A NETWORK ANALYSIS OF TURKISH FINANCIAL CRISIS OF 2000

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A NETWORK ANALYSIS OF TURKISH FINANCIAL CRISIS OF 2000

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Thesis Abstract

Taylan Eren Yenilmez, “A Network Analysis of Turkish Financial Crisis of 2000”

This thesis is an attempt to explain Turkish financial crisis of 2000 in the light of network theory. Our contribution is applying network theory to a very special data that spans pre-crisis and crisis periods. Analyzing time series behavior of network parameters during such a special period is can bring new perspectives for applications of network theory to financial systems.

Turkish overnight money market is considered as a real world network and daily networks of the year 2000 were constructed with the help of market microstructure data. Results showed that during the year network was highly centralized due to the huge borrowing of Demirbank. Centralization around Demirbank changed the structure and broke ties between other institutions which decreased connectivity. November crisis demolished highly central structure around Demirbank and connectivity increased during the crisis. Network illustrations and time series behavior of connectivity, connectivity-volume correlation, backbone volume ratio, Google Pagerank value for the central node all show the centralization around Demirbank before crisis and the collapse of this structure during the crisis. These parameters can be watched to catch this kind of centralization and to prevent turbulences related to the central node.

Tez Özeti

Taylan Eren Yenilmez, “2000 Yılı Türkiye Finansal Krizinin Ağ Analizi”

Bu tez Türkiye’nin 2000 yılında yaşadığı finansal krizi ağ kuramı ışığında açıklamayı amaçlamaktadır. Bu çalışmanın katkısı ağ kuramının kriz öncesi ve kriz dönemini kapsayan çok özel bir veri setine uygulanmasıdır. Ağ değişkenlerinin böyle özel bir dönemdeki zaman serisi davranışlarının analizi, ağ kuramının finansal sistemlere uygulanmasına yeni yaklaşımlar getirebilir.

Türkiye gecelik para piyasası bir ağ olarak ele alınmış ve 2000 yılı içerisindeki günlük ağlar mikro piyasa verisi yardımıyla oluşturulmuştur. Sonuçlar söz konusu ağın yıl içerisinde Demirbank’ın aşırı borçlanması nedeniyle yüksek düzeyde merkezileştiğini göstermiştir. Demirbank etrafındaki merkezileşme ağın yapısını değiştirmiş, diğer kurumlar arasındaki bağların kırılmasına ve böylece ağın bağlanırlığının düşmesine neden olmuştur. Kasım krizi ise Demirbank etrafında merkezileşmiş yapıyı kırmış ve bağlanırlık kriz sırasında yükselmiştir. Ağın değişik günlerdeki grafikleri; bağlanırlığın, bağlanırlık-hacim korelasyonunun, omurga hacim oranının ve merkezi nodun Google Pagerank değerinin zaman serisi davranışları hep kriz öncesi Demirbank etrafındaki merkezileşmeyi ve kriz sırasında önceki yapının çöküşünü göstermektedir. Bu değişkenlerin izlenmesi yoluyla böylesi merkezileşmelerin yakalanması merkezi noda bağlı dalgalanmaları önlemeye yarayacaktır.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

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. These two crises had dramatically negative effects on Turkish financial system. This study aims to analyze causes and effects of the crisis period within the context of network analysis. The year 2000 was studied with high frequency money market data and analyzed by using network theory. It was observed that the structure of the market was changed by a key player and November crisis destroyed the centralized network around this player.

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, De Masi, 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.

Global Financial Crisis and Network Applications

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 mentiones 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.

CHAPTER 2

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 $r = \frac{2}{8} = 25\%$.

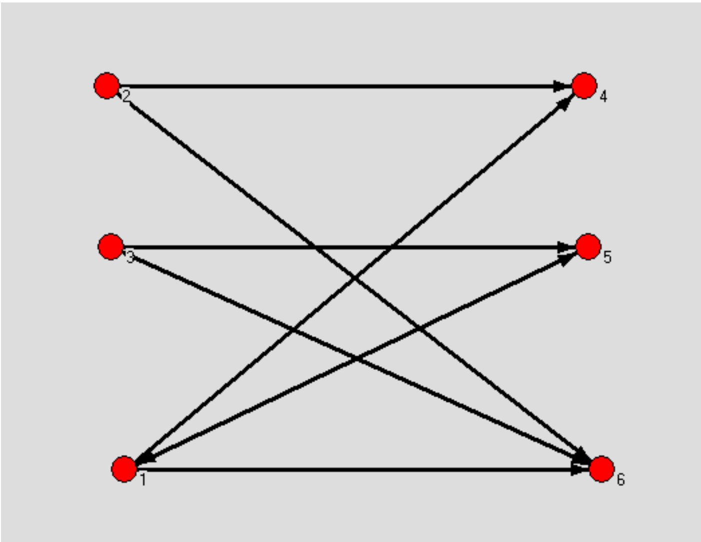


Figure 1- A symbolic network

We also have the degree distribution of this network. Both in-degree and out-degree distributions are as [0, 0, 1, 2, 2, 3].

CHAPTER 3

TURKISH FINANCIAL CRISIS OF 2000 AND MARKET DATA

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. 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. [1]

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.

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

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.

CHAPTER 4

EMPIRICAL FINDINGS

Descriptive Stats

In this section some descriptive stats of the network will be proposed. These statistics form a basis to understand the character and the size of the Turkish overnight money market network.

There are 136 institutions participating to the overnight money market along the analyzed period. These institutions have different codes in the data and only Demirbank was distinguished due to its activity level during the period. 240 daily networks in which these institutions are considered as nodes and their transactions as links are analyzed.

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. 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 76% 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, De Masi, 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 significanly higher size.

The average daily volume of Turkish money market is $(2 \pm 0.33) \times 10^{15} TL$ 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. In this market an institution can choose not to make transaction with another institution. It can be claimed that this selection property decreases connectivity of interbank payment network. On the other hand mechanism of overnight money market is different in that sense. Financial institutions enter their orders to blind brokers and their orders are matched automatically. It means that institutions can not choose their counterparties for transactions. For this kind of network it is more likely that an institution borrows or lends from many institutions during the day since it does not have the option to eliminate some other institutions. This difference between interbank payment systems and overnight money market can be an explanation for the higher level of connectivity in Turkish overnight money market network.

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. If institution A borrowed from B in a given day, B does not borrow from A during the same day. This result is very interesting as institutions can not choose their transaction counterparties. If B does not borrow from A without observing counterparties then B does not borrow at all. This leads to a market which is separated between borrowers and lenders. To check this conclusion top ten borrowers and lenders were listed. These lists are completely different which shows the separation in the market. Another point is the concentration in the borrowing side. Institutions with code number 5 and 3 have a very large share while the lending side is more balanced. 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

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 lines 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 has a huge amount of borrowing. 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.

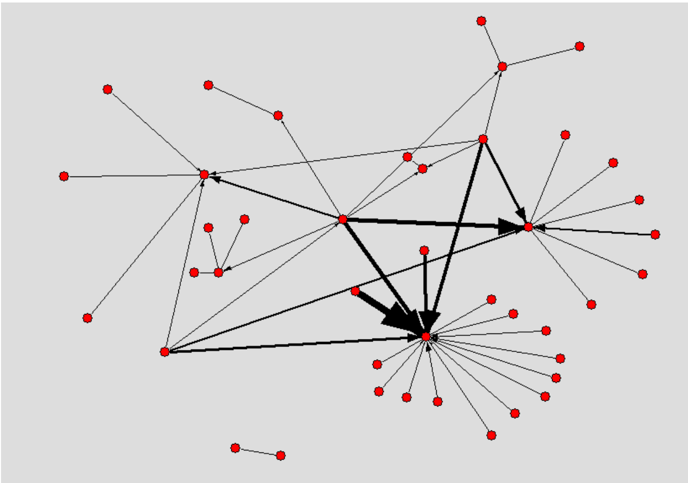
Centralization of the network can be fully observed by 30 October. The backbone is almost fully constructed around Demirbank. The network can be interpreted as Demirbank borrows from everyone and everyone lends to Demirbank. In other words while Demirbank occurs as the unique significant borrower, lending 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.

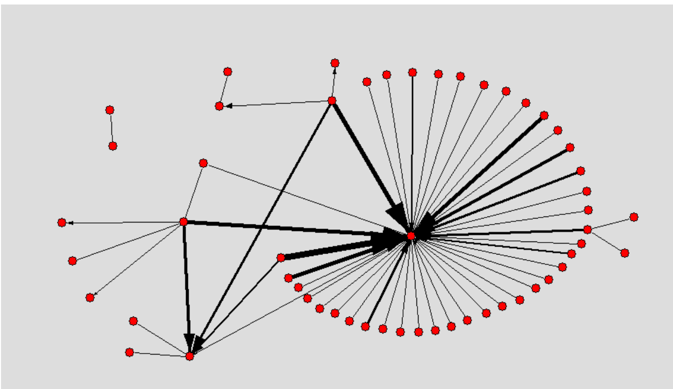
The destruction can be observed better by 1 December, the day that market volume was at its bottom. The third and fourth graphs show the impact of financial crisis. In these days financial institutions stopped lending since borrowing by

Demirbank was considered too risky. The structure which was formed around Demirbank's borrowing collapsed due to the dramatic decrease in risk appetite.

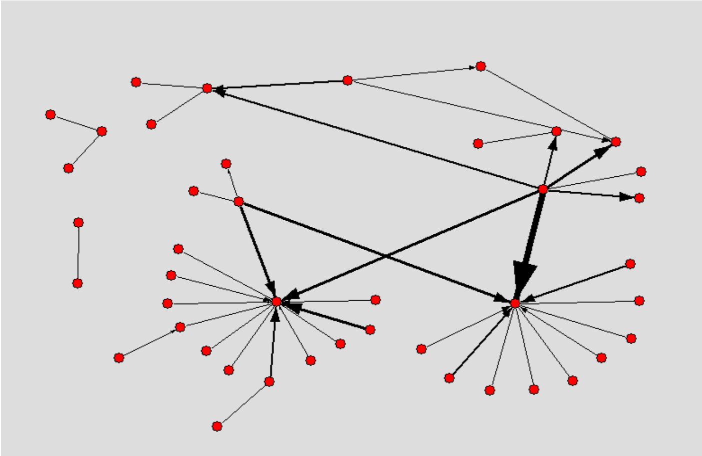
Fifth graph shows a multi-centered structure by the end of the crisis, 5 December. The takeover of Demirbank changed the picture, and backbone got a bit stronger with the normalization of the market. This picture shows the beginning of recovery from the crisis.



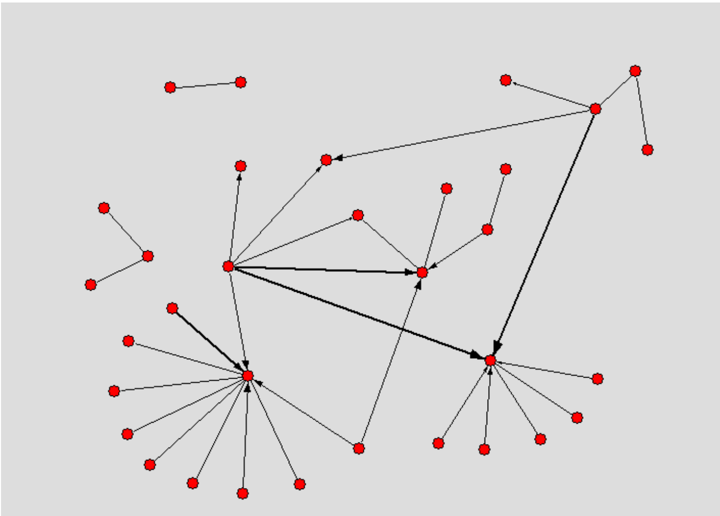
1 March 2000



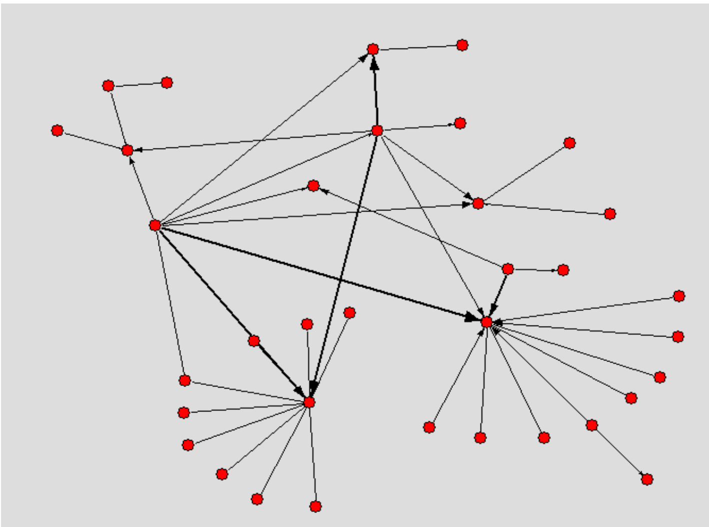
30 October 2000



22 November 2000



1 December 2000



5 December 2000

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

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.

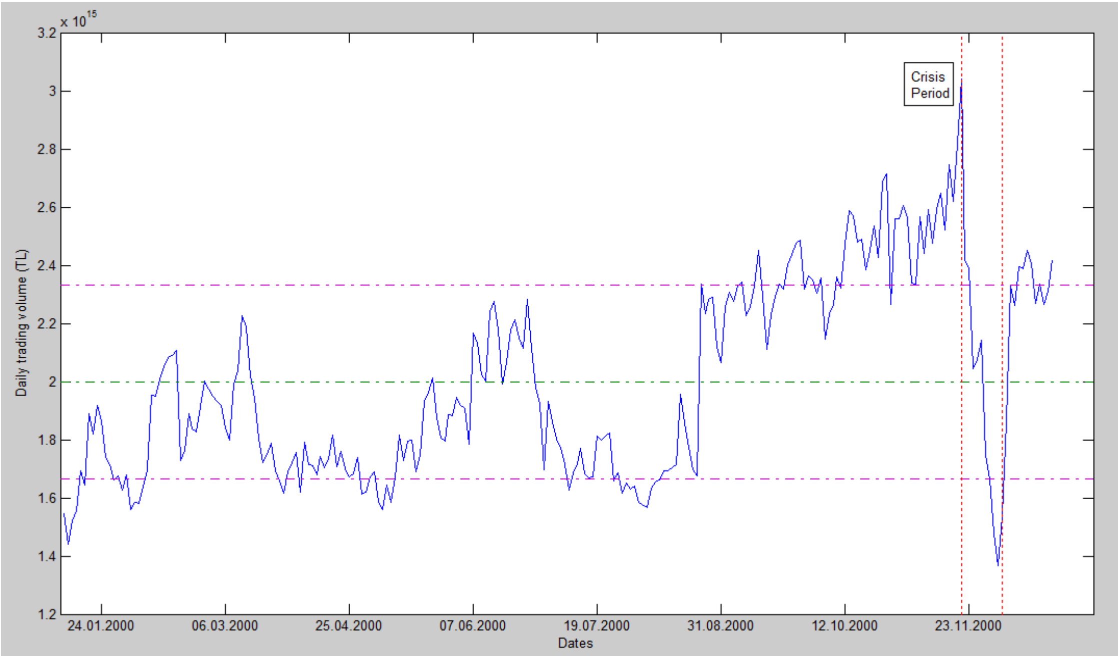


Figure 3- Daily volume of Turkish money market

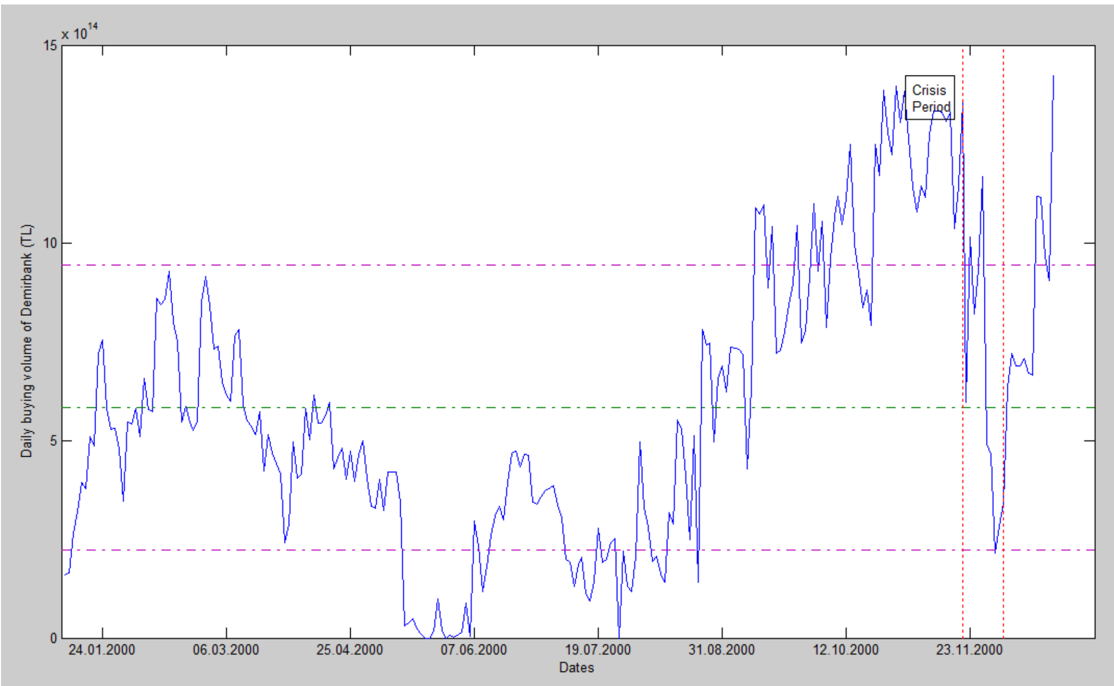


Figure 4- Daily borrowing volume of Demirbank

Demirbank	Mean	Std

borrowing		
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 95% significance, ** means 99% significance.

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.

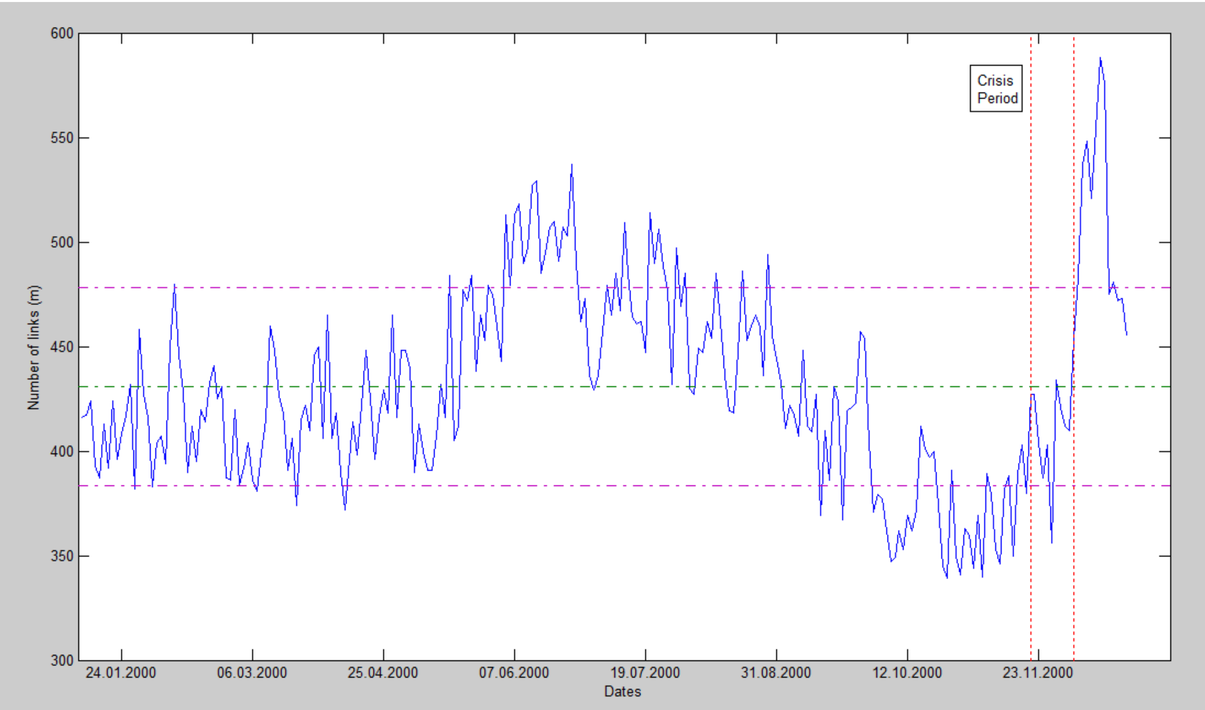


Figure 5- Number of links (*m*) of daily networks

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.

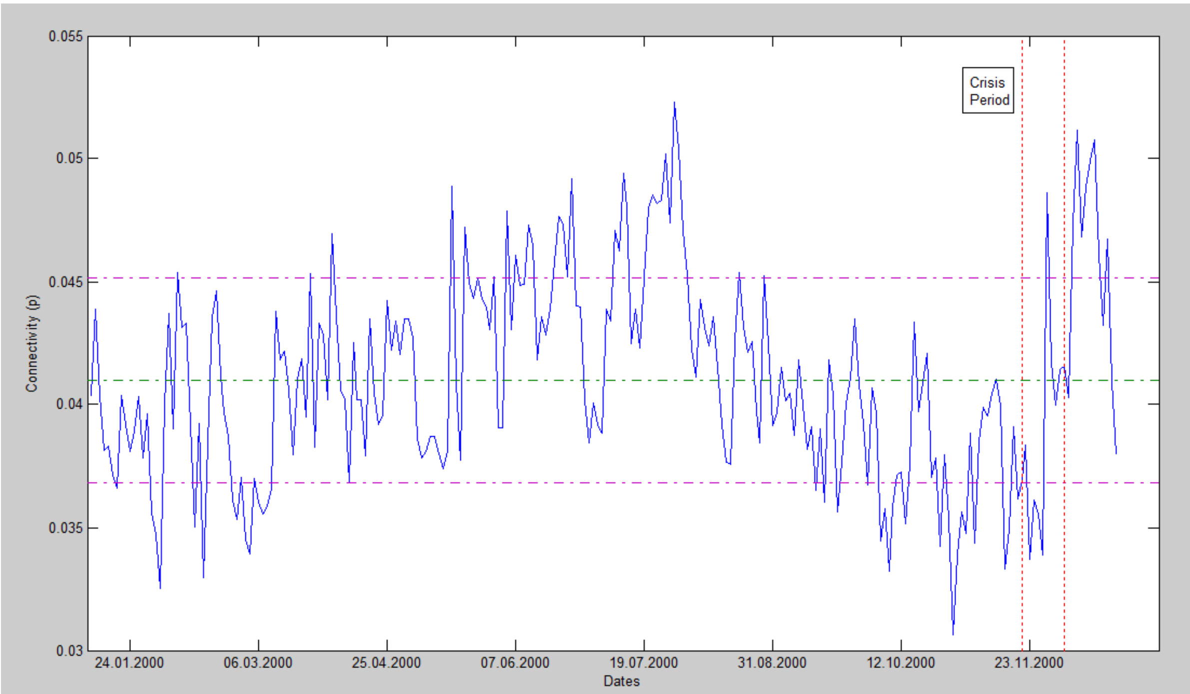


Figure 6- Connectivity (p) of daily networks

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 November crisis led the connectivity rise significantly. This is obviously because Demirbank's falling from the position of the strongest hub. Demirbank was not the unique borrowing center anymore and more number of players could borrow from the market with the collapse of Demirbank's borrowing monopoly. This led to a rise in the number of links and connectivity.

This path of connectivity is unlike other findings and theoretical insights in the literature. Connectivity is expected to decrease during turmoil days due to the lack of confidence and the high level of ambiguity in the market. Fedwire network connectivity decreased significantly due to the 9/11 attacks (Soramaki, et al. 2007). But in our case, connectivity increased in the crisis period in spite of the dramatic decrease in market volume.

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). But 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.

As connectivity-systemic risk relation is one of the most important topics in the literature, it is to be explained in Turkish crisis case. It was mentioned that connectivity increased during the crisis and this is caused by Demirbank's downfall as the central hub of the network. 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. In our case the event was financial. As rumors about Demirbank's failure appeared, 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. It was explained before that the decrease in volume was due to decrease in Demirbank's borrowings. The question is how other financial institutions continued their overnight activities during a financial turmoil with very high interest rates. It is known that overnight money market is used for daily liquidity needs of financial institutions but Demirbank dominated this market for its treasury-bill purchases. It is a straightforward explanation that even though Demirbank bubble did not exist other financial institutions used this market for their daily liquidity needs.

Value

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 months to end 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 another at the end of the day. 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.

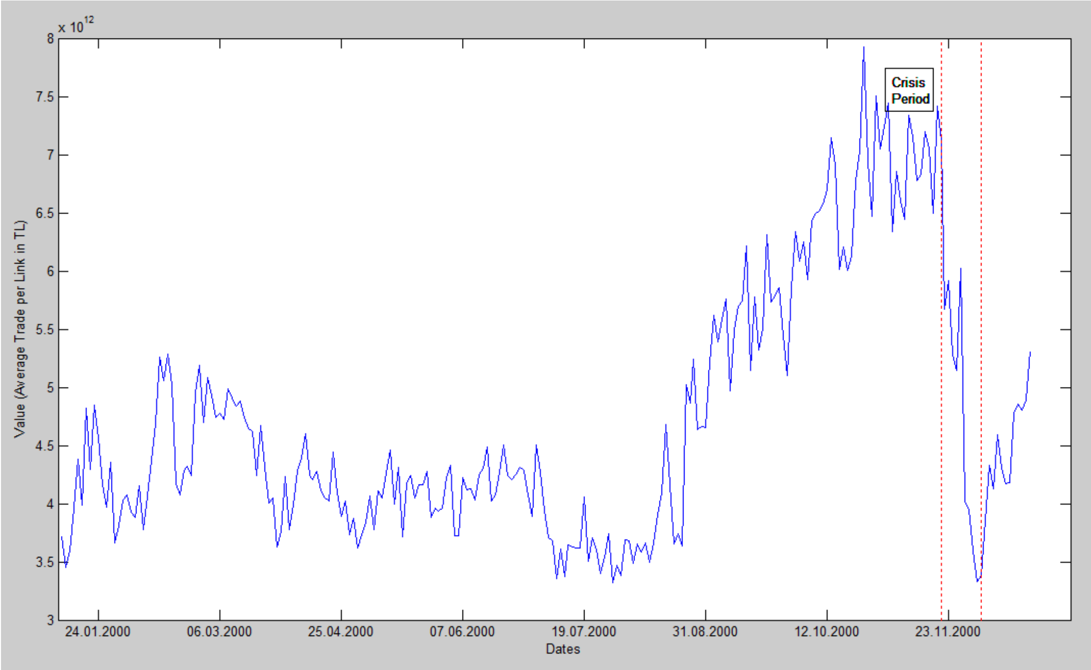


Figure 7- Value (average trade per link) of daily networks

Correlations Between Network Parameters

The most striking component of these observations is the negative correlation between *m(also p)* 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 expectation that number of links must be positively correlated to 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.

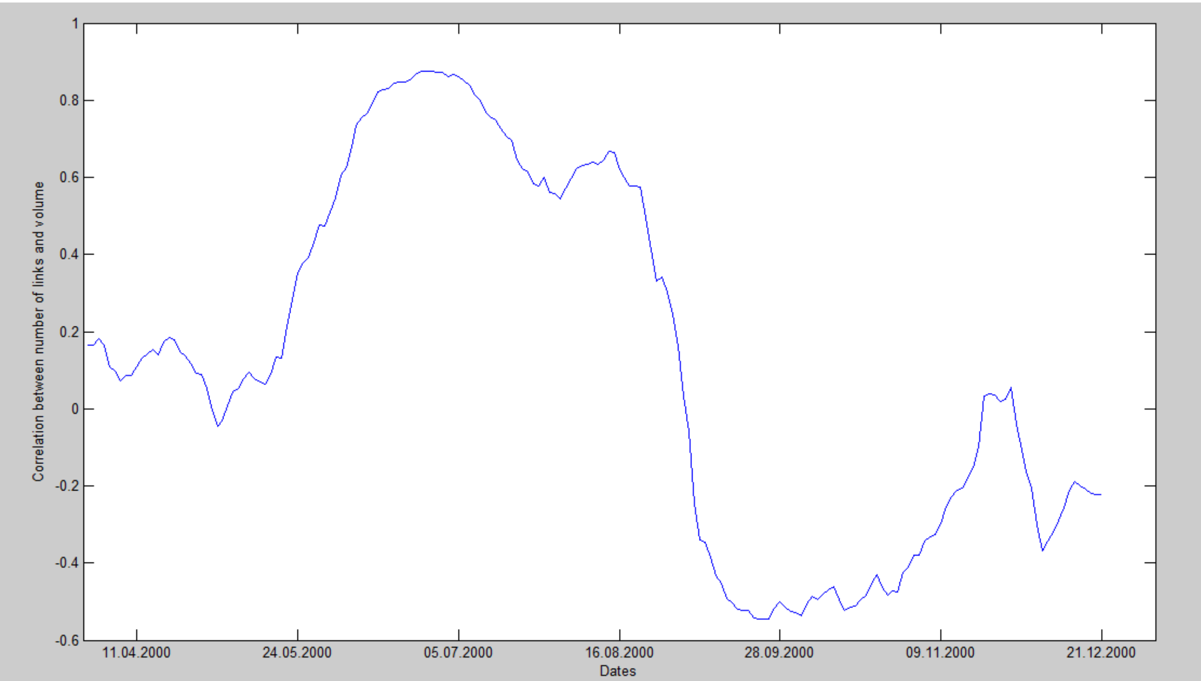


Figure 8- Time varying correlation coefficients between *m* and volume

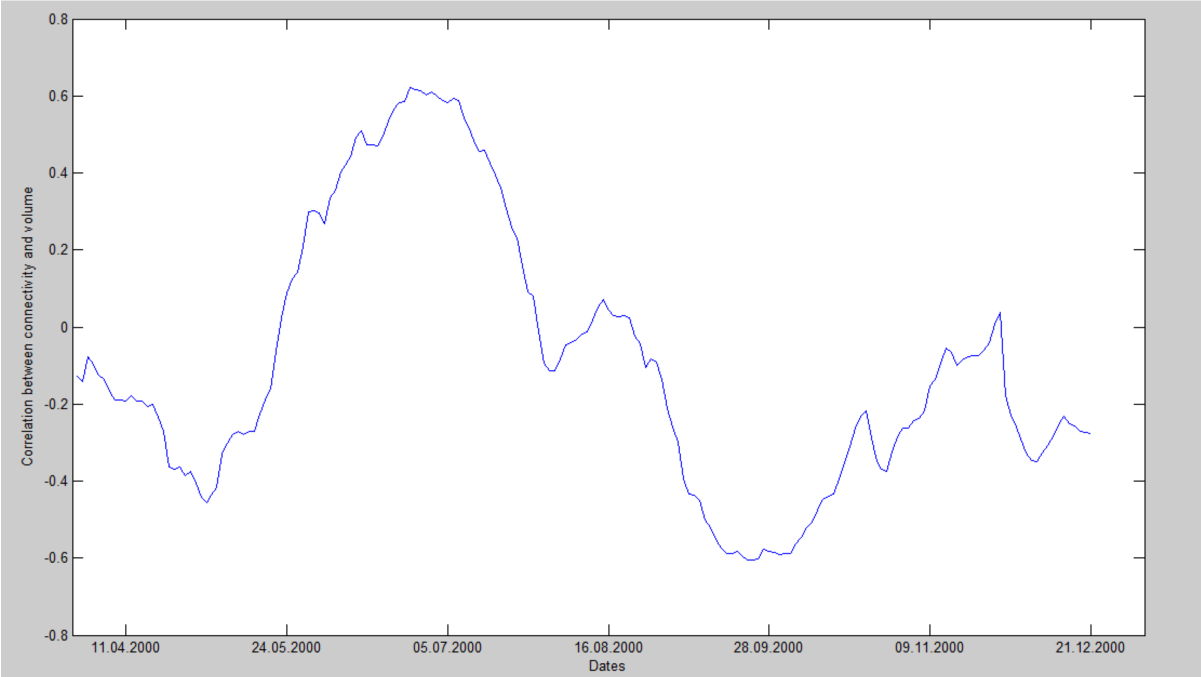


Figure 9- Time varying correlation coefficients between *p* and volume

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 rumours about the failure of Demirbank start the crisis on November 20, and the crisis ended with the takeover of this risk-prone bank 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.

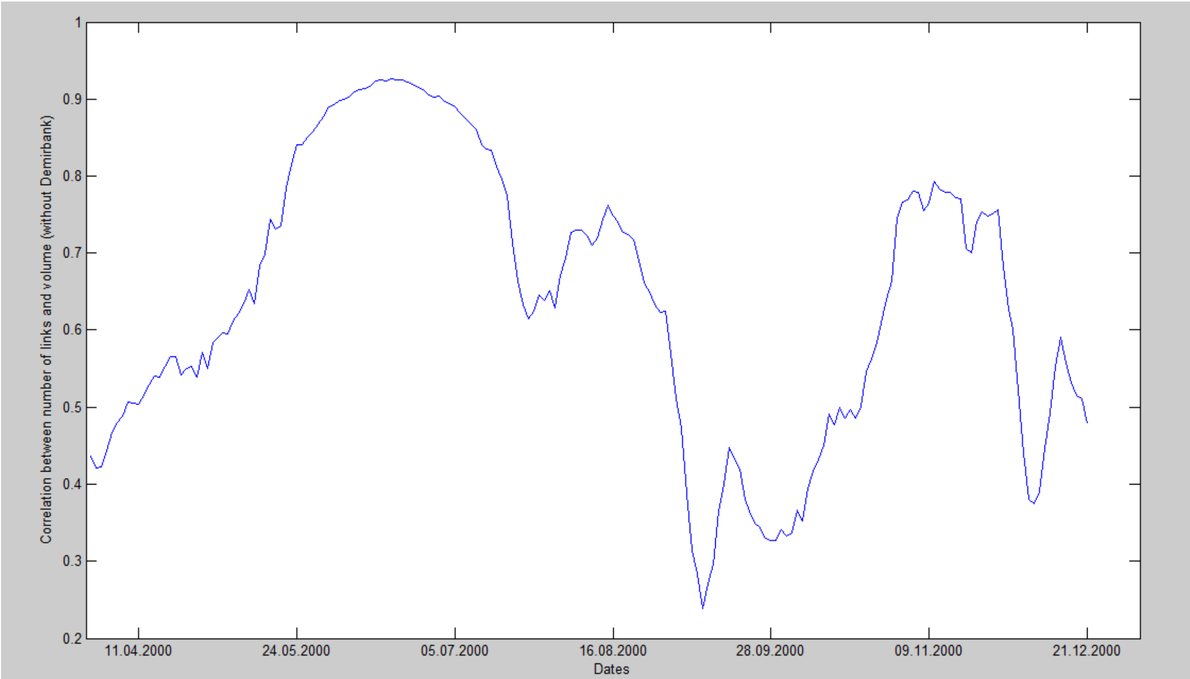


Figure 10- Time varying correlation coefficients between *m* and volume without Demirbank

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 parallized the whole network. The takeover of Demirbank by the Savings Deposit Insurance Fund (SDIF) in December 5, restored confidence about lending behavior. After the takeover of Demirbank, other institutions established links with each other and the star network like structure disappeared.

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.

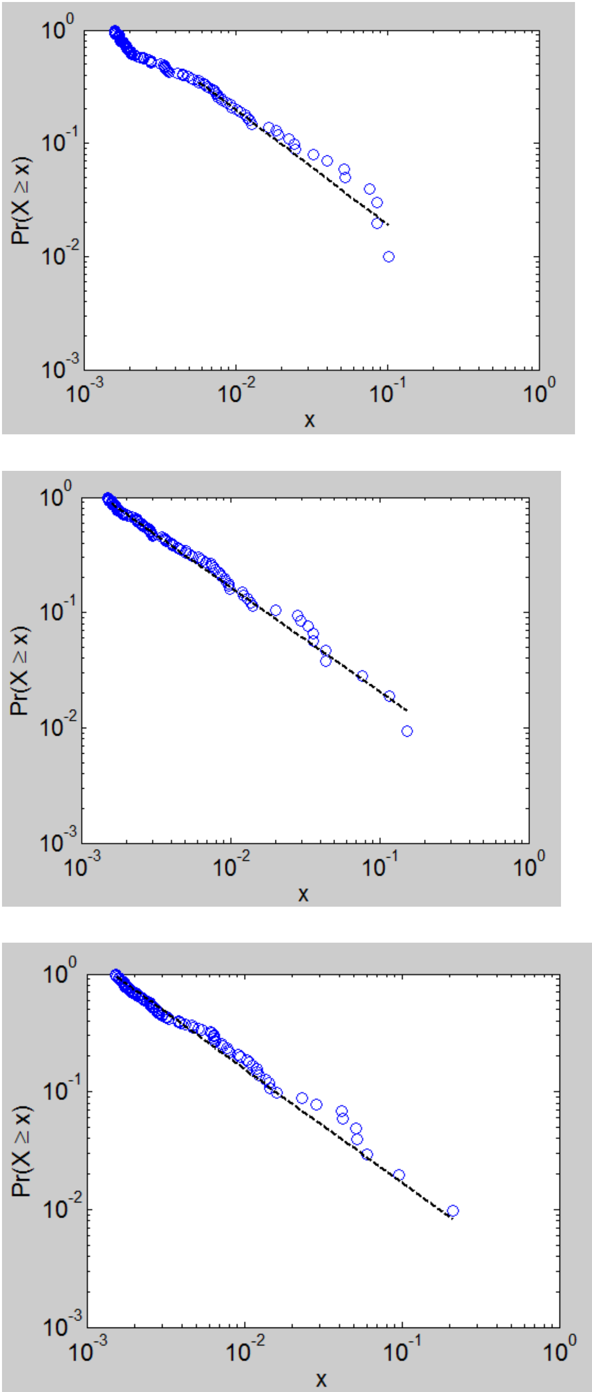


Figure 11- Centrality and fitted power law distributions for days 5, 150, 200 (logarithmicscale)

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 12- Maximum centrality value of the network for different days

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.

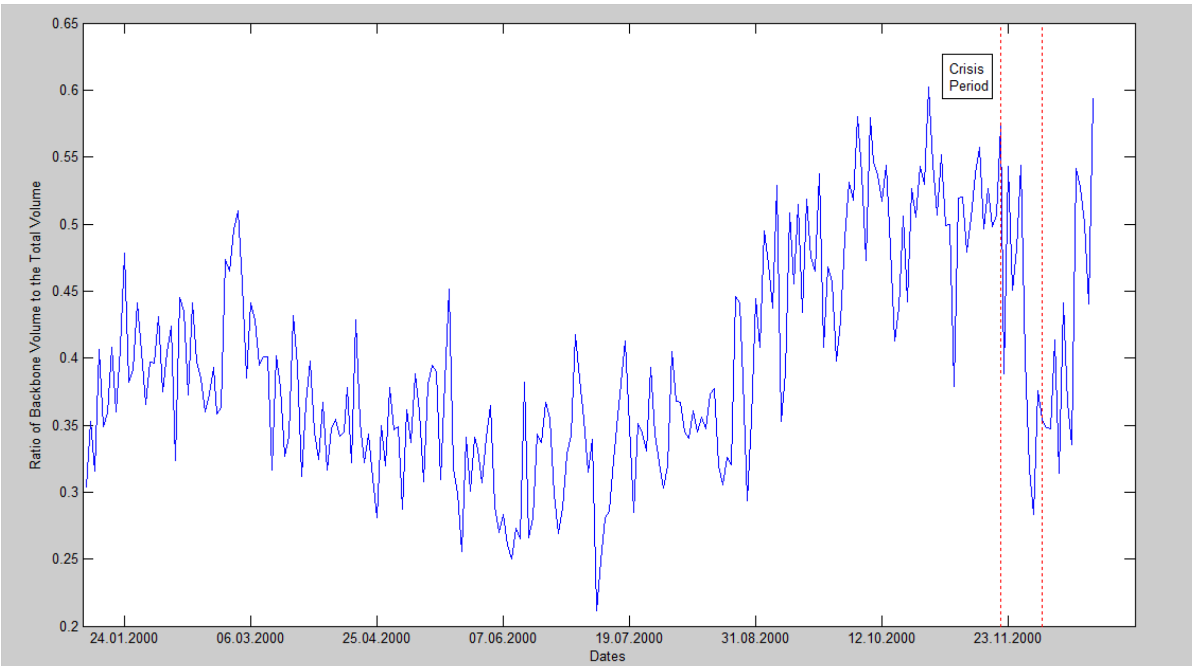


Figure 13- Backbone volume / Total volume (0.01 level of significance)

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.

CHAPTER 5

CONCLUSION

Network theory is a growing field which has applications in many areas. As a result of recent global financial crisis researchers have more interest in network representations of financial systems. Explanations of systemic risk and systemic crisis by network methodology can contribute to better understanding of these circumstances.

This study is an attempt of contribution to this field. Application of network theory to a financial market during a crisis year makes the study unique. Following time-series behavior of network parameters can test some theoretical results derived from application of network theory to systemic risk. Since the study spans pre-crisis and crisis periods, network implementation provides some clues to explain causes of financial crisis. Moreover manipulation of tick by tick overnight money market data provides construction of network

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 some institutions only borrowed while some institutions only lent. Therefore borrowers always had short term needs that increase systemic risk. 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 for network topology is connectivity. It was observed that connectivity decreased during the crisis period. Since connectivity is expected to increase during crisis periods, this phenomenon has to be explained. As Demirbank started financing its Treasury bond portfolio by using overnight borrowing from the end of August, the structure of the network was shaped around Demirbank with a high level of centralization. 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. When Demirbank's domination on the borrowing market collapsed due to the crisis, connectivity increased. 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.

The shock on Demirbank could not be absorbed by other players that are connected to it. High level of connection around Demirbank did not play the role of shock-absorber as it is predicted by some studies in the literature. In contradiction, the rumors about Demirbank affected the whole system since this bank had been seen as the central borrower. Thus, the central role of Demirbank in the borrowing market turned a rumor about a particular institution to a systemic crisis. 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.

After the financial turmoil centralization around Demirbank was destructed. Connectivity increased since other institutions re-established their links. Backbone was weakened significantly. Average volume carried by a link decreased.

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.

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