The Structure of the Mexican Interbank Market*

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Abstract

This paper provides evidence that the Mexican interbank market is tiered. I fit the core-periphery model developed by Craig and von Peter (2010) to 157 daily networks (from January 3 to August 15, 2011) of bilateral exposures (aggregated and disaggregated) between 41 commercial banks and 6 development banks.The main findings are (i) the core-periphery model provides a better fit to the Mexican interbank market than random networks, that is there are money center banks that intermediate with the rest of the banks in the market, (ii) the size and the composition of this group of banks is remarkably stable over time for aggregated (and some disaggregated) networks, (iii) the relations (borrowing and lending) between banks in the core and the periphery are asymmetric. The results are robust and significant.

JEL classification: D85, G21, C63.
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Introduction

The structure of the interbank market is a key element in achieving the two more common mandates of central banks, price stability and financial stability. On the one hand, monetary policymakers would like to know whether it plays a role in the mechanisms through which monetary policy impacts real economic activity and inflation. If any, this role might be played through the bank-based transmission channels, namely the bank lending channel and the bank capital channel.[1] On the other hand, the structure of the interbank network is a critical determinant of systemic risk because the propagation mechanism depends greatly on network topology (Imakubo and Soejima, 2010).[2] In fact, the understanding of systemic risk is of central importance for maintaining financial stability (Martinez-Jaramillo et al., 2010).

Since the novel contribution of Allen and Gale (2000), the application of network theory to the study of financial networks has increased and interbank networks have receive special attention. The lack of detailed data on bilateral relations usually represents a barrier to study the empirical properties of real-world interbank networks. One strategy to address this is to assume that the structure of the interbank relations maximizes the entropy of the network, which means that banks are assumed to spread their borrowing and lending as evenly as possible among the other banks in the market (Sheldon and Maurer, 1998; Upper and Worms, 2004).[3] The maximum entropy assumption tends to generate complete networks; that is, there is a link between (almost) all banks in the market.[4]

Some authors have assumed that the links in interbank networks follow a random process. A model commonly used tend to be the one developed by Erdös and Rényi (1959). According to this model, a bank is likely to have a link with every bank in the market with a probability p. When $p < 1$, the net-

[1]See Boivin et al. (2010) for a practical description of both channels.

[2]It should be acknowledge, however, that the topology of the interbank lending network alone cannot indicate financial fragility. The probability distribution of the initial shock, the size of the losses and the correlations play a key role in the determination of the robustness or fragility of a financial system. See Martinez-Jaramillo et al. (2010).

[3]This assumption has also been used when bilateral relations data exist but in order to fill missing links (van Lelyveld and Liedorp, 2006).

[4]In contagion analysis, Mistrulli (2007) shows that this assumption tends to underestimate the extent of contagion.

work would likely be sparse but incapable to replicate certain characteristics of real-world networks like the small-world property, i.e. some banks tend to connect with their neighbors with a greater probability. This characteristic is captured by the model developed by Watts and Strogatz (1998); however, it cannot generate a network structure in which some banks act as hubs. This feature is replicated by a scale-free network, where the number of links a bank has with other banks follows a power-law distribution. Barabási and Albert (1999) developed a model for generating scale-free networks based on preferential attachment.[5] This model performs better than Erdös-Rényi random graphs or small-world networks in replicating many properties of real-world interbank networks. The fact that some banks are more connected than others raises the question of whether it is possible to identify them.

Craig and von Peter (2010) developed a novel model that uses both network theory and economic concepts to study the structure of financial networks. The model acknowledges that there may be banks that intermediate between the other banks in the market. Unlike complete and random network models, the core-periphery model allows for a tiered structure.

The study of the topology of interbank markets in various countries has shed light on the properties of these networks.[6] The evidence shows that (Ficke and Lux, 2012): (i) interbank networks are sparse,[7] (ii) degree[8] distributions and transaction volumes appear to be scale-free, (iii) clustering coefficients are usually quite small, (iv) interbank networks are close to small-world structures, and (v) the networks show disassortative mixing[9]. These results appear to support the idea of tiering in interbank markets.

Indirect tests of tiering has been conducted for the U.S. (Furfine, 1999)

[5] New banks are likely to be linked to the already more connected banks in the network.

[6] Switzerland (Müller, 2003), Austria (Boss et al., 2004), Japan (Inaoka et al., 2004), United States (Sorämaki et al., 2007), Brazil (Cajueiro and Tabak, 2007), Italy (Iori et al., 2008), Denmark (Rørdam and Bech, 2009). Various network measures have also been computed for Germany (Craig et al., 2010) and Mexico (Martinez-Jaramillo et al., 2012).

[7] This favors avoiding the use of the maximum entropy assumption in the study of interbank markets.

[8] Degree indicates the number of banks to which a bank is connected to. The in-degree of a bank is the number of banks from which it borrows and the out-degree is the number of banks to which it lends.

[9] There are links between dissimilar nodes. In particular, nodes with low-degree tend to trade with high-degree nodes, and vice versa.

and Japan (Imakubo and Soejima, 2010). Minoiu and Reyes (2012) suggest tiering in a global banking network. Direct tests of tiering has been conducted for the interbank market in Germany (Craig and von Peter, 2010), Italy (Ficke and Lux, 2012) and the Netherlands (van Lelyveld and in 't Veld, 2012). All these cases support interbank tiering.

The aim of this paper is to contribute to the literature on direct tests of tiering by applying the core-periphery model to the interbank market in Mexico. Using daily data from Banco de México from January 3 to August 15, 2011 (i.e. 157 matrices), I find that the core-periphery model provides a better fit to the Mexican interbank market than random networks, i.e. there are money center banks that intermediate between the other banks in the market. The size and the composition of this group of banks is remarkably stable over time for aggregated (and some disaggregated) networks. Furthermore, there are asymmetries in the relations (borrowing and lending) between the banks in the core and the periphery.

The paper is structured as follows. The first section briefly describes the core-periphery model. Section 2 explains the data and describes some characteristics of the interbank network. The results as well as the robustness and significance tests are presented in section 3. Section 4 concludes.

1 Interbank tiering

The idea behind the tiering model is that a network can be divided into two tiers, the core and the periphery. In a perfectly tiered structure, banks in the core are linked to each other and to those in the periphery, while banks in the periphery are only linked to those in the core.

In an interbank network, banks can be classified as active or inactive. Active banks in turn can be classified as lenders and/or borrowers. Nonetheless, not all banks perform both activities at the same time. Banks that lend *and* borrow to other banks in the market can be denoted as intermediaries. This does not imply that intermediaries are connected to one another but, at the same time, it does not discard the existence of a *group of intermediaries* where this happens. This group of banks, if it exists, comprises the core and the rest of the banks comprise the periphery.

1.1 Networks

In this paper an interbank network is represented by an adjacency matrix $\mathbf{N}$ of dimension n equal to the number of banks.[10] Therefore, $\mathbf{N}_{ij}$ equals 1 if there is a link between banks i and j $(i, j \in \{1, \ldots, n\})$, where bank i is the lender and bank j is the borrower. Row i thus represents the lending that bank i offers to the market, while column i represents the lending the market provides to bank i. It is important to note that the borrowing bank j receives from bank i is not necessarily equal to the lending provided from bank j to bank i. The interbank network $\mathbf{N}$ is therefore a directed (and non-symmetric) matrix. Finally, it is assumed that no bank lends to itself, thus every entry in the diagonal of $\mathbf{N}$ is equal to zero.

1.2 Model

The core-periphery model can be expressed in terms of bilateral relations. Borgatti and Everett (1999) argue that the defining property of core-periphery structures in social networks are the relations *within* the tiers, namely that top-tier banks (those in the core) lend to each other, while lower-tier banks (those in the periphery) do not. This generates a subgroup of highly connected and another of loosely connected nodes. Craig and von Peter (2010) point out that the relations *between* the tiers are also relevant when analyzing interbank networks, namely that top-tier banks lend to and borrow from (some) lower-tier banks. Thus, the key characteristic of core banks is that they *intermediate* between those in the periphery.[11] All these relations define a 'perfectly' tiered structure, which can be represented by a four-block matrix:

$$\mathbf{T} = \begin{pmatrix} \mathbf{CC} & \mathbf{CP} \\ \mathbf{PC} & \mathbf{PP} \end{pmatrix} = \begin{pmatrix} \mathbf{1} & \mathbf{RR} \\ \mathbf{CR} & \mathbf{0} \end{pmatrix}.$$

The top-left block ($\mathbf{CC}$) comprises the banks in the core; given that

[10] Every bank in the market is a node in the network.

[11] Craig and von Peter (2010) show that the core is a (strict) subset of intermediaries. They also show that intermediaries are not part of the core if they do not lend to, or do not borrow from the periphery, which implies that there will be no errors in the off-diagonal blocks of $\mathbf{T}$. See below.

all banks in the core lend to each other it is represented by **1**, a block of ones (other than the diagonal). Equivalently, the bottom-right block (**PP**) comprises the banks in the periphery, which is represented by a zero block (**0**) given that those banks do not lend to each other. Off-diagonal blocks represent the lending banks in the core provide to those in the periphery (**CP**-block) and the lending provided by periphery banks to those in the core (**PC**-block). Given that core banks must lend to, and must borrow from, at least one bank in the periphery, the top-right block must have at least one 1 per row (Row Regular, **RR**) and the bottom-left block must have at least one 1 per column (Column Regular, **CR**). Note that the four blocks capture the links within and between the tiers.

The model can be fitted to real-world networks in order to test whether they are tiered. The size of **T** will depend on the size of the network and the size of the core is to be determined. Any missing link in the top-left block in **T** (other than the diagonal) is counted as an error. Similarly, any link in the bottom-right block in **T** is also counted as an error. Every row of zeros in **CP** (that is, a core bank that does not lend to the periphery) and every column of zeros in **PC** (that is, a core bank that does not borrow from the periphery) produce as many errors as banks in the periphery, i.e. one error for every periphery bank to which a core bank could have lent or from which it could have borrow. This way of counting errors emphasizes the relation between the core and the periphery. The optimum size of the core is the one which produces the minimum number of errors between the original network and **T**.[12] The number of errors relative to the number of actual links in the network will be referred to as the *error score*, which will allow to compare across periods and types of networks.

2 Data

I use daily data from Banco de México to construct the network **N** of actual bilateral exposures between 41 commercial banks and 6 development banks. The time span for this study goes from January 3 to August 15, 2011, which

[12]Finding the optimal core size is an *NP-hard* problem. Ben Craig and Goetz von Peter kindly provided the sequential optimization algorithm they developed to estimate the optimal size of the core.

gives rise to 157 matrices of bilateral relations. The interbank exposures comprise deposits, credits and loans between the 47 banks considered. Further, Banco de México collects not only interbank exposures but issuer (commercial bank securities), counterparty (repos, derivatives) and FX exposures.[13] Therefore, the results will be reported for the aggregated (or total) and four disaggregated cases.[14]

Over the sample period the value of total interbank positions is MXN 236.8 million (USD 19.3 million)[15] on average, which compares with MXN 5.6 trillion (USD 4.6 billion) of total assets in the banking system at the end of July 2011 (see Figure 1 (a)). The number of unconnected (inactive) banks is 1.34 on average; the number of banks that only lend is 2.8 while the number of banks that only borrow is 1.62. The majority of banks (41.23) are intermediaries as they both borrow and lend (see Figure 1 (b)). Although there are 2,162 possible links (which would give rise to a complete network) between the banks considered, the average density[16] of the networks is 26.51%. The average density relative to active banks is 28.12% (see Figure 1 (c)).[17]

Table 1 summarizes equivalent statistics for every type of exposure over the sample period. As can be seen, the market for bank issuances is the most valuable, representing 62.54% of the total exposures network, followed by the market for deposits, credits and loans. Interestingly, all the banks participating in the FX market act as intermediaries. The market where more banks *intermediate* is that for repos and derivatives followed by the market for deposits, credits and loans. In the interbank and issuer categories the number of banks that only lend is higher than the number of banks that only borrow. Densities per type of exposure are 2 to 4 times lower than those for the total exposures networks. On average, the most sparse network is that for the FX market,which is due to the high number of unconnected banks.

[13]This data provides detailed descriptions of interbank relations which is generally not available to other central banks.

[14]Annex A shows figures for the disaggregated cases equivalent to those for the aggregated case reported in the main part of the paper.

[15]The exchange rate at the end of the sample period was USDMXN 12.2424.

[16]The density of a network represents the actual number of links relative to all possible links $n(n-1)$.

[17]Martinez-Jaramillo et al. (2012) report further network measures for the Mexican interbank market.

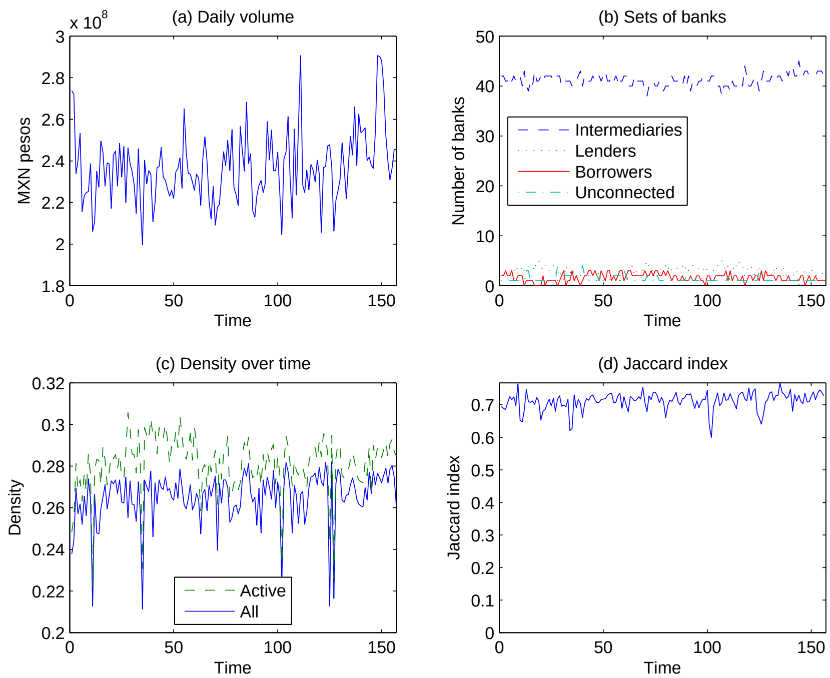

Figure 1: Dynamics of the total exposures network: (a) daily volume, (b) banks' role in the market, (c) daily density and (d) Jaccard index.

	Interbank	Issuer	Countpty	FX
Volume (MXN mill.)	48.2	148.1	14.1	26.4
Intermediaries	29.97	21.29	33.1	25.3
Lenders	5.52	9.75	2.79	0
Borrowers	3.43	2.73	4.44	0.01
Unconnected	8.08	13.24	6.68	21.69
N density (%)	8.16	7.59	11.24	6.92
Density of active (%)	11.98	14.86	15.34	24.64
Jaccard index	0.76	0.96	0.51	0.48

Table 1: Statistics per type of exposure.

Direct tests of tiering have used quarterly data (Craig and von Peter, 2010; Ficke and Lux, 2012; van Lelyveld and in 't Veld, 2012) even when daily data is available (Ficke and Lux, 2012) due to the noise (volatility) daily data may create. The Jaccard index measures the similarity between two sets and can be used to assess the stability of the structure of links in subsequent networks. It is defined as

$$J = \frac{M_{11}}{M_{11} + M_{01} + M_{10}},$$

where M_{11} is the number of existing links that remained, M_{01} is the number of links newly created and M_{10} is the number of links that ceased to exist. According to Snijders et al. (2009), stable (social) networks have values of J above 0.3. The mean value of J for the total exposures networks is 0.7115. Figure 1 (d) shows the Jaccard index over the time span. It can be seen that the link structure obtained from daily data does not change abruptly. The last row in Table 1 shows that the average Jaccard index for every type of exposure is above 0.3.[18]

3 Results

Once the core-periphery model is applied to the Mexican interbank networks for total exposures, the optimal size of the core was equal to 15.8 banks on average, which is equivalent to 38.3% of intermediaries. This contrasts with the usual classification of big, medium and small banks in Mexico based on the size of their assets. For instance, it is commonly said that there are 7 big banks (G7) in the country. According to Sachs (2010), under certain conditions, the stability of a money center system increases with an increasing number of core banks. The relative high number of core banks found in the Mexican interbank market (compared to those in Europe as shown in Table 2) may explain why systemic risk in Mexico is low based on contagion analysis

[18]When density increases from one period to the next, Snijders et al. (2009) propose to look at the remaining links in period t relative to the existing links in period $t-1$, that is $M_{11}/(M_{11} + M_{10})$. They recommend a value higher than 0.6. The mean value of this ratio for the total interbank exposures network is 0.832. The lowest mean value of this ratio for the disaggregated cases is 0.655.

(Martinez-Jaramillo et al., 2010). Furthermore, the core is stable over the time span as can be seen in Figure 2.

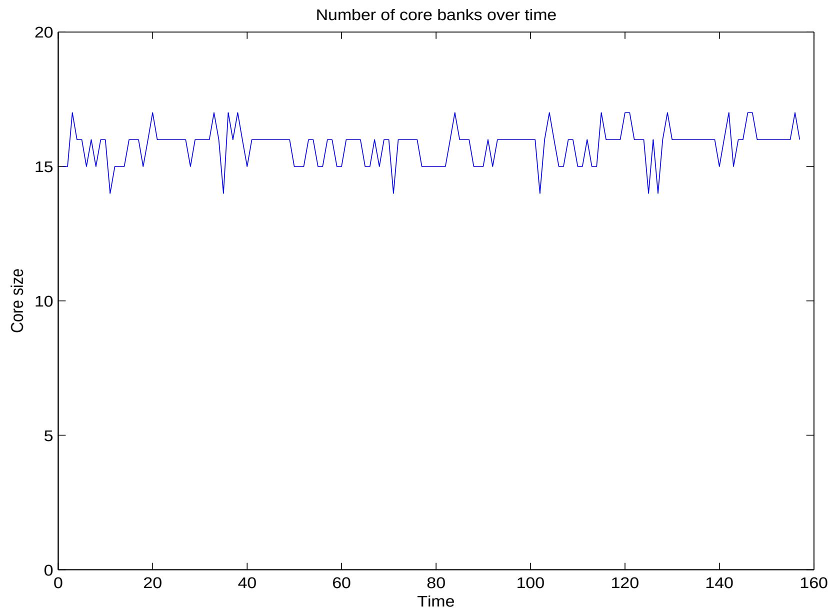

Figure 2: Structural stability over time.

The composition is also stable. From the banks in the core, 94.06% are likely to stay in the core in the next period. Similarly, from the banks in the periphery, 96.96% are likely to stay in that tier in the next period. The probability of a bank to switch from the core to the periphery is 5.94%, while that of switching from the periphery to the core is lower (3.04%). Figure 3 shows the evolution of this probabilities.

All the results described up to now are consistent with those found for the interbank markets in Germany (Craig and von Peter, 2010), Italy (Fricke and Lux, 2012) and the Netherlands (van Lelyveld and in 't Veld, 2012) as can be seen in Table 2. Tiering appears to be independent of the number of banks participating in the interbank market. As previously discussed, the number of banks in the core compared to the number of intermediaries is relatively high in Mexico (38.3%). The probability for a core bank in period $t-1$ to stay in that tier in the next period ($P_{core \rightarrow core}$) is similar for the interbank markets in Germany and Mexico.

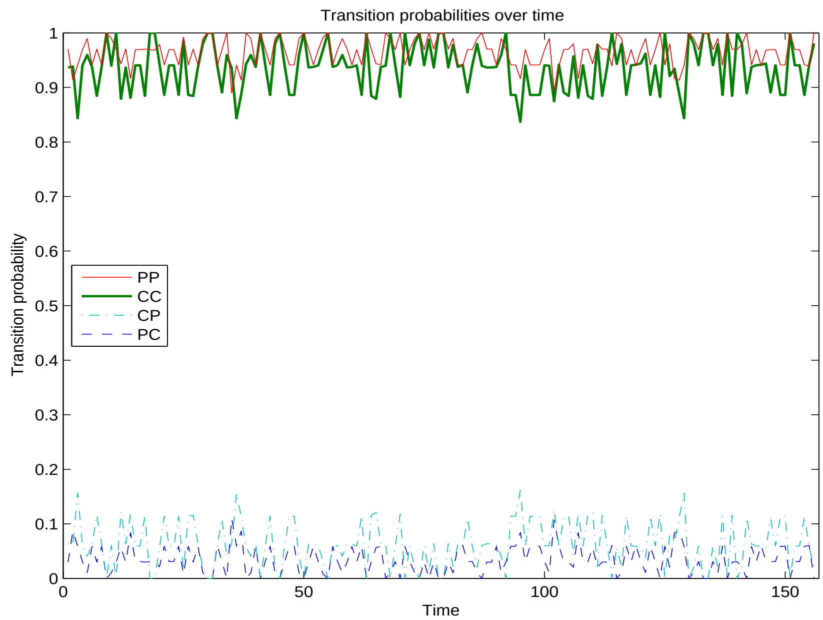

Figure 3: Transition probabilities over time.

	Germany	Italy	Netherlands	Mexico
Banks	2182	118	100	47
Active banks	1802	118	100	46
Intermediaries as % of banks	76.6	75	-	87.7
Core size	45	32	15	16
Core size as % of interm.	2.7	36	-	38.3
Error score	0.12	0.42	0.29	0.25
N density (%)	0.41	21	8	26
CC density (%)	66	56	-	74.2
$P_{core \to core}$ (%)	94	83.2	83	94.06
$P_{periph. \to periph.}$ (%)	99.1	90.5	96	96.96
$P_{core \to periph.}$ (%)	4.9	15.6	16	5.94
$P_{periph. \to core}$ (%)	0.1	5.55	2	3.04
Data frequency	Qtrly.	Qtrly.	Qtrly.	Daily

Table 2: Tiering in Europe and Mexico.

Figure 4 shows the links within and between the tiers. Figure 4 (a) shows the links between the core banks estimated for the last day of the study. According to the **PP**-block in **T**, there should be no links between periphery banks; when fitting the core-periphery model to real-world networks there are, however, some links between those banks. Figure 4 (b) shows the (extra) links in the **PP**-block. The links between the tiers can be seen in figure 4 (c) and (d).[19] Note that it seems to be more lending operations from periphery to core banks than borrowing operations by periphery banks (from core banks). The following subsection shows that this is not a coincidence.

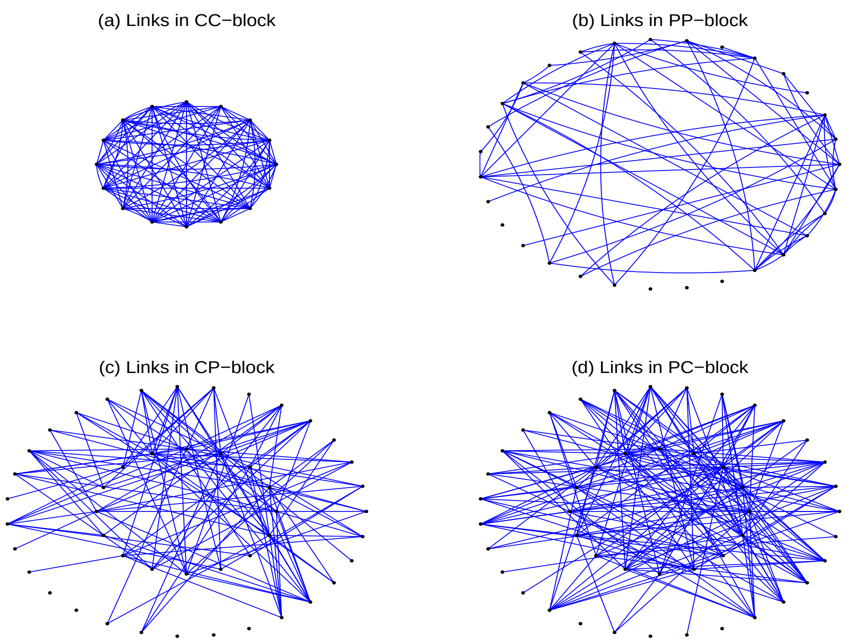

Figure 4: Links within and between the tiers as of August 15, 2011.

3.1 Asymmetry

An interesting finding from applying the core-periphery model to the Mexican interbank networks is that the lending and borrowing between the tiers differ. In other words, there exists asymmetry between the lending core banks

[19]See Annex B for the aggregated core-periphery representation.

provide to those in the periphery (**CP**-block) and the borrowing the former receive from the latter (**PC**-block).

The value of the (extra) links in the periphery provides an idea of the relevance of these transactions in the network. For the total exposures network this is MXN 18.28 million, which represents only 7.76% of the value of total interbank positions; however, Figure 5 shows that the value of the transactions in the **PP**-block has been increasing lately. By contrast, the value of the transactions between the banks in the core is MXN 121.7 million on average. Transaction volumes are slightly higher in the **PC**-block (MXN 48.82 million) than in the **CP**-block (MXN 48.09 million).

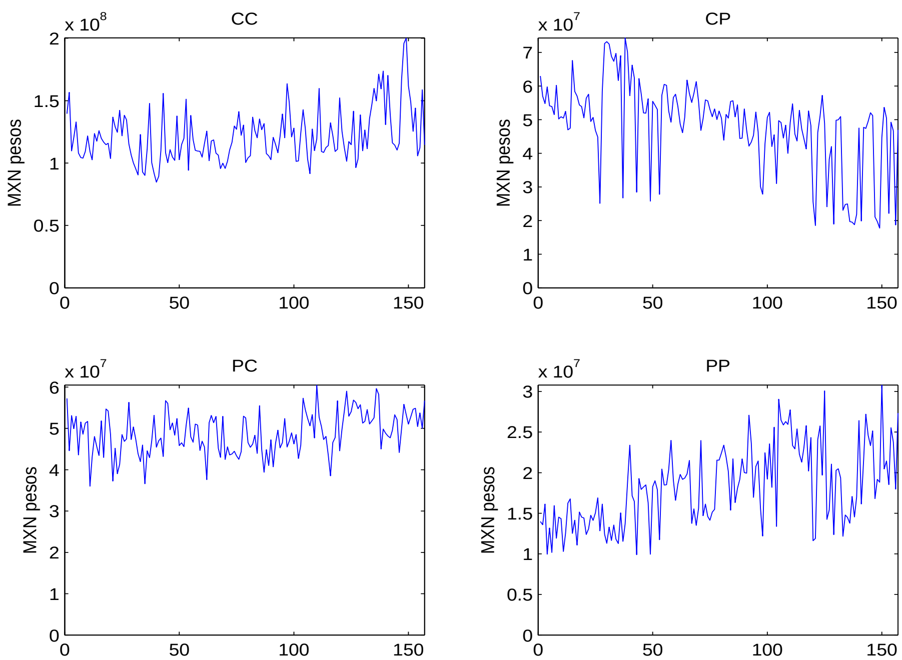

Figure 5: Transaction volumes per block over time.

The density of the core (**CC**-block) is 74.19%, which contrasts with a density of 26.51% for the original networks. The **PP**-block density is 9%. The densities of the **CP**-block and the **PC**-block lie between these extremes but they differ. The average **CP**-block density is 27.93%, while that for the **PC**-block is 35.86%.[20] The difference remains remarkably constant over

[20]Fricke and Lux (2012) find the reverse for the Italian case. For instance, the density

time. A simple two sample t-test rejects that both means are equal. Figure 6 shows the density of the total exposures networks compared to block densities over the time span.

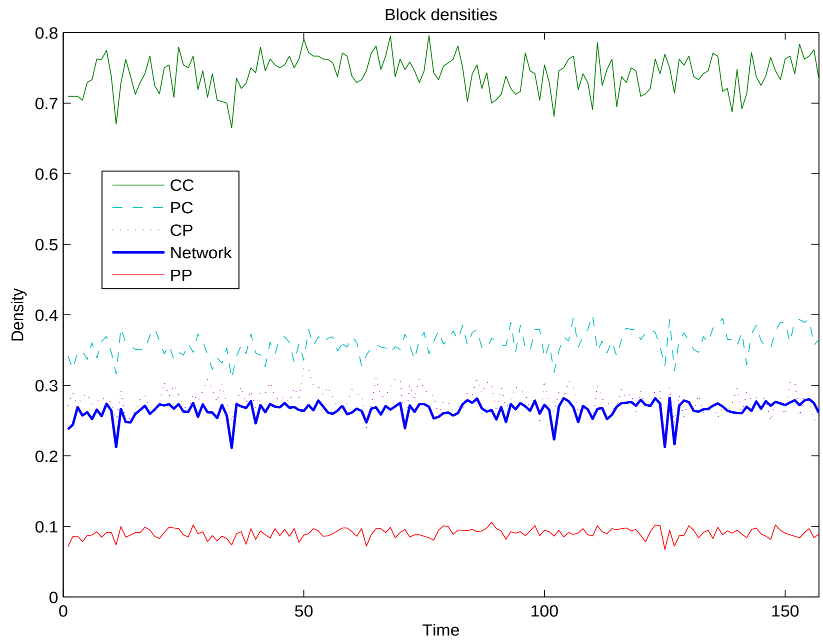

Figure 6: Block densities over time.

Asymmetry is also present in transition probabilities. As mentioned before, the probability of a bank to switch from the core to the periphery is higher (5.94%) than that of switching from the periphery to the core (3.04%).This difference is consistent with what has been found for other markets (see Table 2).

Table 3 summarizes equivalent results (on average over the sample period) for every type of exposure. In all but the FX category transaction volumes in the **PC**-block are higher than in the **CP**-block. The differences in transition probabilities hold when analyzing disaggregated networks, although the transition probabilities to stay in the core decrease slightly while, in general, transition probabilities to stay in the periphery increase slightly.

of the **CP**-block is three times higher than that of the **PC**-block

The difference in off-diagonal block densities only holds for the interbank and issuer exposures.

Table 3 also shows that core sizes per type of exposure are lower than in the total exposures networks. Some core banks in the latter play a role in more than one market while some periphery banks becomes core after disaggregating.

	Interbank	Issuer	Countpty	FX
Core size	8.07	6.7	9.86	7.49
CC volume (MXN mill.)	6.22	31.5	5.71	5.74
PP volume (MXN mill.)	14.22	28.53	0.78	6.97
CP volume (MXN mill.)	10.32	31.57	3.27	6.83
PC volume (MXN mill.)	17.46	56.47	4.37	6.82
CC density (%)	54.71	54.87	71.67	65.91
PP density (%)	3.48	3.77	3.62	1.94
CP density (%)	13.81	8.03	18.15	14.52
PC density (%)	16.06	22.79	17.77	14.5
$P_{core \to core}$ (%)	91.15	90.69	91.19	80.23
$P_{periph. \to periph.}$ (%)	98.16	98.44	97.65	96.15
$P_{core \to periph.}$ (%)	8.84	9.3	8.8	19.76
$P_{periph. \to core}$ (%)	1.83	1.55	2.34	3.84

Table 3: Tiering per type of exposure.

Note that in three cases the relative value of the **PP**-block increases. In fact, in the interbank and the FX categories the value of the **PP**-block is higher than that of the **CC**-block. This will become clear when significance is considered.

3.2 Significance

On average, the error score for the total exposures networks is 0.2562. The total number of links inconsistent with **T** is 146.65, where 61.55 errors are within the core (missing links) and 85.1 are within the periphery (extra links). Figure 7 shows the evolution of the error score over the time span. It also shows the amount due to the errors in the core and in the periphery; on average the periphery accounts for a higher amount of errors than the core.

Table 4 shows the error scores per type of exposure. One important conclusion from Table 4 is that the error score increases significantly from what is obtained aggregating all the exposures. This is the result of sparser (lower density) disaggregated networks (see Table 1). Again, the periphery accounts for a higher amount of errors than the core.

	Interbank	Issuer	Countpty	FX
Error score	0.437	0.476	0.301	0.306
Errors in **CC**	25.85	18.39	24.79	16.62
Errors in **PP**	51.33	59.59	48.38	29.22

Table 4: Error score per type of exposure.

Fitting the model to simulated random networks with similar characteristics (dimension and density) as the original network and calculating the error score from the corresponding $\mathbf{T}$ per simulation, yields a way to assess the extent of tiering observed in $\mathbf{N}$. In other words, if the error score of the optimal core for $\mathbf{N}$ is lower than a predefined percentile of the distribution of error scores obtained from the simulated random networks, it is then rejected

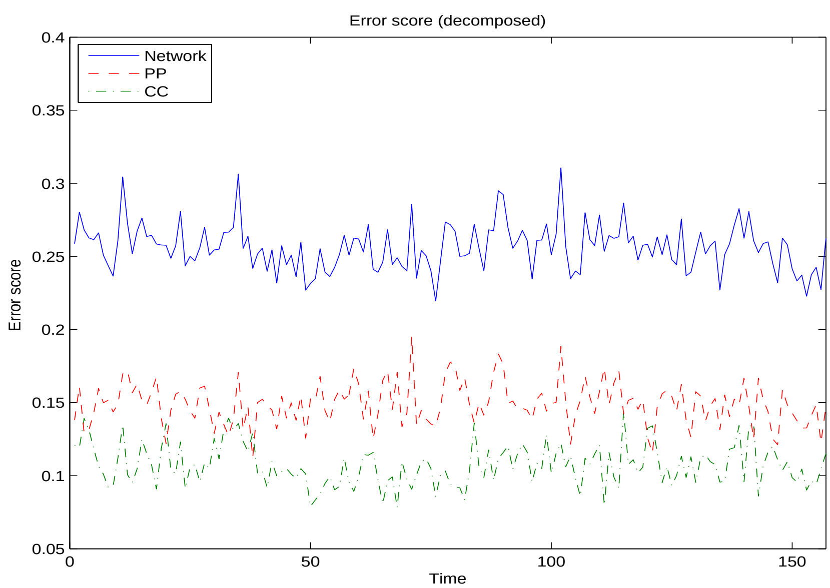

Figure 7: Error score over time.

that the original network is random. In that case, it is said that **N** exhibits tiering.[21]

In this paper, 1,000 random networks are simulated with the same dimension and density (relative to active banks) as the original networks on average. After every realization, the core-periphery model is fitted and the error score is calculated. The random models used for the simulations are: Erdös-Rényi, Small-World, and Scale-Free. Table 5 summarizes the results.

	Erdös-Rényi	Small-World	Scale-Free
Core size	14.02	12.89	13.79
Simulated networks density (%)	28.14	26.67	26.54
1st percentile error score	0.553	0.6539	0.3157

Table 5: Significance test.

From the three types of random networks simulated, the scale-free model is closer to a tiered structure than the Erdös-Rényi and Small-World models. This reflects the fact that scale-free networks tend to give rise to hubs. However, the average error score is quite large compared to that obtained for the total exposures networks. Further, the lowest error score from scale-free networks is 0.3025. In fact, this result rejects the null hypothesis that Mexican interbank networks are random. Figure 8 displays the distribution of errors for every type of random network.

Another way to test for significance is not to use average values for simulations but the actual ones *per observation*.[22] Figure 9 also supports the idea of tiering in the Mexican interbank market.

The same tests were applied for every type of exposure. The Fricke-Lux test allows to conclude that tiering is present in two out of the four categories, namely issuer and counterparty. It cannot be rejected that the interbank and the FX categories are different form a scale-free network. Intuitively, finding tiering in an aggregated network does not imply that it is present in every component.

[21]This test was originally suggested by Craig and von Peter (2010) and has been replicated by van Lelyveld and in 't Veld (2012).

[22]This test was originally suggested by Fricke and Lux (2012).

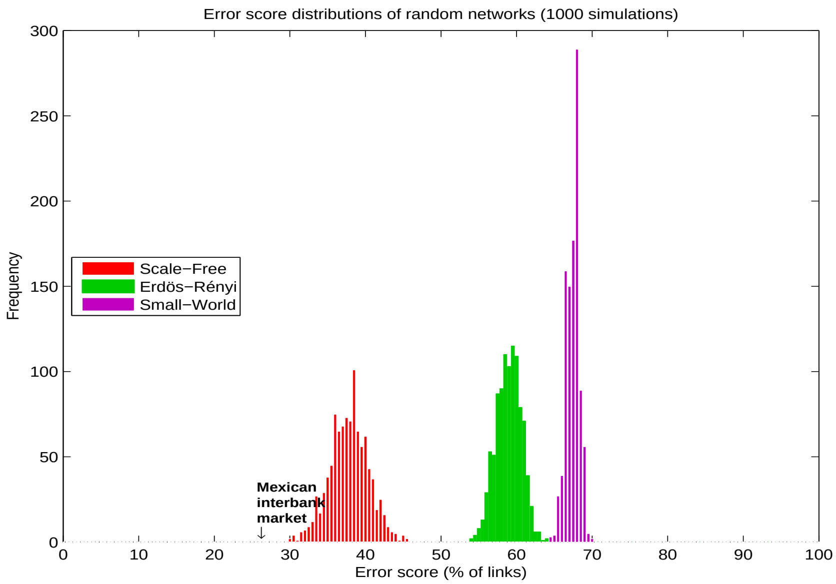

Figure 8: CvP significance test.

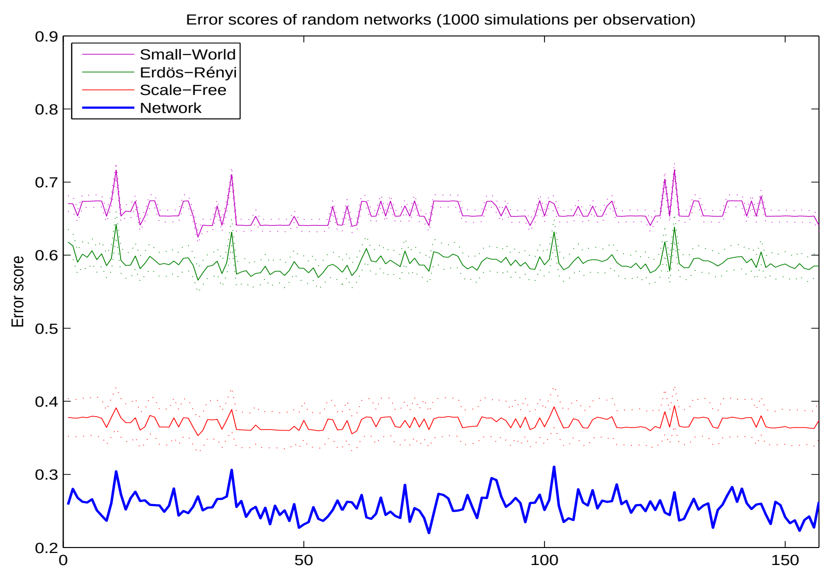

Figure 9: FL significance test.

3.3 Robustness

I perform different robustness checks to assess whether the results are sensible to changes in the network.[23] First, given that the sequential optimization algorithm *estimates* the number of core banks, I run the algorithm 1,000 times per observation to see whether the composition of the core changes simply by re-estimating the core. The average core size was 15.7918 for the total exposures networks, which is just slightly different from the one previously reported.

Removing banks from the network is an interesting test to assess whether tiering continues to appear.[24] I removed one core bank and fit the core-periphery model for the resulting networks. This is done for five different banks originally identified in the core. Table 6 shows the results. The average core size is no lower than 15 banks compared to 15.8 obtained from the aggregated network. The density of the core is slightly lower than the one previously reported. The average error score ranges across 0.259 and 0.269.

	Bank removed				
	A	B	C	D	E
N density (%)	24	24	25	24	24
Core size	15.09	15.01	15.19	15.13	15.08
CC density (%)	73	73	74	72	72
Error score	0.266	0.2686	0.2590	0.2681	0.269

Table 6: Robustness check. Removing banks from the network (core).

Another robustness check is to change the weights of the errors per block. By assigning more weight to the core, every missing link in the core is more penalized. Consequently, it would yield a tighter core than assigning an equal weight to all the errors per block. By contrast, penalizing more every extra link in the periphery would yield a looser core. The aim is to test robustness around the equally-weighted block errors.[25] Table 7 shows that the results are not sensible when varying the weights to the errors in each tier. In fact,

[23] I ran similar tests for every type of exposure and reach the same conclusions.

[24] This is not a systemic contagion analysis. For literature related to financial contagion see Upper (2007).

[25] In a first exercise it is assigned a value of 1.1 and 0.9 instead of 1 to the errors from the **CC**-block and the **PP**-block, respectively. Remember that there are no errors in the off-

the core is tighter when the errors in that tier are more penalized, while the density of the core increases and the error score decreases. The reverse happens when the extra links in the periphery are more penalized.

	Balanced	Tighter core	Tighter periphery
Core size	15.8	15.09	16.83
CC density (%)	74	76	72
Error score	0.2562	0.2476	0.2629

Table 7: Robustness check. Changing the weights to the errors in each tier.

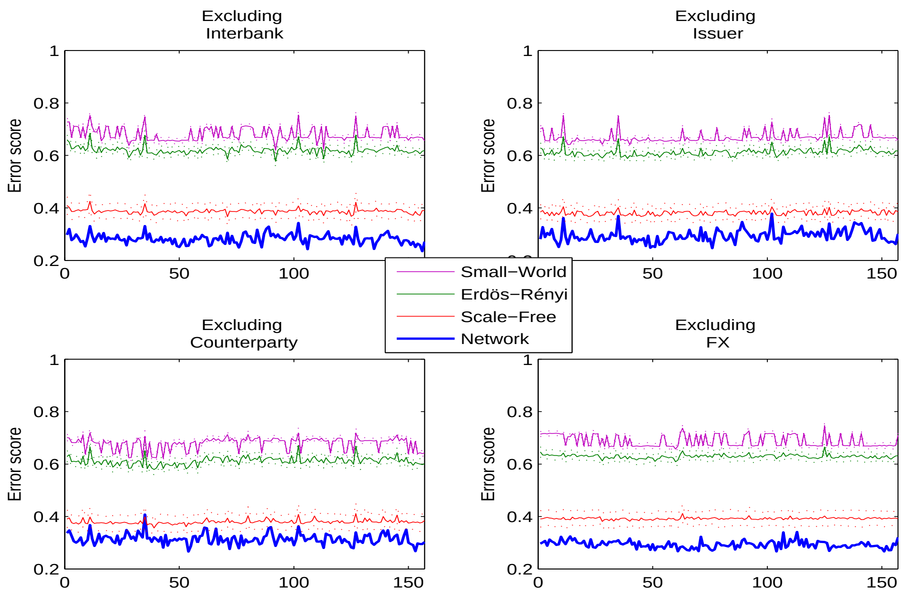

Figure 10: FL significance test.

A final test is to remove each category from the total exposures networks. Table 8 shows the results and Figure 10 displays the FL test for every case. The main result, i.e. a tiered Mexican interbank network, does not change.

diagonal blocks of **T** (see footnote 11). The same exercise is repeated but now penalizing more the extra links in the periphery.

	Category Excluded			
	Interbank	Issuer	Countpty	FX
Volume (MXN mill.)	188.7	88.74	222.7	210.5
Intermediaries	38.29	40.92	36.49	41.18
Lenders	3.2	1.69	3.79	2.85
Borrowers	2.92	1.74	1.48	1.62
Unconnected	2.59	2.65	5.24	1.35
N density (%)	21.7	22.51	19.47	22.19
Density of active (%)	24.34	25.32	24.74	23.54
Core size	14.4	14.55	13.42	14.01
CC volume (MXN mill.)	84.7	46.53	72.1	114.9
PP volume (MXN mill.)	21.1	6.63	28.85	13.87
CP volume (MXN mill.)	39.6	15.6	60.2	40.1
PC volume (MXN mill.)	43.1	19.9	61.5	41.6
CC density (%)	73.98	69.57	67.47	69.59
PP density (%)	7.81	8.08	7.01	7.94
CP density (%)	23.04	27.02	21.32	24.68
PC density (%)	29.27	29.42	30.04	33.13
Error score (ES)	0.282	0.294	0.314	0.293
Errors in **CC**	51.54	60.19	55.35	57.18
Errors in **PP**	80.47	82.48	76.68	83.35
$P_{core \to core}$ (%)	93.48	92.13	91.97	96.01
$P_{periph. \to periph.}$ (%)	97.07	96.43	96.77	98.29
$P_{core \to periph.}$ (%)	6.51	7.86	8.02	3.99
$P_{periph. \to core}$ (%)	2.92	3.56	3.22	1.7
1st prctile ES for S-W (CvP test)	0.679	0.63	0.666	0.644
1st prctile ES for E-R (CvP test)	0.571	0.566	0.565	0.588
1st prctile ES for S-F (CvP test)	0.315	0.307	0.316	0.321
ES for S-W (FL test)	0.679	0.669	0.679	0.687
ES for E-R (FL test)	0.62	0.611	0.611	0.629
ES for S-F (FL test)	0.387	0.381	0.379	0.392

Table 8: Tiering after excluding categories (average figures unless otherwise stated).

4 Conclusions

This paper provides evidence that the Mexican interbank market is tiered. The size and the composition of the core is remarkably stable over time. Core size is in fact higher than what is commonly thought (G7). The findings reported in this paper supports the argument that there are money center banks that intermediate between the other banks in the market. Besides this, it is possible to identify which banks are in the core and the market(s) where they play a significant role. Tests for the extent of tiering observed in the Mexican interbank market show that the results are robust and significant. This may help financial authorities to focus resources when carrying out their duties regarding the financial safety net in Mexico. For instance, after the recent financial crisis it has been highlighted the necessity to identify systemic institutions and to develop effective regimes that allow financial authorities to resolve them.

It has also been found that the relation between the tiers is asymmetric. Periphery banks are more prone to lend to, rather than to borrow from, the core which is reflected in the higher number of links and volume of the **PC**-block relative to the **CP**-block. In addition, it is more likely that a bank leaves the core than becoming part of it.

A similar analysis can be made with a broader set of financial institutions given that the level of detailed information considered in this study is not limited to banks but is also available for other players in the market (insurers, investment firms, pension funds and foreign financial institutions). Further, the findings in this paper can be complemented with the analysis of topological measures of the networks, mainly those using valued networks. Even tiering can be studied with valued networks (Fricke and Lux, 2012).

The work in this paper can also be extended to study the effects of the recent financial crisis on the Mexican interbank structure. Recent studies (van Lelyveld and in 't Veld, 2012; Fricke and Lux, 2012) have pointed out that the structure changes (the core size and the density in the **CC**-block tend to decrease) during a crisis and that a crisis mainly affects the behavior of core banks and the volume of transactions.

These routes of research are a promising avenue as an additional criteria for identifying systemic institutions and for the analysis of stress tests and contagion exercises for the Mexican financial system. It would also enhance our understanding of the structure of the Mexican interbank market and the way it changes during crises.

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Annex A

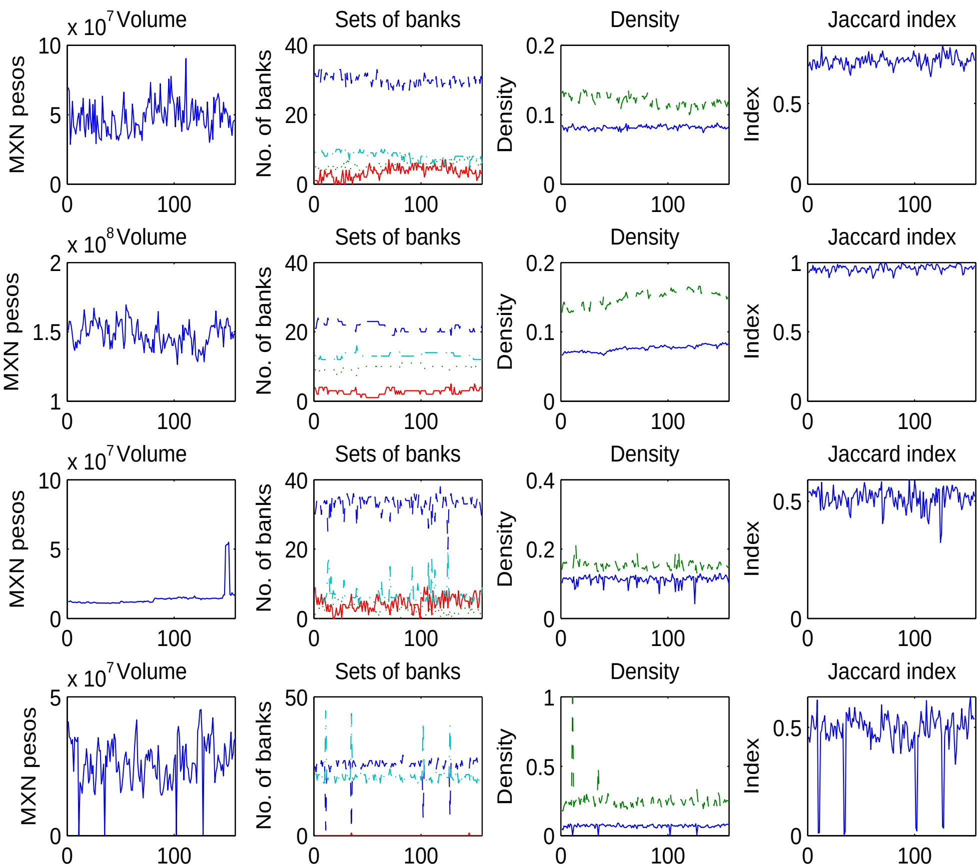

Figure A-1: Statistics per type of exposure. Rows from top to bottom: interbank, issuer, counterparty and FX. Columns from left to right: daily volumes, densities, sets of banks and Jaccard index. Second column: intermediaries (dashed blue line), lenders (dotted green line), borrowers (solid red line) and unconnected banks (dash-dotted cyan line). Third column: density relative to all banks (solid blue line) and density relative to active banks (dashed green line).

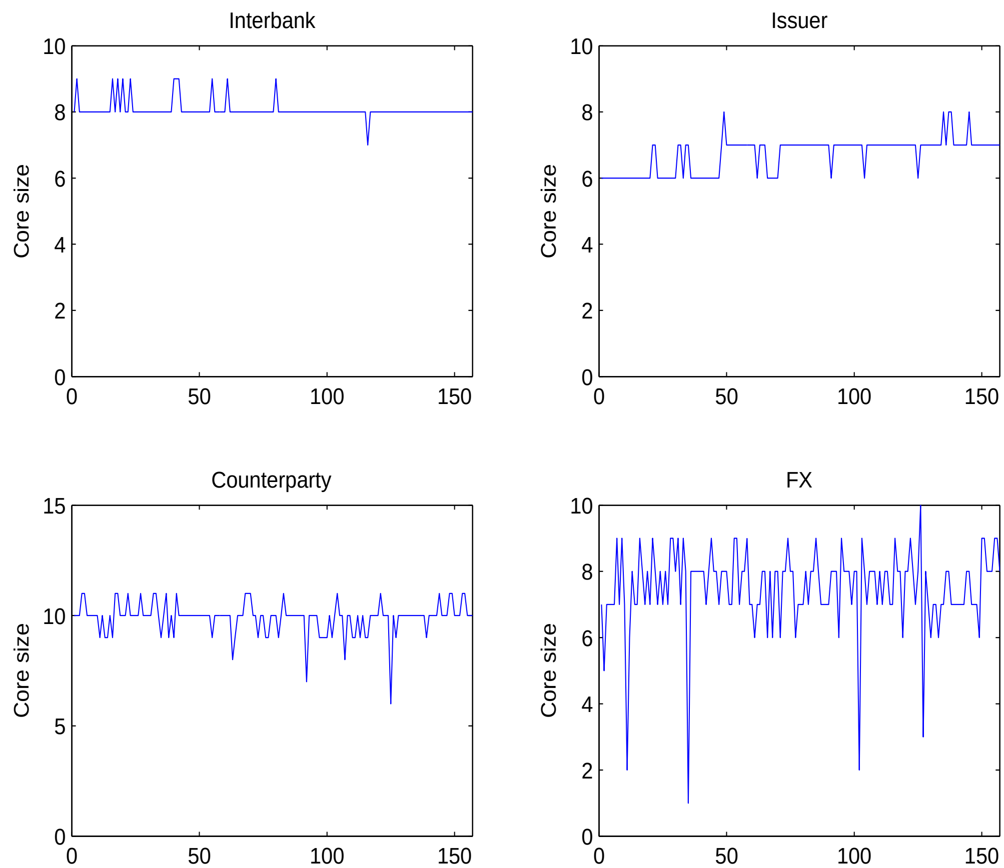

Figure A-2: Core sizes per type of exposure.

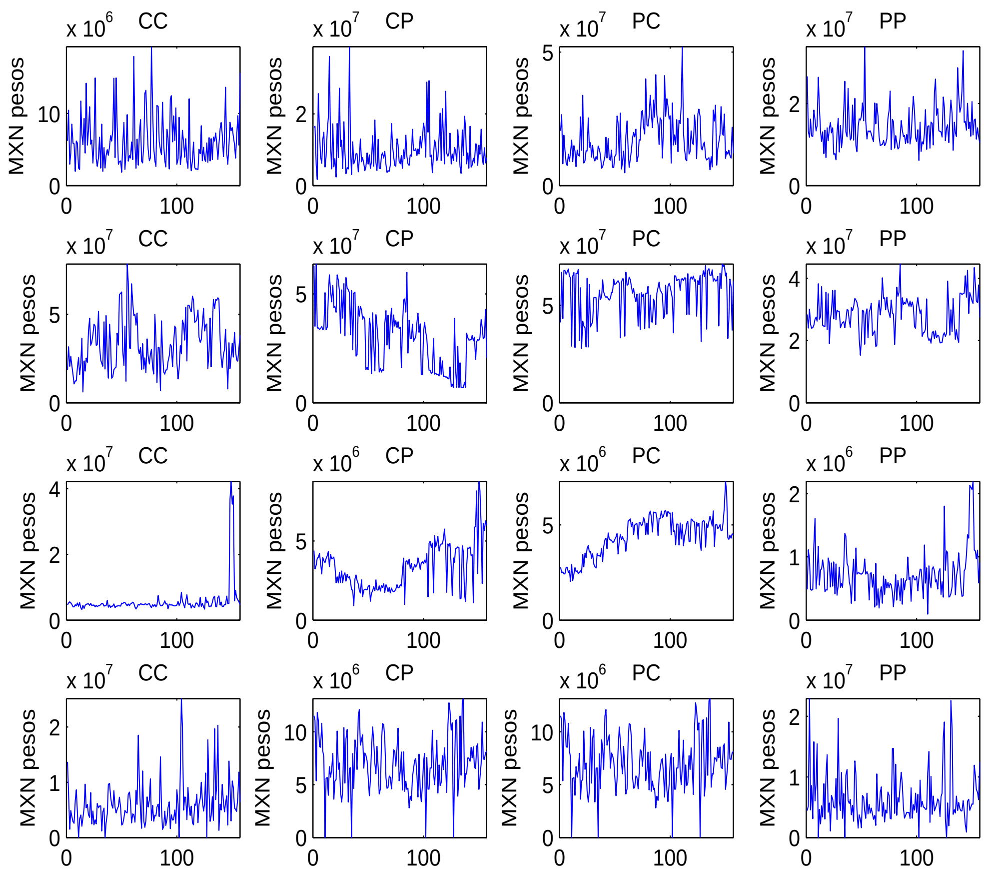

Figure A-3: Transaction volumes per block per type of exposure. Rows from top to bottom: interbank, issuer, counterparty and FX.

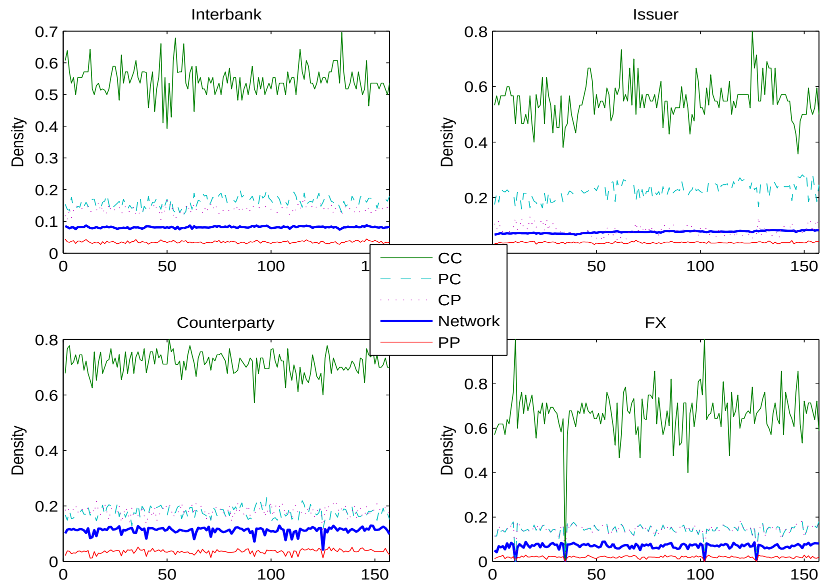

Figure A-4: Block densities per type of exposure

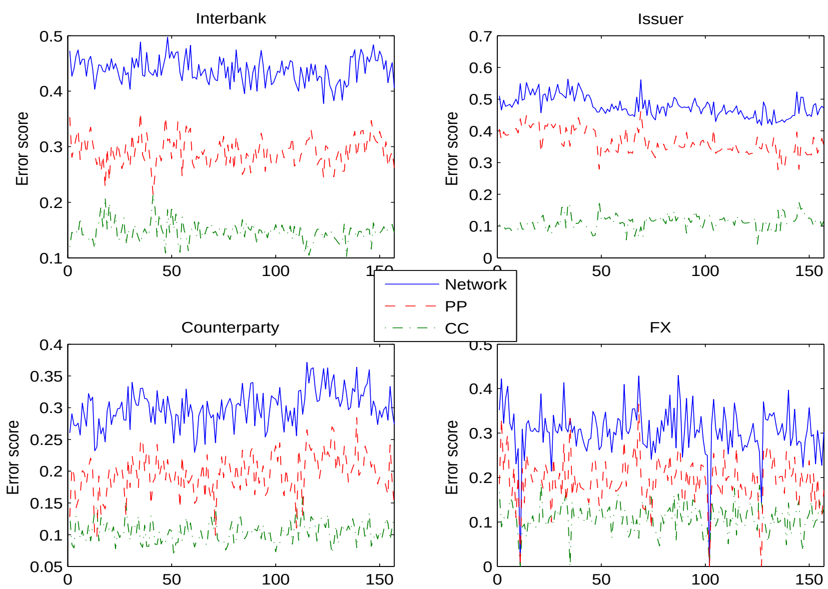

Figure A-5: Error scores (decomposed) per type of exposure

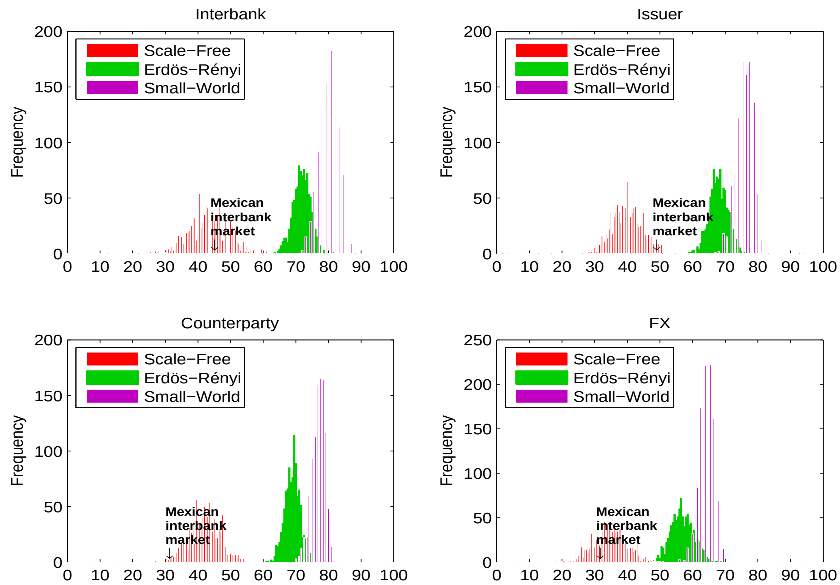

Figure A-6: Craig-von Peter significance test per type of exposure.

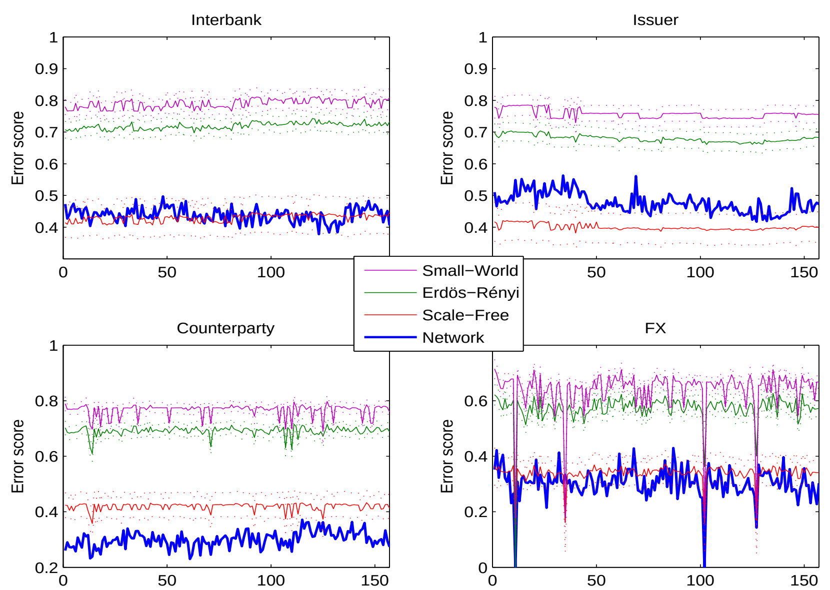

Figure A-7: Fricke-Lux significance test per type of exposure.

Annex B

The links per block shown in Figure 4 can be aggregated in a single graph. Figure B-1 (b) shows the core-periphery representation for the network derived from the original data, Figure B-1 (a). The outer circle in figure B-1 (b) are the estimated periphery banks for the last day of the study, while the inner circle plots the core banks.

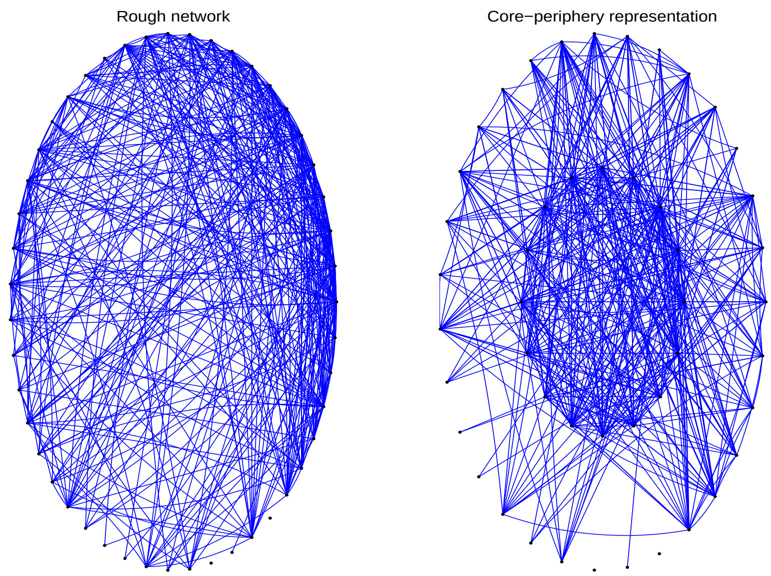

Figure B-1: Mexican interbank network and its core-periphery representation as of August 15, 2011.