Discovering the Core of the Russian Interbank Market

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ABSTRACT

This paper investigates to what extent the structure of the Russian interbank market over the period 1998-2004 can be described by applying the core-periphery model as defined by Craig and von Peter (2014), using a greedy algorithm. It finds that the fit is significant, although the error score of 54 percent is relatively high compared to earlier studies which applied this core-periphery model to more mature interbank markets. Additionally, this paper finds that the fit of the core-periphery model deteriorates as loan maturity increases. Finally, this paper concludes that a bank can also be classified as belonging to the core by doing a probit regression on a single balance sheet variable.

Keywords

Interbank market, Russia, core-periphery model, financial market stability.

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INTRODUCTION

This paper investigates the complex structure of the Russian interbank market using a core-periphery (CP) model, over the period 1998-2004.

The interbank market can be defined as the financial system of banks that trade currency between each other (extend loans to one another) for a specified term (maturity). This market excludes central banks and retail investors. Most interbank loans are made for a maturity of a week or less, and the majority of loans has an overnight maturity.

To be able to more effectively safeguard stability on financial markets, gaining a better insight into the structure of interbank markets is crucial. Recent research (Cocco et al., 2009 and Bräuning and Fecht, 2016) has argued that the interbank market should not be seen as a collection of unrelated transactions, but as a complex system, and should also be treated as such.

Traditionally, the interbank market has been modeled as flat: no attention was paid to any potential complex network structures. However, since the start of the Global Financial Crisis in 2007 it has become clear that an understanding of the complex structure of interbank markets is crucial for safeguarding financial stability. The exact structure of any interbank market network has a clear influence on its stability: theoretical research found that if a network is complete (this translates to all banks being connected to all other banks), a shock to a single bank can easily be shared amongst all agents. However, if few banks have many connections and many banks have few connections, it can have severe consequences if one of the banks with many connections fail (Allen and Gale, 2000). Hence, a better insight in the structure of the interbank market is of vital importance for the health and stability of this market.

This paper aims to contribute the following to the field of interbank structure research: firstly, it applies the core-periphery model as defined by Craig and von Peter (2014) to the Russian interbank market. This core-periphery model has been applied to several interbank markets before, such as the German (Craig and von Peter, 2014), Dutch (in ‘t Veld and van Lelyveld, 2014), UK (Langfield et al., 2014) and Italian (Fricke and Lux, 2015) one. However, all the above interbank markets are generally regarded fully mature. The Russian interbank market is much younger and had not reached full maturity yet between 1998-2004. This makes it an interesting case to investigate. Therefore, another aim of this paper is to investigate to what extent the core-periphery model can provide an accurate description of a young and not yet fully mature interbank market, such as the Russian one.

Additionally, this paper divides the data into three separate layers based on loan maturity (overnight, short-term and long-term) and investigates the fit of the CP model for each layer individually. Previous research has found that most interbank loans have a relatively short maturity (Alfonso and Lagos, 2015). Separating the data into layers will provide insight into the question whether the fit of the core-periphery model deteriorates as maturity grows.

Finally, this paper investigates whether a bank can be classified as belonging to the core or the periphery by performing a simple probit regression on specific bank balance sheet variables. Bilateral interbank transaction data is not available for every market, so this probit approach could prove to be more feasible in many cases. To the best of my knowledge, this specific combination of investigations has not been applied to the Russian interbank market before.

THE CORE-PERIPHERY MODEL

Definition

To gain a better insight into the structure of the Russian interbank market, this paper makes use of the core-periphery (CP) model. This model originates from the field of sociology (Borgatti and Everett, 2000) and was slightly adapted for the purpose of modelling interbank markets by Craig and von Peter (2014) who were also the first to apply this model to an interbank market, in their case the German market. In the remainder of this paper, any reference to a CP model or structure refers to the CP model as defined and used by Craig and von Peter (2014).

Further empirical research on interbank markets in other countries has confirmed that this core-periphery model is an adequate way to describe the complex network of interbank markets. Besides Germany, the interbank markets of the Netherlands (in ‘t Veld and van Lelyveld, 2014), the UK (Langfield et al., 2014) and Italy (Fricke and

Lux, 2015) have all successfully been investigated using the core-periphery model.

The main idea behind the CP structure is that core banks interact with both periphery banks and other core banks, core banks serve as intermediates between periphery banks, and periphery banks only interact with core banks, but not with each other. To summarize this, a perfect core-periphery structure satisfies the following conditions:

- Core banks all lend to and borrow from each other.
- Periphery banks do not lend to or borrow from each other.
- Core banks lend to and borrow from at least one periphery bank.

A visual example of a network that satisfies these conditions is shown in Figure 1.

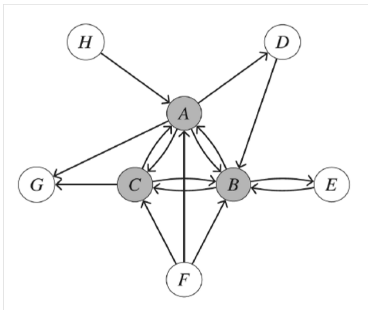

Figure 1: A visual example of a perfect CP structure, where A, B and C form the core and D, E, F, G and H the periphery. Graphic borrowed from in 't Veld and van Lelyveld (2014).

Implementation

The lending and borrowing activities of any interbank market can be represented in a square matrix format. If a market contains *n* active banks, the size of this matrix will be *n*n*.

Since the CP model employed in this paper focuses only on the structure of linkages, not on their relative size, all positive elements in this matrix can be set equal to 1 to obtain a binary matrix. Now, the number 1 represents the existence of a link between two banks, and the number 0 denotes the absence of a link. This is the observed (real) network *N*.

The next step is to compare the observed network *N* to an ideal CP structure of similar size, *M,* and investigate the fit. To be able to do this, this paper makes use of an algorithm that optimizes the fit of *N* for *M* and as a result gives the optimal set of core banks. To obtain the total amount of errors simply add up the inconsistencies between the chosen model *M* and the observed network *N*. By dividing the total error by the total number of links in the observed network, the total error is normalized to obtain the error score.

I follow the approach and part of the coding of Craig and von Peter (2014), who use a greedy algorithm to solve this optimization problem. This greedy algorithm moves banks between core and periphery and does so by following the path of steepest descent, a key feature of greedy algorithms. In practice, this means that in every step the algorithm will switch the bank that contributes most to the error score from one tier to another. It will continue to do so until the total error score cannot be reduced any further.

Testing for significance

To test for significance I have taken the following approach: the CP model *M* is repeatedly applied to other networks. These networks are obtained from a random data-generating process in which tiering is *not* expected to emerge. The distribution of the error scores obtained from applying *M* to these random networks can then be compared to the error score from applying *M* to the original observed network *N* - in which, according to theory, tiering *is* expected to emerge.

In practice, this approach comes down to the following: generate 1000 random networks of the same size and density as the observed interbank network *N*. Fit *M* to every generated random network, obtain the error scores, and plot these error scores. This is the empirical distribution function of the error score for a case where tiering is not expected to emerge. Following Craig and von Peter (2014), only if the error score of the interbank network *N* is lower than the bottom percentile of the empirical distribution function, does *N* have a significant degree of tiering.

The specific type of random networks used in this paper to test for significance will be Erdös-Rényi (ER) random graphs.

Layers

As mentioned before, most interbank loans have a relatively short maturity, the majority being overnight loans. The theory on which the core-periphery model is built also assumes a liquid interbank market with loans of a relatively short maturity. Therefore, it is interesting to investigate whether the core-periphery model still holds for loans with a longer maturity, or whether it indeed deteriorates.

To test for this, I divided the dataset into several layers, each containing loans with a different maturity. For each of these layers, I ran the same analysis as before. Now, the error score of each layer can be compared not only to the overall error score, but also to the other layers. This gives a better insight into the effect of maturity on the fit of the CP model.

DATA DESCRIPTION

Dataset

The dataset used for the analysis describes all the loans issued on the Russian interbank market between August 1998 and November 2004. These loans were reported monthly. Only one month, January 2003, is missing. The database has been constructed by prof. Koen Schoors and dr. Alexei Karas (Karas and Schoors, 2010) from a private information company called Banksrate.ru.

For the purpose of this paper, the dataset has been altered in several ways. First, it was converted from monthly to quarterly. Second, only the entries where either the begin of month balance, the debit turnover, the credit turnover or the end of period balance is higher than 100 million rubles were kept - this to stick to a similar threshold as previous papers (1.5 million euros in the case of Craig and von Peter, 2014 and in 't Veld and van Lelyveld, 2014) have done, for comparison purposes.

The Russian interbank market between 1998-2004

Between 1998-2004, the Russian interbank market evolved from a growing to a mature market. During growth phase, both the number of active banks and the transaction intensity steadily increases. During the mature phase, the number of active banks stabilizes; only the number of transactions still intensifies.

Descriptives

Throughout the sample period, the number of Russian banks active on the interbank market with transactions above 100 million rubles varied between 79 and 458, which is on average 23 percent of the total amount of (licensed) Russian banks. Figure 2 plots the number of banks active.

The network is relatively sparse, with on average only 1.1 percent of all possible links materializing. The sparsity of the Russian interbank market is less than the Dutch and UK markets, which have a respective sparsity of about 8 and 3 percent, but higher than the German interbank market, which has a sparsity of only 0.6 percent (in ‘t Veld and van Lelyveld, 2014).

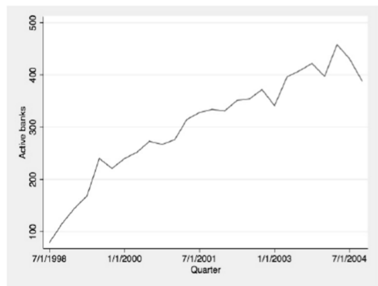

Figure 2: Number of Russian banks active on the interbank market between 1998 and 2004.

RESULTS OF CP-MODEL ESTIMATION

For my analysis I used two software packages: Stata, a general-purpose statistical software package for the basic descriptives and data selection, and MATLAB, a numerical computing environment for running the algorithm and processing the results.

Estimating the core

Similarly to the approach of Craig and von Peter (2014), I will first focus on a mid-sample quarter, namely Q3 of 2002. In this quarter, 345 banks were active on the Russian interbank market (out of 1345 banks registered in total). The optimal core consisted of 17 banks. This is a relatively small subset, namely 4.8 percent of all active banks. The total amount of errors added up to 672, where the total amount of links equaled 1255. This results in an error score of 53.5 percent for the network links. Normalizing instead by the dimension of the network (N*(N-1)) shows that only 0.52 percent of all the cells are not consistent with the model.

Figure 3 shows the fraction of banks belonging to the core estimated per quarter and Figure 4 shows the error score.

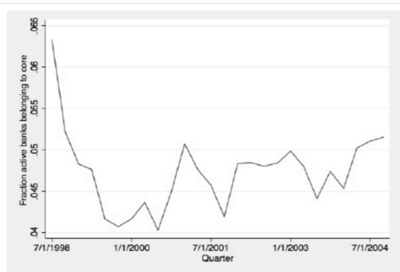

Figure 3: Fraction of all active banks that are classified as a core bank per quarter.

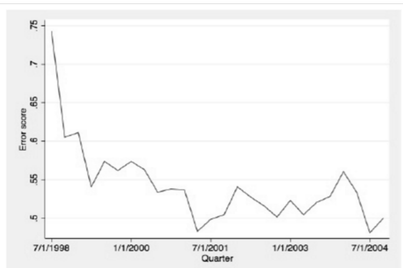

Figure 4: Error score per quarter.

Layers

As mentioned previously, I split the dataset into three layers: overnight (maturity 0-1 days), short term (2-7 days) and long term (> 8 days). As expected, the number of active banks, number of core banks, and total error score drops for all layers, as there are simply fewer entries. However, for both the overnight and the short term layer the total error score and the fraction of active banks belonging to the core is very similar to the baseline. The long term layer is a different story: here, the error score is significantly higher. Table 1 compares the results of all layers, taking the average of the variables over the entire sample period. The results are in accordance with earlier research by Van Soom (2016), which concluded that "it [the CP structure] breaks down for longer terms and time windows".

	Active banks belonging to core (%)	Error score (%)
Baseline (all maturities)	4.7	54
Overnight	5.0	55
Short term	5.3	57
Long term	4.9	67

Table 1: Comparison of active banks belonging to core and error score between the different layers and the baseline.

Significance

The CP model M is applied to 1000 randomly generated Erdös-Rényi (ER) random graphs, with similar size and density as the Russian interbank network N (n=304, p=0.011). The found error score is tightly centered around 0.93. The best-fitting instance has an error score of 0.903. Clearly, these error scores do not come close to the value of 0.54, the error score found by applying the CP model to the Russian interbank data. Hence, I reject the hypothesis that randomly generated ER networks portray a similar degree of tiering as the Russian interbank network N: the tiering observed in N is not purely the result of random statistical processes. Therefore, the results are significant.

Comparison with earlier research

Table 2 compares findings from previous literature that applied the CP model to an interbank market with the findings of this paper. The comparison only includes those papers that used the exact same procedure as this paper: a threshold of 1.5 million euros / 100 million rubles and quarterly data. From Table 2 it is can be concluded that the Russian interbank market in many ways lies inbetween the Dutch and the German interbank market regarding its structure. The only result that truly stands out is the error score: it is much higher for the Russian market.

	Russia	The Netherlands	Germany
Total number of active banks	300	100	1800
Network density	1.1 %	8.0%	0.4 %
Average number of core banks	14	15	45
Average core size	4.3 %	15 %	2.5 %
Error score	54 %	29 %	12 %

Table 2: A comparison of the CP model fit between Russia, The Netherlands (in ‘t Veld and van Lelyveld, 2014) and Germany (Craig and von Peter, 2014).

ESTIMATION VIA BANK SHEET VARIABLES

The previous sections mainly focused on the question to what extent the core-periphery model fits the Russian interbank market. However, such an analysis requires bilateral data on interbank exposure. In practice this data is not available in many countries. Therefore, this section will take a different approach: is it possible to predict what banks make up the core of the network using a single bank-specific feature? This will be investigated by using a probit regression, where the dependent variable is a binary variable denoting core membership as predicted by the CP model: $b_i = 1$ if bank *i* belongs to the core and 0 otherwise. The independent variable is an individual bank sheet variable. The aim is to detect the single independent variable that has the largest predictive value.

Dataset bank balance sheet

The basis of the dataset that was used for this analysis contains balance sheet variables of all Russian banks. It was constructed by dr. Alexei Karas and prof. Koen Schoors as well. Karas and Schoors (2010) provides an overview of how this dataset was assembled.

Result of the probit regression

Table 3 reports the result of the probit regression. This regression tests whether core membership can be predicted using a single bank sheet variable. The regressors are shown in the rows. The columns show the regression outcomes.

	Bank size	Intrinsic size	Interbank liabilities	Intermediation
ML estimator	0.816 (0.144) **	0.724 (0.129)**	0.770 (0.143)**	0.989 (0.20) **
Pseudo-R2	0.519	0.472	0.487	0.627
(%) correctly classified	95.73	95.73	96.58	97.15
P(c|C) core correct	41.18	41.18	41.18	58.82
P(c|P) core false	1.50	1.50	0.60	0.90

*Table 3: Results of probit regression on several independent variables. Significance is denoted by ** ($p < 0.01$) and * ($p < 0.05$) .*

The relevant indicators to look at in the results of the probit regression are as follows: 1) the percentage of all banks that are classified correctly, 2) the percentage of banks that are classified as a core bank (c) given that the true status of the bank is also a core bank (C), and 3) the percentage of banks that are classified as a core bank (c) given that the true status is that of a periphery bank (P). Clearly, the first two indicators (total percentage classified correctly and (c|C) are ideally as high as possible, while (c|P) is ideally as low as possible.

As shown by Table 3, the variable Intermediation has the highest predictive value. This variable measures the volume each bank intermediates, by taking the minimum of its interbank lending and borrowing. It is best able to predict those banks belonging to the core (59 percent classified correctly) and is best at not including periphery banks in the core in its prediction (1 percent of periphery banks classified incorrectly as core banks).

DISCUSSION

Even though this paper found that the core-periphery model provides a relatively good and statistically significant fit to the Russian interbank market, the error score is still remarkably higher than those of comparable papers. This can have several reasons, the most obvious one being that during the sample period (1998-2004), the Russian interbank market could not be classified as mature yet. An alternative explanation is that the sample data covers two crisis periods: in crisis periods, known structures disappear and others arise, which might also explain the poor fit.

Suggestions for further research include additional research into other not fully mature markets, a more thorough investigation of the fit of the CP model during various crises, and looking further into combinations of independent variables yielding the highest predictive value in the probit regression.

CONCLUSION

To conclude, the core-periphery model provides a good fit to the Russian interbank market, although the found error score of 54 % is significantly higher than that of several more mature interbank markets. Furthermore, separating the data into several layers of different maturity reveals that the fit of the core-periphery model deteriorates as maturity increases, in line with expectations. Finally, the core can also be predicted using specific individual bank sheet variables instead of bilateral interbank data. The variable that measures the volume a bank intermediates provides the best fit for this, indicating that intermediation is a key feature of core banks.

ROLE OF THE STUDENT

Marije Sluiskes was an undergraduate student who individually worked on the research in this report, being supervised by dr. Alexei Karas. The topic was proposed by dr. Karas, who also provided Marije with the appropriate datasets. Prof. van Lelyveld provided Marije with relevant MATLAB code used during his own research on the CP model (in ‘t Veld and van Lelyveld, 2014). All other aspects, including the literature research, additional programming, analyses, processing of the results, writing of the report and formulation of the conclusions were done by Marije.

ACKNOWLEDGMENTS

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