

Sümer, Tuba Pelin; Özyıldırım, Süheyla

Article

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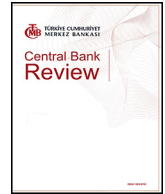
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Network structure of Turkish interbank market[☆]

Tuba Pelin Sümer^{a,*}, Süheyla Özyıldırım^b

^a Central Bank of the Republic of Türkiye, Türkiye

^b Bilkent University, Türkiye



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ABSTRACT

Global financial crisis has shown the importance of understanding the structure of interbank relations. In this study, we investigate the network relations based on interbank exposures in Türkiye. We estimate several network statistics and document how the network relations have changed over the time period of 2002–2021. We find that the network structures vary substantially by financial instruments such as repo, deposit, loan, security issuances, derivatives and other off-balance sheet items showing the significance of covering all type of exposures in network analysis. Using network statistics, we show that Turkish interbank network structure shows a core-periphery structure which is found to be more resilient during stress times in the literature. Finally, we find that larger banks are characterized as having higher network centrality measures as degree, clustering coefficient and closeness centrality showing the importance of these banks in terms of intermediation and substitutability.

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1. Introduction

Banks establish interbank links to protect themselves from random liquidity shocks and to increase the proportion of their assets held in long-term high profit assets. However, interbank relations may cause solvent banks to become insolvent due to contagion effect and may have adverse effects on the real economy (Allen and Babus, 2009).¹ Global financial crisis has shown the importance of understanding the structure of interbank relations and determining systemically important institutions. Following the work of the IMF, FSB and BIS for the G20, systemic risk is defined as

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* Corresponding author.

E-mail addresses: pelin.sumer@tcmb.gov.tr (T.P. Sümer), suheyla@bilkent.edu.tr (S. Özyıldırım).

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¹ According to a study of Basel Committee on Banking Supervision (2010), banking crisis caused on average 9% output loss which is calculated from the change in GDP at the beginning and end of the crisis period, i.e., period from peak to trough. If the cumulative losses in the recovery periods are also taken into account, the loss increases to 19%.

“a risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy” (Financial Stability Board, 2010).

Default of systemically important institutions causes a higher damage for the real economy compared to the other institutions and public sector intervention to rescue these institutions increases moral hazard problems. In this respect, Basel Committee has formed an indicator-based methodology to determine systemically important institutions and impose higher capital requirements to these institutions and hence reduce the probability of future distress (Basel Committee on Banking Supervision, 2012). At the country level, regulatory authorities are expected to determine their domestic systemically important institutions using size, interconnectedness, substitutability and complexity indicators, where interconnectedness is measured with the total size of interbank assets/liabilities. However, aggregated balance sheet information may hinder the real picture of the complex transactions between institutions. Moreover, systemic importance of an institution is not determined solely by the impact of failure of this institution on the other institutions since there may be second and further round contagion effects depending on the network relations of the connected counterparty. From this point of view, network structure analysis carry systemic importance assessment one step further compared to the use of aggregated balance sheet indicators. However, lack of bilateral exposure reportings between

banks has limited the number of studies in network analysis. Glasserman and Young (2016) argue that knowing the network structure is important not only for regulators but also for market participants, since in stress times opacity of interbank relations may contribute to contagion. In the literature, there are papers that work with derived networks from total interbank exposures via maximum entropy method (Upper and Worms, 2004; Elsinger et al., 2006). However, Mistrulli (2005) and Van Lelyveld and Liedorp (2006) show that working with estimated networks cause biased results compared to working with actual network data.

Theoretical literature has shown that network structure or network completeness is important for the propagation of contagion (Allen and Gale, 2000; Freixas et al., 2000).² However, since actual networks are more complex compared to the networks covered in theoretical models, empirical literature has emerged more recently. The first strand of the empirical literature analyzes the relation between network structure and contagion risk over artificial networks (see e.g., Nier et al., 2007; Georg, 2013). These papers show that there is a nonlinear relation between network resilience and level of connectivity. For very low levels of connectivity, an increase in connectivity reduces system resilience, since connectivity increases the chance of shock transmission (shock-amplifier). On the other hand, when connectivity is sufficiently high, further increases in connectivity decrease contagion as the shock-absorption effect starts to dominate. The second strand of empirical literature conducts contagious failure studies to explore the effect of failure of a bank on the banking system via simulations (Degryse and Nguyen, 2007; Furfine, 2003; Van Lelyveld and Liedorp, 2006). In these studies, a bank causing capital losses above a threshold in the system is assessed as systemically important. While these studies are beneficial for understanding contagion risk in the banking system, the use of the findings of these studies is limited mainly due to the validity of assumptions such as the use of constant loss-given-default (LGD) parameter and seniority of non-bank liabilities over interbank liabilities (Upper, 2011). The third strand of the literature aims to understand which “typical” network structures explain the actual banking networks better.³ It is shown that banking networks fit to core-periphery model, in which there are core banks connected to each other and periphery banks that are only connected to the core banks, better compared to other structures (see Craig and von Peter, 2014 for Netherlands; In't Veld and Van Lelyveld, 2014 for Netherlands; Fricke and Lux, 2015 for Italy; Langfield et al., 2014 for UK; Silva et al., 2016 for Brazil; Martinez-Jaramillo et al., 2014 for Mexico; Aldasoro and Alves, 2018 for a group of European countries; Sümer and Özyıldırım, 2019 for Türkiye). Georg (2013) shows that while in normal times network structure does not have a substantial effect on financial stability, in stress times core-periphery models are seen to be more stable than random networks. Core banks can act as fire stops against shocks coming to periphery banks since they can diversify counterparty credit risk. Fourth strand of the literature

aims to understand the network structure or topology and identify systemically important institutions using several network statistics (Boss et al., 2004; Battiston et al., 2012; Iori et al., 2008; Bech and Atalay, 2010). These studies rely on that topology of a network affects its functionality and stability (Albert and Barabasi, 2002; Newman, 2004). While, in contagious failure studies, bank's systemic importance is assessed by calculating the effects of its failure on other banks, in these studies, banks with higher centrality measures are considered as systemically important. In this study, we aim to contribute to the literature via exploring the network structure of Turkish interbank market.

The studies that explore network characteristics of Turkish interbank market are limited. Saltoglu and Yenilmez (2010) examine repo relations by using the default of a large private bank, Demirbank in 2000 as a case study. They propose a tool to detect systemically important institutions 5 months prior to the financial crisis in Türkiye which is a modification of PageRank methodology. They show that connectivity of the banking sector decreases before the crisis and increases again after the takeover of Demirbank. By using the same dataset, Kuzubaş et al. (2014) test the effectiveness of several centrality measures (degree centrality, betweenness centrality, closeness centrality and Bonacich's centrality) to identify the fail of Demirbank. They show that centrality value of Demirbank increase for all centrality measures prior to the crisis. Özdemir (2015) studies repo, deposit and loan type relations between Turkish banks for 2007–2014 period and conducts a contagion analysis. She shows that failures of banks with higher out-degree centrality which are state-owned banks and largest privately-owned banks seem to cause more bank failures. Sümer and Özyıldırım (2019) analyze repo, deposit, loan, security, derivative and other off-balance sheet relations for 2003–2017 period and show that Turkish network fits to core-periphery structure by using Craig and von Peter (2014) algorithm.

We believe that this study makes an important contribution for understanding the characteristics of the Turkish interbank network structure. The studies that use interbank data of Turkish market make analysis for only limited number of periods or instruments. In this study, we cover all types of on-balance and off-balance sheet interbank relations for 20 year period and analyze network properties by using several network statistics. To the best of our knowledge, independent of the country of focus, there is not any network study using such a comprehensive data. We document that network structures and dynamics of the relations through time have distinct properties. First, we observe that density, showing the level of connectedness, of Turkish interbank market increased through time as financial deepening⁴ progressed. However, central bank policies regarding the provision of liquidity via repo transactions also seems to be effective on the density of network relations. Second, we document that banks that are larger in asset size have higher network centrality measures (degree centrality, betweenness centrality and closeness centrality) which measures the importance of banks in terms of level of connectedness, intermediation role and substitutability. Third, we find that Turkish banks that are larger in asset size receive funds from higher number of banks, however they do not necessarily extend funds to higher number of banks probably reflecting the fact that they can more easily place the excess liquidity to non-financial counterparties thanks to geographically well diversified branch network. Finally, we show that Turkish interbank network structure fits to core-periphery model using rich-club and assortativity statistics which measures the level of connectedness between highly connected

² In Allen and Gale (2000), some typical network structures are considered which are complete, incomplete and disconnected incomplete. In complete network structure, four banks/banking systems are assumed to be connected in both ways, i.e. they both lend and borrow. In incomplete network structure, four banks are assumed to be connected in one way and in disconnected incomplete network structure, two banks are connected in both ways, however they are not connected with the other two banks. Similarly, Freixas et al. (2000) consider diversified lending, credit chain and money center structures.

³ In the literature, as the “typical” network structures, random networks, scale-free networks, core-periphery model and nested-split graphs are proposed. For random networks, see Erdős and Renyi (1959); for scale-free networks, see Barabasi and Albert (1999); for core-periphery networks, see Craig and von Peter (2014); for nested-split graphs, see König et al. (2014).

⁴ Asset size of Turkish banks as ratio of GDP increased from the level of 58.7% in 2002 December to 109.3% in 2021 September.

Table 1
Details of interbank transactions.

Instrument Types	Reporting Period	Reporting Frequency	Number of Transactions
Repo	2002:12–2021:9	Monthly	93,273
Deposit	2002:12–2021:9	Monthly	184,512
Loan	2002:12–2021:9	Monthly	2,176,552
Other Off-Balance Sheet	2002:12–2021:9	Monthly	4,284,470
Security	2007:1–2021:9	Daily	114,869
Derivative	2014:1–2021:9	Daily	88,080
Total			6,941,756

Notes: The table shows the reporting details of interbank instruments. Security includes bond and equity holdings of banks. Other off-balance sheet items cover guarantee letter, bank acceptances and other guarantees. As the derivative transactions, we include all type of derivative contracts as swaps, forwards, futures and options. We only exclude derivatives (mostly interest rate swaps) which exchanges the same currency unit in the forward and spot leg since misreportings are observed in these transactions.

banks and tendency of highly connected banks to connect with lowly connected banks. The remainder of the paper is organized as follows: In Section 2, we introduce the dataset and document total size and breakdown of the interbank relations. In Section 3, we present several network statistics and examine the dynamics of network relations. We conclude the paper in Section 4.

2. Data description

In this study, we use transaction-level reportings that are collected by Banking Regulation and Supervision Agency of Türkiye (BRSA). All types of interbank instruments including repo, deposit, loan, security holdings, derivatives and other off-balance sheet items are covered in the analysis. We use four different datasets each having different reporting frequency and starting date of reporting (see Table 1 for the details of interbank transaction reportings). While securities and derivatives are reported in a daily frequency, other instruments are reported in a monthly frequency. To make the reporting frequencies compatible, we use outstanding balances at the end of months for securities and derivatives. Due to data gaps, security holdings and derivatives of banks are started to be reported in 2007 and 2014 respectively, while the other instruments are available since December 2002.

In total, we have 6.9 million transactions to construct monthly interbank networks between 2002 and 2021. In these transactions, if banks have reported swift codes or tax numbers of the counterparty banks, we used these fields to uniquely identify the counterparties. However, if these fields are not reported, we used the names of the counterparties reported in many formats to identify the counterparty banks which is a daunting task. We have 65 banks in our sample and the dataset is unbalanced, meaning that banks may exit due to mergers/acquisitions or failures and newly established banks may enter during the analysis period. As of September 2021, there are 55 banks actively operating in Türkiye. İstanbul Settlement and Custody Bank (Takasbank) and two banks that are managed by Savings Deposit Insurance Fund are excluded in our analysis since they do not operate as other commercial banks.⁵ Central Bank is excluded from the analysis as well.

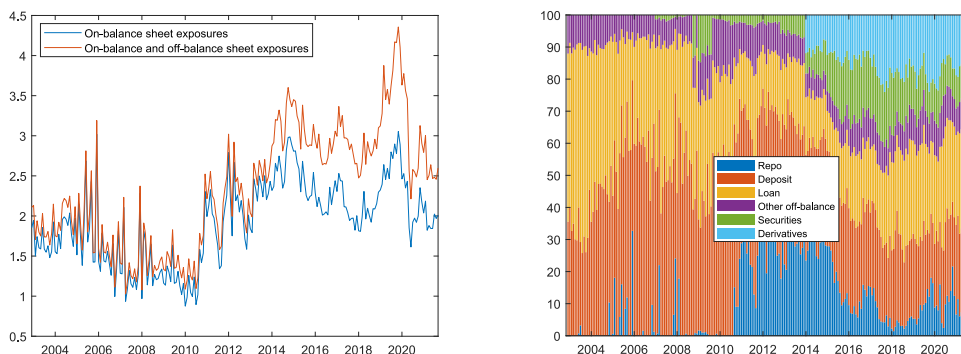
Fig. 1a shows the size of interbank exposures as a share in total banking sector assets. We present the share of interbank exposures that is recorded in on-balance sheet (repo, deposit, loan and security holdings) separately, since these transactions are different than off-balance sheet transactions in terms of implied losses for the counterparty in case of defaults. If the counterparty is in distress and the derivative positions are needed to be closed, market value of the derivative matters instead of notional amount. Similarly, in case of distress, counterparty may not need to convert total/whole of other off-balance sheet items to cash loans. In the

analysis period, while the share of on-balance sheet receivables in total assets range between 0.9% and 3.1%; the share of sum of on-balance and off-balance sheet receivables range between 1.0% and 4.4%.⁶ Volatility in interbank repo volume explains most of the fluctuations of the share of interbank exposures in total assets. Between the beginning/start of the pandemic (February 2020) and the end of first economic close-down (June 2020), the share of on-balance sheet exposures in assets decreased from 2.5% to 1.6%, and the share of on-balance and off-balance sheet exposures decreased from 3.8% to 2.2%. In this period, we observe the size of interbank repo, deposit and derivative transactions decreased. During the pandemic, BRSA and Central Bank of the Republic of Türkiye (CBRT) announced several measures to support the economic activity which were effective in the volume of interbank transactions. CBRT opened the repo facility with 91 day maturity for the banks that extend loans to the real sector. BRSA limited the amount of right-way derivatives with foreign counterparties as 10% of regulatory capital and introduced asset ratio to promote banks to lend to the real economy, hold government securities and make swaps with CBRT. With the increased funding from CBRT during the beginning/start of the pandemic, banks' need for making repo with other banks decreased. As documented in Sümer and Özyıldırım (2019), foreign banks are more active in interbank derivative transactions in Türkiye since they have comparative advantage to offset these transactions with their foreign parents. With the limitation of the derivatives with foreign counterparties, the interbank derivative volume contracted as well.

Fig. 1b shows the percentage share of each instrument (repo, deposits, loans, securities, derivatives and other off-balance sheet items) in total interbank exposures. We observe that the composition of interbank exposures has changed through time. As of September 2021 (last observation period), deposit (30.2%) and loan (29.8%) instruments have the highest shares. While the repo share in total interbank exposures increased up to 48% in 2012, it is around 8% as of September 2021. Start of derivative reporting in 2014 is also effective in this decrease. Sümer and Özyıldırım (2019) show for the 2002–2017 period that as the interest rate differential between average Central Bank funding and Borsa İstanbul (BIST) interbank market increases, banks find arbitrage opportunities by buying from Central Bank and selling in the interbank market which increases interbank repo volume. They find that changes in Central Bank funding strategy and decrease in funding through one-week auctions is explaining the decrease in interbank repo volume in 2016 and 2017. For the years following 2017, we observe that interbank repo volume increased slightly. As mentioned above,

⁶ The minimum and maximum share for on-balance sheet exposures are observed during January 2010 and November 2019 respectively. For the share of total exposures, while maximum happened at the same date, the minimum is observed on April 2007.

⁵ Thus, in our sample, we have 52 banks as of September 2021.



(a) Share of interbank exposures in total assets (b) Composition of interbank exposures

Fig. 1. Size and Composition of Interbank Exposures. Fig. 1a shows the share of on-balance sheet and total (on-balance + off-balance) interbank exposures in total assets of banks. Notional value of derivatives are used. Fig. 1b shows the percentage share of each instrument in total interbank exposures.

Central Bank opened 91 day repo auctions to limit the effects of pandemic between March 17, 2020 and November 19, 2020, and then announced that one-week repo auctions will be the only funding strategy.

Fig. 2 shows network relations for different instruments for September 2021. We observe that limited number of banks are connected in repo transactions and banks are much more connected in especially deposit and other off-balance sheet type relations. It is also seen that in repo, deposit and loan relations, size of interbank relations for some banks are higher compared to other ones (arrow and line size of the relation of these banks are larger), meaning that these banks act as core banks in these instruments. Moreover, the importance of the relations of bank changes from instrument to instrument. Since the structures are different in instrument-level networks, it is important to analyze all type of exposures. The losses in case of default of the counterparty bank will be limited if the exposure is covered by any collateral. Since, collateral structures are different, systemic risk implication of the instruments differ as well. While repo is secured by government debt instruments; deposits and security issuances have unsecured structure and loans may be partially covered with collaterals depending on the contract between banks. Swaps constitute an important share of derivative volume of the Turkish banks and in swap transactions mostly banks either exchange currencies (e.g. TRY vs USD) or interest rates (e.g. fixed rate vs floating rate). From that point of view, derivatives may be considered as secured transactions as well. For the other off-balance sheet relations, the loss will be realized if the exposure is converted to the cash loans, however the failing counterparty may not need to convert whole of other off-balance sheet items. Therefore, in other off-balance sheet relations, credit conversion ratio will be an important driver for the systemic risk losses. To summarize, since collateral structures and characteristics vary from instrument to instrument, systemic risk implications also differ showing the contribution of analyzing instrument-level networks as well.

3. Network statistics

We calculate several network statistics such as degree, density, assortativity, rich-club coefficient, clustering coefficient, closeness centrality and betweenness centrality. While the statistics as clustering coefficient, density or rich-club coefficient help to understand the network structure, statistics as degree, closeness centrality and betweenness centrality are used to identify

systemically important or more connected banks. In this section, first the mathematical definitions and explanations of the statistics are given and then the evolvement of these measures through time are discussed.

3.1. Degree

Degree is a statistic showing the number of counterparties of a bank. More specifically, out-degree shows to how many banks a bank is lending or extending funds and in-degree shows from how many banks a bank is borrowing or receiving funds. Total degree is the sum of in-degree and out-degree statistics. In other words, total degree is showing the sum of number of lending and borrowing counterparties of bank. As the number of connections of the bank increase, the bank becomes more important for the system considering the possibility that its failure will affect more banks. Total degree is the most simple network centrality measure. Let the matrix A denotes the adjacency matrix, where the element of matrix A , a_{ij} takes value of 1 if bank i is lending to bank j and 0 otherwise. Then, mathematically, in-degree and out-degree statistics are expressed as follows:

$$\text{In-degree} = k_i^{\text{in}} = \sum_j a_{ji} \tag{1}$$

$$\text{Out-degree} = k_i^{\text{out}} = \sum_j a_{ij} \tag{2}$$

To calculate the average degree in the network, only the degrees of the banks that are active are considered. Over the analysis period, some banks exit the system due to mergers/acquisitions or termination of the banking operations and some banks enter the system, so active banks are the banks that continue its banking activities in the analysis month.

Fig. 3 shows average in-degree statistics for each instrument-level network and total exposures networks. Since in-degree and out-degree shows number of borrowing and lending counterparties respectively and debt of a bank is the credit of the other bank in domestic interbank network analysis, average in-degree and out-degree statistics are equal and average total degree is the double of the average in-degree measure. Fig. 3 shows that average number of counterparties in repo and security type relations are less compared to other instruments. While at most there has been, on average, 2–2.5 counterparties on average for repo and security

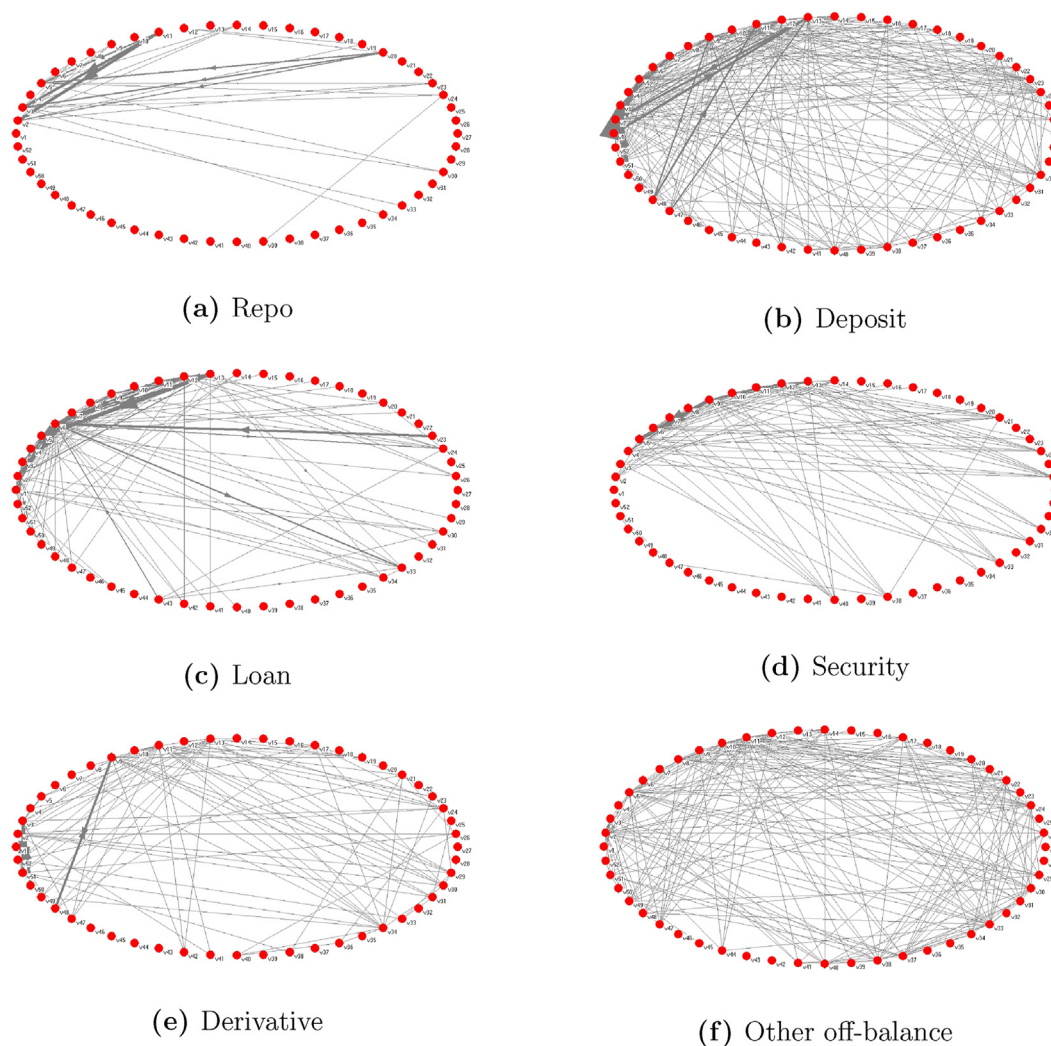


Fig. 2. Instrument Level Interbank Relations. Network graphs show the interbank relations between 52 banks that are active as of September 2021. Red circles denote banks and lines show edges between banks. Line and arrow size becomes thicker as the comparative weight of the relation increases. Network graphs are plotted using Pajek.

relations (Fig. 3a and d), number of counterparties increased up to 7 in deposit network (Fig. 3b) and up to 5 in other off-balance sheet network (Fig. 3f). For the total on-balance sheet exposures, average in-degree increased through time with financial deepening until 2015 although the total number of banks in the system did not change significantly (Fig. 3g). While there were, on average, 11 counterparties of a bank in total on-balance sheet relations in 2014, this average ranges around 8.5 for 2015–2021. The evolution of average degree for total on-balance and off-balance sheet relations is similar to on-balance sheet relations, a break in the series is observed in 2014 when derivative transactions started to be reported (Fig. 3h).

Degree is one of the most basic network statistics that show systemic importance of a bank in interbank relations. The asset size of a bank is among the indicators that is used to determine domestic systemically important banks (D-SIBs) in Basel regulations (Basel Committee on Banking Supervision, 2012). In order to test the relation between systemic importance of the bank in interbank relations and asset size, we check how the average degree changes as the asset size of the bank decreases. First, we group banks as top five, second top five (top 6–10) and third top five (top 11–15) banks in terms of their asset size and analyze whether the average degrees among these groups are different. Table 2 shows our findings

for each instrument. First, we observe that as the asset size decreases, average total degree decreases for all type of exposures. For example, while the average total degree for total interbank exposures for top five banks is 57.1, the average decreases to 45.2 for top 6–10 banks and to 29.6 for top 11–15 banks. The finding of decrease in average degree as asset size decreases is also valid for in-degree statistic for each instrument except other off-balance sheet relations suggesting that larger banks in terms of asset size receive funds from higher number of banks. On the other hand, this relation is not valid for repo, deposit and loan relations for out-degree. These findings show that while large Turkish banks receive funds from higher number of banks, they do not necessarily extend funds to higher number of banks. This finding is similar to Iori et al. (2008), which shows that large Italian banks have higher in-degree, while the small Italian banks have the highest out-degree.

As a final analysis in this subsection, we present degree distributions in Fig. 4. Fig. 4a shows in-degree and out-degree distributions of total exposures for 2021 September. From this graph, it is seen that in-degree and out-degree distributions are different slightly, so analyzing both degree measure adds value. In Fig. 4b, we compare degree distributions of the actual network with random network having same network characteristics with the actual network. In random networks, banks interact with each other

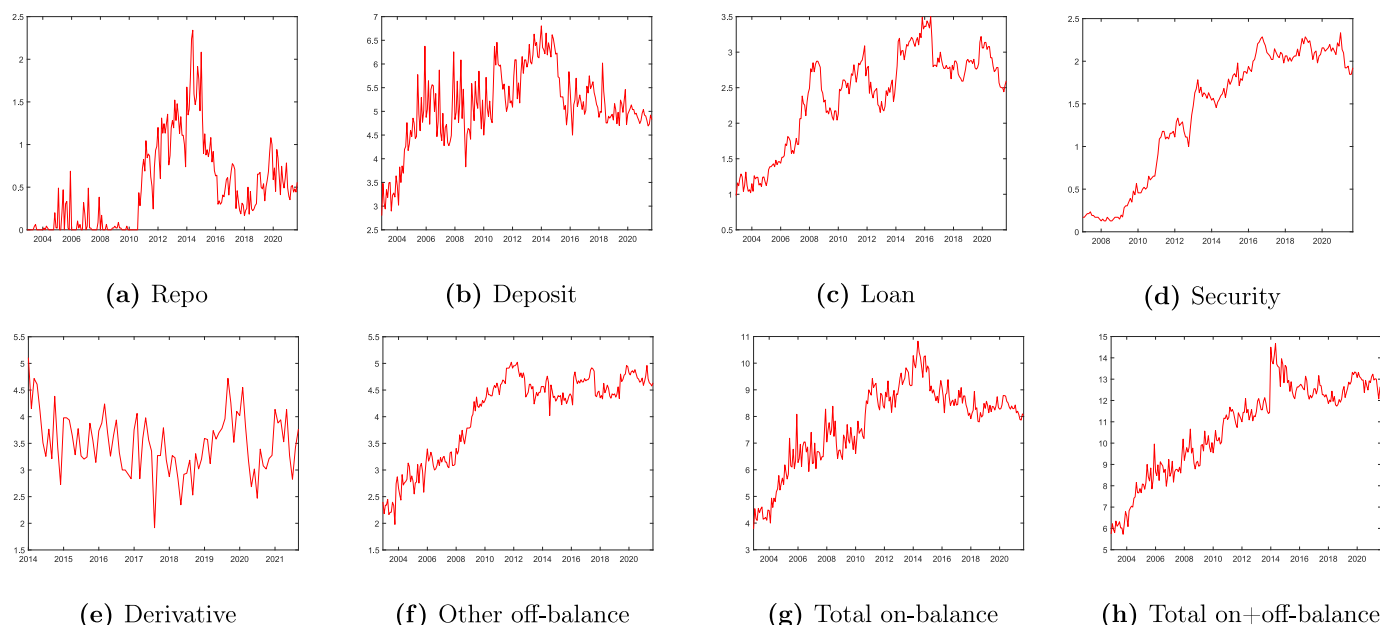


Fig. 3. Average Degree. Average in-degree statistics in each instrument level network is shown. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off-balance shows sum of on-balance and off-balance sheet relations.

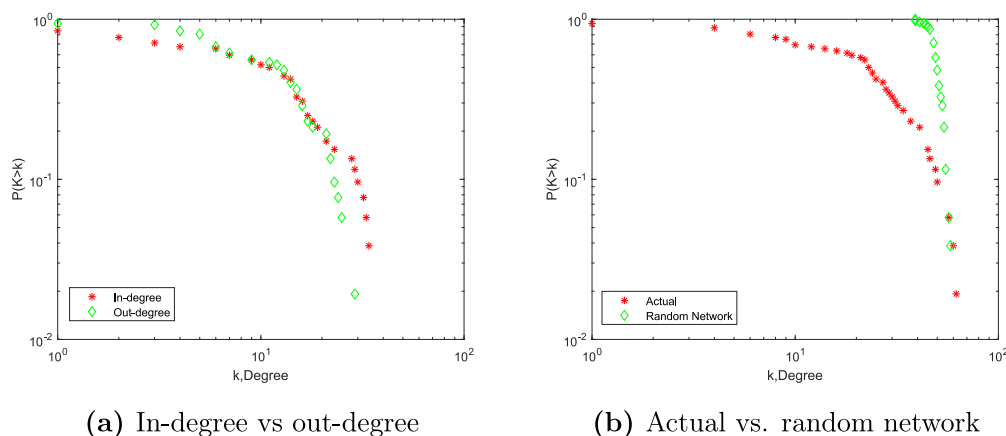


Fig. 4. Degree Plots. Fig. 4a shows in and out-degree log-log distributions for 2021 September for total exposures network. Fig. 4b shows total-degree distribution for total exposures network in 2021 September and random network having same network characteristics (number of banks and network density) with the actual network.

Table 2
Average degrees based on asset rank of banks.

	Top 5 Banks			Top 6–10 Banks			Top 11–15 Banks		
	In	Out	Total	In	Out	Total	In	Out	Total
Repo	4.0	0.6	4.6	1.3	1.1	2.5	0.0	1.2	1.3
Deposit	21.7	5.7	27.5	11.0	6.9	17.9	4.0	6.8	10.8
Loan	7.6	10.1	17.6	7.6	5.4	13.1	4.5	5.8	10.3
Security	8.5	4.4	12.9	6.2	3.4	9.6	1.2	0.5	1.6
Derivative	10.4	10.3	20.7	7.0	6.8	13.9	4.6	4.5	9.1
Other off-balance	6.4	12.7	19.1	8.2	7.4	15.6	7.0	3.9	10.8
On-balance	29.8	14.4	44.2	19.7	12.7	32.4	8.3	11.7	20.0
Total	33.2	23.9	57.1	25.6	19.6	45.2	14.9	14.7	29.6

Notes: Banks are ranked based on their asset size in each month and Top 5, Top 6–10 and Top 11–15 banks are determined. Then, average degree of the Top banks for 2014–2021 period is calculated. While on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total shows sum of on-balance and off-balance sheet relations.

randomly. Fig. 4b shows that network structure of Turkish interbank market is different than random networks. The other network structures proposed in the literature are scale-free networks, core-periphery networks and nested-split graphs. Sümer and Özyıldırım (2019) find that Turkish interbank market fits to core-periphery model, in which there are core banks connected to each other and periphery banks that are only connected to the core banks, better compared to the fit to random networks. Degree distributions presented in this study are also inline with the findings in the literature.

3.2. Density

Density is calculated as the share of actual relationships over all possible relationships in the network. If the number of banks in the network is denoted as N , the denominator of the following density formula shows the number of all possible connections. Density

takes values between 0 and 1 and as the density becomes closer to 1, then the network resembles a complete network.

$$\text{Density} = d = \frac{\sum_i \sum_j a_{ij}}{N(N-1)} \quad (3)$$

Table 3 shows descriptive statistics for densities. Average density is smaller in repo and security relations and much higher in deposit type relations. In repo relations, minimum value of density is close to zero, since there are times that banks do not establish any interbank links. For on-balance sheet relations, density ranges between 15.5% and 24.1% in 2014–2021 period with average density being 18.1%. If off-balance sheet relations are included as well, in total interbank relations, density ranges between 23.9% and 32.9%.

Table 4 summarizes the characteristics of interbank data and network density statistic for selected five countries: Germany, Netherlands, Italy, UK and Mexico. In this way, we aim to compare and contrast network structures of these countries with Türkiye. First, we note that interbank data coverage across five countries and Türkiye are different. The studies by Craig and von Peter (2014) for Germany, In't Veld and Lelyveld (2014) for Netherlands and Langfield et al. (2014) for UK focus only on large interbank loans. However, the use of only interbank exposures exceeding some threshold amount disables to monitor interbank links with smaller banks and results in a decrease in network densities. Therefore, network densities in these countries are smaller compared to other countries and Türkiye. In Germany, there are many small credit union banks having limited number of links with other banks, that characterize density of interbank market to be small as well. While in Fricke and Lux (2015), only unsecured money market transactions are considered, Solis-Montes (2013), similar to our study, covers different type of interbank relations in Mexico. Therefore, we may argue that Turkish interbank market is much more similar to Mexican interbank market in terms of density of the market as well as the number of banks operating.

Fig. 5 shows how network densities changed through time. Density graphs are similar to average degree graphs since the formulas are nearly same except the $N-1$ term in the denominator of density. While the density of the repo market is close to zero until 2010, density increases after that time and increases up to 5% in 2014. CBRT announced on April 2010 that in terms of the steps taken for the normalization of the monetary policy after the global financial crisis, one-week repo rate has been started to be used as policy rate instead of overnight rate. Moreover, the excess liquidity provided to the market with monetary policy operations was aimed to be decreased (Central Bank of the Republic of Türkiye, 2010). After these changes, due to arbitrage opportunities, some banks borrowed from Central Bank in one-week repo auctions and sold this money in overnight interbank market which stimulated repo transactions. Densities of deposit, loan, security holdings and other

Table 3
Descriptive statistics for density.

	Min	Max	Average	Median	Std. Dev.
Repo	0.004	0.051	0.015	0.012	0.011
Deposit	0.092	0.151	0.111	0.106	0.014
Loan	0.048	0.073	0.061	0.060	0.006
Security	0.032	0.048	0.041	0.042	0.004
Derivative	0.041	0.114	0.073	0.072	0.012
Other off-balance	0.089	0.109	0.098	0.098	0.004
On-balance	0.155	0.241	0.181	0.176	0.019
Total	0.239	0.329	0.268	0.263	0.017

Notes: Descriptive statistics are calculated over 2014–2021 period for each instrument. While on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total shows sum of on-balance and off-balance sheet relations.

off-balance sheet networks increased from 2002 to 2016 due to financial deepening and moved in a stable path afterwards. Density involvement of derivative network is different than other networks since there is not a increasing trend and density fluctuates around average value of 7.3%. One reason for that finding may be due to the fact that derivatives started to be reported in year 2014 when the networks of other instruments have already moved in a stable path.

3.3. Assortativity

Assortativity is a global network measure showing the tendency of banks to connect with banks having similar degrees. It is indeed a correlation coefficient between the degrees of banks on the same edge and takes values between -1 and 1 . A positive assortativity coefficient indicates that banks tend to link to the other banks with similar degree, on the other hand a negative assortativity coefficient shows that banks tend to link to the other banks with dissimilar degree. In other words, if the network has a positive assortativity measure, then the banks having higher number of degrees tend to connect to the banks also having higher degrees.

Assortativity measure, r , is calculated as follows where l denoting the total number of edges, i_e and j_e showing the number of degrees of bank i and j on the same edge, e (Newman, 2002).

$$r = \frac{l^{-1} \sum_{e \in E} i_e j_e - \left[\frac{l^{-1} \sum_{e \in E} (i_e + j_e) \right]^2}{\frac{l^{-1} \sum_{e \in E} (i_e^2 + j_e^2) - \left[\frac{l^{-1} \sum_{e \in E} (i_e + j_e) \right]^2}}{2}} \quad (4)$$

Fig. 6 shows time-series evolution of assortativity measure for each instrument. First, we observe that negative assortativity is seen in all exposures except security holdings suggesting that banks having larger number of degrees tend to connect to banks having smaller number of degrees. Since, large banks have larger degrees, negative assortativity also indicates that tendency of larger banks to connect with smaller banks is higher. This finding is compatible with the literature suggesting that interbank markets have a core-periphery structure. Contrary to the other instruments, positive assortativity is observed for security relations for some periods due to the nature of these relations. In Türkiye, large banks issue securities (i.e. they borrow) since these banks have better credit scores and can borrow by issuing bonds at cheaper rates. If larger banks which aim to diversify their assets invest in these issuances (i.e. they lend) then banks having higher number of degrees are connected to the other banks with larger degrees causing assortativeness measure to be positive. In Fig. 6d, we observe that there are some periods in which assortativity is negative in securities. Depending on the size/number of degrees of the lender bank, assortativity in Turkish interbank market may be positive or negative. Second, we observe that the general tendency in assortativity of deposit, on-balance and total exposures is to be more negative compared to the initial analysis periods.

3.4. Rich-club coefficient

Rich-club coefficient is a measure showing whether banks having higher degrees are connected with each other. Rich club coefficient is calculated with the following formula where $E_{>k}$ shows the number of edges between nodes having degree more than k and $N_{>k}$ shows the number of banks having degrees more than k . While the numerator of the formula shows the number of actual links between banks having degrees more than k , the denominator shows the number of all possible links between banks having degree more than k .

Table 4
Country comparison for densities of interbank markets.

	Germany	Netherlands	Italy	UK	Mexico	Türkiye
Number of Banks	1732 ± 85	91–103	125–200	176	47	47.7 ± 1.8
Type of Exposures	Large loans (extended credit in the amount of at least EUR 1.5 million or 10% of the liable capital of the bank)	Large loans (extended credit in the amount of at least EUR 1.5 million)	Unsecured money-market transactions in Italian interbank market (e-MID)	Exposures to top 20 banks (loans, deposits, equity and security holdings, security lending, repo, derivatives)	Loans, deposits, securities, repos, derivatives	Loans, deposits, securities, repos, derivatives, other off-balance
Time Period	1999–2012	1998–2008	1999–2010	2011	2011	2002–2021
Density	0.41%	8%	8%–18%	7%	26.5%	23.3% ± 4.5%
Source	Craig and von Peter (2014)	In't Veld and Langfield et al. (2014)	Fricke and Lux (2015)	Langfield et al. (2014)	Solis-Montes (2013)	

Notes: Craig and von Peter (2014) report that density increases to 0.66% when banks with no interbank positions are excluded. Similarly, Solis-Montes (2013) reports that average density relative to active banks is 28.12%. Density of UK is not reported specifically in Langfield et al. (2014), however it is estimated using mean degree reported as 12.3 and number of banks as 176 in the paper.

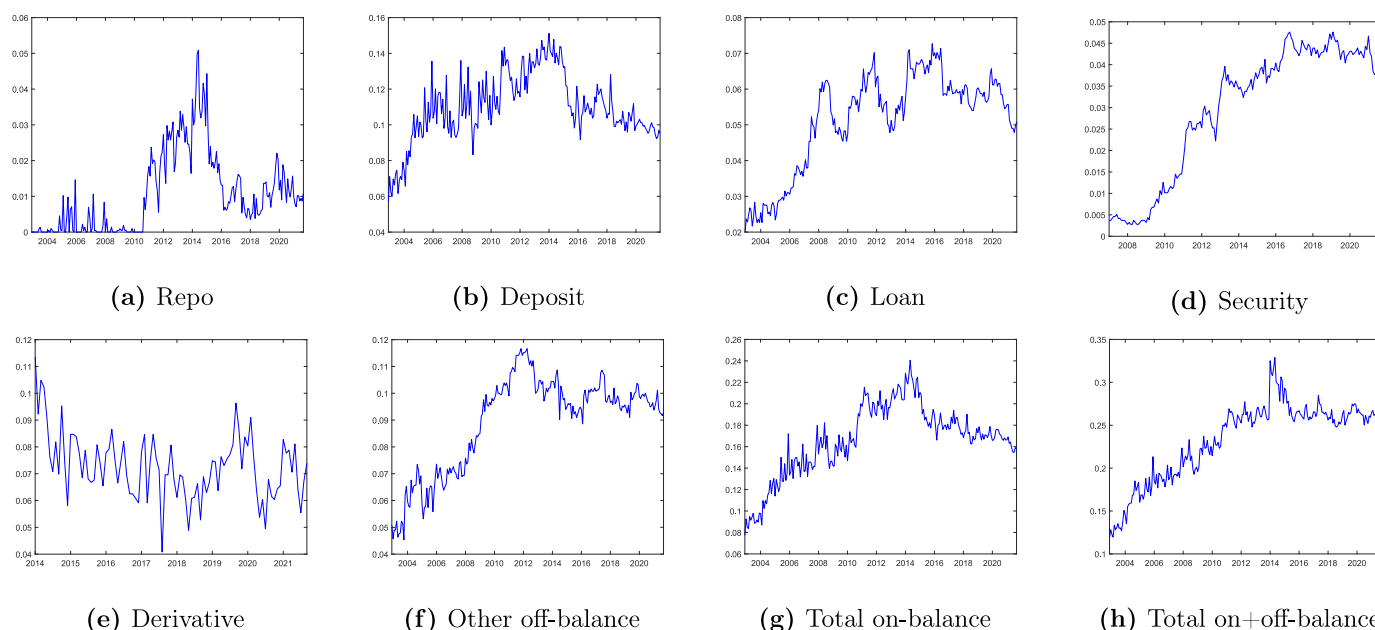


Fig. 5. Density. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off balance shows sum of on-balance and off-balance sheet relations.

$$\theta(k) = \frac{2E_{>k}}{N_{>k}(N_{>k} - 1)} \tag{5}$$

If the rich-club coefficient is high for large k , this means that large degree banks are connected with each other. Rich-club coefficient estimation for Turkish interbank market on-balance sheet relations (Fig. 7a) shows that if as a threshold of $k = 5$ is used, then only the 20–30% of links that is possible between the banks having more than 5° are present in the actual network. We observe that, as k increases, rich club coefficient increases and if $k = 25$ is used, then coefficient increases up to 90% showing the presence of rich-club effect. For total relations including off-balance sheet relations (Fig. 7b), we observe similar findings with on-balance sheet relations except the value of rich-club coefficient. For $k = 5$, rich-club coefficient can be up to 40%, however, for $k = 25$, rich-club coefficient increases up to 80%.

Silva et al. (2016) suggest that if a network is showing negative assortativity indicating that large degree nodes (core banks) are connected with small degree nodes (periphery banks) and a high rich-club coefficient is present, showing that large degree nodes are

connected with each other, then the network shows a core-periphery structure. Similar to the finding of Silva et al. (2016) for Brazilian interbank relations, we find that Turkish interbank fits to core-periphery structure by employing assortativity and rich-club coefficient. This is also compatible with the finding of Sümer and Özyıldırım (2019) which uses Craig and von Peter (2014) algorithm to show Turkish interbank market has a core-periphery structure.

3.5. Clustering coefficient

Clustering coefficient of node i shows the probability of being connected of two other nodes, j and k that are connected to node i . Clustering coefficient is also a measure of the substitutability of a node. If a node has large clustering coefficient, neighbors of this node has already established relations with each other, so this node has less intermediating role to connect other nodes which means the node is more substitutable. Clustering coefficient (C_i) of node i is calculated as the total number of links between the neighbors of the node over total number of connections that is possible between

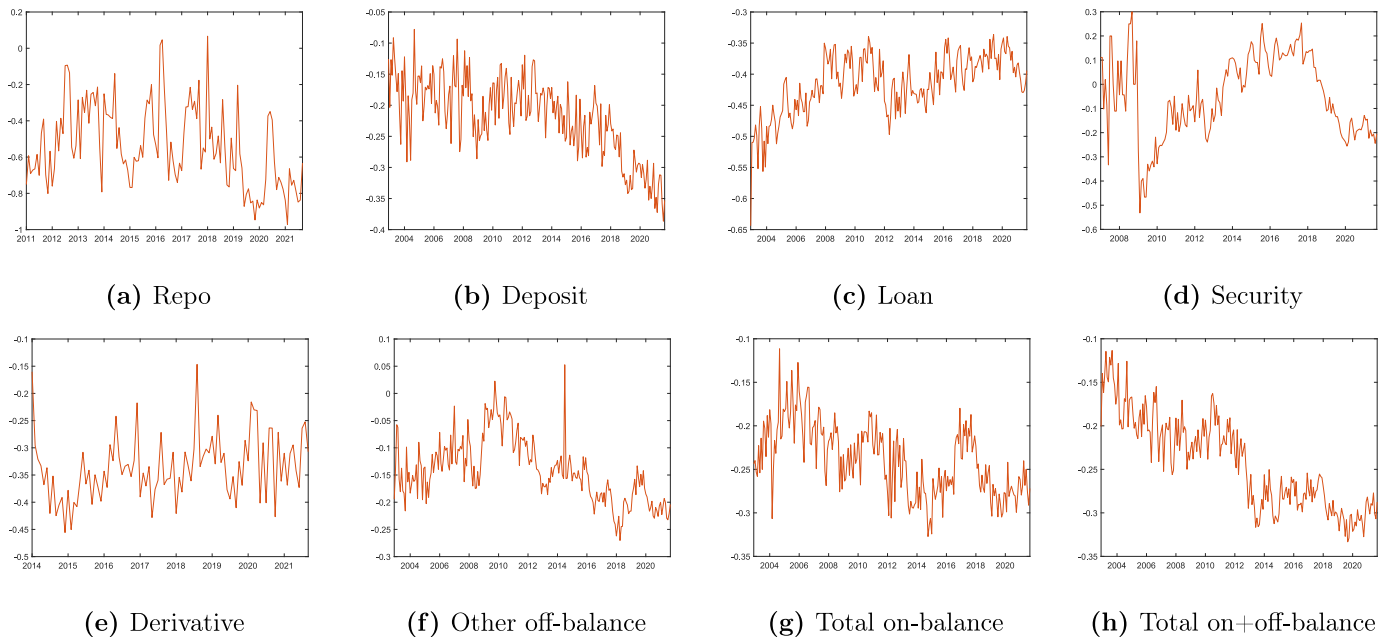


Fig. 6. Assortativity. In this figure, assortativity of repo transactions is shown starting from year 2011 since before that date, in most of the periods there is only two banks connected to each other, so there is only one edge and assortativity of the network can not be estimated. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off balance shows sum of on-balance and off-balance sheet relations.

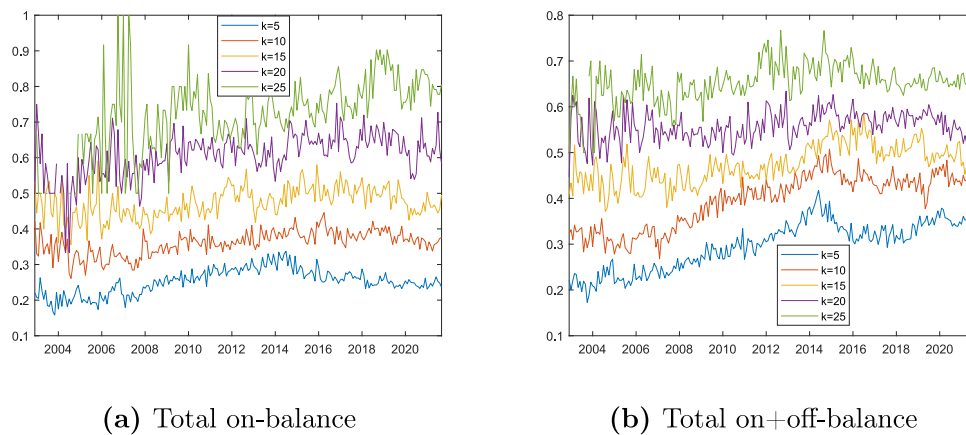


Fig. 7. Rich-club Coefficient. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off-balance shows sum of on-balance and off-balance sheet relations.

these neighbor nodes:

$$C_i = \frac{\sum_j \sum_k a_{ij} a_{ik} a_{jk}}{k_i(k_i - 1)} \quad (6)$$

where k_i denoting total degree of node i .

Fig. 8 shows average clustering coefficient for each instrument. Average clustering coefficient is calculated by dividing the sum of clustering coefficient of each node over total number of active nodes. For repo relations, average clustering coefficient is close to 0 until 2010 due to small number of banks having repo relations. With the change in monetary policy applications of Central Bank, clustering coefficient increased slightly after year 2011 (Fig. 8a). Compared to 2002, average clustering coefficient in deposit, loan, security and other off-balance sheet relations increased, meaning that intermediating role of banks decreased and substitutability of

the banks increased in these relations (Fig. 8b, c, Fig. 8d and f). However, for derivative relations, there is no increasing or decreasing trend in average clustering coefficient (Fig. 8e).

Similar to the analysis made for degree measure, we calculate average clustering coefficient based on asset ranks of banks which is presented in Table 5. For total exposures, while average clustering coefficient is 8.1% for top five banks, it increases to 10.8%, 15.4% and 23.7% for top 6–10, top 11–15 and all banks respectively. Thus, large banks have lower clustering coefficient which means that their counterparties are generally not connected with each other and for that reason they are less substitutable in terms of intermediating role. This result is similar to the findings in the literature. For example, Silva et al. (2016) show for Brazil interbank market that from the borrower perspective, large banks have less clustering coefficient compared to non-large banks for all the periods, however from the lending perspective the comparison result changes

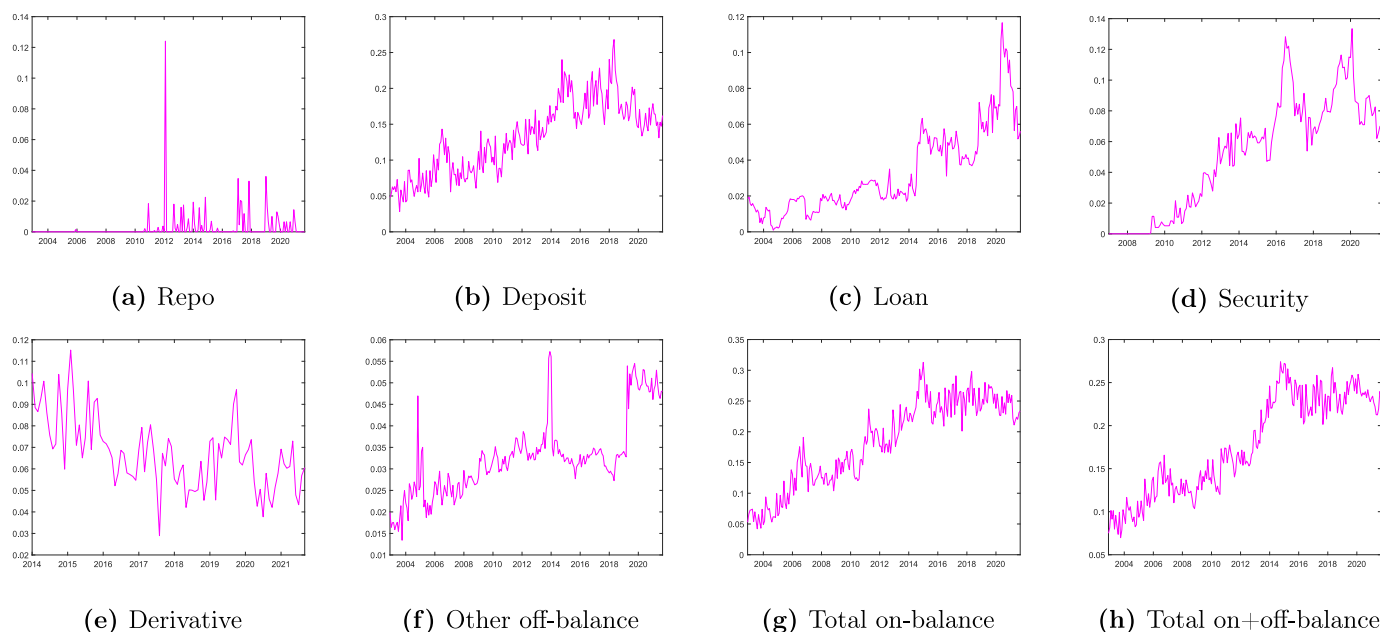


Fig. 8. Average Clustering Coefficient. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off-balance shows sum of on-balance and off-balance sheet relations.

depending on the analysis period. We observe that besides total exposures, the pattern of increase in average clustering coefficient as asset size decreases is observed in on-balance sheet exposures and deposit exposures.

3.6. Closeness centrality

Shortest path distance between two banks is the length of the path linking these banks with minimum number of edges. For example, if a bank is directly linked to another bank, then their distance is 1, if they are not directly connected but there is only one bank intermediating between these banks, then their distance is 2. Closeness centrality of a bank shows the average distance of the bank to all banks in the network. Closeness centrality for bank i , is calculated with the following formula where d is denoting the shortest path distance between bank i and bank j .

$$C_C(i) = \left[\sum_{j=1}^n d(i,j) \right]^{-1} \tag{7}$$

If there are some disconnected banks in the system, then the distance to these disconnected banks become infinity and calculation of closeness centrality with the above formula becomes

impossible. Since, there are also disconnected banks in Turkish interbank market, the following formula is used as suggested by Opsahl et al. (2010), where the sum of inverse of the distances is taken and it is normalized by dividing this sum to total number of banks.

$$C_C(i) = \left[\sum_{j=1}^n 1/d(i,j) \right] / N \tag{8}$$

A bank that has higher closeness centrality means that bank is closer to the other banks in the network and serves intermediary function. If a shock hits this bank, then this bank may transmit this shock to the other banks, so the bank with higher closeness centrality measure has higher systemic importance. Fig. 9 shows average closeness centrality for each instrument. For repo exposures, similar to other network measures, average closeness centrality was close to zero until 2010. The change in Central Bank monetary policy applications in 2010, closeness centrality increased slightly, however average closeness centrality in repo transactions is quite small compared to other instruments. For deposit exposures, average closeness centrality increased to 30% in year 2006 and fluctuated around this value in the following years. Average closeness centrality is higher in deposit and other off-

Table 5
Average clustering coefficient based on asset rank of banks.

	Top 5 Banks	Top 6–10 Banks	Top 11–15 Banks	All Banks
Repo	0.002	0.004	0.009	0.004
Deposit	0.020	0.090	0.206	0.179
Loan	0.069	0.035	0.068	0.056
Security	0.038	0.119	0.013	0.080
Derivative	0.101	0.101	0.106	0.067
Other off-balance	0.069	0.052	0.015	0.038
On-balance	0.051	0.089	0.170	0.249
Total	0.081	0.108	0.154	0.237

Notes: Banks are ranked based on their asset size in each month and Top 5, Top 6–10 and Top 11–15 banks are determined. Then, average clustering coefficient of the top banks for 2014–2021 period is calculated. All banks column shows the average clustering coefficient of all active banks. While on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total shows sum of on-balance and off-balance sheet relations.

balance sheet exposures compared to other instruments. An increasing trend in average closeness centrality is observed in loan and security exposures through years. For derivative exposures, average closeness centrality fluctuated around 22%. For other off-balance sheet items, average closeness centrality increased up to year 2012 to the level of 35% and then stabilized around 25%. The outlook for on-balance sheet exposures and total exposures is similar, with financial deepening and increase in number of inter-bank links and exposures, we observe that average closeness centrality increased up to year 2014 and stabilized around 43% and 55% respectively.

Similar to degree and clustering coefficient, average of closeness centrality measure based on asset rank of the banks is used to analyze whether larger banks are closer to the remaining banks in the network. Table 6 shows that for total exposures while average closeness centrality for top five banks is 68.7%, the average decreases to 64.1% for top 6–10 banks and to 58.9% for top 11–15 banks which supports the hypothesis that larger banks are also the banks closer to the other banks. The similar pattern is seen in all instruments except repo and deposit. For repo transactions, Central Bank is the main liquidity provider and intermediating role of the banks in repo transactions is less since banks can conduct repo transactions directly with each other in Borsa İstanbul. For deposit relations, some smaller banks are also active and closer to the remaining banks and for that reason closeness centrality of the banks do not change significantly in these relations.

3.7. Betweenness centrality

Betweenness centrality is a network centrality measure showing the importance of the bank for the money flow between banks. A bank that is between the flow path of many other banks is a central bank/systemically important bank since the default of that bank would distort the money flow between other banks that passes through it. Betweenness centrality for a bank is calculated as the ratio of number of times a node acts as an intermediating bank over the shortest banks of two other banks with the following formula:

$$C_b(i) = \sum_{s \neq t \neq i} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{9}$$

where σ_{st} denotes the number of shortest paths going from bank s to t and $\sigma_{st}(i)$ is the number of shortest paths from s to t that passes through bank i . Betweenness centrality measure of each bank is normalized by dividing with the number of two-pair combinations in the network which is shown by C_b^* as follows:

$$C_b^* = \frac{2}{(n-1)(n-2)} C_b(i) \tag{10}$$

Fig. 10 presents average betweenness centrality measure for each instrument for 2002–2021 period. Similar to other measures, average betweenness centrality for repo relations was close to zero until 2010 and then increased slightly. While average betweenness centrality measure is much more smaller in repo relations, it is highest in deposit relations indicating that there are more banks serving as intermediary in deposit network. For total on-balance sheet relations (Fig. 10g) and total on-balance and off-balance sheet relations (Fig. 10h), we observe a decreasing trend in average betweenness centrality. This finding indicates that as the number of banks started to be more connected through time and density increased, intermediating role of the banks decreased.

Similar to the other network measures, average betweenness centrality is calculated for top five, top 6–10, top 11–15 banks based on banks' asset size which is presented in Table 7. We observe that, in all instruments, top five banks have larger average betweenness centrality and this measure decreases smoothly as the asset size decreases. This suggests that, larger banks have larger betweenness centrality and higher importance in terms of intermediary role for the banking network.

While Table 5, Tables 6 and 7 show the averages between 2014 and 2021 for clustering coefficient, closeness centrality and betweenness centrality, we also present time-series evolution of these measures in Fig. 11. This figure shows that, in all analysis period, larger banks have smaller clustering coefficient and larger closeness centrality and betweenness centrality. Moreover, we

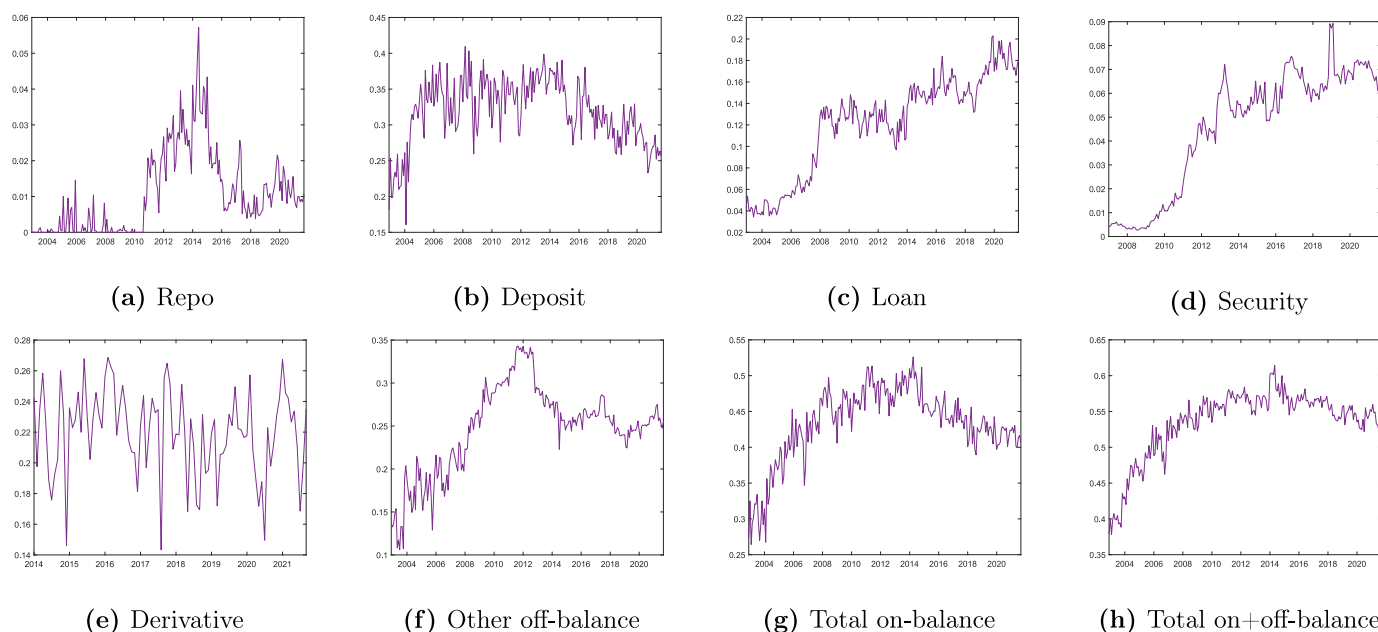


Fig. 9. Average Closeness Centrality. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off-balance shows sum of on-balance and off-balance sheet relations.

Table 6
Average closeness centrality based on asset rank of banks.

	Top 5 Banks	Top 6–10 Banks	Top 11–15 Banks	All Banks
Repo	0.013	0.025	0.026	0.016
Deposit	0.313	0.334	0.343	0.307
Loan	0.395	0.318	0.247	0.161
Security	0.120	0.100	0.021	0.064
Derivative	0.394	0.343	0.317	0.220
Other off-balance	0.418	0.385	0.274	0.256
On-balance	0.520	0.500	0.484	0.440
Total	0.687	0.641	0.589	0.558

Notes: Banks are ranked based on their asset size in each month and Top 5, Top 6–10 and Top 11–15 banks are determined. Then, average closeness centrality of the Top banks for 2014–2021 period is calculated. All banks column shows the average closeness centrality of all active banks. While on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total shows sum of on-balance and off-balance sheet relations.

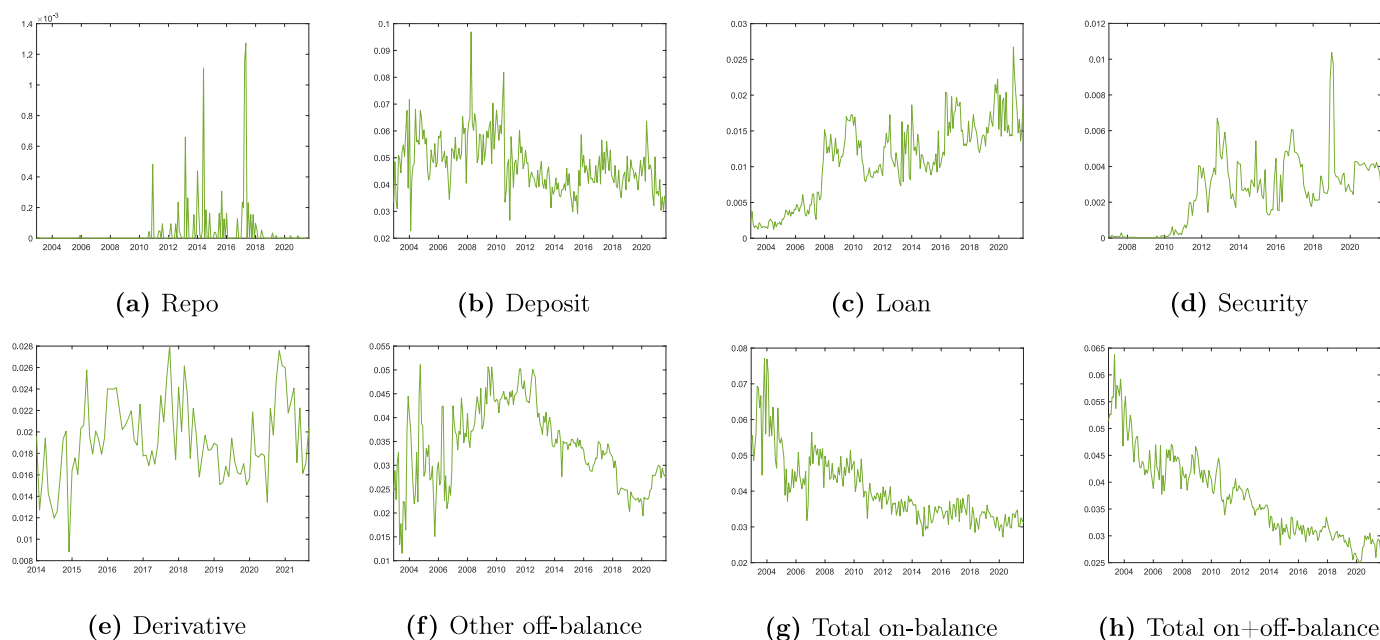


Fig. 10. Average Betweenness Centrality. While total on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total on + off-balance shows sum of on-balance and off-balance sheet relations.

Table 7
Average betweenness centrality based on asset rank of banks.

	Top 5 Banks	Top 6–10 Banks	Top 11–15 Banks	All Banks
Repo	0.000	0.000	0.000	0.000
Deposit	0.134	0.076	0.049	0.043
Loan	0.057	0.049	0.028	0.015
Security	0.015	0.008	0.000	0.003
Derivative	0.102	0.031	0.015	0.019
Other off-balance	0.089	0.059	0.032	0.029
On-balance	0.149	0.073	0.032	0.033
Total	0.157	0.058	0.017	0.030

Notes: Banks are ranked based on their asset size in each month and Top 5, Top 6–10 and Top 11–15 banks are determined. Then, average closeness centrality of the Top banks for 2014–2021 period is calculated. All banks column shows the average closeness centrality of all active banks. While on-balance shows the total of on-balance sheet relations (repo, deposit, loan and security), total shows sum of on-balance and off-balance sheet relations.

observe that discrepancy between large banks and all banks scaled up from 2002 to 2014 suggesting that the role of large banks has increased with the financial deepening.

4. Conclusion

Default of systemically important institutions during the global financial crisis has shown the importance of understanding the structure of interbank relations. The identification of the

characteristics of interbank relations by regulatory authorities especially in stable times would allow any financially integrated economy to be ready for the risks that may result from shock spillovers. Due to data gaps, interbank relations has been studied with derived networks from total payables/receivables or for only limited number of periods or instruments. In the interbank network literature, the studies either aim to reveal network structure or aim to identify systemically important banks via contagion models. In this study, we aim to contribute to the

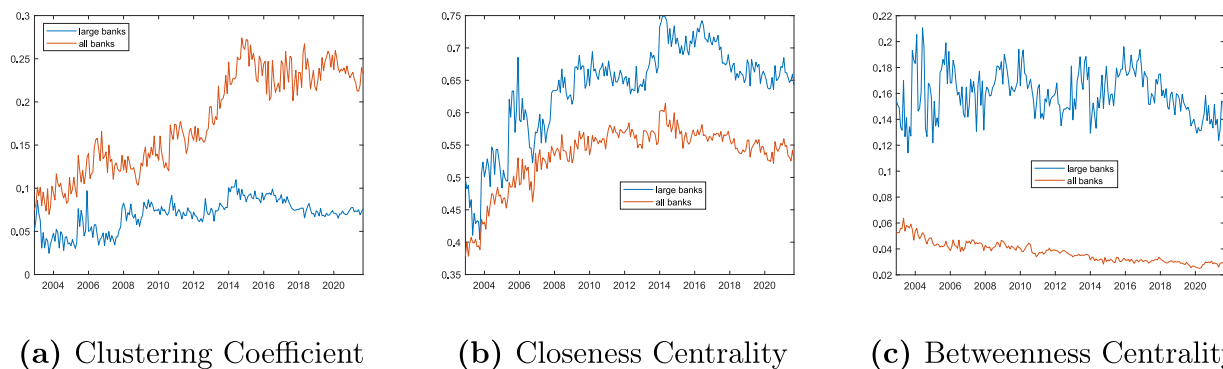


Fig. 11. Comparison for Large Banks and All Banks. In this graph, averages for total on-balance and off-balance sheet relations are shown. Large banks show top 5 banks in terms of asset size in each month.

literature via exploring the network characteristics of Turkish interbank market for a period of 20 years from 2002 to 2021. We show that analysis of all interbank relations matter since instrument level networks show different characteristics. In this study, we cover all type of on-balance and off-balance sheet interbank relations.

We find that density of Turkish interbank market increased through time, which indicates that banks have been more connected as of 2021 compared to previous years. Therefore, we suggest that regulatory authorities should pay more attention to understand the possible risks that may occur due to interbank relations. We show that banks that are larger in asset size have higher degree, betweenness centrality and closeness centrality measures indicating the importance of these banks in terms of intermediation and substitutability. So, we believe that network centrality measures can be used to identify systemically important banks which are large and have important roles for interbank relations. Finally, with assortativity and rich-club coefficient measures, we demonstrate that Turkish interbank market shows a core-periphery structure. While the network resiliency of different network models are similar during stable times, core-periphery models are more stable in crisis periods. On the other hand, as suggested in the literature, resiliency of core-periphery models depend on the degree of risk diversification of core bank and loss absorbing capacity/capital. Therefore, we believe that after identifying core banks with the suggested network measures in this study, monitoring credit risk diversification and capital levels of these banks would help to improve the resilience of Turkish banking sector.

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