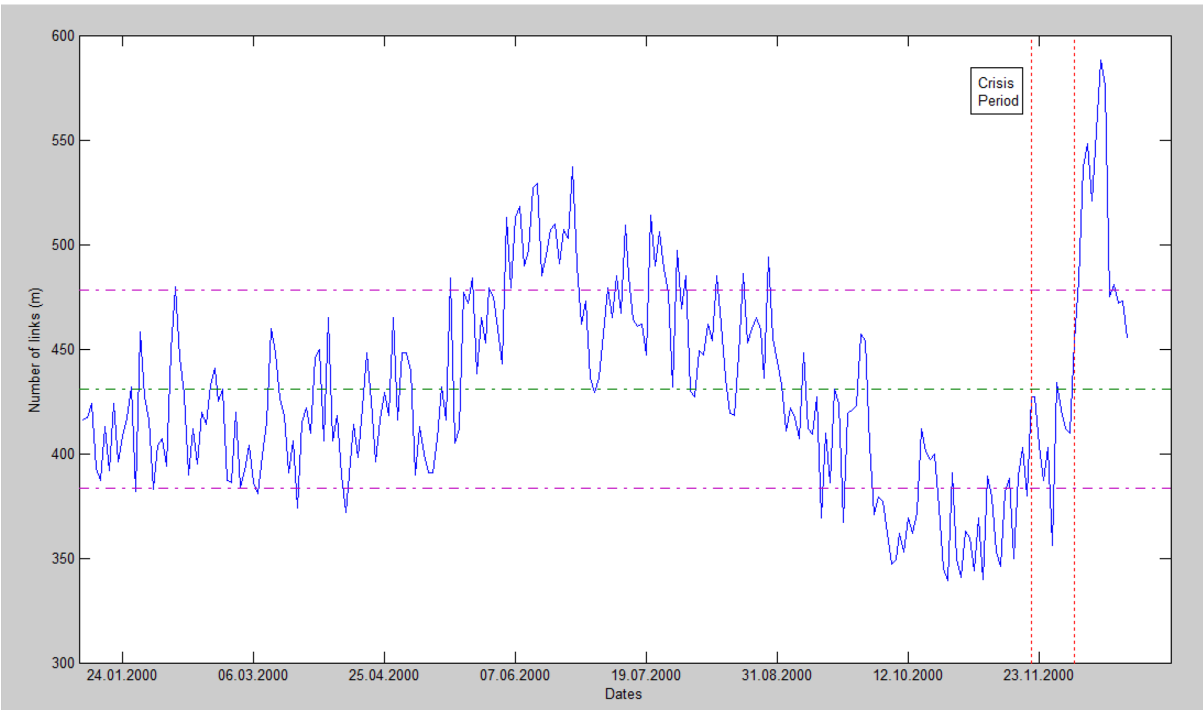


Figure 5- Number of links (m) of daily networks

Figure 6 sketches time series of network connectivity. Connectivity follows a very similar pattern to number of links. Since connectivity includes the number of nodes which are included in the network, it will be used as a measure of density.

Connectivity	Mean	Std
Pre-Crisis	3.84	0.29
Crisis	4.28	0.55
t value	**4.72	

Table 5: Connectivity in pre-crisis and crisis periods. t value tests the significance of difference between two periods. * means 95% significance, ** means 99% significance.

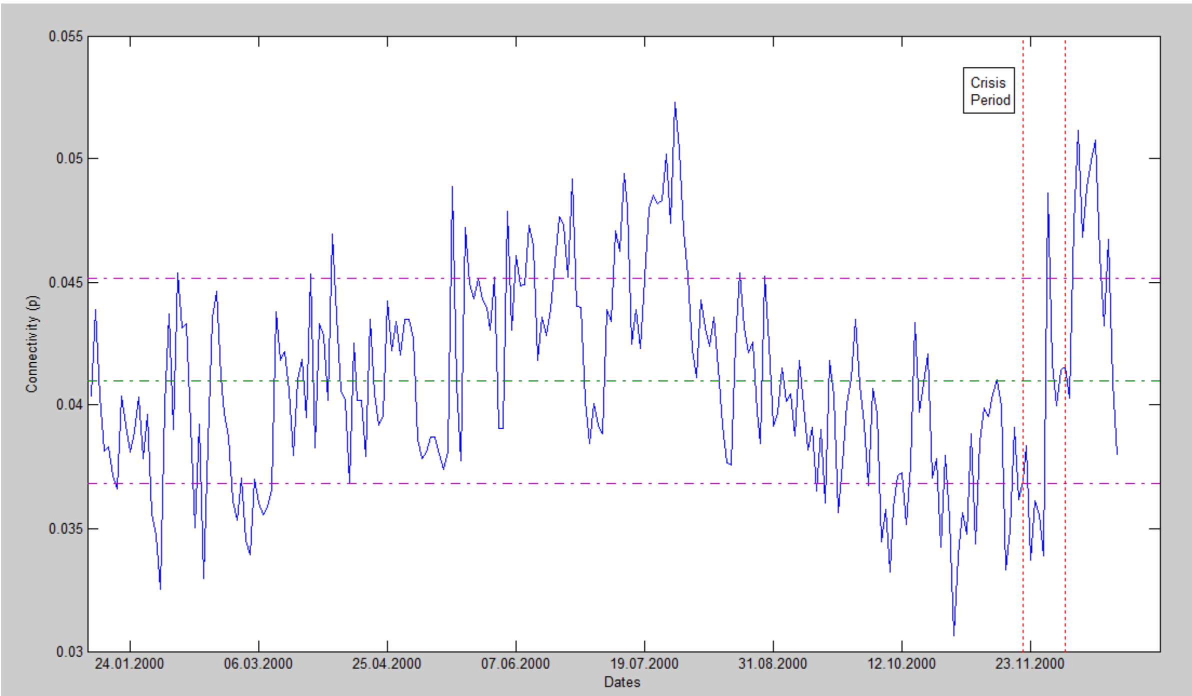


Figure 6- Connectivity (p) of daily networks

It is seen that connectivity is significantly higher in the crisis period. The decrease in connectivity started with the increase in Demirbank's borrowing. As Demirbank became the strongest hub of the network and network became centralized the links between other parties started to fade away. Since Demirbank was a borrowing center, lenders' connections with other borrowers were interrupted. This case changed the structure of the network and it was nearly shaped around a borrower. The decreasing trend in connectivity continued until the end of November. As it was explained above connectivity decreased continuously from August to November due to the role of Demirbank as a borrowing monopoly. In other words most of the lenders were connected to Demirbank but this decreased the connectivity of the whole system. It is the situation that a large player is connected to many others. The theory suggests that a shock to large player can be absorbed by its connections (Nier, et al. 2007). Therefore, a low interconnectivity can be detrimental to the viability of the system. Since, the shock about Demirbank's credibility was not absorbed by its connections and turned to a systemic crisis, even though Demirbank was the central node of the network.The liquidity crisis began in 20th of November and reached its peak in 22nd of November (see Van Rijckeghem and Üçer(2005)). Our findings here are in line with the network literature since, during a financial crash, connectivity is expected to drop. As connectivity drops system will be more open to many factors that may trigger a systemic risk event. In our empirical analysis, we clearly observe a decline in the connectivity level until 29th of November. Then we notice a somewhat increase in connectivity until the end of crisis (5th of December 2000). However, we should note that the volume in the overnight money market dried sharply towards to end the crisis. So we can conclude connectivity trend in a financial system can be an important investigative tool for systemic risk.

There are very few comparable empirical studies in this context. For instance, Soramaki, et al. (2007), stated that Fedwire network connectivity decreased significantly due to the 9/11 attacks. Our results have similarities with this study while our connectivity decreased monotonically until the mid of the financial crisis. It should also be stated that September 11 event is a very sudden shock to the system while our episode is more of a gradual one. During 9/11 attacks connectivity decreased due to physical destructions caused by attacks. Not only financial connectivity but also connectivity in transportation, communication networks decreased dramatically in the United States. Therefore, the increase in connectivity towards the end of the crisis is understandable. As rumors about Demirbank's failure spreaded in the market, interest rates started to increase. Increase in interest rates made huge borrowings more and more costly for Demirbank. As a result the bank lost its central position in the network. As uni-center structure collapsed many institutions borrowed from many lenders that caused an increase in number of links and connectivity.

Our empirical results suggest that, a decrease in connectivity, ceteris paribus, can be a sign for an increasing stress in the system. However, other factors particularly, change in the volume and centrality of various critical players in the system, should be closely watched as well. Low interconnectivity with monopolized players can be even more damaging. We will investigate these aspects in the later sections.

4.5 Correlation Between Network Parameters

As discussed above, even though connectivity can be used as a systemic risk measure, it should be complemented with other statistics such as volume. In this way we may also monitor the source of systemic risk. We have observed a very strong negative correlation between links (and connectivity) and volume especially before the November crisis. Soramäki et. al (2007) and Boss et. al (2008) find high correlation coefficients between these variables. To capture the behaviour of correlation between *m* and volume a time varying approach can be applied. The time varying correlation: $\rho_t^{m,vol} = \rho_{m_{t,j}, vol_{t,j}}$ where $m_{t,j}$ and $vol_{t,j}$ are series include observations from day $t-j$ to day t. The fixed window size, j is selected 50 that is each element in series denotes to the correlation of two series of size 50. Figure 8 shows time varying correlation coefficients between *m* and volume.

The explanation for positive correlation between the number of links and trading volume is very straightforward. If market expands with higher volume, new links will be established between financial institutions, and vice versa. But the Turkish money market data of 2000 has significant differences in this respect. The correlation is insignificant at the beginning of the April, and then it starts to increase up to value of 0.85. After reaching its peak at the end of January, it turns to a monotonically decreasing trend. The same situation exists for the time trend of correlation between connectivity and volume (Figure 9). Since connectivity is almost determined by number of links we will analyze the time varying correlation between *m* and volume. At the end of September the correlation is on its bottom with a value of -0.54. The question is that which factor reversed the relation between volume and number of links.

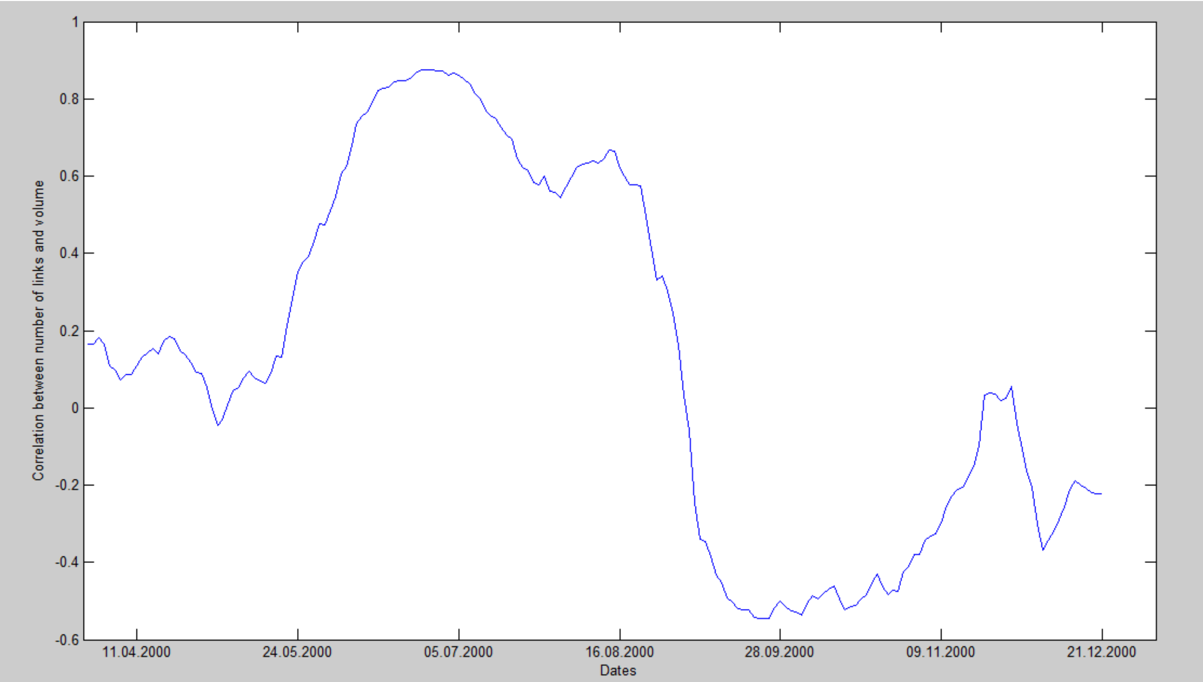


Figure 8- Time varying correlation coefficients between *m* and volume

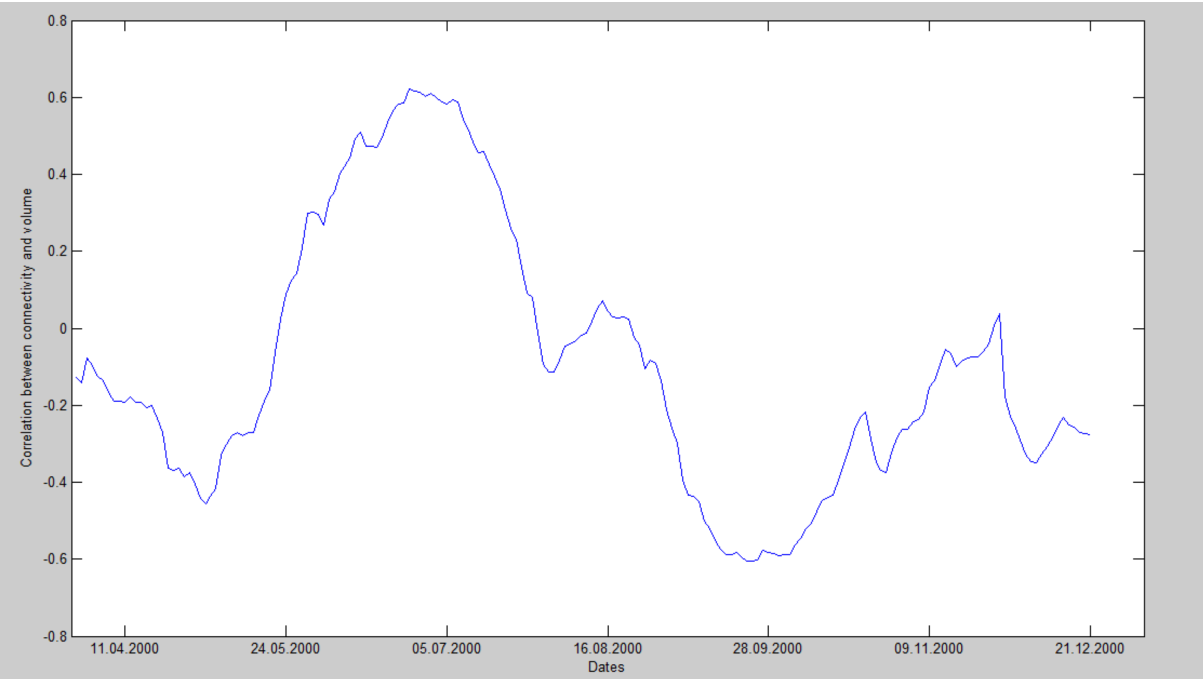


Figure 9- Time varying correlation coefficients between *p* and volume

The answer lies on the role of a single institution. Danielsson and Saltoglu (2003) point out the role of Demirbank- the private bank finances its longer maturity treasury assets with borrowings from the overnight market- on the crisis. It is widely known that rumors about the failure of Demirbank start the crisis on November 20, and the crisis ended with the takeover of this institution on December 5. The time varying correlation shows that negative correlation took place months before the crisis, because of the huge overnight borrowings of Demirbank.

To prove the high negative correlation between *m* and volume occurred due to borrowings of Demirbank a control analysis is applied. Demirbank is taken out of the network and variables are regenerated. And the time varying correlations of daily networks without Demirbank are recalculated.

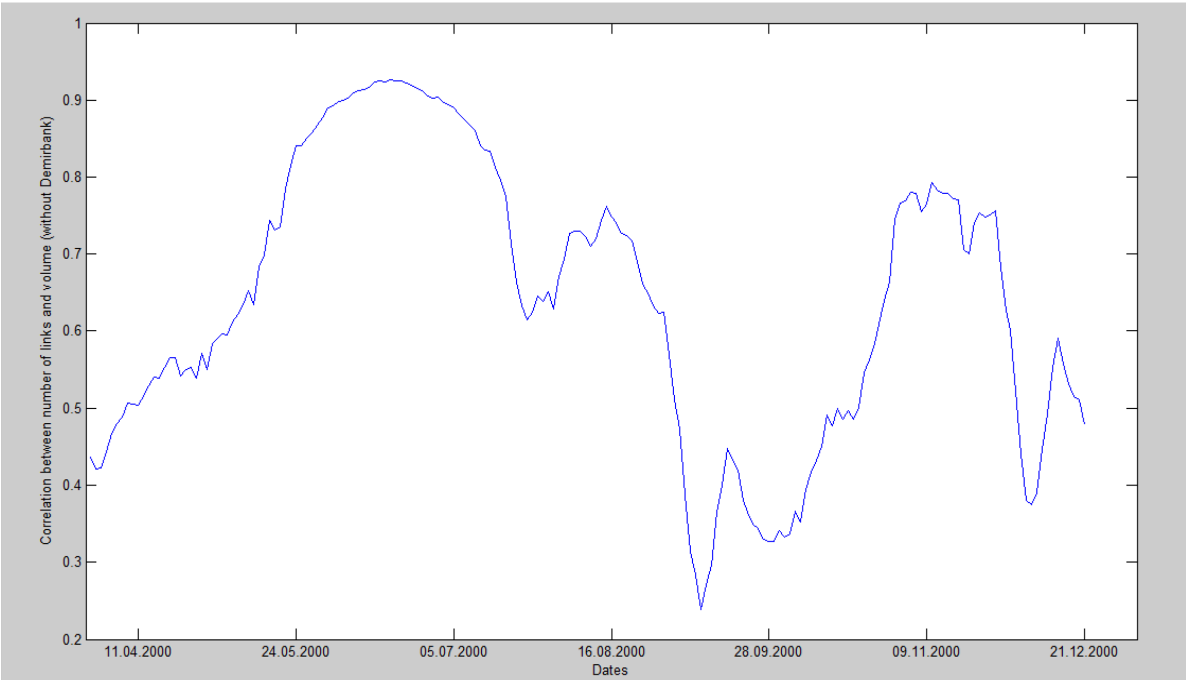


Figure 10- Time varying correlation coefficients between *m* and volume without Demirbank

It is clearly seen from the Figure 9 that when Demirbank is taken out from the network the time varying correlation between *m* and volume has positive values until the end of the year. Thus it can be concluded that Demirbank has the biggest share of responsibility for negative correlations values before the November crisis. On the other hand, the negative correlation between these variables can be considered as a sign that one or few players change the market structure significantly.

These results provide us a more powerful explanation for the road to the crisis. Demirbank started to increase its borrowing by the mid July and the increase continued monotonically until the November crisis. Strong hubs are seen in almost all real life networks (Albert and Barabasi 2002) and there is nothing surprising that Turkish money market had a strong hub. But Demirbank's position went beyond and approached the market to a star network structure where all nodes are connected to a single hub and links between non-hub nodes do not exist. In other words the increasing borrowing volume of Demirbank broke the links between other nodes which is the reason of negative correlations between *m* and volume. In such a structure, concerns about the sustainability of Demirbank's debt paralyzed the whole network.

On the basis of our findings, we can conclude that, while the interconnectivity is an important tool its relationship between volume can also help in understanding the systemic risk. The correlation between volume and links (or interconnectivity) clearly signals the evolution of the network. However, correlation breakdown signals that there might have some anomalies in the network. This is what we observed in our empirical study.

4.6 Average Trade Per Link

Another important parameter is value which is the average trade per a link. This measure shows the trade load for each link therefore it shows average borrowing-lending for a pair of institutions in a given day.

Value graph clearly shows that average trade per link increased by three times from summer to the end of November. Demirbank's huge borrowings not only increased total volume but also increased the average daily trade for a pair of institutions. This means that an institution borrowed much more from the other banks. It can be considered that system was heated since it started carrying much more load. This trade load decreased with the crisis as the centralization around Demirbank has collapsed.

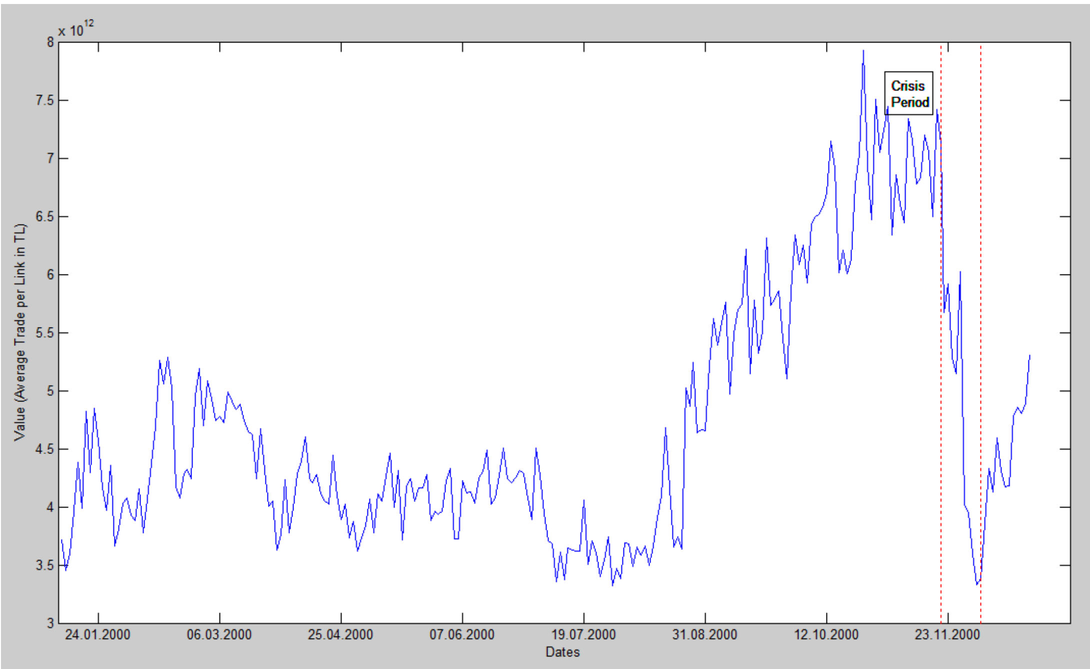


Figure 7- Value (average trade per link) of daily networks

This measure can be helpful in analyzing the evolution of a monopolistic power. We can better understand the causes of interconnectivity changes.

4.7 Implementation of PageRank Algorithm

Measuring centrality is a very critical point for our study since the causes of crises lie on behaviors of central node. For the Turkish overnight money market PageRank algorithm is used to determine node centralities.

The algorithm was proposed by (Page, et al. 1998) to develop a better internet search engine. The algorithm is based on the idea that pagerank of a web page is determined by not only number of links directed to it but also the centrality of the pages which give link to it.

To apply the algorithm to overnight market a modification is to be applied. In the internet a web page gives link to another one or not, that is links have no volumes. But in borrowing-lending networks each link has a weight which is the volume of transaction between nodes. Thus the PageRank algorithm is modified such as:

$$PR(i) = (1-d) + d \times \sum_{j \in M} \left(\frac{PR(j) \times w_{j,i}}{\sum_{z \in N} w_{j,z}} \right)$$

where N is the set of all nodes in the network and M is the set of nodes that has a link to node j. $w_{j,i}$ is the weight of link from j to i. With the definition of W matrix, three different centrality measures can be implemented. Suppose that $w_{j,i}$ gives the volume of transaction where j is the lender and i is the borrower. Then the node borrows more will have a higher centrality. This measure is defined as *borrowing centrality*.

Also suppose that $w_{j,i}$ gives the volume of transaction where j is the borrower and i is the lender. Then we will have a centrality measure opposite to the above one. This is defined as *lending centrality*. This type of weighted ranking algorithm was proposed by Mihalcela (2004) for text summarization tasks.

Both variables described above have directed meanings. One of them focuses on borrowing while the other focuses on lending. There is not such a problem for the internet, a web page is central if others give links to it. So we need to define another variable which is not directed in the above sense. Suppose that $w_{j,i}$ gives the total volume of transaction where j is the borrower, i is the lender and i is the borrower, j is the lender. It can be noticed that $w_{j,i} = w_{i,j}$. Then we will have a centrality measure which is undirected. The last one is *centrality*.

To sum up if we use W matrix defined in the previous section, we will reach to borrowing centrality. If transpose of this matrix W' is used lending centrality occurs. If $W+W'$ takes us to undirected centrality measure.

Brin and Page (1998) suggest that the best value for d is 0.85. The same value is used in this study. As they proposed every node is given PageRank 1 initially and PageRank equations are recalculated for 100 iterations.

To compare the centrality values across days we need normalization. The sum of centrality values converges to the number of nodes participating to the network. Thus centrality values are divided by the number of nodes participating in the network at that day. As a result sum of centrality values for a daily network is equal to 1. And also the centrality values can be considered as shares from the total centrality.

Another important point is that we can use undirected centrality measure in this study. As it is mentioned before there are pure borrowers and pure lenders in the market. Now suppose that borrowing centrality is in calculation process. An institution has borrowed from a very important lender that is there is a link from important lender to borrower. But the important lender does not borrow so its borrowing centrality is negligible. Consequently the institution borrowed from a very important lender can not take any PageRank value. To overcome the problem we used only undirected centrality measure.

Results show that distribution of PageRank's follows a power law distribution. Figure 10 shows the distribution and the fitted power law curve to the undirected *centrality* on day 5, 150, 200 respectively. Bechetti and Castillo (2006) suggest the same observation for d values around 0.85.

It is clear that the distribution of centrality is consistent with power law. As most of real-life networks have power-law degree distributions, reaching the same result for centrality distribution is straightforward. The next step is defining the time series behavior of centrality. Figure 11 gives information about the PageRank value of the strongest node of the network along time horizon. We see that prior to the November crisis the value increases monotonically since Demirbank borrows more and more during the period. The pagerank value of Demirbank increases up to 0.25 which means that one institution has the one fourth of total pagerank values. While this value is below 0.1 during the summer months, Demirbank's bet made the network more and more centralized. After the crisis occurs the maximum centralization value decreases significantly. The time path of maximum pagerank value is consistent with other observations. Demibank's borrowings made the network more and more centralized up to the financial turmoil.

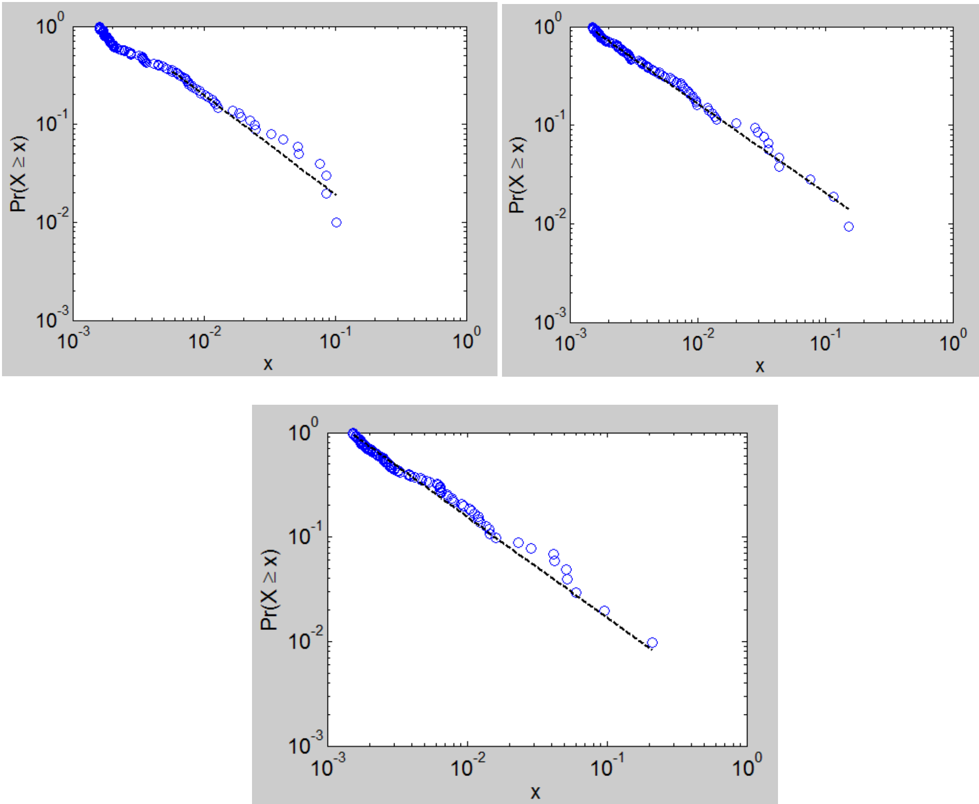


Figure 11- Centrality and fitted power law distributions for days 5, 150, 200 (logarithmicscale)

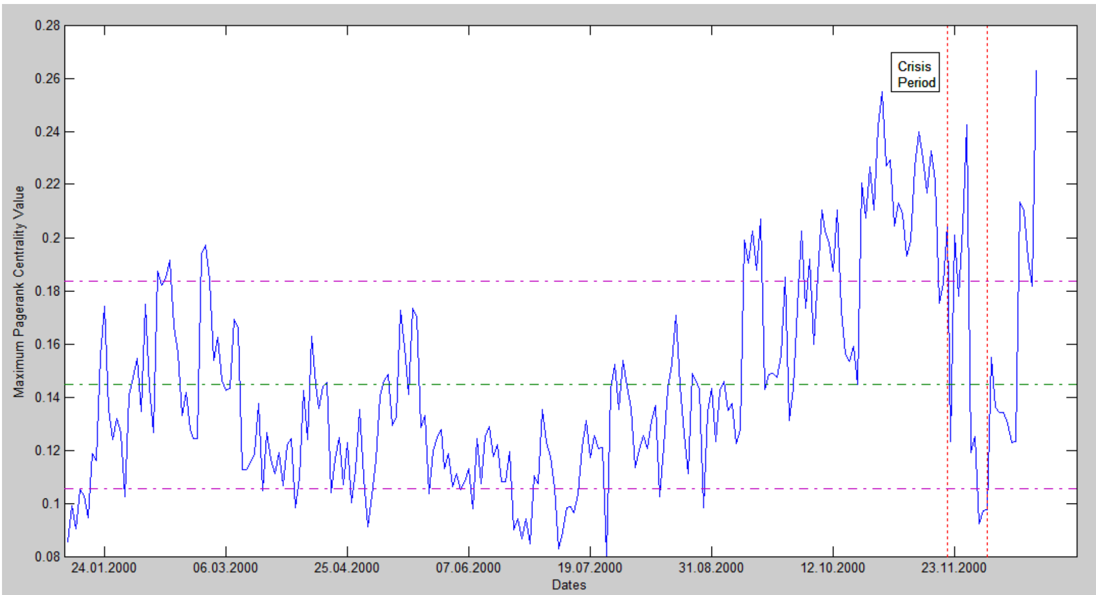


Figure 12- Maximum centrality value of the network for different days

One very important implication of centrality measure is that it can be used to distinguish the 'Systemically Important Financial Institution' in the financial system. In the previous regulatory studies, it was suggested that, the asset size of an institution or a similar metric can be used to define who could be considered to be a SIFI. However, this type of plain aggregates might hide the complex transactions among various players. But the centrality measure we have proposed here also addresses the following problems as well. Since it also involves the financial transaction with the other critical players in the market.

4.8 Backbone

Backbone induction method was used above to illustrate the network for selected days. The method calculates the probability of links and links which are above a selected level of significance establish the backbone (Serrano, Boguna ve Vespignani 2007). Illustrations of backbones of different days were presented before. The next step is proposing a new metric related to backbone.

This new metric which is the ratio of volume of backbone to the total volume can be used to measure effects of the crisis better. It shows the percentage of market volume that 1% significant backbone includes. Since significance of backbone does not change, changes in the ratio represent the centrality of backbone in the network.

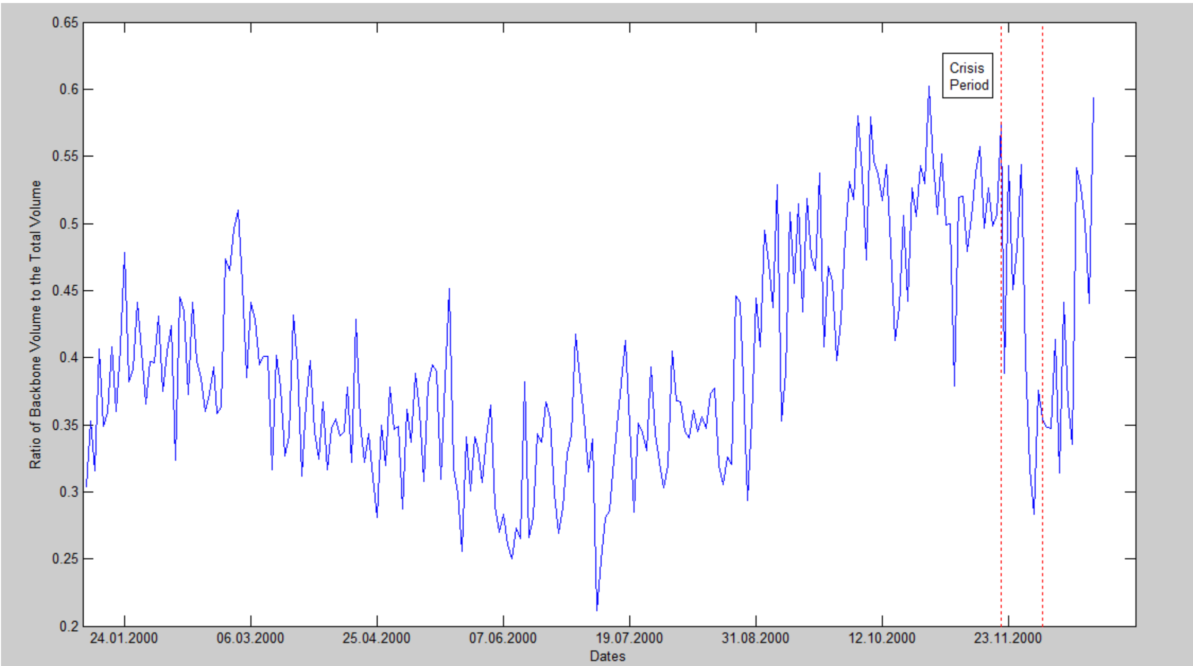


Figure 13- Backbone volume / Total volume (0.01 level of significance)

The metric shows the structural change of the network clearly. As Demirbank centralized the network around itself, the backbone contained a significantly higher percentage of the market volume. This observation is consistent to graph representations. Centralization of the network around a hub makes backbone stronger.

The figure shows that ratio of market volume included in the backbone decreased dramatically with the crisis. Since the centralization around Demirbank disappeared backbone became weaker. After the recovery, backbone again gained strength due to the continuation of Demirbank's borrowings.

The backbone algorithm can reduce the dimensionality in the actual implementation of networks on systemic risk regulation. As there are a lot of financial institutions some of which have a very marginal impact on the financial transactions. The backbone algorithm can be used to eliminate these marginal institutions from the financial network.

5. Conclusion

Network theory is a growing field which has applications in many areas. After the recent global financial crisis researchers and policy makers have shown a clear interest in network representations of financial systems. This study is an attempt of contribution to this field. By applying various aspects of the financial network theory to a financial market during a crisis enabled us to draw some policy recommendations in the context of systemic risk regulation.

We have four major results. First, very low average reciprocity value of the network proved a separated structure between lenders and borrowers in the Turkish overnight money market. Almost all links have one direction which led to the conclusion that there is a clear segmentation in the market where there are some institutions which are only borrowers and others are only lenders. Average reciprocity value which is below 1% is a significant character of Turkish overnight money market and it has to be considered as an indicator of systemic risk.

Another key parameter to investigate in network topology is connectivity. It was observed that connectivity decreased during the crisis period. In the literature, the direct impact of connectivity is not clear. In our analysis, we have seen that connectivity decreases during crisis. We have concluded that interconnectivity should be investigated with other tools such as concentration. With high concentration low interconnectivity has increased the contagion particularly if the shock hits the hub directly. This was our conclusion. The centralization around Demirbank decreased connectivity since links between other banks were broken. Demirbank not only became the strongest hub but also changed the network structure towards a star-liked network. This finding is due to the original structure of the Turkish overnight market before the crisis.

Moreover negative correlation coefficients between connectivity and market volume were found to be related to the Demirbank's domination in the borrowing market. As Demirbank borrowed more volume increased and number of links decreased due to the monopoly in the borrowing side. This type of correlation can be considered as an indicator of market structure that is under dominance of few institutions. When all of these findings are synthesized time path of connectivity becomes an indicator about the structure of the network. Anomaly of connectivity-volume correlation shows that the network structure is fully around a unique hub.

Financial turmoil changed the structure of the network. Volume decreased and the backbone around Demirbank disappeared. On the other hand, as Demirbank pulled out from the market connectivity increased. Links between other banks were re-established.

Thus connections around Demirbank spread the idiosyncratic shock to whole system. Since the market constructed around Demirbank, the idiosyncratic shock was easily understood as a systemic shock by the market participants. As lending activity was likely equal to lending to Demirbank because of connections lenders became much more suspicious on participating the market. Therefore we should think connections not only bilateral links between two institutions but also entities that construct the market structure and market perception.

Findings of this study can be summarized around a single idea: Highly centralization of the network around Demirbank changed the structure. Connectivity decreased while volume increased significantly. Average volume carried by a link increased which loaded the system more. Backbone started to carry a significantly higher percentage of total volume.

With the help of these results we can propose some policy prescriptions. As this crisis case is very particular due to high centralization around Demirbank, results derived from this phenomenon can not be easily generalized. On the other hand, network analysis of this crisis showed that some indicators can be beneficial since they show heating of the market in this case. Regulators and policy makers can follow these network parameters to detect some unusual structure in the market.

If reciprocity value is very low, there is a separation between buyer and sellers in the market. This separation means that some institutions borrow from overnight market for longer term purposes. This kind of separation can be a subject of regulatory body.

If connectivity volume correlation is significantly negative, average volume carried by a link increases, and the percentage of total volume carried by the backbone is very high there might be a centralization that changes the structure of the market. Actions of central nodes should be watched and possible effects of centralization should be forecasted.

After the November crisis of 2000, Turkey witnessed another financial turmoil in February 2001. Network analysis of February crisis and its comparison to this study is a further research area. Since Demirbank's role is not central in February crisis, it is estimated that network in February crisis is not as central as it is before November crisis. Comparison in terms of centralization will provide a better explanation on systemic risk and crisis.

Appendix A. Turkish Overnight Money Market of Year 2000

The Bonds and Bills Market which works under the Istanbul Stock Exchange (ISE) is the only organized, semi–automated market for both outright purchases and sales and repo/reverse repo transactions in Turkey. Financial institutions communicate their orders via telephone to ISE staff who act as blind brokers. The repo market operates on a multiple price–continuous trading system. All orders are continuously entered into the computer system and the orders automatically matched. Members are subsequently informed about the executed transaction. In order to trade on the ISE, member institutions need to provide collateral in the form of Tbills. If this collateral is eroded institutions can no longer trade. Historically, practically no institution has defaulted on ISE trading obligations, and traders in ISE consider counterparty credit risk to be negligible. Traders do not know the identity of counterparties prior to trading, and other traders do not know that the trade took place, except by observing that a particular limit order has vanished from the screen. The limit orders are one–sided, i.e., traders either enter lend or borrow quotes where these quotes are firm in the sense that the quoting institution is committed to lend/borrow until it either withdraws the quote or another institution hits the limit order with a market order. Each trader sees the five best bid/ask limits. The actual deal finalizes at 4:30 pm, i.e. the daily deals settle just at the end of same day at 4:30 pm. Transaction costs for overnight repos are 0.00075%. Trading takes place between 10 am and 2 pm. For details see the ISE fact book at website www.ise.gov.tr.

We have the tick by tick data of the Turkish overnight money market. This market is one of the main channels that financial institutions borrow or lend for short periods in Turkey. The period between 11 January 2000 and 21 December 2000 is included in the analysis. The days near the religious holidays are excluded because of the abnormally low trading volume. Within a day trading occurs between 9:30 am and 5:30 pm. The transactions with volume less than 5×10^{11} (app. $ 800,000 at the time) were not included since they have a very minor effect in the market. Moreover, transactions between different accounts of the same institution were cleared from the data.

Consequently there are 240 trading days and 264,039 transactions exist in our data. For each transaction, we know date, time, volume, interest rate and identities of borrower and lender.

Appendix B. Definitions of Network Parameters

As many real life systems can be considered as networks, financial systems can also be analyzed by network theory. In this case where overnight money market is analyzed, financial institutions form a network where each institution is a node. If there is a transaction between two nodes during a day, these nodes are connected by a link. This link has a direction from lender to borrower.

Similar to Iori et. al (2008), 3 matrices can be defined for the ease of network analysis. These are adjacency matrix *A,* the connectivity matrix C, and the weighted connectivity matrix W. To capture the information of borrowing and lending, these matrices reflect directed links. Each element of matrix *A*, $a_{i,j}$ takes the value 1 if a there is a link between *i* and *j* where *i* is the lender and *j* is the borrower and 0 otherwise. The each element of matrix *C*, $c_{i,j}$ takes the number of transactions between *i* and *j* where *i* is the lender and *j* is the borrower. For each transaction during the day, $c_{i,j}$ increases by one. The each element of matrix *W*, $w_{i,j}$ is the amount of money that *i* lends and *j* borrows during the trading day. Because of directed links $a_{i,j} \neq a_{j,i}$, $c_{i,j} \neq c_{j,i}$ and $w_{i,j} \neq w_{j,i}$.

Soramäki et. al (2007) divides their US interbank network to components. The biggest component is GWCC (Giant Weakly Connected Component) which consists of a GSCC (Giant Strongly Connected Component), a giant out-component (GOUT), a giant in-component (GIN) and tendrils. GSCC is the core of the network in which nodes are connected with two sided directed links. If a node is connected to another node which is in GSCC with in and out links, then this node is in GSCC too. GIN includes nodes which are connected to GSCC only through one sided links from GIN to GSCC. GOUT has one sided links from GSCC to itself. If a node is connected to the system through a link from GIN or into GOUT it is one of tendrils. Other than GWCC there are disconnected components (DCs) which are isolated islands of the network.

Even though Soramäki et. al (2007) and Boss et. al (2008) use analysis of GSCC in their studies, we analyzed GWCC because of a major characteristic property of the network. Since institutions in Turkish money market only borrow or only lend in general, the network has a very low reciprocity and there is not a core which includes nodes linked in both ways.

The number of nodes which is denoted by n, is the total number of participating nodes in the network.

The number of links, $m = \sum_{i,j} a_{i,j}$, measures how many borrowing-lending combinations occurred on that day.

The connectivity of the network $p = m / n \times (n-1)$ denotes the fraction of used capacity.

The daily volume of the market can be considered as the sum of flows on directed links which can be formulated as $volume = \sum_i \sum_j w_{i,j}$.

Reciprocity is the fraction of links for which the link with opposite direction exists in the network.

As it is mentioned before, degree distribution is a very critical aspect of scale free networks. A node's in-degree is the number of incoming links to that node and out-degree is the number of outgoing links from that node.

$$k_{in}^{i} = \sum_{j \neq i} a_{j,i}$$

$$k_{out}^{i} = \sum_{j \neq i} a_{i,j}$$

Suppose that we have network as in Figure 1 There are 6 nodes and 8 links in the network. Hence the network connectivity is $p = \frac{m}{n \times (n-1)} = \frac{8}{6 \times 5} = 27\%$. There is only a pair of links which are in reverse direction. There are links from node 1 to 5 and node 5 to 1. Thus reciprocity is calculated as $r = \frac{2}{8} = 25\%$.

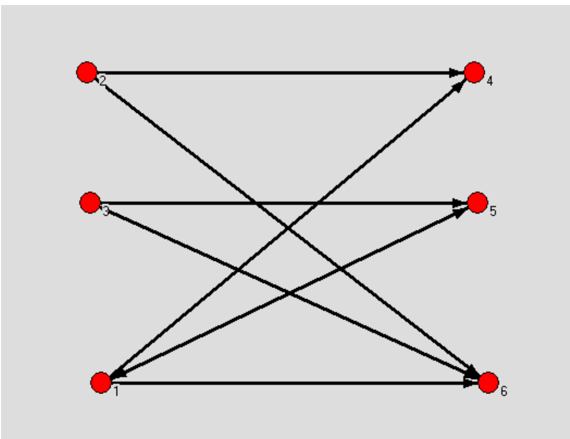


Figure 1- A symbolic network

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