ANALYZING SYSTEMIC RISK IN FINANCIAL NETWORKS USING NETWORK TOOLS: FOR THE CASE OF FINANCIAL BREAK DOWN OF TURKISH MONEY MARKET IN 2000

İNCİ ÖMERCİKOĞLU

BOĞAZİÇİ UNIVERSITY

2013

ANALYZING SYSTEMIC RISK IN FINANCIAL NETWORKS USING NETWORK TOOLS: FOR THE CASE OF FINANCIAL BREAK DOWN OF TURKISH MONEY MARKET IN 2000

Thesis submitted to the
Institute for Graduate Studies in the Social Sciences
in partial fulfillment of the requirements for the degree of

Masters of Arts
in
Economics

by
İnci Ömercikoğlu

Boğaziçi University
2013

Thesis Abstract

İnci Ömercikoğlu, " Analyzing Systemic Risk in Financial Networks Using Network Tools: For the case of Financial Break Down of Turkish Money Market in 2000"

This thesis analyzes performance of several network centrality measures in assesing systemic risk relying on data from the Turkish money market during financial crisis 2000. In order to gain clearer picture of network topology of Turkish money market various network investigation tools such as volume, transactions, links, connectivity and reciprocity are employed. The main borrower role of Demirbank in the collapse of banking system has been studied with several centrality measures. It is shown that those measures can be used as strong signals much before crisis. In an ex-post analysis of crisis, it is shown that centrality measures perform well in detecting systemically important agent, which Demirbank in our case. Network topology of Turkish interbank market satisfies the scale free property which enables us to monitor response to the failure of the central agent. This thesis adds to the new and growing literature on network topological analysis of interbank money markets.

Tez Özeti

İnci Ömercikoğlu, " Ağ Araçları Kullanılarak Finansal Ağların Sistemik Risk Analizi: Türk Para Piyasası 2000 yılı finansal krizi için bir uygulama "

Bu tez, 2000 yılı Türk para piyasasının mali krizi verilerine dayanarak sistemik riski ölçen çeşitli ağ merkeziliği araçlarının performansını analiz etmektedir. İşlem hacimleri, bağlantılar, bağlılık düzeyleri, karşılıklılık gibi farklı ağ inceleme araçları sistemin daha net bir görüntüsünü elde etmek için kullanılmaktadır. Bankacılık sisteminin çöküşü sürecinde Demirbank'ın temel borçlu rolü değişik ağ merkeziliği araçları ile incelenmiştir. Bu değerlerin kriz öncesi güçlü sinyaller olarak kullanılabileceği gösterilmiştir. Geçmiş bir krizin analizde, merkezi konumdaki oyuncunun, bizim durumumuzda Demirbank'ın, tespit edilmesinde merkezilik araçlarırının iyi çalıştığı gözlenmiştir. Türk bankalar arası piyasası ağ topolojisinin ölçeksizlik özelliği, sistemin merkezi oyuncunun başarısızlığına verdiği tepkinin gözlenmesini sağlamıştır. Bu tez bankalar arası para piyasalarının topolojik ağ analizi konusunda yeni ve büyüyen akademik arşive katkı sağlamaktadır.

ACKNOWLEDGMENTS

To my beloved fiance, Serkan Ün: This thesis is the result of your support, love, encouragement and help at every stage.Your understanding, patience and continued love makes the completion of this thesis possible.Thanks for everything you did for me...Thanks must go to my wonderful family, for their prayers, encouragement and patience, especially my parents Sema and Mustafa Ömercikoğlu, who got me to and through university. I am very lucky to have you...

I am grateful to my advisor Assist. Prof Tolga Umut Kuzubaş for his invaluable input and contribution to my thesis. I thank him for his positive attitude, kind patience and trust in this work during this year. I am also grateful to Professor Burak Saltoğlu guiding and inspiring me with his distinct research ideas and for teaching me consistent and critical attitude towards econometric thinking.

Special acknowledgement must go to Sertan Ün, my dear brother, who patiently assisted me with technical parts and helped me to gain working discipline.Without his guidance, I would not be able to finish this study.

Many thanks to people from Boğaziçi University Departmens of Economics, especially Can Sever and Oğuz Karahan for their assistance in computation and many other issues. I should thank to my dear friends Eren Odabaşı, Dila Asfuroğlu, Deniz Bayram, Bektaş Torun for their warm friendship and support for the last two years.

I thank God for giving me strength and patience to complete this thesis on my own...

CONTENTS

TABLES

FIGURES

PICTURES

CHAPTER 1

INTRODUCTION

ln the last fifty years, there have been many global and local crises. The last financial turmoil has highlighted the central role played by the interbank money markets for the smooth functioning of the financial system and implementation of monetary policy. Investigation of behaviour of systemically important institutions is crucial through their role in affecting the entire system in the case of their failures.

The high complexity level of system has made it hard to analyse whole framework and detect the most problematic agents or institutions. Especially the last global financial crisis between 2007-2009 has shown that a more comprehensive analysis of financial system required. Besides, the failure of existing tools to signal the coming financial crisis led authorities pave out the way to development of more effective tools.

Modern financial markets exhibit a high degree interdependence and interconnectedness. Those connections stem from agents' balance sheets both for the asset and liability sides. In a comprehensive analyis of these interconnections, for finance and insurance sectors Lo and Pelizzon (2010) proposed a formal measure which also captures linkages and balance sheet transactions. Besides, the recent study committee of G-20 has shown that systemically important institutions are not only the largest ones but also those which are interconnected and capable of affecting the whole financial system.

There exist several tools to measure the systemic risk. However, these tools and the existing tecniques at best give indirect indications of the system. Considering the fact that modern financial systems have a very complex structure, network representation gives the crucial picture of the whole system. Mapping the networks, taking financial institutions as nodes, is the first and main step to understand today's modern intricate financial system.

Network topology provides a framework for analyzing the inner working of interbank money flows. During the last five years, the physical theory of financial networks has developed rapidly since it has been shown that many physical networks have many characteristics in common. In other words, interbank money marktes share many properties with other physical networks like the internet or networks for electricity or water supply. A growing literature on the functioning of money markets has emerged using the network topological approach.

In this thesis, it is aimed to analyse the Turkish financial crash in 2000 with network tools in a systematic way. In particular, the following questions have been raised. Firstly, how can a financial system can be understood as a network which involves financial institutions as agents? Secondly, how central and how important an agent in the newtork and how this centrality can be measured with various network measurement tools? Finally, why disruptions for a single bank, Demirbank, can affect all other banks in the network?

A crisis signal is needed to be discovered because the existing ones lag behind the real time. Hence, instead of diagnose of a problem, they are like to provide autopsy like conclusions. So, in that sense it is claimed that this crisis would have been forecasted if the trends of relevant network tools had been realized better at that time. Since, an innovative analysis of financial network during an actual crash has been made in this thesis, the outcomes and findings made here can be helpful in similar cases to draw policy recommendations.

Data from the transactions in the over night Turkish money market in 2000 is used to analyze evolution of crisis and the role of Demirbank in this process. The year 2000 is a very important year for the Turkish economy since markets suffered from financial crises in November 2000 where annual interest rates reached 2500% overnight. It has been observed that market structure has changed by the central agent and crisis destructed the highly centralized shape of network around that agent.

It has been detected the volume, transaction, link and nodes behaviours during the different periods of 2000. Besides, connectivity and reciprocity trends are used to derive general conclusions. Correlations among those network values are calculated. Moreover, we focus on the degree, closeness, betweenness and Bonachic centrality measures of Demirbank. Again, the correlations of those measures are illustrated to understand the robustness of centrality measures. Then, we prove that our network exhibits a scale free structure with reference to Barabasi-Albert model. With the understanding of general properties of such scale free networks, the behaviour of our network will be analysed better. In the last part, network representations of 6 delibaretely chosen dates will be shown. Those illustration are drawn within two layouts: circular and Kamada-Kawai. The network representations enable us to see the changes in the structure through the periods clearly.

This thesis is organized as follows. In chapter 2 definitons of basic network terms and properties are given. The relevant literature and the existing centrality measures are explained in a compact way. Chapter 3 is devoted to the describtion data and the graphs of various network metrics are drawn for 240 days of 2000. Besides the summary statistics of topological measures are compared. In chapter 4, Demirbanks centrality measure values are examined. The correlations and statistics of those measures are provided. In chapter 5 we analyze the scale free structure of our network and Demirbanks preferential attachment values are illustrated across time. Illustrations of different dated networks are presented in chapter 6. The final part involves comparative statistics for different periods. Finally, chapter 7 concludes.

Systemic Risk

To understand the importance and potential effects of systemic risk, first we need to define it formally. Although the exact meaning of systemic risk is ambigous, according to existing literature, it is examined under three general concepts in banking sector. The first definition is rather in macro level. It defines systemic risk as the shock that creates adverse impacts on most or all of the agents of an economy or a system simultaneously or near simultaneously. Bartholomew and Whalen (1995) proposes a definiton of systemic risk refering ” to an event having effects on the entire banking, financial, or economic system, rather than just one or a few institutions.” Similarly, Mishkin (1995) defines systemic risk as ”the likelihood of a sudden, usually unexpected, event that disrupts information in financial markets, making them unable to effectively channel funds to those parties with the most productive investment opportunities.” Allen and Gale (1998) suggests a model to observe how the transmission of effects from a macro shock to individual units.

The second definition focuses on micro level. Kaufman (1995) has defined systemic risk as the ”probability that cumulative losses will accrue from an event that sets in motion a series of successive losses along a chain of institutions or markets comprising a system.” In that sense, systemic risk similar to risk of falling of interconnected domino stones. Federal reserve has a similar approach so that systemic risk tends to occur if an institution participating in large dollar payment system fails to or unwilling to settle its net debt position.

Bank for International Settlements (BIS) (1994) defines systemic risk as ”the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties.” Governor George of the Bank of England (1998) has described systemic risk as occurring ”through the direct financial exposures which tie firms together like mountaineers, so that if one falls off the rock face others are pulled off too.” Likewise, Crockett (1997) explained systemic risk so that for banks, it may occur if Bank X, defaults on a loan, deposit, or other payment to Bank Y that produces a loss greater than Y’s capital and forces it to default on payment to Bank Z with losses that are larger than Z’s capital, and so on down the chain.

The third definition of systemic risk focuses on spillover of an initial exogenous or external shock. However, it does not involve direct neither correlation nor causation. Instead it depends on weaker and more indirect interconnections. This definition refers to similarities of an agent with the initial unit agent who is the source of systemic risk. The more similar the risk exposure profile with the initial unit economically or politically, or otherwise, the greater is the probability of loss and damage. This indirect causation situation represents correlation without direct causation. It may be referred to as a ”common shock” or ”reassessment shock” effect.

There are several reasons of why we need to measure systemic risk. First of all, it is hard to control something that we can not measure and appearently we need to control systemic risk to keep the economy stable and consistent. Secondly, if the systemic risk is measured properly and accurately, the measurement results have direct policy implications regarding precautionary measures such as capital requirements. Moreover, determining relative systemic importance of financial institutions may allow a regulator to detect a systemically important financial institution (SIFI) and treating banks heterogeneously in terms of their relative systemic importance.

CHAPTER 2

FORMAL DEFINININITIONS AND LITERATURE REVIEW

There are standard ways of denoting networks. In this chapter, some formal definitions of graphs that represent networks will be explained.

A graph is represented as (N,g) where N is the set of nodes N=1,....,n and g is the real valued nxn matrix such that g_{ij} refers to the relation between i and j. This matrix g is called adjency matrix. If the entries of g take more than one values, then this graph is called weighted graph. If otherwise, it is unweighted graph and the entries take the values either 0 or 1.

A network is called undirected if the conditon $g_{ij} = g_{ji}$ is required. If the case $g_{ij} \neq g_{ji}$ is possible , then it is called directed graph.

Nodes can be referred to as links, vertices, edges or ties. Besides, $ij \in g$ means that $g_{ij} = 1$.

A walk is defined in a network g, between nodes i and j is a sequence of links $i_1 i_2, ...i_{k-1} i_k$ so that $i_k i_{k+1} \in g$ for every $k \in 1, ...K - 1$ with $i_1 = 1$ and $i_k = j$. A walk is allowed to come to any given node more than once, however a path is defined as a walk in which none of the nodes are visited twice. So , the main diffrence between walk and path is about the distinction of nodes involved. A walk that the only node that appears more than once is the starting-ending node is called a cycle. A cycle can be formed from any path by adding a link from the ending point to starting point. Similarly, any cycle can be converted to a path by eliminating a link that connects the starting point to ending point.

The shortest between the nodes i and j is called geodesic, i.e. It is the path which contains no other points than i and j.

As a summary:

1.A walk is a set of links which connect set of nodes.

2.A cycle is a particular walk which has the same starting and ending point and every other nodes are visited only once.

3.A path is a particular walk which does not any twice visited nodes.

4.A geodesic between to nodes is the shortes path between them.

5.A network (N,g) is called a connected path if for any node $i \in N$ and $j \in N$ there exists a path in (N,g) connecting i and j. A connected network which has no cycle is called a tree. Hence, in a tree there exists a unique path for any given nodes in that tree. A star is a network in which there exists a node i such that every link in this network should include node i. In such a star netwok, i is called the center of the star.

6.A network is called connected where $g_{ij} = 1$ for all $i \neq j$.

The neighborhood of a node i is the set of points that are connected to, i.e $N_i(g) = \{j : g_{ij} = 1\}$.

Centrality Measures

In the network analysis, it might be needed to compare the nodes and to reach the information how a given node relates and effects the whole network. The information about how central a node in the network is very important especially for the connected networks. Central individuals affect information flow and decision making within a network. For these reasons, various ways have been developed to measure the centrality of any node.

Centrality measures can be grouped into four main groups. The categorization is mainly depended on the statistics on which they are based. Those main measurement groups are: Degree, Closeness, Betweenness, Neighbors' characteristics. Degree centrality measures how connected a node is where as closeness centrality measures how easily a node can reach other points. It also measures how easily a node can be reached. Betweenness centrality refers to how important a node is in terms of connecting other nodes. Finally, neighbors' characteristics measures how important, central, or influential a node's neighbors are.

Without getting deeper into formal definitions of these measures, it is easy to understand that each measure will catch complementary aspects of a node's position. Hence, some specific measure will suit better for some applications and less for another application. In other words, there exists no best measure. It depends on the network structure and the information needed that should be extracted from that structure. Choice of a centrality measure is a matter of comparison against each other based on network, e.g. when, only a local view of relationships between nodes are needed, then degree measure is appropriate to use.

High centrality scores may signal agents with the greatest structural importance in networks and these agents are naturally expected to have a great impact on the behaviour of network.

Degree Centrality

Nieman (1974) proposed a measure that counts the degree of a node. The degree of a node is defined as the number links that involves that node. It is actually the cardinality of i's neighborhood and denoted by d_i(g) which is:

$$d_i(\text{g}) = \text{card}\ \{j : g_{ji} = 1\}$$

The degree of a node is large if it is adjacent to, or in direct contact with a large number of other nodes. The degree of a node is small if it that node tends be to cut off from such direct contacts.

The degree of a point is viewed as important as an index of its potential communication activity defined by Freeman (1978).

The magnitude d_i(g) is a function of the size of the network on which the degree is calculated. Hence, when comparing the nodes of two different sized networks, it is irrelevant and misleading. For some applications, it may be desirable to have a measure which does not depend on the size of the network. To compare the centrality levels of two nodes from two different graphs, it is needed to have a measure from which the network size impact has been omitted. For this reason, a normalized degree measure is defined as follows:

$$d_i^*(g) = \frac{d_i(g)}{n-1}$$

It may be used when a degree based relative measure is needed in the context of the application. So, both $d_i^*(g)$ and $d_i(g)$ are structural measures of centrality based on the degree of node i.

The density of a network is the relative fraction of links that are present and is calculated as the average degree of nodes divided by n-1, where n is the number of nodes in the network.

In the case of undirected network we have $g_{ij} = g_{ji}$. So, the in-degree and out-degree coincide. However, for the directed networks the above calculation refers to in-degree and out-degree is calculated as cardinality of $\{j : g_{ij} = 1\}$.

In-degree centrality measure is the number of links incident upon a node, hence for the financial network, it refers to the number of counterparties from which a bank receives overnight (O/N) liquidity. It is interpreted as a measure of prestige due to the support received from a node's direct contacts.

Similarly, out-degree is the number of links outgoing from a node, thus for the financial network it refers to the number of counterparties to which a bank lends (O/N) liquidity. Moreover, it is interpreted as a measure of the influence that a node exerts on its direct contacts.

The weighted in-degree and weighted out-degree are derived measures of degree centrality, which actually refers to borrowing strength and lending strength respectively. Weighted in-degree is the sum of the weights of all incoming links whereas weighted out-degree is the sum of the weights of all outgoing links. Moreover, weighted in-degree can be described as the total amount borrowed from a bank's direct contacts and weighted out-degree as the total amount lent to a bank's direct contacts. These arguments will play a key role especially when the indirect lent/borrowed amounts' effects need to be eliminated.(Bavelas, 1950; Nieminen 1974)

To summarize, degree centrality generally compares the degrees of nodes against the maximum possible degree for a network of the given size. Despite its easy application to any network type, degree centrality reflects only a local view of relationships between nodes and therefore does not provide an information about the whole framework of network.

Closeness Centrality

The second view of node centrality is related to its reachabilty from/to other nodes. Closeness-based measures of centrality have been developed by Bavelas (1950), Beauchamp (1965), Sabidussi (1966), Moxley and Moxley (1974) and Rogers (1974). From these measures, the simplest and most widely used one was Sabidussi's (1966).

Sabidussi proposed that the centrality of a node should be measured by adding the geodesic (shortest-path) distances from that node to all other nodes in the network. Interestingly, Sabidussi's measure is a measure of node decentrality or inverse centrality, since it grows as points are far apart. Unlike degree centrality measure, high closeness centrality levels refers to less centralized nodes.

For the node $i \in N$, it is calculated as $C_{Sb}(i) = \frac{1}{\sum_{i \neq j} d(i,j)}$, again where d(i,j) is the shortest-path distance between nodes i and j.

It is easy to observe that $C_{Sb}(i)$ increases with the increasing distance between i and other nodes. However, it is a simple measure and has a very natural interpretation since it depends on sums of distances. Besides, it is meaningful only for connected graphs whereas degree centrality is defined both for connected and disconnected graphs. Since, in a disconnected graph any point is infinitely far away from at least one other point, we have $\sum_{i \neq j} d(i,j) = \infty$ for all $i \in N$.

All other distance based centrality measures are subjected to such restrictions, valid for connected graphs. Otherwise, it is complicated and misleading to interpret them. Sabidussi's measure is widely used because of its simplicity and the directness of interpretation (Freeman 1978).

It is again easy to observe that, this measure depends upon the cardinality of network. Hence, the values $C_{Sb}(i)$ of points choosen from different graphs (with different sizes) can not be compared. So again, as in the case of degree centrality there is a need for a measure in which the effect of network size has been eliminated.

Beauchamp (1965) has developed a closeness measure to overcome this problem. He proposed that relative node centrality can be measured as:

$$C_c(i)=\frac{n-1}{\sum_{i\neq j} d(i,j)}=\frac{1}{AVG_{i\neq j}d(i,j)}$$

As it can be seen from expression, Beauchamp's measure is based on the sum of the distances of node i to other n-1 nodes. Besides $C_c(i)$ can be seen as an inverse of the average distances between node i and others. Sum of the distances to point i can take the minimum value n-1, if point i is adjacent to every other points. $C_c(i)$ takes the minimum value 1 if the point i is maximally close to each other node. The value of $C_c(i)$ decreases while average distance between point i and others increases. Hence $C_c(i)$ can be interpreted as an inverse measure and it is a direct measure of distance.

In statistical mechanics, it is interpreted as an index of the expected time until arrival of something flowing through the network. The higher the score, the lower the distance separeting a node from the others, hence the lower the waiting time clapsing before the flow reaches that node. In financial networks, for example, that flow can thought as overnight liquidity. (Gabrieli 2012).

Dekker (2005) proposed a new closeness centrality measure: Valued Centrality (C_V) . It is introduced as an alternative to regular closeness centrality. This measure is originally intented for valued networks,the network with the ties of changing strength. However, it is at the same time can be applied to ordinary networks. C_V can be defined similarly to Beauchamp's centrality, but rather than reciprocal of the average distance, it is the average of the reciprocal distances:

$$C_V(i)=\frac{1}{n-1}(\sum_{i\neq j}(\frac{1}{d(i,j})=AVG_{i\neq j}(\frac{1}{d(i,j)})$$

Another closeness measure was introduced implicitly by Hage & Harary (1995). It is derived by Jordan centre of a network and denoted as C_J. It only uses the largest of the distances d(i,j):

$$C_J(i)=\frac{1}{MAX_{i\neq j}(d(i,j)}$$

Hage & Harary suggested that identifying the nodes with the highest C_J can serve as a useful insights of network.

The measures C_{Sb},$C_c(i)$, C_V, C_J are closeness based indexes of point centrality. Any of them can be used when measures based on independence or efficiency are needed.

Betweenness Centrality

The third view of point centrality depends on the frequency with which a point falls between pairs of other points on the shortest or geodesic paths connecting them. (Freeman 1978). This measure refers how much a vertex controls the information flow between all pairs of vertices in a graph. It calculates how important a node is in terms of connecting other nodes. As in the cases of degree and closeness centrality, kind of trajectories are shortest paths and geodesics.

Formally, betweenness of a node means the number of geodesics between any starting and ending nodes that passes through that node. Equivalently, it means the share of all paths between pairs that use that node.

Bavelas (1948) and Shaw (1954) proposed that when a person is strategically located on the communication paths linking pairs of others then that person should be central. Such an agent can control the group by transferring the information or distorting the transmission mechanism. Shimbel (1953) focused on the responsibility of such agents having placed such central positions. These agents have significant roles for the sustainability of communication. Cohn and Marriott (1958) stressed their possible roles as coordinators.

Shaw (1954) introduced betweenness counts in a complex empirically based measure of centrality but he did not developed a measure of betweenness. Instead, direct measures are invented independently by Anthonisse (1977) and Freeman (1977).

Calculating betweennes measure is an easy application if a unique geodesic connects each pair of points. In such a case, the central point is capable of controlling the communication completely between pairs of others. However, for the cases when there are several geodesics connecting pairs of nodes, the situation becomes more complicated. Then, a node which falls on some but not all geodesics connecting a pair of other nodes, has a limited power of control. Partial betweenness of this kind can be measured via probabilities.

Betweenness centrality C_B is based on counting the number of geodesics g_{ij} between actors i and j, and looking at the number $g_{ij}(k)$ which travel via the node k:

$$C_B(k)=\sum_{i\neq k}\sum_{i\leq j\neq k}(\frac{g_{ij}(k)}{g_{ij}})$$

The value $C_B(k)$ is an index of the overall partial betweenness of point k. It is easy to observe that whenever k falls on the geodesic connecting a pair of points, the value of $C_B(k)$ increases by 1. If there are other geodesics then $C_B(k)$ grows proportion to the frequency of occurance of k among those geodesics.

When networks are larger, it is difficult to locate and count the geodesics. However Harary (1965) developed a matrix modelling which permits the development of simple computer program to calculate C_B.

As in the case of degree centality C_{Sb}, C_c, C_B also depends on the size of the network which requires a normalization.Therefore, they are not applicable to compare nodes lying on different networks. For this reason, Freeman (1977) proved that the maximum value of C_B can be achieved only by the central point of a star which is given by:

$$\frac{(n-1)(n-2)}{2}.$$

The relative betweenness centrality is calculated by normalization by this value. The new betweenness measure is calculated as:

$$C_B^*(k)=\frac{2}{(n-1)(n-2)}\sum_{i\neq k}\sum_{i\leq j\neq k}(\frac{g_{ij}(k)}{g_{ij}})$$

which yields:

$$C_B^*(k)=\frac{2C_B(k)}{(n-1)(n-2)}$$

The values of C_B^* can be compared between graphs. Freeman showed that the maximum value of $C_B^*(k)$ is 1 for the case of star and when k is central point of that star structure. Besides, $C_B^*(k)$ gives the value zero for the other points in the star.

Flow centrality C_F was developed by Freeman, Borgatti, White in 1991. This gives an alternative way to betweenness centrality and is more suitable for the valued networks. It is based on the maximum flow m_{ij} between actors i and j and looking at the amount of flow $m_{ij}(k)$ that travels through node k:

$$C_F(k)=\frac{\sum_{i\neq k}\sum_{ilj\neq k}(m_{ij}(k))}{\sum_{i\neq k}\sum_{ilj\neq k}m_{ij}}$$

It should be noted flow centrality is more time consuming to calculate.

In terms of financial networks, betweenness of an institution refers to a connecting pairs of nodes in the network is a measure of the dependence of these other banks from this institution to transfer loans. Thus, betweenness provides an indication of the exclusivity of the position of a node in the network, of the control that a certain node can exert on what is flowing across the nodes (Gabrieli 2012).

All in all, both C_B^* and C_B can be determined for any graph whether connected or not. They measure the centrality based on the structural property of the betweenness of nodes. Betweenness measure is a useful measure of control in the communication.

Up to this point, we examined the direct measure of centrality. Beyond these direct and relatively easy calculated measures, there are also more intricate ones. These measures are determined by how important its neighbors are. They depend on the relative importance of the surrounding nodes. That is, nodes not only connected or close to other points, but that are connected or close to many other important nodes are more central. This notion resembles the Google Page Rankings. However, the difficulty aroses from the self-referencial nodes. For example, the centrality of a node depends on its neighborhors and that depends on their neighborhors' neighborhors. There are various ways of dealing with this problem such as using matrix algebra and fixed point theory.

PageRank Centrality

PageRank measure was introduced by Brin & Page in 1996. This measure bases on eigenvector algorithm for trajectories, which are unrestricted paths or walks. Improving the random walk model, this measure adds a probability of jumping to any other vertex that acts as a sort of score smoothing parameter. The PageRank score of any node can be interpreted as the fraction of time spent visiting that node in a random walk over the vertices.

PageRank centrality measures the effect of a node in a network. The algorithm of this measure is vey similar to Google's PageRank's algorithm. It is used to understand the relevance of search results. For example, pages which are connected to pages with a high PageRank gain a higher PageRank in turn. In financial networks, in interbank context, a bank gets a higher score if the banks to whom it lends are more central. (Gabrieli 2012)

Katz's Prestige Centrality

Katz defines a measure of centrality which he termed as prestige. This measure has a self calling formulation using itself in the definiton. As in the case of PageRank, the node i gains prestige from having a neighbor j who has high prestige. This is corrected by how many connections j has. As j has more neighbors then i gets less prestige from having j as a neighbor, since the prestige j gives is divided to other neighbors as well. So Katz'prestige of a node i :

$$P_i^K = \sum_{j \neq i} g_{ij} \frac{P_j^K}{d_j}$$

That is the prestige of a node i is the sumof the prestige of i's neighborsdivided by their respective degrees which is calculated as $\frac{g_{ij}}{d_j}$)

Again, it is a self refering definiton. Katz's prestige works better for directed network than undirected ones. Katz also introduced another way of calculating power of prestige of a node. It is calculated as such: A walk of lenght 1 is worth of a, a walk of length 2 is worth of a^2, and so forth, for some $0 \leq a \leq 1$. Thus, this measure is higher for the walk of shorter distances. Hence, it can be seen as looking at all of the nodes from some given node and weighting them by their distance.

Degree, closeness and betweenness measures are all based on the assumption that communications use the geodesics, shortest paths. One of the elegant ones of these flow measures is developed by Bonacich (1972). He proposed two indices which consider all possible communication paths.

Bonacich Centrality

Bonacich Centrality can be seen as an alternative to the Katz prestige centrality. It is also referred as eigenvector centrality and defined as the fraction of time that a random walker will spend at that node over an infinite time horizon. This measure is known as the influence measure. A node with a high score is one that is adjacent to nodes that have themselves high scores.

Bonacich Centrality is an iterative version of degree centrality so that a node's centrality depends iteratively on the centralities of its neighbors. The transmission mechanism is the most suitable method of spread for overnight interbank loans: liquidity flows from the lender to the borrower so that the former loses it the moment the borrower receives it.

The calculation of Bonacich centrality requires introduction of new definitions. Let $A(m) = [a(i, j; m)]$ denote the number of all walks from node i to node j of lenght not exceeding m. Then the number of all walks from node i of lenght not exceeding m equals:

$$\text{v(i,m)}=\sum_{j \in \epsilon} a(i, j, m)$$

Let $v^*(m)$=max{v(i;m) : i $\in$ ϵ}, then Bonacich index for node i is defined by:

$$\text{B(i)}=lim_{m \to \infty} \frac{v(i,m)}{v^*(m)}$$

While the above definitions are some measures of centrality, theya re certainly not the only measures of centrality. There are many other measures capturing the distinct aspects of the positioning of the nodes.

Integration Centrality

Integration centrality is first introduced by Valente and Foreman (1998). It measures the degree nominations received integrate a node into the network. Computationally, integration is similar to closeness centrality. Closeness centrality sums the geodesics values and takes the reciprocal, while integration sums the reverse distances between nodes. The distinction of reversing and reciprocating the total of geodesics enables integration to be a directed measure.

Radiality Centrality

Radiality centrality is also first introduced by Valente and Foreman in 1998. It measures the degree nominations sent reach out into the network. It is calculated by computing integration on the transpose of the adjacency matrix. An individual with a radial network has direct contact with individuals who do not have direct contact with each other. An individual with high radiality is able to reach everyone else in the network in fewer steps, on average, than an individual who has contact with individuals who are connected to each other.

CHAPTER 3

CENTRALITY BIBLIOGRAPHY

This section of thesis surveys the literarure on centrality measures will be made. Even though, centrality concept is first developed in social network analysis to measure centrality reflect in sociological origin, today centrality measures concept have been used widely in economics and finance. Analysis of social networks is an inherently interdisciplinary academic field born from sociology, statistics and graph theory. Recent studies in finance drawn attention on network tools. Evolution of social networks into a network science will be discussed in 3 parts starting from the early studies to most recent ones.

History

Most of the current knowledge about network centrality had been found by the works of Freeman(1979) and Bonacich (1972). Bonacich's centrality measure was closely related to Hubbell's (1965) measure of sociometric status. Coleman's (1973) measure of power and Burt's (1982) measure of prestige have been the anchestors of variety of centrality measures. Freeman's influential analysis have provided a framework of literature for the further investigations on power and influence measures.

For the following years, derived centrality measures had been seem to be competing hypothesis of relationship between network's one specific property and its members' behaviours. For such kind of intuitive foundations Freeman (1979 p.217) was prudent: ”Ideally, measures should grow out of advanced theoretical efforts; they should be defined in the context of explicit models. Before such models can be developed, however, a certain amount of conceptual specification is necessary; the basic parameters of the problem must be set down. Thus, the introduction of measures in the present context must be understood simply as a way of clarifying the centrality concept.

In the following part the theory of centrality measures will be disccused. Theory literature for the centrality measures will be reviewed.

Theory

The transfromation of centrality concept from sociology to numerical sciences had first emerged in Leo Katz's paper ”A new status index” derived from sociometric data analysis which is published in psychometrika. As name reveals, this paper was a soft transaction of sociologically used terms into a derived index. In this paper, Katz aimed to evaluate agents' status without forcing them into a popularity competition. He argues a new method of detecting the central agent(s) according to who chooses and how many chooses them as central agents.

To calculate his new status index, he introduces matrix representation of sociometric data. For the sake of completeness, he assumes certain link among agents exist and if there exist no links, then there is not neither communication nor influence. Besides, he assumes each existing links have independently same probabilty of being effective. He calculates the weights of column sums and those values turns out to be constant real numbers. To obtain the centrality status index, it is only needed to solve system of linear equations. The new status index is actually a vector and is in much more nearly correct relative position.

Charles H. Hubbell (1965) in his paper ”An input-output approach to clique identification” defines the cliques as a subset of members who are more closely identified with one another than they are with the remaining members of their group. Links are interpreted as input-output channels of transmission of influence. Magnitudes of transmitted influences serve as a basis of identification of cliques. Hubbell’s clique model stands different from ingoing-outgoing choice patterns since his model allows links to have fractional and/or negative strength and simultaneous direct/indirect linkages. He uses cohesiveness index to identify cliques as an analogue of central agents.

The purpose of Hubbell’s paper (1965) is to present an advanced method of clique identification. He uses Leontief’s input-output model for the economic system as a basement and generalizes for the sociometric data analyzed by MacRae. Then, he compares the existing method of identifying cliques and the factor analytic method presented by MacRae.

Phillip Bonacich has been a great contributor of centrality literature. He first appears in that field with his paper ”Factoring and weighting approaches to status scores and clique identification”. He introduces very different techniques to devise centrality. In the factor analysis approach , he defines a matrix W as a correlation matrix and S_i as individual i’s propensity to from friendships. He decomposes W even when it is not symmetric. He calculates the column vector S such that the sum of the squarred differences between SS’ and W is minimized. Individuals having a high factor all of whose elements are greater than zero will be especially popular in their clique. The factor analysis of a correlation matrix these eigenvalues will be shown how much of variance each factor accounts for.

The final popularity index of an agent reprsented by an eigenvector of the largest eigenvalue. In the convergence of an infinite sequence method, he is after the most powerful factor in a factor analysis, if the eigenvector is standardized so that its length is the eigenvalue. Simultaneous linear equations method constructs a system of homogenous linear equations for the unknown popularity scores. For individual i:

$$S_i = W_{i1}S_1 + W_{i2}S_2 + ... + W_{in}S_n$$

This system of equations in matrix form is S=WS . In the end, it turns out to be that each clique will have a positive λ such that all elements of its eigenvector are greater than zero. Thus, all three approaches basically give the same conclusions. The solution always turns out to be the eigenvector of the largest eigenvalue for each clique. He also compares Hubbell's paper(1965) with his technique and explains relative advantages and disadvantages.

Mathematical sociologist J. Coleman (1973) developed an alternative measure to centrality in his paper ”Mathematics of collective action”. He proposed three measures of power: Power of a collectivity to act, the power to prevent action and power to initiate action. Similarly, R. Burt (1982) derived a measure to prestige in his book ”Toward a structural theory of action: network models of social structure, perception, and action”.

N. E. Friedkin (1991) in his paper ”Theoretical Foundations for Centrality Measures”, defines three measures of actors' centrality that are derived from an elementary process model of social influence. First of these measures is total effects centarlity shows the total relative effect of an actor on the other agents in the network. The second measure is immediate effects centrality indicates the rapidity with which an actor's total effects are realized. The third measure is mediative effects centrality shows the extent to which particular actors have a role in transmitting the total effects of other actors.

Unlike previous measures, these measures are complementary rather than competitive since each is asking different question about the social structure of a group. He has shown that actors' status may arise from the flows of interpersonal influence in a network. It is also indicated that how the social organization of status which has been assumed by Hubbell, Bonacich, Coleman, and Burt can be derived by a micro-level process model of social influence. In other words, this article shows a new theoretical material.

Everett and Borgatti (1999) extended the centrality of measures of degree, closeness and betweenness to apply to groups and classes as well as individuals. They also formalized a measure of group centrality efficiency, which indicates the extent to which a group centrality is principally due to a small subset of its members. The measures are illustrated using two classic network data sets using both a priori classes of nodes such as age and sex and empirically derived groups such as cliques.

Using group centrality measures, Everett and Borgatti (1999) proposed a definition to the core of a network as that subset of actors whose group centrality is greater than all others. They also claimed that group centrality measures provide a way to operationalize the concept of social capital which means the set of benefits that accrue from the set of ties that an individual or group possesses with others in the network. For the strategic networking literature, they contributed so that group centrality measures may provide a guide for selecting partners, either among persons or corporations.

Analyses of Centrality Measures

The definitions, characteristics and the robustness of different centrality measures have been extensively discussed. There are numerous empirical and conceptual studies investigating the application of centrality measures used on various real or simulated networks. Centrality measures' properties and their eligibility for different usage have created debates. The relevant contributions to analyses of centrality measures will be discussed in this part.

Sabidussi (1966) has been the pioneer of social network analysis with his prominent paper ”The centrality index of a graph”. He has been the first scientist modelling the relationships within a social network as a graph G with a set V_G of nodes and a set E_G of edges between these nodes. With a structural point of view, he claimed the set V_G represents the members of the social network, while the set E_G refers to the relationships between them and hence describes social ties and interaction potentials between the actors.

Sabidussi (1966) identified the point centrality index of a graph and claimed that one graph is more centralized than another is meaningful only relative to a given point-centrality function σ. He used axioms phrased in terms of two simple graph-theoretic operations: adding an edge and switching an edge. Basically, for quality of a centrality measure Sabidussi relied on the axiomatic requirements. He set up quantitative and testable formulation to analyse the centrality measures.

Nieman's (1974) book ”Construction of communication graphs the properties of which are determined by a given matrix” conceptionally focused on degree centrality which has relatively easy interpretability and transmissibility of conclusions. As

Sabidussi did, Nieminen approached to quality of centrality measures through the theoretical axioms.

Nieminen (1974) focused on the simplest centrality measure; degree centrality determining the number of direct contacts as an indicator of the quality of a network members interconnectedness. A measure to quantify interconnectedness of a node x in a graph G is a mapping σ^G:$V_G \rightarrow R^+$ which assigns a non-negative real number to each x∈G, where a higher value of σ^G indicates a better interconnectedness. In case of an identical network structure of two nodes x and y in the network the application of the centrality measure should have the same value σ^G(x)=σ^G(y) for both nodes. (Nieminen 1974).

Freeman (1979) reviews the intuitive backgrounds of degree, closeness and betweenness centrality. He evaluates the centrality measures in terms of their consistency with intuitions and their interpretability. The paper focuses on the partly significant differences in the rankings of the different actors in a social network when using different centrality measures. He concludes that the order of the different actors varies enormously when using different measures. This observation is also confirmed by the work of Freeman et al. (1980). The latter applies the three centrality measures to other sample networks. In addition, this article evaluates the suitability of the three centrality measures to identify key agents in the context of ”problem solving in groups”.

Freeman (1979) explains the benefits of a smaller distance between two actors and concludes that a path is more valuable the shorter it is. He assures that if there are multiple paths of shortest length from one network member to another, this actor also becomes more independent from the influence of individual actors in between.

Freeman et al. (1980) focuses on the cases of problem solutions in groups by means of experimental results. The group of five agents is formed and experimented for the hypotheses of communication structure and group problem-solving. It is shown that although two of the three kinds of measures (betweenness and closeness) of centrality have a demonstrable effect on individual responses and group processes, the classic measure (degree) of centrality based on distance is unrelated to any experimental variable.

Bolland's (1988) paper ”Sorting Out Centrality: An Analysis of the Performance of Four Centrality Models In Real and Simulated Networks.” is a both empirical and conceptional study assessing the performance of four centrality models (degree centrality, closeness centrality, betweenness centrality, and the centrality measure by Bonacich in random and systematic variation) under a variety of known and controlled situations. It begins by examining the assumptions underlying each model and its behavior in a community influence network. It then assesses the robustness and sensitivity of each model under conditions of random and systematic variation introduced into this network.

Bolland (1988) explains for each of the centrality measures two assumptions on the nature of network flow. Firstly, the one concerning the decay of resources (e.g. information) over distance and time and then concerning the paths through which resources are able to flow. He concludes that different measures are based on different assumptions on the losses that incur in transferring a resource from one actor to another. The degree centrality assumes immediate deterioration of the transferred resource after a transfer starts. Betweenness and Bonacichs centrality measures assume no deterioration of the resource. In case of closeness centrality, there is a gradual loss of the resource with increasing number of transfers.

According to robustness tests, Bolland (1988) shown that the centrality measure of Bonacich is the least sensitive one in terms of a random or systematic variation of the network structure. Betweenness centrality comes off less successfully than the other three measures, indicating a fundamentally distinct conception of centrality for this measure.

Costenbader and Valente (2003) used bootstrap sampling to investigate how sampling procedures affect the stability of eleven different network centrality measures: in-degree, out-degree, degree symmetrized, betweenness directed and betweenness symmetrized, closeness directed and closeness symmetrized,the simple eigenvector, Bonacichs 1972 eigenvector centrality,radiality and integration.They compare the performance of centrality measures at eight different study setting containing 59 networks. They discover the factors improving or challenging the stability. The outcomes emphasize the importance of how the network measures are calculated while selecting the most appropriate measure.

They also analyze the stability of different measures in presence of incorrect or incomplete information on the structure of a network. For undirected and unweighted social networks they conclude that the centrality scores of actors have the highest average correlations with the centrality scores of the individual actors in the overall network in the case of eigenvalue centrality before degree, closeness and betweenness centrality. Their tentative conclusion is that some measures such as in-degree, integration and simple eigenvector centralities are relatively more stable.

Borgatti (2005) gives a new and useful thinking about centrality measures. It is claimed that given traffic flows of model, centrality measures can be seen as expected values of certain node outcomes, e.g. speed and frequency of reception. He starts with giving the typology of common flow processes. He, then, matches centrality measures to suitable flow processes depending on the flow characteristics they assume and runs simulations to test these ideas and compares the results with centrality measures. After giving an explanation of new methods for flows which are not suitable for any existing centrality measures, finally he discusses a new way of thinking for flow processes making centrality measures, expected values of nodal participation.

A further contribution to the discussion on the robustness of different centrality measures is provided by Borgatti et al. (2006) who first define four different types of error (adding or deleting an edge or a node). He, then compares the degree, closeness, betweenness and eigenvector centrality with regard to these different types of errors. He finds that the four centrality measures react similarly to manipulations of the network structure. However, betweenness centrality is a little bit worse than the other three.

Borgatti and Everett (2006) develops a framework for centrality measures. They assign each centrality measures to a node's involvement in the walk structure of a network. Using Freeman's (1979) categorization, they invent a new typology of centrality measures varying along four dimensions: type of nodal involvement assessed, type of walk considered, property of walk assessed, and choice of summary measure. They conclude that centrality is intimately connected with the cohesive subgroup structure of a network.

CHAPTER 4

THE INTERBANK NETWORK

Interbank lending markets have been extensively discussed in literature. Recently, loans on assets part and liabilities on deposit part composes banks' balance sheets together. In the recent years, banks have started to lead higher loans and deposits daily due to globalized economies and amplified trade volumes worldwide. Higher loans and deposits are likely to cause imbalances in banks' balance sheets. Those imbalances can be compansated and corrected by short term, mostly overnight, interbank lending and borrowings. For instance, a bank holding 3000 dollars in loans, 2200 dollars in deposits and 600 dollars in equity is likely to use interbank market to borrow additional 200 dollars to fund its balance sheet fully.

Topology of the interbank networks can be described as directed, weighted and built at a daily frequency. Besides, centrality measures are all computed at a daily frequency.

In the finance literature, due to the lack of available data for different dates, stationarity of distributions of in-degree, out-degree and total degree gain importance to predict the unknown dates. That is, we need to know that stationarity of distribution do not change across time. In this paper, degrees do not change in a day, but we see that stationarity of distribution may change daily.

In general, real money market networks are not strongly connected, i.e. each node is not reachable from every other node in the network. Furthermore, real money market networks not all links are reciprocal (so that for each loan transferred from bank A to bank B, another loan is also transferred back from B to A in the same day). Turkish overnight money network between the years 2000 and 2001 exhibits a graph sturucture which is internally connected but links are very rarely reciprocal. The task of finding available funds or lending excess deposits belongs to treasury departments of banks through the end of the working day.

In the times when the interbank market was very liquid, some banks may prefer to use the market to fund a large portion of their balance sheet. They rely on the presence of the market in each subsequent day. A bank can simply issue loans and fill the liability side of the balance sheet with interbank deposits instead of collecting deposits.

In the pre-crisis and crisis times, interbank market faces many difficulties including liquidity shortages and credit quality fears (Afonso et al., 2011). In the past, various G-20 country Central banks have had to intervene to enable the banks continue accessing to fund.

Understanding the network structure of interbank market is important in determininig banks' access, profitability and liquidity. It has been shown that interbank markets are not complete networks. In normal times banks may create relationships with other banks either through repeated transactions or through commitments to future lendings. During crisis periods, banks check established relationships as a primary source of funding for additional liquidity.

Descriptive Statistics

We use overnight money market data spanning the period 11 January 2000 and 21 December 2000. The data is given by interbank lending and borrowing volumes taken from the electronic interbank market Istanbul Stock Exchange . There were 240 daily networks in which participating institutions are taken as nodes and their transactions are taken as links in network language. There were 136 institutions participating in ISE overnight money market during the interval studied. 29 of those institutions in the network will be filtered out the analysis because their total transaction volume fall behind 800 000 dollars and their effects are very minor to the market. Such a filtering will make us work with 107 relatively more important and bigger agents in the network. All participating nodes have distinct codes in the data mostly the abbreviations of their formal names. During the period, Demirbank was obviously distinguished with its high participation level.

The Turkish overnight market is an open access one i.e. all banks (not necessariliy Turkish) in the Turkish interbank market can participate. The money market opens at 8am and closes at 6pm Central European Time. Some religious holidays and days around those days will be eliminated from the data due to abnormally less trading volume.

Bid and ask prices along with the quantities are posted on the exchange. However, posting prices and quantities does not bind the agents i.e it is still acceptable to post a bid price and quantity to exchange and then not to sell it even though the expectations are met. Any trader can realize the transaction with any of the counterparties with price and quantity posted on the common screen. In that sense, two agents bilaterally negotiate the trade which enables agents to limit lending and borrowing amounts to each specific party.

Descriptive statistics are shown in Table 1 below. Average daily volume of total lending amounts are reported daily. It is also included the proportion of lending made by the 25 largest market participants. The averages are about 20% prior to the crisis and 5-10% after. The network changes from being heavily centralized to considerably less centralized after the crisis period. Furthermore, total transaction volumes and number of transactions drop dramatically after depression period. We will be looking at the evolution of centrality in more details, but it is clear from the descriptive statistics that the importance of being central declines after crisis.

Table 1: Monthly Summary Statistics

	January	February	March	April	June	July	August	September	October	November	December
Avarage Monthly Volume(mm TLs)	1397925	1494891	1495500	1444724	1349803	1483989	1502739	1512345	1517382	1519374	13453921
Daily standard deviation of volume	165559	175132	170835	168537	159441	158220	190837	193843	189374	237923	22039
Daily standard deviation of prices	7,81	13,97	18,7 0	4,90	5,38	6,41	3,11	7,92	6,52	19,23	98,92
Number of loans	55578	66740	60608	59220	69627	67783	65536	66273	64921	70183	716273
Largest 25 lenders in each month											
Total lending(mm TLs)	124689	118293	131479	128923	142783	153893	291831	300928	312393	279193	180383
Fraction of total	21%	20%	19%	22%	21%	21%	23%	21%	24%	25%	22%

The data includes 1,355,604 tick by tick transactions of Turkish overnight money market. It is a package that has lended/borrowed amounts, strike prices and time of the transactions made. We simplify those 1,355,604 lines, first by clearing the transactions between different accounts of the same institution and then combining the transactions of same two agents in one line. Besides, all transactions are stated in two duplicated lines differing only buyer/seller place. For example, to represent a transaction between agent DEM and YAT, there exist two lines in which DEM lies in a previous column and it is initialized as B (buyer) where YAT lies in latter column. This transaction can also be represented in a line in which YAT lies in previous column and initialized by letter S (seller) where DEM lies in latter column.

Table 2: A Sample Transaction

date	bank1	seconds left	buyer/seller	bank2	borrowed/lended amount	paid/gained amount
04.01.2000	DEM	200001040000160	B	YAT	2000000000000	2001617830137
04.01.2000	YAT	200001040000160	S	DEM	2000000000000	2001617830137

Clearing these duplicated lines from data, we end up with a data set including 264,039 transactions for which date, time, volume interest rates and identities of borrower and lender. For the 107 agents and 240 days of a deliberately chosen period, an empirical analysis will be made in the next part. We will check the central agents and their behaviour through the according to different centrality measures.

CHAPTER 5

EMPIRICAL FINDINGS

A detailed analysis of the structural changes between the networks across time is hard to visualize. Therefore, we consider a set of statistical measures common in the network topological approach in this section. Below in Table 3, summary statistics of the money market network are shown.

Table 3: Summary Statistics of Network Values

	Mean	Median	Max	Min	Std
Volume	2007,4	2093,7	3142,5	910	413,6
Transactions	824	773	1114	44	141,1
Nodes (buyer)	23,5	25	34	13	4,40
Nodes (seller)	58,9	60,5	72	12	6,30
Links	286,4	288	374	30	42,43
Connectivity	4,76	4,80	6,22	0,49	0,70
Reciprocity	0,99	0,45	1,08	0,38	0,10
Link weight, vol.	0,14	0,16	0,33	0,07	0,03
Link weight, tran.	0,35	0,68	0,38	0,22	0,06
Node strength, vol.	80,9	74,7	150,0	7	25,4
Node strength, tran.	42,5	42,2	56,8	2,25	7,11

Volume

Volume represents the total amount of transaction made in each day in Turkish Liras. The transaction figure represents the number of distinct transaction made in each day. The daily volume of the market can be considered as the sum of flows on directed links on a given day. Volume of transactions can be a risk measure itself. High levels of transfer volume indicates that agents borrowed and lended large amounts in that day so that agents are more vulnarable. One critisim to this measure might be that the

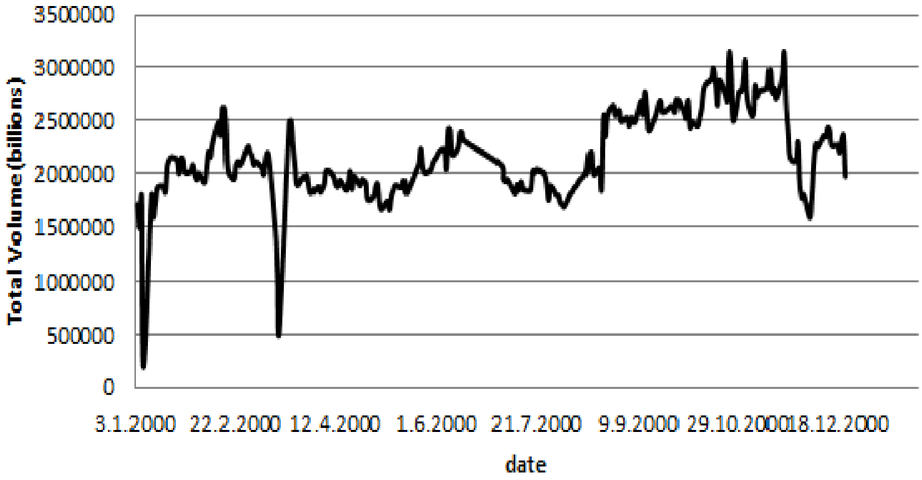


Figure 1: Daily volume of over night money market

weights of transfers differ from node to node. Therefore, we derive a new statistical measure that will be explained in details. As the volume carried by links (it will be called link weight. vol), the systemic risk that the network has increased.

Figure 1 shows the volume of transactions in the Turkish over night money market during 2000. It is seen that the volume decreased slowly through summer months and then by the end of the August it increased radically. This increase also continued at fast pace from September to November. This clear upward shift was due to the radical increase in Demirbanks overnight borrowings. The market volume during the crisis period shifted downward dramatically with the start of panic atmosphere in 22 November 2000. The bottom levels were seen on 1 December 2000, the date at which crisis had started.

There is another observation in the trend of volume during the crisis period. As it can be observed from the Figure 2, level of total volume is close to volume of borrowings of Demirbank. In other words, the volume increase during summer

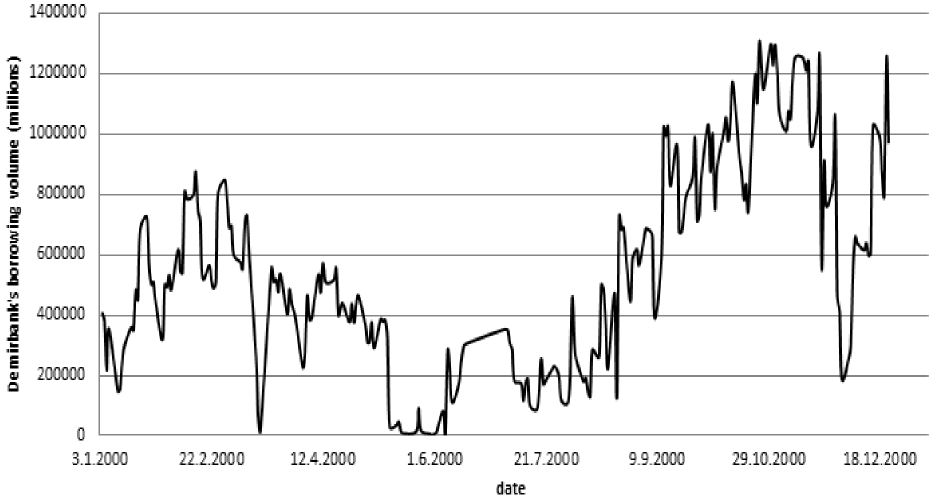


Figure 2: Daily borrowing volume of Demirbank

months was due to Demirbank's start of its "bet" and the volume decrease in crisis period was due to huge decrease in Demirbanks borrowings.

Transaction

As expected, the number transactions (borrowing) made in that day has an increasing pattern as well. The number transaction increased during summer months and decreased sharply at crisis period due to decreased risk appetite and inconsistent market conditions.

The increase in total number of transactions is mainly due to a sharp increase in Demirbank's transactions. This can be seen in Figure 3 in which only Demirbank's daily transaction numbers are shown.

Instead of using the number of transactions itself, the volume per transaction can provide a better measure to understand the density of network. The volume carried by a transaction shows the amount of burden that a unit transaction carried. During

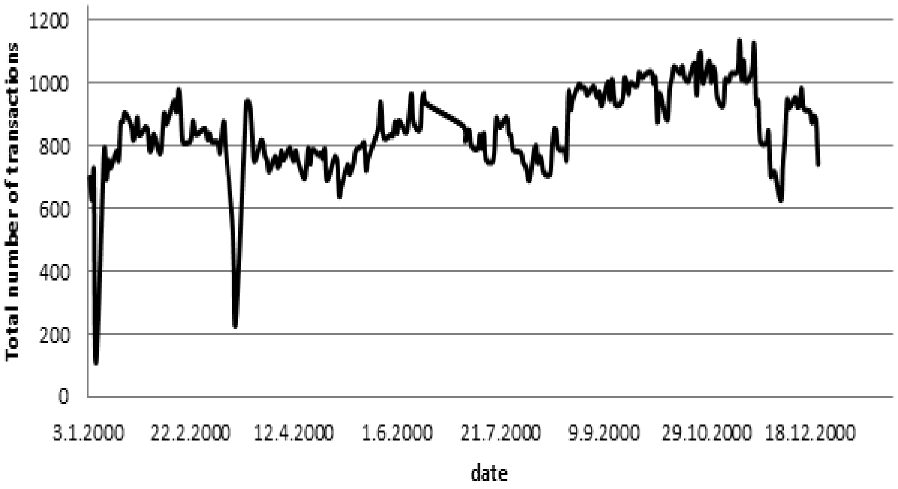


Figure 3: Total number of transactions

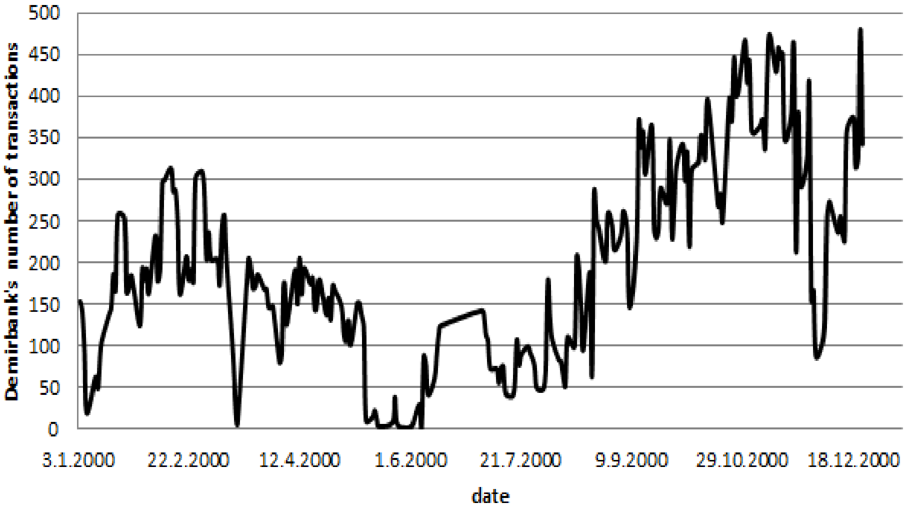


Figure 4: Demirbank's number of transactions

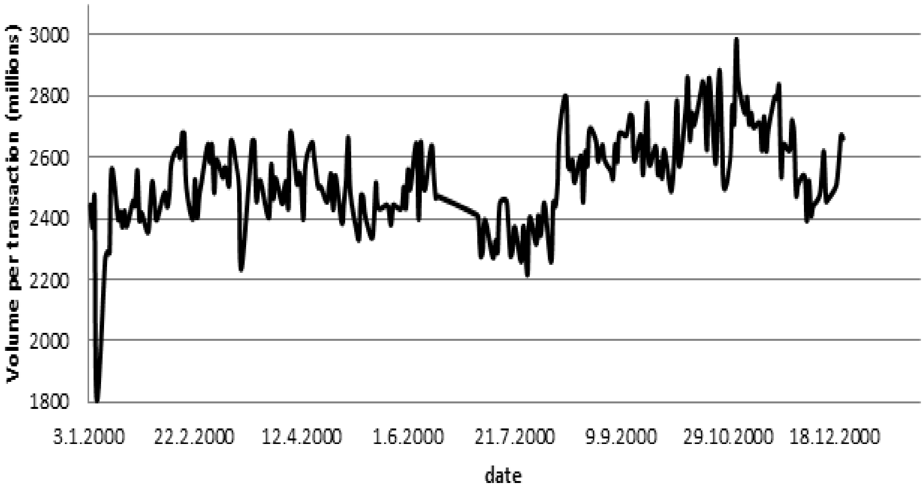


Figure 5: Volume per transaction

summer months, both total volume and number of transactions have increased. However, increase in volume dominates the increase in transactions so that volume per transaction increases till the beginning of crisis and then decreased since the volume decreased more drastically than number of transactions.

Links and Nodes

An important characteristic of a node in a network is the number of links, which originate from a node and the number of links terminating in a node. Since we focus on borrowing side to investigate the road map of the crisis, total number of (borrowing sided) links are given in Figure 6.

Interestingly, the number of links decreased through the beginning of the crisis period where the number of transactions increased. This means, one link carries more data on it and more frequently. This increased carried amounts of links can be signal as an increase in tension and risk of the system.

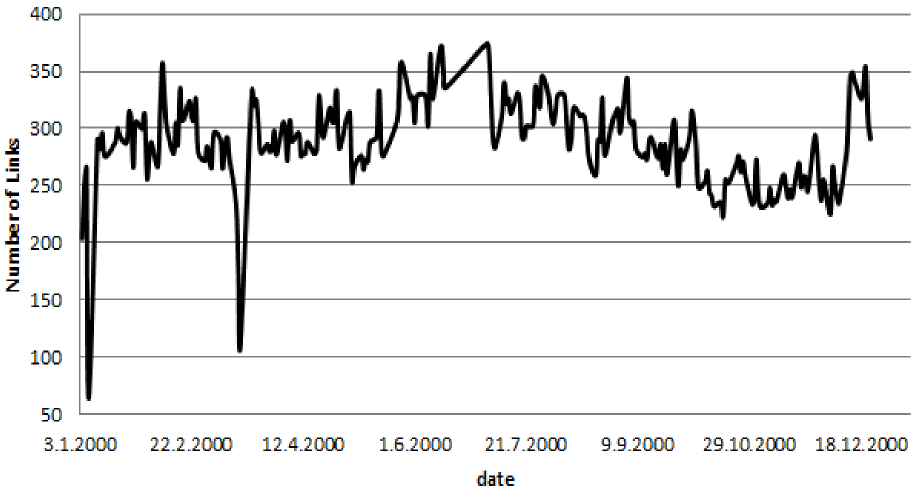


Figure 6: Total number of Links

In Figure 7, the number of active borrowers are shown. From spring to June, the number of agents who want to borrow increased. However, from the beginning of August number of active borrowers declined since Demirbank became the major borrower with high interest payments so other borrowers fell behind Demirbank and stopped borrowing. After take over period, market normalized with pre domination interest rates and hence number of borrowers increased again.

In Figure 8, the number of active sellers are shown. The peak was attained in the beginning of October when Demirbank was the main borrower. Interestingly, there was not a sharp decrease in the number of sellers i.e agents still continued lending money during crisis period. However, both the number and volume of transactions had decreased drastically. Besides, the lending agents were not willing to lend to Demirbank but to some other important borrowers such as IKT, TIB, UBN.

The average node degree is equal to the number of links divided by the number of active banks i.e average node degree is a measure of the average number of links

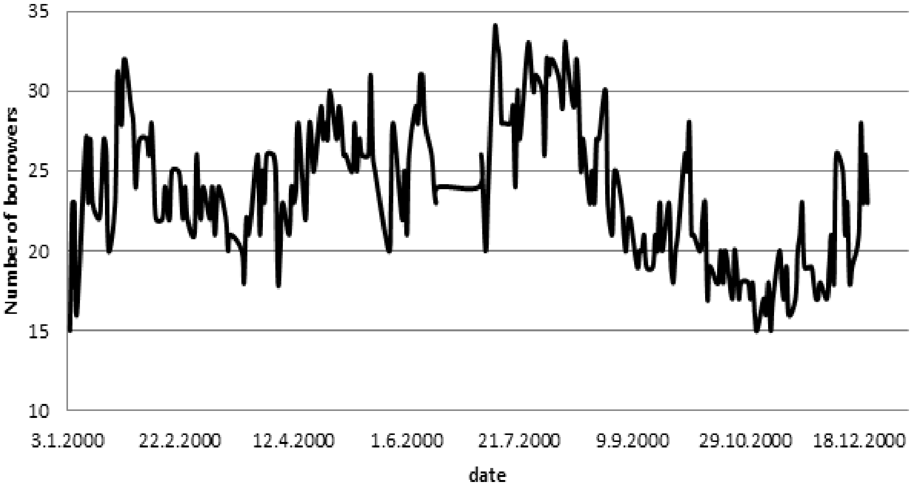


Figure 7: Total number of borrowers

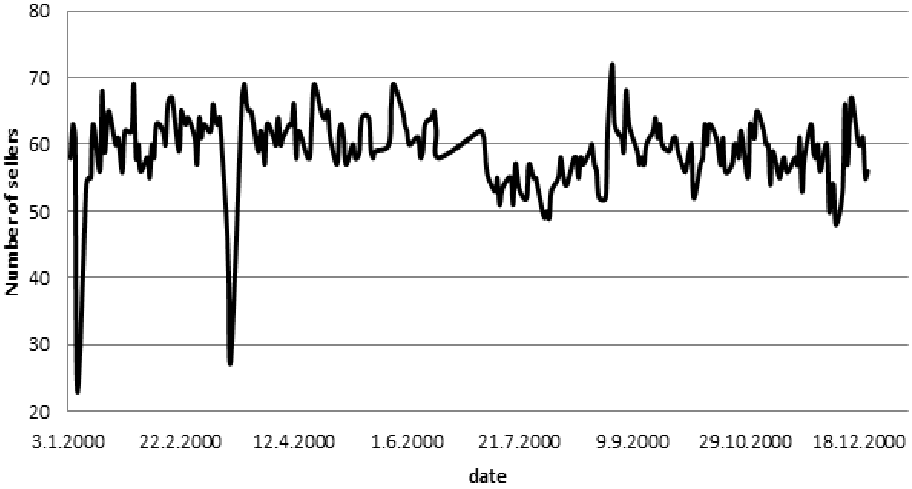


Figure 8: Total number of sellers

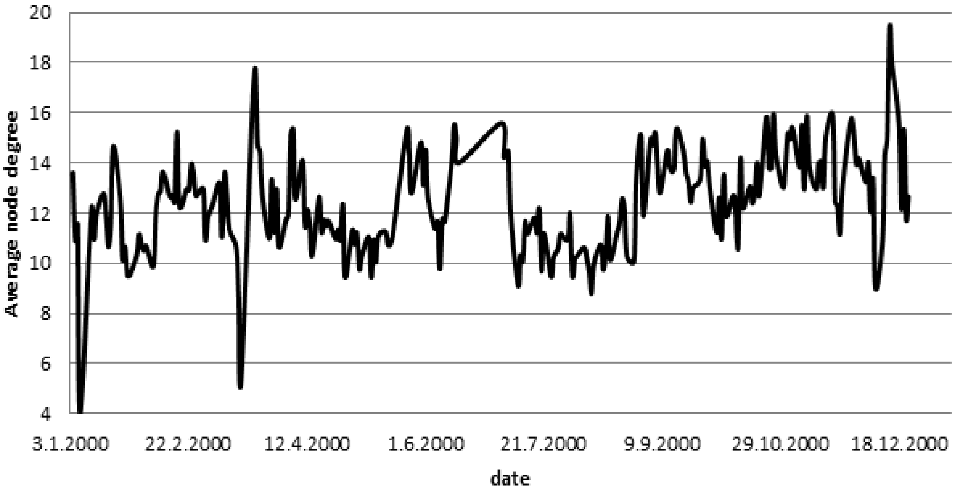


Figure 9: Average node degree

per node. The average path length measures the average number of links connecting two nodes in a network via the shortest possible path, i.e. this is a measure of the number of links a transaction must pass to reach another bank in the network. The average path length can be estimated using payments received in or submitted from a node.

Figure 9 shows the average node degree for different time periods. From the beginning of autumn average node degree started to increase which shows either agents leave the network or new link formations have been made. However, from Figure 7 we know that the former case is not valid. Hence, nodes become more connected with each other which can be interpreted as evidence for the increased tension and systemic risk in the system.

Connectivity

Connectivity is the share of actual links out of potential links (per cent). The connectivity varies between $\frac{1}{nodes}$ (tree network) and 1 (complete network). It is calculated as the number nodes divided by the number of distinct links times the number of distinct links minus 1 which basically measures how much connected is a single node to the system as a whole. We substract one from denominator since a node is obviously connected to herself.

In Figure 10, it is seen that connectivity is relatively higher in the crisis period. When Demirbank became the strongest center of the network and network became more centralized, then links between other agents started to vanish. Demirbank was the chief borrower and institutions would like to lend only to Demirbank. Therefore, lending connections with other borrowers were destructed by Demirbank.

Until the end of November, connectivity kept on decreasing more and more because of monopolized borrowing market. This means most of the lenders were only connected to Demirbank but this decreased the connectivity of the whole system since those agents broke up their connections with other pre-borrowers.

When connectivity declines, system becomes more systemic risk event vulnerable to macroeconomic shocks. It is seen that connectivity level decreased until 29 November. Then it somehow increased until the end of crisis (5 December 2000). It can be concluded decreasing connectivity could be a good signal of increased systemic risk and tension.

Another interesting measure is the reciprocity, which measures the share of links between banks for which there is a link in the opposite direction. In other words, it is the fraction of links for which the link with opposite direction exists in the network.

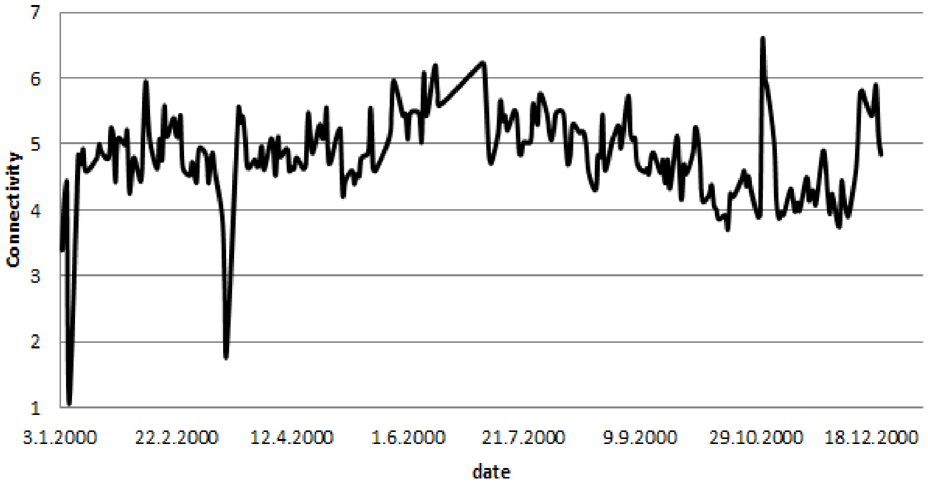


Figure 10: Connectivity

We see a lower average reciprocity value in crisis period showing the separated structure between lenders and borrowers in the Turkish overnight money market.

At that time, most of the links are one directional which proves that there is an obvious segmentation in the market i.e some institutions are only borrowers and others are only lenders. This situation also creates systemic risk, since the system is not flexible in terms of absorbing shocks. One directional links are likely to send the infection and the system is likely to be infected at a faster pace.

Maximum in-degree of a node (max k_{in}) is a measure of the maximum number of links that terminate in a node. Maximum out-degree of a node (max k_{out}) is a measure of the maximum number of links that originates from a node.

The link weight is a measure, which take the value respectively the volume of the transactions, which go via a certain link, into account. This is a measure of the importance of the links, when the links are corrected for how many transactions (or value of transactions) they handle. That is, a link, which handles 10 transactions, is

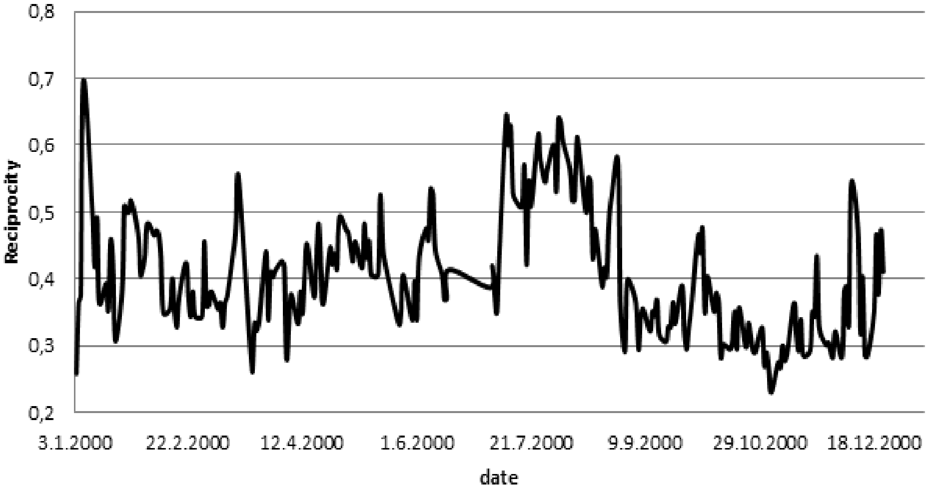


Figure 11: Reciprocity

more important than a link, which handles one transaction and vice versa for links weighted by values transferred.

Node strength measures of the importance of the nodes weighted by the number (of value) of transactions through each node. That is, a node, which handles 50 transactions, is more important than a node, which handles 10 transactions and vice versa for nodes weighted by values handled.

Note that the value and the link weight and node strength in value are in billion Turkish Liras with six zeros deleted. The reported summary statistics refer to the average of the daily observations for the all agents.

The time series pattern over the time period for the turnover in value and volume, the activity in nodes and links and the connectivity and reciprocity for both networks are shown in figures above.

Correlations of Basic Network Properties

The basic network statistics are not independent of each other. For instance, a larger network is likely to imply more links in that network. In this section the correlation among the various network characteristics will be examined.

Table 4: Correlations of Basic Network Properties

	Volume	Transactions	Nodes	Links	Connectivity	Reciprocity
Volume		0,961	-0,401	0,196	0,196	-0,673
Transactions			-0,248	0,371	0,371	-0,610
Nodes				0,560	0,553	0,682
Links					0,98	-0,03
Connectivity						-0,01
Reciprocity						

The number of banks active (nodes) is positively correlated with the number of interactions (links) in our network. Moreover, more activity in terms of value and volume generate more links and nodes in the networks. Furthermore, the value and volume of the networks are positively correlated. This is reflected by the patterns in Figure 11, where the activity in volume and transaction tend to covariate with the size of the networks (nodes and links).

The connectivity in the money market is negatively related to any measure of activity (value and volume) and size (nodes and links). In general, the denseness of the money market network (reciprocity) is uncorrelated with any other measure with the possible exception of the slightly positive correlation between reciprocity and connectivity. This reflects that a bank, which becomes active in the money market, tend to have only a few links to other banks. In the payments network, connectivity is negatively correlated with the number of active banks and slightly negatively

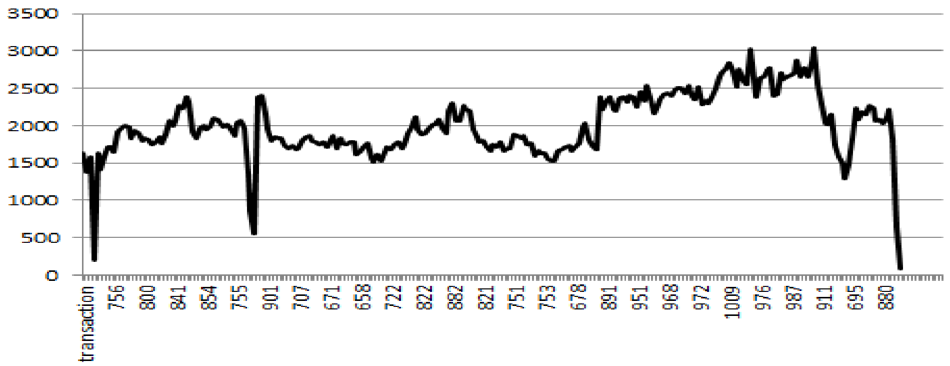


Figure 12: Correlation of volume and transaction

correlated with the number of links, whereas the connectivity is virtually uncorrelated with the activity in the payments network.

The reciprocity is negatively correlated with the number of active banks and positively correlated with the connectivity, but almost uncorrelated with the remaining variables. That is, the payments network does not become denser as the activity increases. This result may seem contrary to Soramki et al. (2007), in which it is found that the correlation between nodes (links) and connectivity are quite strong and positive in Fedwire.

CHAPTER 6

DEMIRBANK'S CENTRALITY VALUES

In this chapter, we empirically investigate the centrality values of Demirbank for four centrality measures, which are those commonly used in network analysis: degree, betweenness, closeness, and Bonacich (eigenvector).

Degree Centrality

First and conceptually simplest centrality is degree centrality and it is defined as the number of links incident upon a node. The degree can be interpreted in terms of the immediate risk of a node for catching whatever is flowing through the network. Since we want to discover the borrowing behaviour of Demirbank and it is a directed network, the in-degree counts will be taken as the degree measure. In-degree value is the number of ties directed to the node in that day.

From the beginning of July, Demirbank started to borrow from many different institutions which increases its degree centrality gradually. The peak value was seen in 30 October 2000 in the day that Demirbank fully dominated the market. In the first day of crisis, 1 December 2000, the degree centrality of Demirbank fell dramatically due to precautionary credit squeeze by other institutions. Most of the pre-connections stopped lending money to Demirbank until the take over normalized the market.

As in Figure 13, the total degree centrality of network, which is number of formed links decreased until the take over. However, Demirbank's degree centrality increased during this period, which proves the inevitable dominance of Demirbank. This enhanced domination continued until the take over and afterwards market

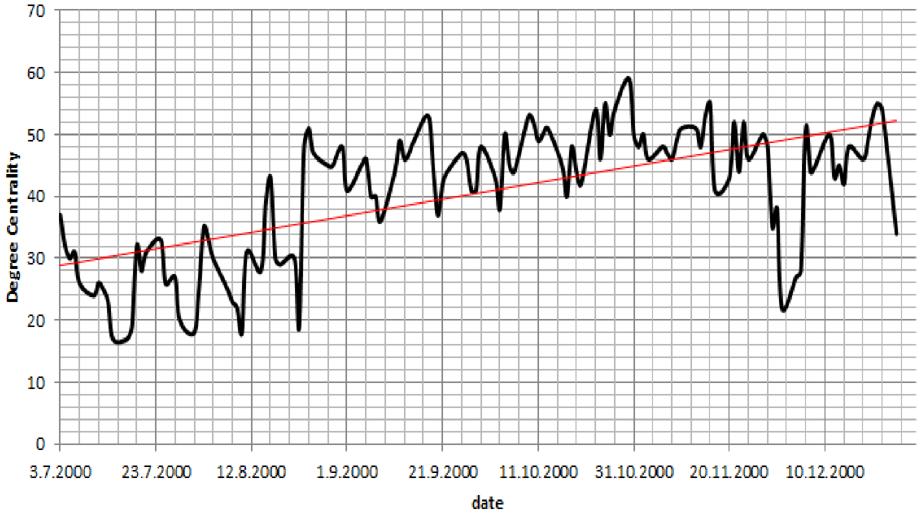


Figure 13: Degree centrality values of Demirbank

normalized as well as Demirbank became a normal node with pre-domination degree values.

Closeness Centrality

An institution is considered important if it is relatively close to all other institutions. Closeness centrality indicates the influence of a node on the entire network. We observe that centrality values of Demirbank have an increasing trend. Again the peak values are attained just before crisis. With the start of crisis, closeness centrality values of Demirbank drastically fell as well as other agents' values. After the take over, market normalized again and Demirbank achieved a slowly increasing trend.

The red line shows the maximum closeness centrality values attained by an institution in the network whereas black line shows the closeness centrality values of Demirbank. It should be noted that as of the mid September, Demirbank leads the market i.e the maximum closeness values belong to Demirbank. This situation ends in

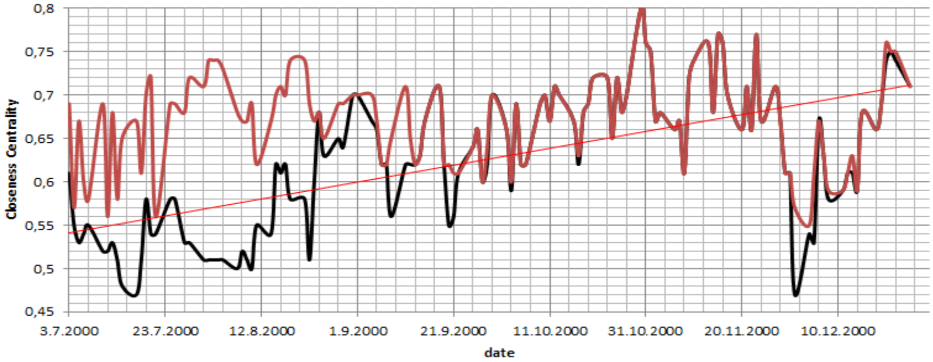


Figure 14: Closeness centrality values of Demirbank

the crisis period since the Demirbank was the most badly hurt agent in that crisis. Thus, Demirbank's values are below the maximum values. Within 124 days, Demirbank has been the leader in terms closeness centrality in 67 days. The institutions TIB , IKT and UBN are leaders in other days.

Betweenness Centrality

Betweenness centrality builds on the notion that a vertex is central if it is needed to connect other pair of vertices. A node with high betweenness centrality can potentially influence the spread of information through the network. The betweenness centrality of Demirbank increases as it dominates the market. The value reaches the peak again in 30 October 2000. During the crisis the centrality values decreased below the maximum value and increased after normalization. Within 124 days, Demirbank has been leader in terms of betweenness centrality in 68 days. The institutions TIB, IKT or UBN are leaders in other remaining days.

This conclusion is in line with closeness centrality measures, which also supports the high correlation among these two measures.

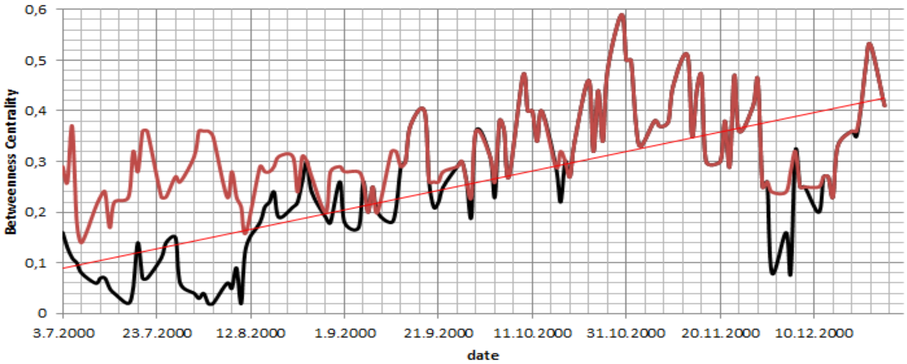


Figure 15: Betweenness centrality values of Demirbank

Bonacich's Centrality

Bonacich's centrality which is also known as the eigenvector centrality is based on the idea that a node is more central when there are more connections within its local network. More connections in its local area means that node is more powerful. This also means that power comes from being connected to those that are powerless. It assigns relative scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes.

The Bonacich's centrality values of Demirbank have been calculated via recursive methods. The function takes adjacency matrix and a values ϕ as its arguments and calculates a column vector showing the eigenvector centrality of all banks forming links in that day. Given parameter ϕ value represents the importance of neighborhoods with different degrees. For example, primary connections are weighted by ϕ whereas secondary connections are weighted by ϕ^2 and so on... As long as the given ϕ values are smaller than the largest eigenvalue of the adjacency

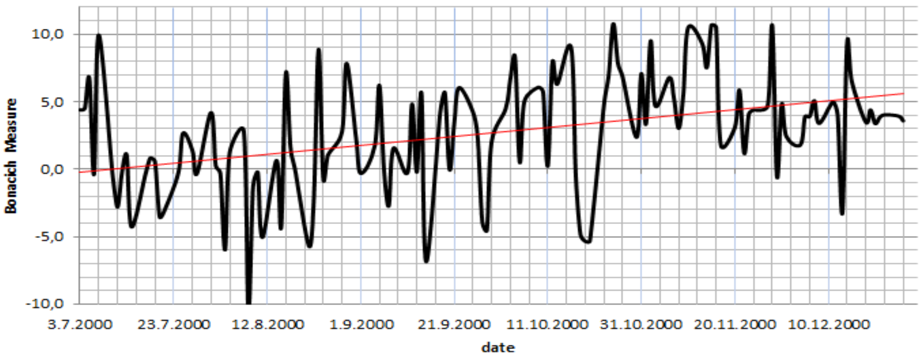


Figure 16: Bonacich centrality values of Demirbank

matrix, the ϕ can be arbitrarily chosen and Bonacich measure can be written as a convergent sum.

Our focus in on the centrality measures of Demirbank, so we keep the corresponding value (25th entry) of that column vector. After repeating this process 240 times, we reach a time series of Bonacich centrality values of Demirbank.

We focus on the period after June since domination of Demirbank becomes more apperant. Bonacich centrality values exhibit an increasing trend reaching its peak at 30 October 2000. As Demirbank dominates the market, Bonacich centrality of Demirbank increases. Although, negative values have been seen before crisis period, just before and during crisis Bonacich values of Demirbank are all above zero. Hence, it can be said that domination period average is much higher than the overall average. During crisis, the values do not dramatically falls below the pre domination period values since the overall tension of the market decreased and power comes from being connected to those that are powerless . After the take over, the values are again increased with the normalization of market structure.

Summary Statistics of Centrality Measures

Some summary statistics will be shown in Table 5 below. The most striking fact from table is that Bonacich centrality has relatively higher standard deviation. The most consistent measure seems to be closeness centrality having relatively smaller standard deviation and a better fit to time series.

Table 5: Summary Statistics of the Centrality Measures

	Degree	Closeness	Betweenness	Bonacich
Average	40,58	0,62	0,25	2,672
Max	59	0,80	0,59	10,76
Mean	44	0,62	0,26	3,20
Min	17	0,47	0,02	-10,39
St. Dev.	10,57	0,07	0,13	4,300

Correlations of Centrality Measures

For Turkish over night money market, it is empirically investigated the correlation among four centrality measures: degree, betweenness, closeness, and Bonacich (eigenvector) . These are most frequently used centrality measures in social network analysis in general. The first three were proposed by Freeman (1979) and eigenvector was proposed by Bonacich (1972). All centrality measures are derived from the adjacency matrix and so constitute different mathematical computations on the same underlying data.

As it is illustrated in correlation table, overall degree, closeness, and betweenness centrality were strongly intercorrelated, while Bonacich remained relatively uncorrelated with the other three measures. As we expected measures of degree and closeness centrality will be more highly correlated with each other than with other measures, because they are both based on direct ties. Betweenness centrality measures the extent to which an actor lies between other actors on their geodesics. Actors high on betweenness centrality, therefore, have the potential to influence others near them in a network (Friedkin, 1991). Similarly, those high on Bonacich centrality are linked to well-connected actors and may influence many others in the network through their connections. In that sense , it was expected an higher correlation among betweenness and Bonacich centrality, but it is not as expected in our case. We are unsure, however, how the other centrality measures should correlate with one another.

Conceptually, each centrality measure represents a different process by which key players might influence the flow of information through links.

Table 6: Correlation Coefficients among Four Main Centrality Measures

	Degree	Closeness	Betweenness	Bonacich
Degree		0,8972	0,8535	0,5514
Closeness			0,8894	0,4003
Betweenness				0,4768
Bonacich				

Degree Distribution

In this section, it will be shown that the existing overnight money market network is a scale free network. A scale-free network is defined by a power-law degree distribution, which is expressed mathematically as $P(k) \sim k^{-\gamma}$. Scale free networks follow the power-law distribution which shows the greater probability of nodes with a

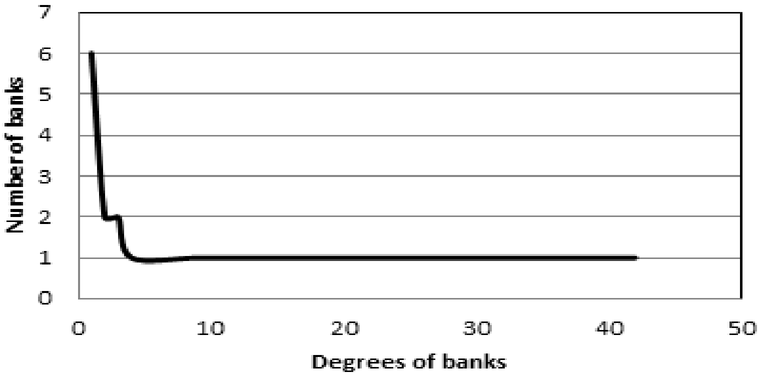


Figure 17: Sample degree distribution

number of links close to the average of all links and a greater probability of nodes with many links.

We start with using daily transaction data. For each day, a graph is drawn in which the distribution of degrees are shown. In the graph below, a random day is chosen to show the distribution. Degree of each node in the initial network should be at least 1, otherwise it will always remain disconnected from the rest of the network. For that purpose, we need to use the banks as nodes, which are actively making any transaction in that day. For the randomly chosen day 04.04.2000, 6 of the banks are connected only to 1 bank, 2 of the banks are connected to 3 banks, 1 of the banks is connected to 9 banks, 1 of the banks is connected to 14 banks, 1 of the banks is connected to 17 banks, 1 of the banks is connected to 19 banks, 1 of the banks is connected to 25 banks, 1 of the banks is connected to 27 banks, 1 of the banks is connected to 36 banks, 1 of the banks is connected to 42 banks. So, as a result 19 banks are borrowing loans from 43 distinct banks in 199 transaction counts. The figure below shows this distribution only for a given day.

To show Power-law distribution, empirical distribution function is approximated by power function $y = x^{-\gamma}$. For this particular day, the best fitting function in the

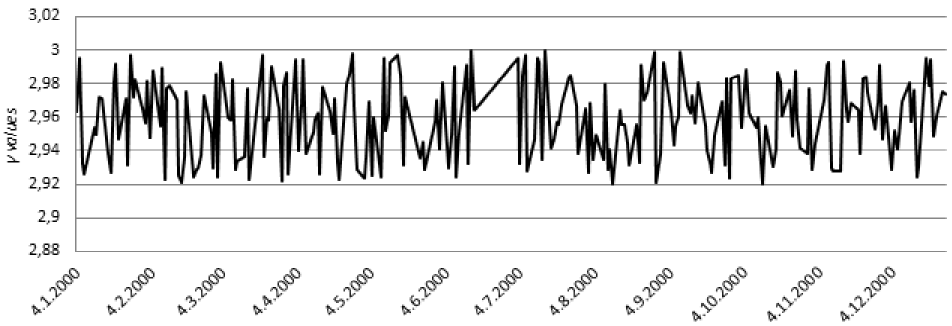


Figure 18: γ values over time

form of power function is $y = x^{-2.97}$ in which $\gamma = 2.97$. The Barabasi-Albert model (a.k.a. BA model) introduced in 1998 explains the power-law degree distribution of networks. According to the form of the distribution, when $\gamma<2$ the average degree diverges and when $\gamma<3$ the standard deviation of the degree diverges. It has found that most scale-free networks have exponents between 2 and 3. Thus, they lack a characteristic degree or scale. Numerical simulations and analytic results indicate that this network evolves into a scale-invariant state with the probability that a node has k edges following a power law with an exponent $\gamma = 3$. The scaling exponent γ is independent of size of the network and number of degrees, which are the only parameters in the model.

However, here in this thesis we have another dimension for degree distribution, which is time. Since, there are 240 days in this time interval, we need to check the behaviour of network for the whole period before concluding it is a scale-free or a random network. For this purpose, the above approximation will be done for each day and γ values will be calculated. If the average of γ's <3, then it can be concluded that our network is actually scale-free. The below figure shows the values of γ values for the dates of concern.

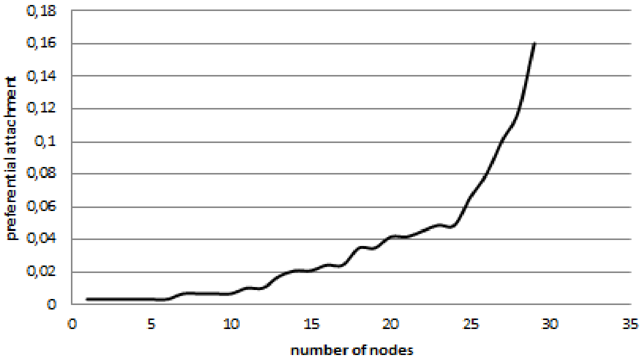


Figure 19: Preferential attachment

According to Barabasi-Albert model (a.k.a. BA model) introduced in 1998 , new nodes tend to connect to nodes with large degree. This argument is naively argued that for large networks it is not informative because it requires a global knowledge of the network and knowledge about the high degree nodes. However, it is not the case and there are several local mechanisms that introduce preferential attachment. In mathematical terms, preferential attachment refers to the probability that a node with degree k_i acquires a link is equal to P(k_i)= $\frac{k_i}{\sum_j k_j}$. The process of ”preferential attachment” can be thought as by simply linking to new nodes, the node exercise and reinforce a bias toward them. For example, in the graph of randomly choosen day 17.05.2000, we see that as the number of already connected banks increases, the probabilty of forming new connections increases as well.

This situation is actually valid throughout our time interval. From the mid of 2000, Demirbank was becoming a hub node at increasing pace. This preferential attachment property enhanced the growth of Demirbank and accelerated the domination of other banks. In the graph below, the evolution of Demirbank's preferential attachment has been shown. As it is said before, Demirbank was a quite normal agent till the end of May and had started to become a major hub from the beginning of June 2000. In the graph, the preferential attachment of Demirbank shows that after some date, more links are likely to be formed with Demirbank. In fact, the rapid increase of preferential attachment of Demirbank exhibits that the domination period happened very quickly. We see the peek of preferential attachment around 30 October, the days just before crisis and in which Demirbank had become a massive borrower. From that time, the probability of forming new connections has started to decrease rapidly till 1 December, the day of collapse of Demirbank.

Knowing that our network introduced by interbank money market data is actually a scale-free network, will help us to develope some important arguments. Scale-free networks have qualitatively different properties from strictly random, Erdos and Renyi, networks. Firstly, scale-free networks are more robust against accidental failures. By this we mean that the network is more likely to stay connected than a random network after the removal of randomly chosen nodes. The random removal of nodes will take out mainly the small ones because they are much more plentiful than hubs. The elimination of small nodes will not disrupt the network topology significantly, since the small nodes have fewer links compared with the hubs.However hubs are connected to nearly everything, hence a reliance on hubs has a serious drawback: vulnerability to attacks. As will shown in the next section, removal of just a key hub (at the day of collapse of Demirbank) from the network splintered the system into tiny groups of hopelessly isolated routers.

Any accidental shock given to this network would remain the system in more robust shape when compared with random networks. However, this network is highly vulnerable to any collapse of any of the hubs. Since, at that time Demirbank was the main hub, an attack to that node had affected whole network and changed the shape as a whole. This congestion along the specific node’s links creates a negative spillover

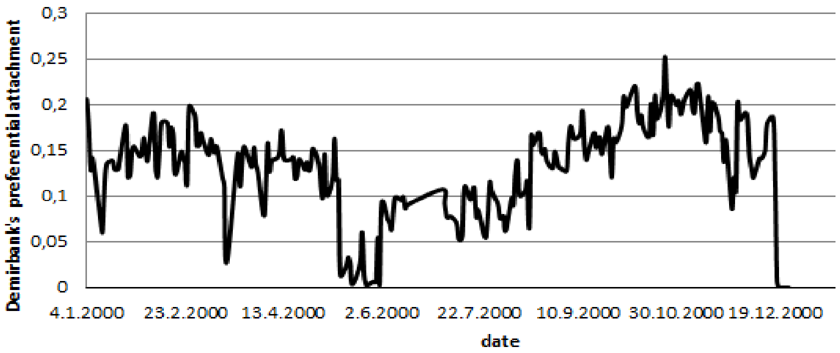


Figure 20: Preferential attachment of Demirbank

which increases riskiness of the connected banks. In our case, if that potential of failure had been recognized by the those banks operating with Demirbank, then they would probably lessen the number/volume of transactions. This would decrease the preferential attachment of Demirbank and slower the process of being such a mojor hub. These actions would definitely alleviate the impacts of collapse. All in all, the reason beyond collapse of just a single bank had affected the whole network so severely is that that node was actually hub of a scale free network. Indeed, the growing preferential attachment of that node was a great signal to discover the potential risk of failure.

In that sense, if the riskiness of a scale free network is desired to be calculated, then the growth rate of preferential attachments could be examined. Since, most of the risk carried by the agents that are more central, their behaviour in the network have more impact in all agents. The schock given to hubs can be easily transmitted by the links and should be handled as an epidemic disease. Morever, it should be noted that the recovery period also starts with recuperation of the pre-hub agent. As in our case, after the take over of Demirbank (5th of December), the system had relieved and the other surviving agents started to making transactions as before although it took some time to reach the before-crisis volume of transactions.

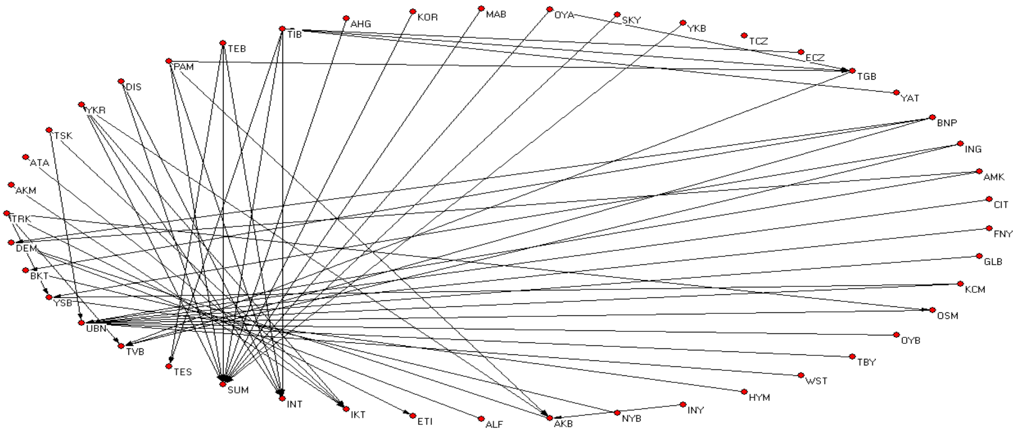
CHAPTER 7

GRAPH REPRESENTATIONS

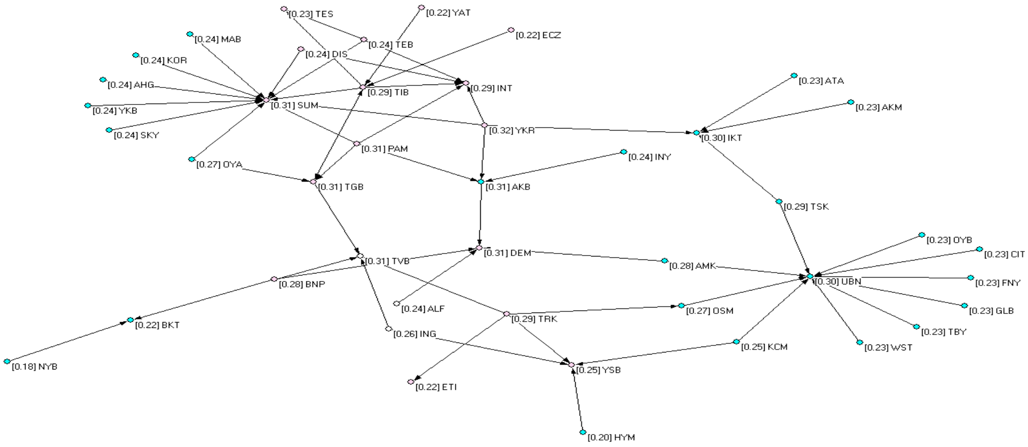
In this session, for some selected days Turkish overnight market network is represented as graphs. Graphs are obtained by using Pajek software. For selected days, all banks making transactions over 100 000 Turkish Liras have been illustrated in the graph, so the links carrying volume more than 100 000 Turkish Liras have been drawn. Hence, these graphs do not show all links formed in that choosen day but they represent only fundamental links. Unlike Saltoglu and Yenilmez (2009) paper, here the graphs will be unweighted to see the adjanceny relationship purified from volume dimension.

Six days were deliberately selected from the different periods of year 2000 to represent distict periods throughout the year. Those days are 28 February, 9 May, 30 October, 20 November, 1 December and 5 December. 28 February exhibits the pre-Demirbank domination period. 9 May belongs to the period that Demirbank was not a massive borrower but gradually started to become an important borrower. 30 October is before crisis and one of the days in which Demirbank was a main borrower and a hub. 20 November is the beginning of the financial turn over. 1 December is the day in which Demirbank collapsed and 5 December is the day in which Demirbank is taken over by TMSF.

In 28 February, there is a multi-centered heterogeneous network. Since this overnight money market network is a scale free network, there exists some central nodes. It can be observed from the graph that in 28 February, there are 2 borrowing centers. Since there are many other local centers in distinct neighborhoods, those centers are not concentrated as hubs. It should be noted that neither of the centers were Demirbank. Although, Demirbank is seen to be one of the active banks making transactions, Demirbank had not started its ”bet” yet and not dominated the system. These representations refer to the period of pre-Demirbank domination. Two different graph layout have been used to show the network elaboratively: Circular and Energy Kamada-Kawai. Circular layout is good to detect the betweenness property whereas Energy Kamada-Kawai layout is used to detect closeness having closeness measure of each node in paranthesis.

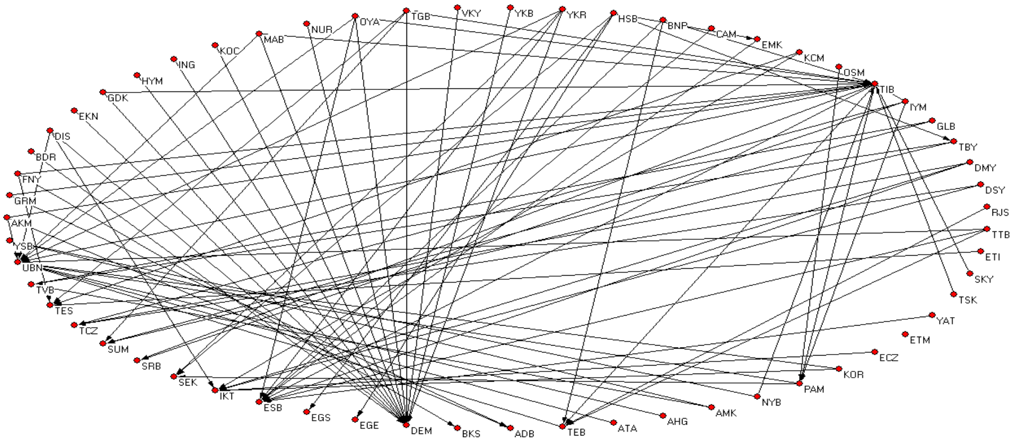


Picture 1: Circular layout representation of 28 February 2000

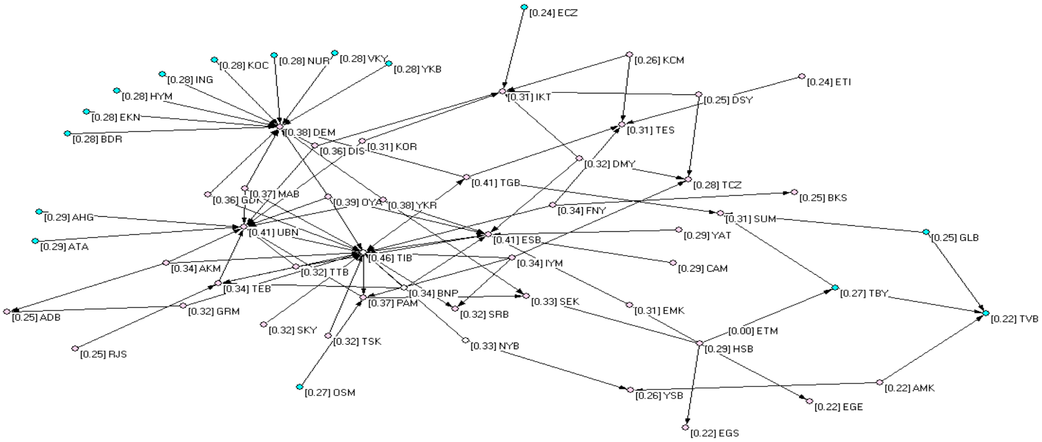


Picture 2: Energy Kamada-Kawai layout representation of 28 February 2000

In 9 may, Demirbank was becoming one of the massive borrowers although still not being the unique borrower. Most of the banks were lending to Demirbank though there were some banks not lending to Demirbank but other centers instead. Both lending and borrowing market have a multi-player structure. It can be seen that the network become more densed including more transaction with various agents. The software pajek calculates the network density indices and it is shown that all indices are getting larger as Demirbank getting centralized.

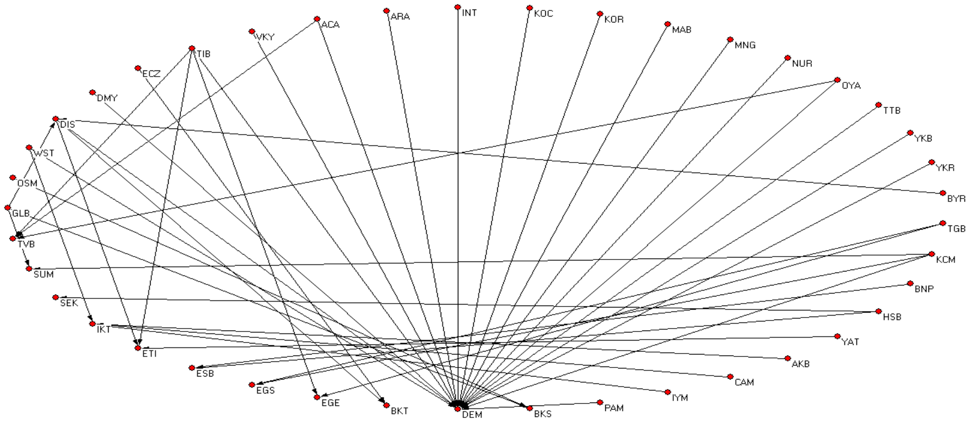


Picture 3: Circular layout representation of 9 May 2000

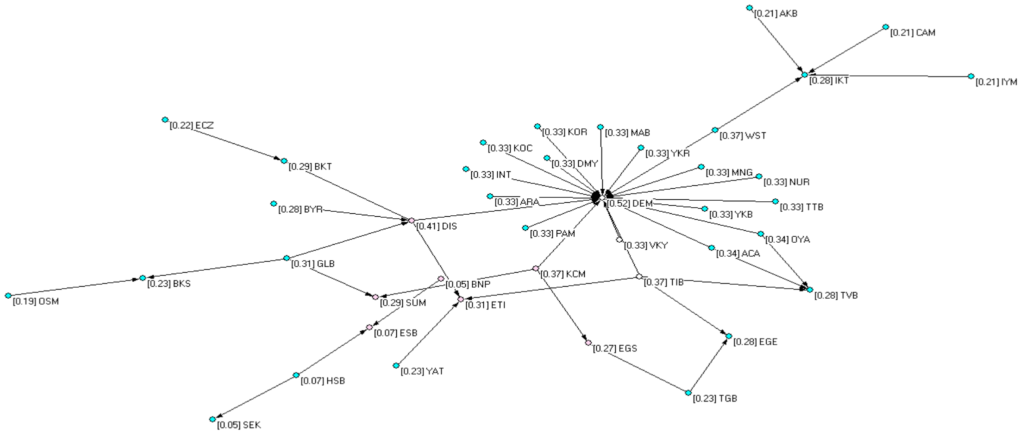


Picture 4: Energy Kamada-Kawai layout representation of 9 May 2000

In 30 October, market domination of Demirbank is apperant. The representation can be interpreted as Demirbank being the main borrower borrowing from every other agent and every agent lending to Demirbank. This means Demirbank was the unique noteworthy borrower whereas lending market has a multi-player structure each willing to make transaction with the central. This picture illustrates the Turkish overnight money market just before the coming crisis.

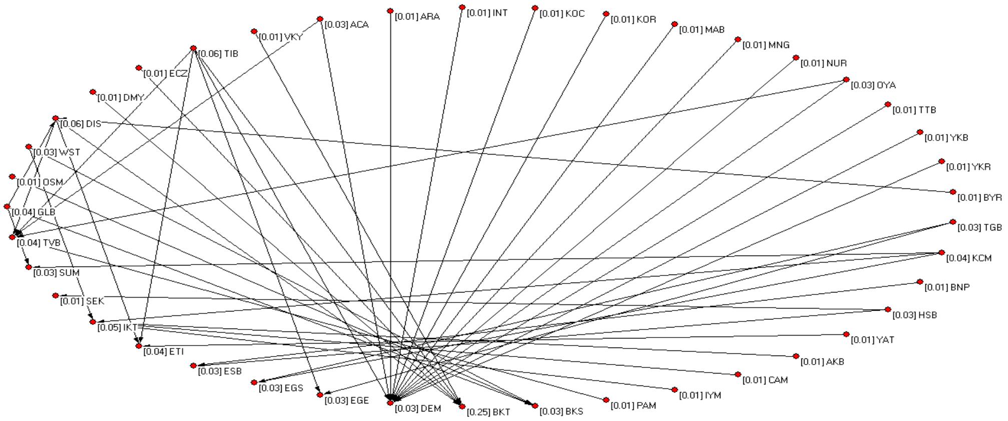


Picture 5: Circular layout representation of 30 October 2000

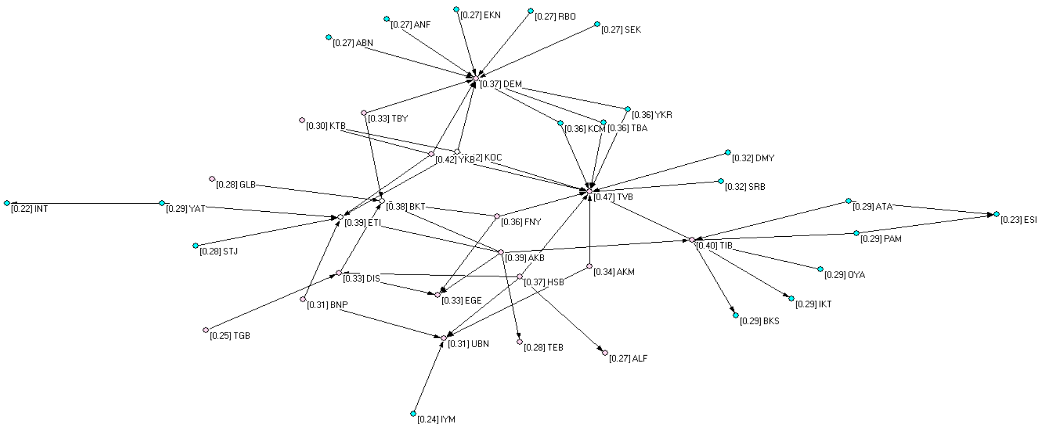


Picture 6: Energy Kamada-Kawai layout representation of 30 October 2000

20 November 2000 can be taken as the first day of financial turmoil. The totally centralized structure of the network was destroyed and the power of Demirbank was weakened. Demirbank is not the unique borrower and there are other borrowing centers. Now, there are fewer nodes lending to Demirbank. For the first time after June 2000, the closeness, betweenness and degree centrality measure values of Demirbank all decreased and fell beyond the values of other main borrowers. Limitation of borrowing to Demirbank by 20 November can be seen very well. The sharp decrease of density, volume and other concentration indices of graph also indicates the downturn of the economy.

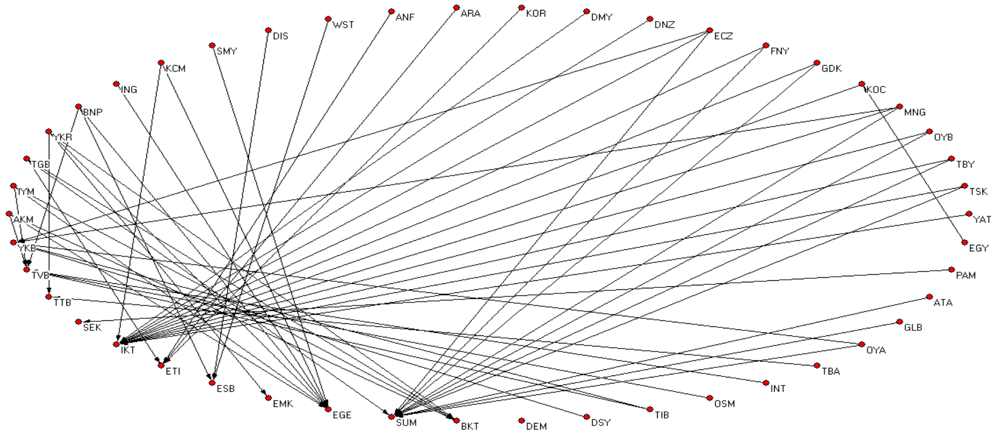


Picture 7: Circular layout representation of 20 November 2000

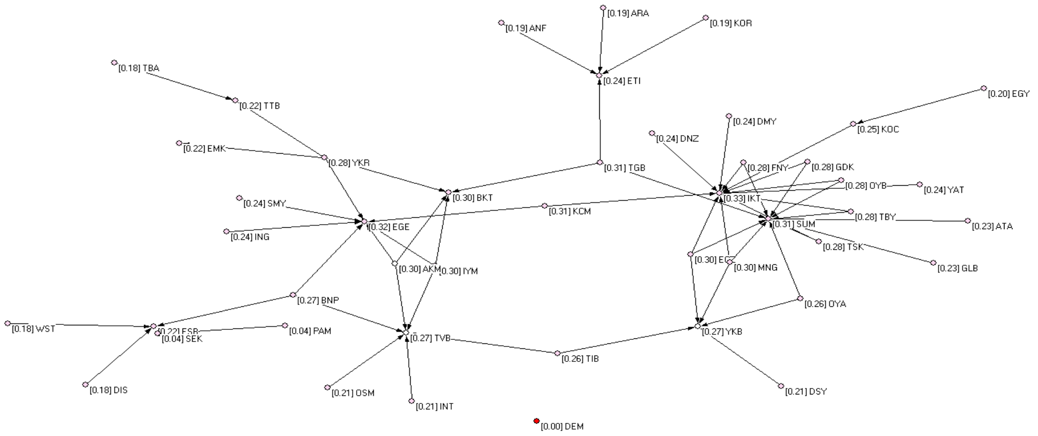


Picture 8: Energy Kamada-Kawai layout representation of 20 November 2000

By 1 December 2000, the destructed structure can fully be observed. In 1 December, Demirbank's transaction volume as well as total volume were at their bottom levels in year 2000. Financial institutions had stopped lending to Demirbank as it can be seen from graph Demirbank was an isolated point with connectivity, betweenness and degree measure values equal to zero. The overall risk appetite was very low because the pre-main borrower is now too risky to borrow. The density,volume and concentration indices decreased dramatically showing unwillingness to make transactions in 1 December.

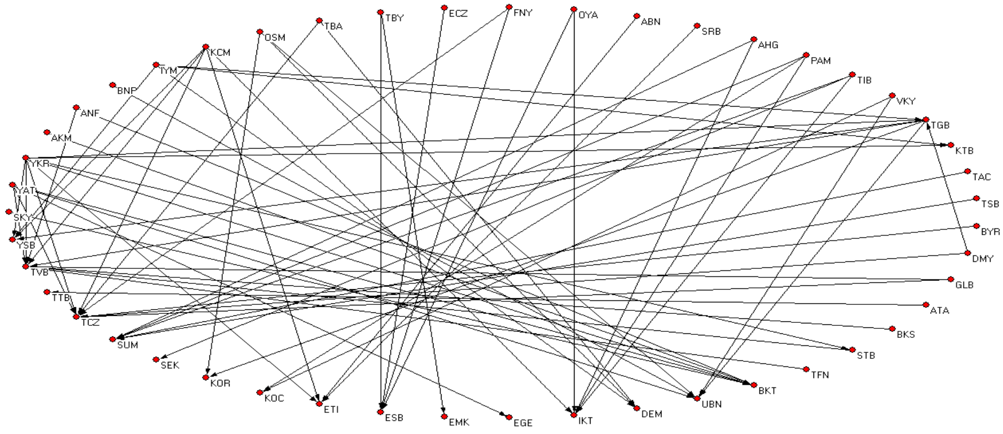


Picture 9: Circular layout representation of 1 December 2000

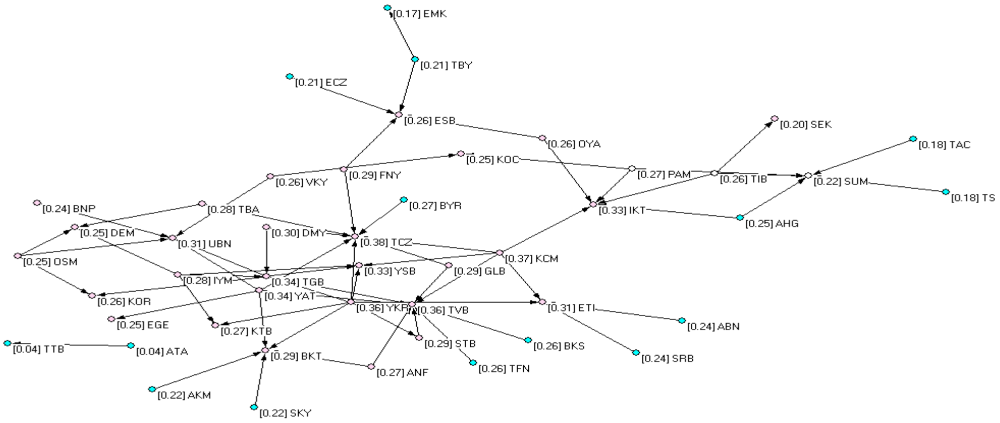


Picture 10: Energy Kamada-Kawai layout representation of 1 December 2000

5 December 2000 is the day in which Demirbank was taken over and this date can be taken as the end of the crisis. The take over of Demirbank changed the structure. The market volume and density increased a bit with the normalization of the market. These two representations show the beginning of recovery from the crisis. There is a multi-centered structure none of them being a massive hub.



Picture 11: Circular layout representation of 5 December 2000



Picture 12: Energy Kamada-Kawai layout representation of 5 December 2000

Density is simply the ratio of the number of adjacencies that are present divided by the number of pairs, which is usually defined as the sum of the values of all ties divided by the number of possible ties.Density of money market network was increasing as Demirbank started to borrowing. However, density has decreased during the Demirbank domination period since most of the agents became connected only to Demirbank which decreased number of adjacencies.

Lines, vertices and crossings(1)/(2) follow the same pattern as density. These values are very high in the pre-domination period and getting lower as Demirbank dominates the market. Here, number of crossings(1) and crossings(2) refers to the number of intersection points of links when drawn in layouts circular and Kamada-Kawai respectively. These values help to understand the density and denseness of the representation. However, number of loops are random and do not say anything about the denseness of the network. Instead, their existence prevent the calculation of degree centarlization since degree centralization cannot be computed since the network contains multiple lines or loops.

Network centralization is a measure of how central its most central node is in relation to how central all the other nodes are. The details will be explained in Appendix. Not for all days, all network centralization calculation is possible. In the Table 7, there are some n/a values because closeness centralization cannot be computed since the network is not weakly connected. Especially, from the first days of crisis until the end of take over, network is so isolated that closeness centratlization can not be calculated. Similarly, degree centralization is not calculated in the presence of multiple lines or loops.

Table 7: Different Periods Statistics

	28 Feb	9 May	30 Oct	20 Nov	1 Dec	5 Dec
Density	0,0299	0,0961	0,0274	0,0274	0,0264	0,0303
Lines	58	89	45	41	36	57
Loops	1	1	0	0	0	1
Crossings(1)	916	1841	447	563	470	843
Crossings(2)	18	86	3	5	13	23
Vertices	44	59	41	41	36	47
Closeness Centralization	0,1396	0,2752	0,3001	0,3128	n/a	n/a
Betweenness Centralization	0,0086	0,0305	0,0038	0,0039	0,0005	0,004
Degree Centralization	n/a	n/a	0,176	0,141	0,112	n/a
Total adjacency index	59	89	45	45	38	67
The Zagreb group index 1	558	1126	568	388	350	588
The Zagreb group index 2	1036	2651	904	542	493	1243
The Randic connectivity index	17,76	22,87	15,13	16,00	14,46	20,40
The Platt index	440	948	478	298	234	354

All three centralization values more or less follow the same pattern for the chosen six days. These values are increasing as Demirbank dominates the market and reach the peak as Demirbank became a massive hub. With the start of crisis, they start to fall below the pre-domination period values. Closeness centralization values even can not be calculated since the network does not have the minimum requirement of connectedness.

In the third part, various connectivity indices have been illustrated to compare the connectedness of different periods. The details about their calculation will be explained in Appendix. However, it is easy to see that all 5 indices follow the same pattern: increasing with the domination of Demirbank, decreasing when market is fully dominated by Demirbank since most of the agents only forming links with Demirbank. The bottom values were seen in the first day of crisis because of decreased risk appetite and then increasing again with the take over of Demirbank and normalization of market.

CHAPTER 8

CONCLUSION

Network theory has gained importance in the last decade in each science. Financial economists and policy makers also interested in network theory since it gives clear pictures of todays complex and interlinked financial markets. Specifically understanding the inner workings of the money market has become crucially important in terms of analyzing and responding to financial turmoil. This thesis aims to contribute to existing financial network literature by analyzing an old financial break down of Turkish economy in 2000. In fact, this study is an attempt to make an extension of Saltoglu and Yenilmez (2010) paper with the introduction of other centrality measures and new network tools such as node strength and link weight etc.

Various key parameters of network topology are investigated. It was observed that connectivity of the system decreases during crisis since Demirbank became the major borrower and the system centralized around Demirbank. Domination of Demirbank decrased the connections of other borrowers which decreased the total number of links and connectivity as a whole. With the growing centralization values of Demirbank, the shape of network evolved to a star-liked network with Demirbank in the middle.

Information about the relative importance of nodes and edges in a graph can be obtained through centrality measures. Therefore, Demirbanks centrality values are calculated for four main centrality measures: degree, closeness, betweenness and Bonachic. It is found that in terms of those centrality measures, Demirbanks values have an increasing trend till the beginning of financial turmoil and then decline sharply in the crisis period. After take over of Demirbank, market normalizes and

Demirbanks values turn back to pre domination period values. Besides, the correlations of those four centrality measures have been calculated and observed that the most striking correlation exists among degree and closeness. Betweenness centrality comes in second to be correlated with degree and closeness whereas Bonacich measure is found to be most uncorrelated with others.

Inspired from Barabasi and Albert (1999), Turkish over night money market networks degree distribution have been calculated. Demirbank's formation of links through preferential attachment has been shown. The new nodes link to existing nodes with probabilities proportional to the existing nodes' numbers of links at the distribution of number of links per node in a network follows a power-law distribution. That is, the probability that a node in a network interacts with other nodes decays as a power law. This suggests that very few nodes have a large number of links, a large number of nodes have very few link. Our network has been shown to be scale free network in which degree distribuitions follow power law. Infact, it is valid for whole period of concern. This enables us to explain Demirbank's rapid and strong domination.

APPENDIX: CENTRALIZATION

Measuring the density of a network gives us a ready index of the degree of dyadic connection in a population. For binary data, density is simply the ratio of the number of adjacencies that are present divided by the number of pairs - what proportion of all possible dyadic connections are actually present. If we have measured the ties among actors with values (strengths, closeness, probabilities, etc.) density is usually defined as the sum of the values of all ties divided by the number of possible ties. That is, with valued data, density is usually defined as the average strength of ties across all possible (not all actual) ties. Where the data are symmetric or undirected, density is calculated relative to the number of unique pairs $\frac{n-1.n}{2}$; where the data are directed, density is calculated across the total number of pairs.

Centralization refers to the extent to which a network revolves around a single node. More specifically, measured as share of all centrality possessed by the most central node. In a star network, the central point has complete centrality, and all other points have minimum centrality: the star is a maximally centralized graph. Defined formally, if$C_x(p_i)$ is any centrality measure of point i, if $C_x(p_*)$ is the largest such measure in the network, and if $max \sum_{j=1}^{N} C_x(p_i) - C_x(p_*)$ is the largest sum of differences in point centrality C_x for any graph of with the same number of nodes, then the centralization of the network is:

$$C_x = \frac{\sum_{i=1}^{N} C_x(p_i) - C_x(p_*)}{max \sum_{i=1}^{N} C_x(p_i) - C_x(p_*)}$$

The Zagreb group indices 1 and 2 are defined respectively as follows: M_1= $\sum_{vertices} d(i)d(i)$ and M_2= $\sum_{edges} d(i)d(i)$ where d(i) is the degree of vertex i and d(i) d(j) is the weight of edge i-j.The total adjacency index may be considered as the precursor to the M_1 index: A =$\sum_{vertices} d(i)$.

The Randic connectivity index, also called the vertex connectivity index is given by: χ=$\sum_{edges} (d(i)d(j))^{-0,5}$. The Platt index F of a graph G is equal to the total sum of edge-degrees $\epsilon(i)$ in G: F =$\sum_{edges} \epsilon(i)$ The degree $\epsilon(i)$ of an edge i is equal to the number of its adjacent edges.

REFERENCES

Allen, F 2000, 'Financial Contagion', *The Journal of Political Economy*, vol. 108, no. 1, pp. 1-33.

Allen F, Babus A, Carletti, E 2010, ' Financial Connections and Systemic Risk', *European Banking Center Discussion*, 2010-23S.

Allen F, Carletti ,E 2011, 'Systemic Risk and Macroprudential Regulation', vol. 15, no. 2, retrieved 15 Agust 2011,
$< http : //www.iea - world.com/docs/1043.pdf >$.

Barabasi, A, Reka, A, Jeong, H 1999, ' Diameter of the World', *Wide Web. Nature*,vol 401, no 130.

Barabasi, A, Reka, A 2002, ' Statistical Mechanics of Complex Networks', *Review of Modern Physics*,vol 74, no. 1, pp. 47-97.

Bollen J, Rodriguez M.A, Sompel, H.V.D 2006, 'Journal Status', *Scientometrics*, Vol. 69, No. 3, pp. 669687.

Bonacich, P 1972, ' Factoring and weighting approaches to clique identification', *Journal of Mathematical Sociology*,vol. 2, no:65, pp. 113-120.

Borgatti, S.P 2002, 'Net Draw Software for Network Visualization',*Analytic Technologies*.

Boss M, Krenn G, Metz V, Claus P, Schmitz, S.W 2008, ' Systemically Important Accounts', *Network Topology and Contagion in ARTIS. Oesterreichische Nationalbank (Austrian Central Bank) Financial StabilityReport*, no. 15, pp. 93-111.

Boss M, Helmut E, Martin S, Stefan,T 2003, 'An empirical analysis of the network structure of the Austian interbank market' , *Financial stability report*, no 7, pp. 77-87.

Chang, E 2008, ' Measures of Interbank Market Structure: An Application to Brazil', *Brazilian Review of Econometrics*, Vol. 28, No. 2.

Clauset A, Shalizi C.R, Newman, M.E.J 2009, ' Power-Law distributions in empirical data',*SIAM Review*, Vol. 51(4), pp. 661-703.

Clifford R, Joni, S 2012, 'Global Systemic Risk Regulation since the Financial Crisis : A framework for understanding effectiveness, impacts, and harmonization of macroprudential regulation', *Deloitte Development LLC*, no.7, pp 22.

Cocco J. F, Gomes F. J, Martins N, 2003, ' Lending Relationships in the Interbank Market', *IFA Working Paper*, No.384.

Degryse H, Nguyen, G 2004, ' Interbank Exposures: AnEmpirical Examination of System Risk in the Belgian Banking System', *Working Paper Nationale Bank van Belgi*, no.43.

Diamond D, Dybvig, P 1983, ' Bank Runs, Deposit Insuranceand Liquidity ', *Journal of Political Economy*, no. 91 (3), pp. 401419.

Dorogovtsev S.N, Mendes J.F.F, Samukhin, A.N 2001, ' Giant strongly connected component of directed networks', *Phys. Rev.*, vol 64, no. 6, pp. 1-4.

Erds P, Renyi, A 1959, ' On random graphs', *Publicationes Mathematica*, vol. 6, pp. 290297.

Erlend N, Yang J, Yorulmazer T, Alentorn, A 2007, 'Network Models and Financial stability', *Journal of Economic Dynamics Control*, vol.31, pp 20332060.

Freixas X, Parigi L, Rochet, J. C 2000, 'Systemic Risk, Interbank Relations and Liquidity Provisionby the Central Bank' , *Journal of Money, Credit and Banking*, vol. 32, pp.26-29.

Furfine, C. H 1999, 'Interbank Exposures: Quantifying the Risk of Contagion', *Journal of Money, Credit and Banking*, Vol. 35, No.1 , pp. 111-128.

Freeman, L. C 1977, 'A Set of Measures of Centrality Based on Betweenness', *Sociometry*, Vol.40, No.1, pp. 35-41.

G20 London Summit, 2009, 'Declaration on Strengthening the Financial System', *Information Centre*,
$< http://www.g20.org/images/stories/canalfinan/docs/uk/08deps.pdf >$.

Haldane, A G2009, 'Rethinking the Financial Network', *Bank of England*, < *http : //www.bankofengland.co.uk/publications/Documents/speeches.pdf* >

Giulia I, Masi G.D, Precup O.V, Gabbid G., Caldarelli, G 2007, 'A Network Analysis of the Italian Overnight Money Market', *Journal of Economic Dynamics Control*, vol. 32, pp. 259278.

Giulia I, Jafarey S, Padilla, F.G 2006, 'Systemic Risk on the Interbank Market',*Journal of Economic Behavior and Organization*, vol. 61, pp. 525-542.

Inaoka H, Ninomiya T, Taniguchi K, Shimizu T, Takayasu, H 2004, ' Fractal Network derived from banking transaction', *An analysis of network structures formed by financial institutions Bank of Japan Working Paper Series*, No. 04.

Jollieffe, I.T 2002, *Principal Component Analysis*, Springer-Verlag Inc, NewYork, pp. 234.

Leonidov A. V, Rumyantsev, E. L 2012, ' Russian interbank networks: main characteristics and stability with respect to contagion', *Quantitative Finance Papers*, vol. 34, no.6, pp.9-12.

Marco E, Andy J, Charles K, Kazuhiro M, Juan, S 2010, 'Systemic Risk and theRe-Design of Financial Regulation', *Global Financial Stability Report (GFSR)*, April

Muller, J 2006, 'Interbank Credit Lines as a Channel of Contagion', *Journal of Financial Services Research*, vol. 29, no. 1, pp. 37-60.

Nacaskul, P 2010, 'Application of Entropic Eigenvector Centrality (EEC) Criterion for A Priori Ranking of Financial Institutions in terms of Regulatory-Supervisory Concern, with Demonstrations on Stylised Small Network Topologies', *Systemic Import Analysis (SIA)*

Nier, E 2008, ' Network models and financial stability', *Bank of England working papers*, pp. 346.

Hartmann, P 2000, 'Systemic Risk: A Survey. European CentralBank Working Paper Series', *Working Paper*, No. 35, pp. 68

Page, L 1999, ’The PageRank Citation Ranking: Bringing order to the web’, *Standford InfoLab*

Prpper M, Lelyveld I. V, Heijmans, R 2008, ’Towards a Network Description of Interbank Payment Flows’, *De Nederlandsche Bank NV Working Paper*, No. 177.

Rochet J.-C, Jean, T 1996, ’Interbank Lending and Systemic Risk’, *Journal of Money, Credit and Banking*, vol. 28, no. 4, pp 733-762.

Reinhart C, Rogoff, K 2009, *This time is different: eight centuries of financial folly*, Princeton University Press, New Jersey

Saltoglu B, Yenilmez, T 2010, ’Analyzing Systemic Risk with Financial Networks An Application During a Financial Crash’, *MPRA Paper*, University Library of Munich, Germany

Soramki, K 2007, ’The Topology of Interbank Payment Flows’, *Physica A*, vol. 379, pp.317- 333.

Soramki, K 2012, ’Algorithm for Identifying Systemically Important Banks in Payment Systems’, *Economics The Open-Access, Open-Assessment E-Journal*, Discussion Paper No. 2012-43.

Thornton, J 2009, ’On Systemically Important Financial Institutions and Progressive Systemic Mitigation’, *FED Cleveland Policy Discussion Papers*

Tumpell-Gugerell, G 2010, ’Recent Advances in Modelling Systemis Risk UsingNetwork Analysis’, *European Central Bank* , no. 69.

Upper, C 2002, ’Estimating Bilateral Exposures in the German Interbank Market: Is there a Danger of Contagion?’, *Deutsche Bundesbank*, Discussion paper 09.

Wells, S 2002, ’UK interbank exposures: systemic risk implications’,*Bank of England’s Financial Stability Review*, December 2002

Veld, D 2012, ’ Finding the core: Network structure in interbank markets’,*DNB Working Papers Netherlands Central Bank, Research Department*, pp. 648.