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Loan maturity aggregation in interbank lending networks obscures mesoscale structure and economic functions

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ABSTRACT

Since the 2007-2009 financial crisis, substantial academic effort was dedicated to improving our understanding of interbank lending networks (ILNs). Because of data limitations, the literature largely lacks loan maturity information. We employ a complete interbank loan contract dataset to investigate whether maturity details are informative of the network structure. Applying the layered stochastic block model of Peixoto (2015)[1] and other tools from network science on a time series of bilateral loans with multiple maturity layers in the Russian ILN, we find that collapsing all such layers consistently obscures mesoscale structure. The optimal maturity granularity lies between completely collapsing and completely separating the maturity layers and depends on the development phase of the interbank market, with a more developed market requiring more layers for optimal description. Closer inspection of the inferred maturity bins associated with the optimal maturity granularity reveals specific economic functions, from liquidity intermediation to financing. Collapsing a network with multiple underlying maturity layers, common in interbank research, is therefore not only an incomplete representation of the ILN's mesoscale structure, but also conceals existing economic functions. This holds important insights and opportunities for theoretical and empirical studies on interbank market contagion, stability, and on the desirable level of regulatory data disclosure.

Introduction and overview

Interbank lending networks (ILNs) are complex network models of the interbank money markets, often called the plumbing of modern financial systems[2]. Banks make interbank loans on such markets to accommodate daily liquidity imbalances. For example, a bank holding more cash than desired may profitably lend this cash to other banks in need of cash[3].

The financial crisis of 2007-2009 has brought the interbank money markets in the public eye because their “drying up” (failure to lend cash to banks in need) was a major channel of financial contagion[4]. Since then, substantial academic effort has been dedicated towards improving our understanding of these markets. It turns out that representing the interbank money market as a network is a simple and powerful abstraction[5], that is arguably more realistic than modelling it as one representative bank, as is customary in traditional macro-finance[6]. Network analysis are therefore now one of the standard tools of financial stability experts worldwide, i.a. at the IMF[7] and ECB[8].

A thorough understanding of the interbank money market is vital to prevent systemic meltdowns[9,10], implying a need for ever more realistic models of ILNs. We contribute by studying a much neglected aspect of ILNs, i.e. the maturities of their loans. The maturity of a loan, i.e. the period after which the loan must be repaid, is an important instrument for banks to organise their lending and borrowing activity in function of risk minimisation[11,12]. The vast majority of empirical financial network papers study the overnight interbank market[6], which contains only one type of loan maturity. Due to data limitations the empirical ILN literature cannot differentiate between loan maturities. This limitation also impacts agent-based models of ILNs that often either neglect loan maturities or limit it to a modelling detail[13,14], although maturity choices reflect bank risk strategies. For example, stress testing models would benefit from exposure data enriched with maturity information[6]. Enabled by a particularly granular dataset, a panel of all lending contracts issued in the Russian ILN[15], we investigate qualitatively what kind of information is lost by not differentiating between the loan maturities. We further try to estimate the pitfalls of this common practice. The approach we take consists of explicitly modelling the Russian ILN by layered stochastic block models (SBMs). This allows us to determine to what extent the loan maturities are informative of the Russian ILN's mesoscale, i.e. the higher-level organisation of the banks into bank groups.

The dataset used in this work consists of 57 monthly ILNs constructed from the complete panel of contracts on the Russian domestic unsecured interbank lending market, one for each month in the period from January 2000 to October 2004, except for January 2003 (see Methods). There are a total of 2.4 million loans, each annotated with its lender, borrower, month of issuance, loan size and *maturity class*. The data came preassigned into eight contiguous maturity classes, so that we know to which maturity class a loan belongs (e.g. 2-7 days). Fig. 1 shows the monthly number of active banks, loans issued, and outstanding loans per maturity class, together with a list of the eight maturity classes (further details on the dataset are in Methods). We look at the monthly ILNs as layered networks such that each maturity class corresponds to one *maturity layer*. By putting contiguous maturity layers into bins, they can be coarse-grained to achieve various levels of *layer granularity*, ranging from complete differentiation (eight bins, one layer per bin) to complete aggregation (all layers merged into one bin, the collapsed network). Note that the latter degree of layer granularity, i.e. not differentiating between the loan maturities, corresponds to the situation prevalent in literature and is the granularity to which we compare our results.

First, we provide descriptive statistics of the monthly ILNs in a comparative framework. We characterise the network topology of each maturity layer separately using the typical network measures from ILN literature (listed in the leftmost column of Table 1) and compare the results across the maturity layers and across the literature. Broadly speaking and integrating over time, we find layer non-homogeneity for most topology measures. This means that, while stylised facts found in the literature

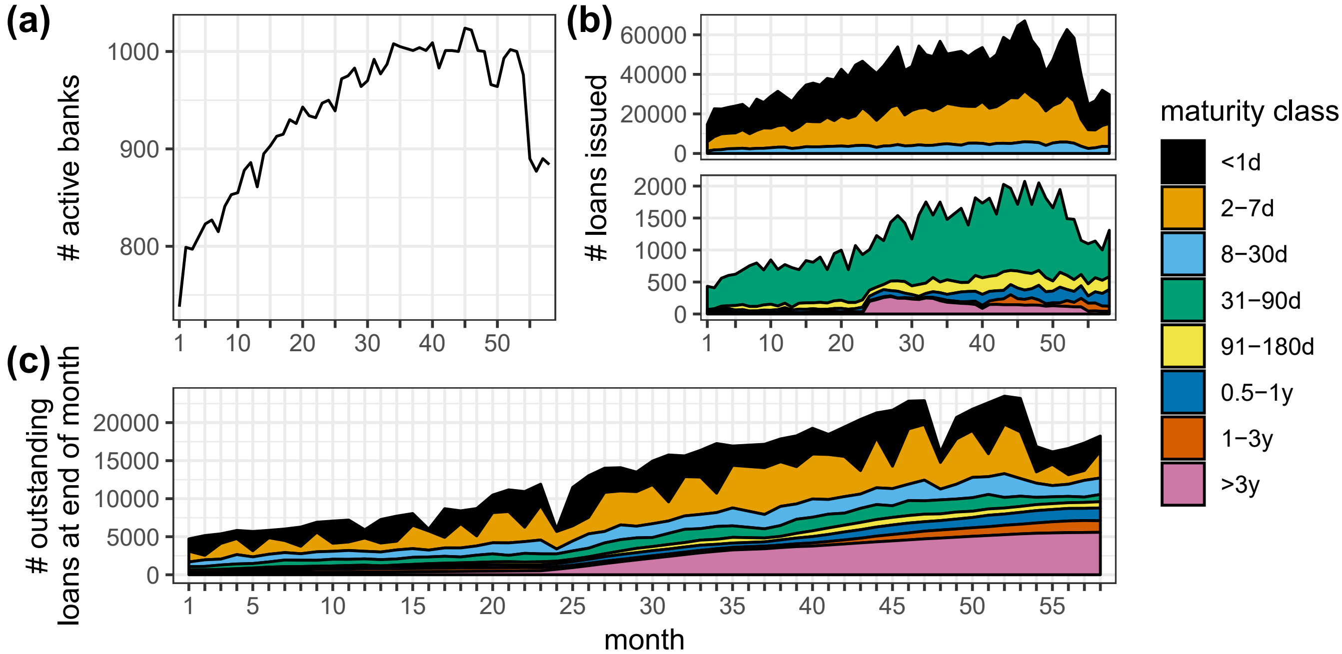

Figure 1. Temporal evolution of the lending activity in the Russian interbank lending network. Month 1 corresponds with January 2000. **(a)** The number of active banks on the lending market per month. A bank is active whenever it is the originator or the beneficiary of at least one new interbank loan in the given month. **(b)** The number of loans issued per month and per maturity. Note the different scales on the vertical axis of the two panels: The majority of issued loans have "short" ($\leq$ 30 days) maturities. **(c)** The number of outstanding loans, i.e. loans open on the last working day of each month. From this perspective the loans with longer maturities now play an equally important role as the short ones. Note that we have included loans issued before January 2000 for this panel (see Methods).

were also detected found in some of the maturity layers, the topology measures do not take on similar values for all maturity layers simultaneously. Layer non-homogeneity points to the fact that complete aggregation involves the loss of the topological diversity present in the maturity layers, although some layers do share similar lending patterns in specific months (by lending pattern we mean a topological pattern in an ILN). For example the three most dense layers —the "short" layers, i.e. all maturities below 30 days— display a strong similarity throughout the full time period. The short layers' topological similarity, together with their dominant share in the number of loans issued, could suggest that complete aggregation might not be harmful after all, irrespective of what the found layer non-homogeneity suggests. The question then becomes whether the information lost by complete aggregation is "relevant" for ILN structure and economic function. Because financial stability plays a central role in literature and policy, we are interested in the money markets' mesoscale organisation, which can effectuate the propagation of instability and risk[16], rather than individual banks' lending strategies. Relevant information is thus any set of information that allows for characterisation of the mesoscale structure rather than other, more specific, more "noisy", information about local lending patterns (e.g. clustering).

To infer the mesoscale structure of the monthly ILNs we explicitly model them by layered SBMs. SBMs detect and describe statistically significant modular structure in networks, without making a priori assumptions about the type of mesostructure itself. They model the mesoscale of a network by assuming that the nodes in a network behave "group-like" rather than on individual account. Layered SBMs are then models of layered networks that provide additional degrees of freedom by allowing the group structure to have a different topological pattern on each layer. As a concrete example, imagine a network with two layers representing the mating (layer 1) and conflict (layer 2) interactions in a population of deer (the nodes). One possible layered SBM of this network is the division of the deer into two groups, male and female, so that observed occurrences of mating and fighting between two deer are explained only by their sexes. Note that such a simple model —which does not take things like social status etc. into account to explain the observed interactions— could well suffice to infer the deer's sexes if these were unknown.

Layered SBMs formulated in a Bayesian setting can be extended to the *coarse-grained* layered SBM in order to infer the appropriate level of layer granularity (the optimal granularity, OG) along with the group structure. The bins in the OG correspond to lending patterns between the bank groups that differ from each other in a statistically significant way. We explain this in detail in the next section, but the essence of how an OG can be inferred can already be understood by a simple regularisation argument. The complexity and modelling power of a layered SBM is determined to large extent by the number of groups and the degree of layer granularity, as these parameters simultaneously define the "resolution" available to model the observed layered network. To prevent overfitting (i.e. modelling noise), any increase in model complexity should be warranted by enough statistical evidence in the data. Thus the OG may be determined in general by any regularisation principle to balance model complexity and quality of fit; we use Bayesian model comparison for this. One specific advantage of this approach is that there is formally no difference between inferring the number of groups —and in fact the groups themselves— and the OG; both are determined as part of a single inference for each monthly ILN.

The inferred monthly OGs are displayed in Fig. 3(a). Each OG consists of a set of bins numbered from short to long maturity by the OG bin index (OGB index). We mention here two findings easily deduced from Fig. 3(a). First, we find that the OG always lies between complete differentiation and complete aggregation. This means that on the one hand the eight available maturity classes are partly redundant and that the lending patterns may be described more effectively by merging maturity layers into bins, as is indeed the case for the short layers mentioned before; on the other hand complete aggregation discards important information needed to model the monthly ILN's mesostructure. Second, the monthly number of bins in the OG correlate roughly with the known two phases in the Russian money market's development: early development (roughly before month 35) and emerging maturity (from month 35 onward) (see Methods). This points to a natural ordering in number and complexity of lending patterns emerging at different phases of market development.

To interpret the patterns, we take a closer look at the monthly OG bins at the network and individual bank level. (Note that this goes beyond the previously established network measures of the individual maturity layers, as these are now merged according to whether they form a statistically significant lending pattern.) The notable result here is that the bins may be characterised by a simple aspect of the most important banks' individual lending behaviour: At monthly time scales the important banks in "short" bins tend to both lend and borrow equal amounts of cash (indicative of financial intermediation), while the important banks in the "long" bins tend to either lend or borrow (indicative of financing). For the development phases, this suggest that patterns of financial intermediation are present at all phases of development, while patterns more in line with financing only appear at later phases.

Our coarse-grained layered SBM of the ILN thus uncovers a correlation between statistically significant lending patterns between groups of banks, the economic functions of important banks, and the maturity classes of the loans involved, showing that maturity information matters for the understanding of ILNs.

Results

The adopted notation is in line with the one of[1,17]. An ILN at month t is denoted as $\{G_l\}$, with G_l the network for one of the eight maturity layers: $G_{\text{<1d}}$, $G_{\text{2-7d}}$, $G_{\text{8-30d}}$, $G_{\text{31-90d}}$, $G_{\text{91-180d}}$, $G_{\text{0.5-1y}}$, $G_{\text{1-3y}}$, $G_{\text{>3y}}$. As we treat each month independently we do not attach a time label to $\{G_l\}$. The G_l are directed weighted multigraphs. In addition to the asymmetrical adjacency matrix $A^l_{ij} \in \mathbb{N}_0$ of layer l, the G_l possesses the unordered edge covariates x^l_{ijk} ($k \in [1, A^l_{ij}]$ for $A^l_{ij} > 0$). Thereby, each kth parallel edge between banks i and j represents a loan lent from bank i to bank j with a maturity in maturity class l and of size x^l_{ijk}. The *collapsed network* G_c corresponds to complete maturity aggregation. Its adjacency matrix $A_{ij} = \sum_l A^l_{ij}$ and the edge covariates x_{ijk} are constructed by flattening (i.e. collapsing) the x^l_{ijk} along the k, l axes. We denote a level of granularity by the maturity bin set $\{\ell\}$ where ℓ specifies a set of merged layers. For example, the OG of month 58 (see the last month in Fig. 3(a)) corresponds to $\{\ell\} = \{\{\text{<1d}, \text{2-7d}\}, \{\text{8-30d}\}, \{\text{31-90d}\}, \{\text{91-180d}, \text{0.5-1y}, \text{1-3y}, \text{>3y}\}\}$. The ILN $\{G_\ell\}$ representing the level of granularity specified by $\{\ell\}$ is constructed from $\{G_l\}$ by merging maturity layers according to $\{\ell\}$.

Descriptive statistics of the Russian ILN in a comparative framework

We start by characterising the maturity layers and the collapsed form of the Russian ILN in terms of monthly (and occasionally yearly) time series of several ILN measures typically used in the literature. Layer analysis of layered ILNs has been performed for the interbank money markets of several countries, e.g. Italy[2], Mexico[18] and the UK[19]. The layers in those works, however, do typically not differentiate between maturity classes[6]. The measures that we analyse are: density, degree distribution, clustering coefficients, average shortest path length, degree mixing (as a proxy for bank size mixing), loan activity, and loan size. The results are compared to the stylised facts found in literature. A summary of this analysis is given in Table 1, while details of the analysis can be found in the Supplementary Material, Appendix A.

The stylised facts describing prototypical ILNs are most often deduced from collapsed loan maturity networks. Looking at the maturity layers separately, we find layer non-homogeneity for all measures in Table 1 except for the distribution of degree and transaction volumes. This means that variations of the ILN measures across the maturity layers are observed. While the stylised features are valid for the short maturity layers ($G_{\text{<1d}}$, $G_{\text{2-7d}}$, $G_{\text{8-30d}}$) and for the collapsed network (G_c), they become progressively invalid with growing loan maturities. As a matter of fact, we find that the stylised facts of the collapsed Russian ILN do not hold over all maturity layers. Given the similarities in the stylised facts across countries, we anticipate a similar behaviour for the ILNs of other countries. The short layers $G_{\text{<1d}}$, $G_{\text{2-7d}}$, $G_{\text{8-30d}}$ contain 97% of all issued loans. Upon merging those we more or less retrieve the collapsed Russian ILN with all the loan issuances. The longer maturity loans represent a

Table 1. Stylized network properties of interbank lending networks (ILNs) according to selected studies. For some ILN measures conflicting values are reported, in which case we separate them by a backslash. For example, low clustering coefficients are reported by[20]. The values for the ILN measures in bold apply to the collapsed Russian ILN (see[21] and Appendix A). With the layer homogeneity we indicate whether the quoted ILN measures apply to all maturity layers of the Russian ILN.

ILN measure	Value	Layer homogeneity	Selected studies
density	**sparse**	No	2, 6, 20, 22–24
degree distribution (in and out degrees)	**heavy-tailed**	Yes	2, 6, 20–22, 25
topological structure	scale-free / core-periphery		2, 26, 27 / 6, 22–25
clustering coefficients	low / **high**	No	20 / 2, 6, 22, 27
average shortest path length	**small** / "small world"	No	22, 24 / 6, 20, 27
bank size mixing	**disassortative**	No	6, 18, 20, 22, 24, 26
distribution of transaction volumes	**heavy-tailed**	Yes	20, 21

few percent of the issuance but they are of sizeable economic relevance due to their specific turnover and their weight in the outstanding loans (see Fig. 1(c)). During times of turmoil the short-term loans are often not renewed, but the long-term ones remain on the books till maturity, making them important for the stability of the ILN.

Core-periphery (CP) structure has been observed in many real-world networks[28] and in ILNs[5,6]. The seminal work of Craig and von Peter[25] introduced an economic foundation for its occurrence in ILNs, i.e. the elementary function of economic intermediation performed by banks. CP structure breaks with traditional theoretical banking literature where the interbank money market is modelled as a centralised exchange in which banks smooth out liquidity shocks. In contrast to the centralised exchange model, an ILN with CP structure gives rise to a sparse network. Thereby, a group of densely connected "core" banks perform the economic function of financial intermediation between numerous smaller, sparsely connected "periphery" banks. Formally, an ILN has CP structure if the lending patterns can be fully explained by grouping the banks into either "core banks" or "periphery banks". In the ideal situation, the bilateral relations between the banks define the group memberships (i.e. whether a bank is core or periphery) by the following set of rules: (i) core banks lend to each other; (ii) periphery banks do not lend to each other; (iii) core banks lend to periphery banks; (iv) core banks borrow from periphery banks. For real-world ILNs with imperfect CP structure, several algorithms have been proposed (e.g.[25,29]) to detect CP structure and to determine the group memberships. We believe however that the proper way to establish CP structure in networks is by Bayesian inference of SBMs as these are ideally suited to parametrise the CP two-group structure and the four rules mentioned above, rather than minimising an objective function that might detect spurious CP structure, as shown by some recent literature[2,30,31]. Inferring CP structure by Bayesian inference of SBMs has been proposed in[32] and applied to the Italian e-MID ILN in[33,34] where depending on the time scale and SBM model extension, a bipartite or CP structure was found. We find some indications supporting a CP structure in the Russian ILN for G_c and $G_{<1\text{d}}$, $G_{2\text{-}7\text{d}}$, $G_{8\text{-}30\text{d}}$. As explained in Appendix A these indications stem from the heavy-tailed degree distributions, disassortative degree mixing and the small average shortest path length.

Modelling the Russian ILN with the coarse-grained layered SBM

The idea of banks behaving in groups with respect to lending and borrowing because of trading relationships in the interbank money market has been posited in various forms in the literature[6,12,23,25,35–39], though not often explicitly in the form of

SBMs[5,33,34]. Such group structure, also called network mesoscale structure, is abundant in real-life complex networks[40], notably social networks[41]. In the Russian interbank money market, there are several reasons to anticipate that the group structure is important: relationships are a way to solve problems with asymmetric information, a pervasive problem in the Russian banking sector and economy at large[42]; fragmentation of the Russian financial market due to the country's size (i.e. eight time-zones); the presence of institutions controlled by the state to various degrees[43]. The most important advantages of using SBMs to detect the group or mesoscale structure are[44]: (i) Theoretical guarantees against overfitting; (ii) They can be extended easily when formulated in a Bayesian setting; (iii) The ability to describe a wide variety of lending patterns (e.g. ILNs modelled by community structure, bipartite structure, CP structure or Erdős–Rényi graphs). As mentioned before, the SBM flavor we use to model the monthly ILNs is called the coarse-grained layered SBM, which extends the layered SBM, itself an extension of the standard SBM. We shortly introduce these two flavors before discussing the coarse-grained layered SBM. A comprehensive discussion about SBMs in a Bayesian setting can be found in[44] and the details about the layered SBM used in this work in[1,17].

Introduction to SBMs and layered SBMs

SBMs are canonical models to study clustering and perform community detection[45,46]. SBMs model topological patterns by assuming that the nodes "behave group-like" rather than on individual account, i.e. for a network with N nodes modelled by $B \leq N$ groups, one assumes that the amount of connections between any two nodes $1 \leq i, j \leq N$ depends only on their group memberships $1 \leq b_i, b_j \leq B$, where b_i is the group assignment of the ith node. When formulated in a Bayesian setting, the basic goal of SBMs is to determine the posterior probability distribution of all possible group assignments $\{b_i\}$ (where $B = \max_i b_i$) given the observed network G, a quantity written as $p(\{b_i\}|G)$. Because this is intractable for networks with more than a few nodes and edges, one is typically content with the maximum a posteriori probability (MAP) estimate $\{\hat{b_i}\} = \operatorname{argmax}_{\{b_i\}} p(\{b_i\}|G)$, a quantity that one refers to as "the fit" to the observed network G. Maximising the posterior $p(\{b_i\}|G)$ in search for the MAP estimate equivalently minimises the information-theoretic *description length* (DL) of the data G, i.e. $\Sigma = -\log_2 p(G, \{b_i\}) = \mathscr{S} + \mathscr{L}$ with $\mathscr{S} = -\log_2 p(G|\{b_i\})$ and $\mathscr{L} = -\log_2 p(\{b_i\})$. Here $\mathscr{S}$ is the number of bits needed to describe the data (G) given the model parameters (i.a. $\{b_i\}$) and $\mathscr{L}$ is the number of bits necessary to describe the model parameters. In other words, the best fit to the data is the one that *compresses* it most, i.e. yields the shortest DL. This is the minimum description length principle (MDL).

We invoke the MDL as it provides an intuitive explanation to how SBMs formulated in a Bayesian setting achieve robustness against overfitting[44]. In the case of SBMs the relevant model order that controls the model's complexity is the number of groups B. Increasing B improves the likelihood fit $p(G|\{b_i\})$, as new groups become available to account for any possibly insignificant deviation from the group's behaviour. More complicated models (larger B) are only preferred if there is sufficient evidence available in the data to compensate the extra degrees of freedom. This is achieved in the Bayesian formalism by specifying a prior $p(\{b_i\})$ and subsequent model selection based on statistical significance. From the MDL view this robustness against overfitting is achieved in the following manner: If B becomes large, it decreases $\mathscr{S}$ but increases $\mathscr{L}$. The latter functions as a "penalty" that disfavours overly complex models[47]. The optimal choice of B minimises the DL Σ, which induces a proper balance between $\mathscr{S}$ and $\mathscr{L}$. In other words, the optimal choice of B and $\{b_i\}$ corresponds with the model that compresses the data most.

Layered SBMs are extensions of SBMs that additionally allow the group behaviour to depend on the network layers. In this work we use exclusively a specific layered SBM known as the independent layers SBM. It starts from the idea that the network can be modelled as one group structure which exhibits a topological pattern in each layer. In other words, each layer is modelled by an independent SBM constrained by the fact that the group memberships of the nodes are the same across all layers. This increased modelling power again raises the question of overfitting as each new layer is another degree of freedom to model the observed network. For example, given a group structure $\{b_i\}$ two layers may be merged if their topological patterns induced by $\{b_i\}$ are sufficiently similar, decreasing the number of layers and thus reducing the complexity of the layered SBM. The OG in the form of a set of layer bins is inferred simultaneously with the number of groups B by searching for the layered model that most compresses the data. An OG that is different from complete maturity aggregation points to a topological pattern that is too complicated to be understood at the collapsed network level. The OG merges layers until the bins "acquire meaning" so that at the bin interfaces the topological patterns between the groups change in a statistically significant way.

The coarse-grained layered SBM

We approach the Russian ILN as a time series of independent monthly ILNs and model each separately by the coarse-grained layered SBM. Note that the "coarse-grained layered SBM" is our name for an unnamed extension to the layered SBM developed in[1] which allows the OG to be inferred along with the bank groups and other SBM parameters. The specific flavor of the layered SBM that we use is the microcanonical independent layers weighted DCSBM, which takes the following features (above the expected group structure captured by the standard SBM) into account:

- Edge directedness and the possibility of parallel edges, i.e. multiple loans can be made between two banks in a given month.
- Heavy-tailed degree distributions (see Appendix A). This is captured by the degree-corrected SBM (DCSBM)[48].
- Heavy-tailed loan size distributions[21]. This is captured by extending the DCSBM to the weighted DCSBM[17] where the sizes of the loans between bank groups are modelled by log-normal distributions. In this way each ordered pair of bank groups has a lending pattern modelled as consisting of loans whose size's magnitude has a characteristic scale[49]
- Maturity classes, modelled as network layers. This is captured by the independent layer SBM. The lending pattern in each layer is modelled by an independent weighted DCSBM with the constraint that the bank groups are identical in each layer.

Properties of the Russian ILN that are not taken into account are the loan interest rates, the balance sheet or bank ownership information, the monthly time correlations and local structures such as dense subgraphs that fall beyond current SBMs' potential to capture mesoscale structure[44]. In the Methods section we motivate the choice to treat the monthly ILNs as independent.

The coarse-grained layered SBM augments the parameter set of the layered SBM $\{\theta\}$ by the maturity bin set specifying the level of granularity $\{\ell\}$. Thus its parameters are denoted as $(\{\theta\},\{\ell\})$. The coarse-grained layered SBM of a monthly ILN $\{G_l\}$ is a generative model given by[1]

$$p(\{G_l\},\{\theta\},\{\ell\}) = p(\{G_l\}|\{\theta\},\{\ell\}) \times p(\{\theta\}) \times p(\{\ell\}), \tag{1}$$

Expressions for the model likelihood $p(\{G_l\}|\{\theta\},\{\ell\}) \propto p(\{G_\ell\}|\{\theta\})$ and prior probabilities $p(\{\theta\})$ and $p(\{\ell\})$ can be found in[1,17] where $p(\{G_\ell\}|\{\theta\})$ and $p(\{\theta\})$ are defined by the layered SBM and $p(\{G_l\}|\{\theta\},\{\ell\})$ and $p(\{\ell\})$ are defined by the coarse-grained extension. As the underlying maturity classes are inherently ordered, the prior probability for the maturity bin set $p(\{\ell\})$ is determined by the constraint that only contiguous layers may be binned. In Appendix B of the Supplementary Materials we infer the OGs under the more general non-contiguous binning assumption (with a different prior $p(\{\ell\})$) and find qualitatively similar results as in Fig. 3.

The posterior probability of the parameters $\{\theta\},\{\ell\}$ is proportional to Eq. 1:

$$p(\{\theta\},\{\ell\}|\{G_l\}) = \frac{p(\{G_l\},\{\theta\},\{\ell\})}{p(\{G_l\})}, \tag{2}$$

where $p(\{G_l\})$ is independent of $\{\theta\}$ and $\{\ell\}$. We may infer the bank groups $\{b_i\} \in \{\theta\}$ and the OG as the maximum a posteriori probability (MAP) estimate by searching for the mode of Eq. 2 (or equivalently Eq. 1) with the inference algorithm explained in the Methods. In addition, we can compare the posterior odds ratio (POR) Λ between two different levels of granularity $\{\ell\}_a,\{\ell\}_b$ by evaluating the ratio:

$$\Lambda = \frac{p(\{\theta\}_a,\{\ell\}_a,\mathscr{H}_a|\{G_l\})}{p(\{\theta\}_b,\{\ell\}_b,\mathscr{H}_b|\{G_l\})} = \frac{p(\{\theta\}_a,\{\ell\}_a|\{G_l\})}{p(\{\theta\}_b,\{\ell\}_b|\{G_l\})} = \frac{p(\{G_l\},\{\theta\}_a,\{\ell\}_a)}{p(\{G_l\},\{\theta\}_b,\{\ell\}_b)}, \tag{3}$$

where the constant $p(\{G_l\})$ and the prior beliefs $p(\mathscr{H}_a), p(\mathscr{H}_b)$ for hypotheses $\mathscr{H}_a$ and $\mathscr{H}_b$ have cancelled out, as we had no prior preference with regard to the granularity (i.e. $p(\mathscr{H}_a) = p(\mathscr{H}_b)$). Values of $\Lambda > 1$ indicate that according to the data, $\{\ell\}_a$ is preferred over $\{\ell\}_b$ with a degree of statistical significance given by the magnitude of Λ[17]. We use $\log_{10}\Lambda$ to determine confidence levels for rejecting complete differentiation and complete aggregation as OG for the monthly ILNs. This is achieved by setting in Eq. 3 $\{\ell\}_b$ to the OG inferred from the algorithm and $\{\ell\}_a$ to either complete differentiation or complete aggregation. Note that these confidence levels of rejection give rise to values $\log_{10}\Lambda \leq 0$. Large negative values of $\log_{10}\Lambda$ point to strong evidence for rejecting complete differentiation and/or complete aggregation.

Example for a small layered network

As an illustration, we determine the OG for a small network of 50 nodes with three generic interactions (A, B and C) drawn in bundles (Fig. 2(a)). Instead of specifying the individual interactions, one can describe the network in a more parsimonious way by specifying the "wiring patterns" between groups of nodes. The nodes are grouped in circles, squares and triangles, so as to encode a specific high-level description of the network. For example, interaction type A does not occur between

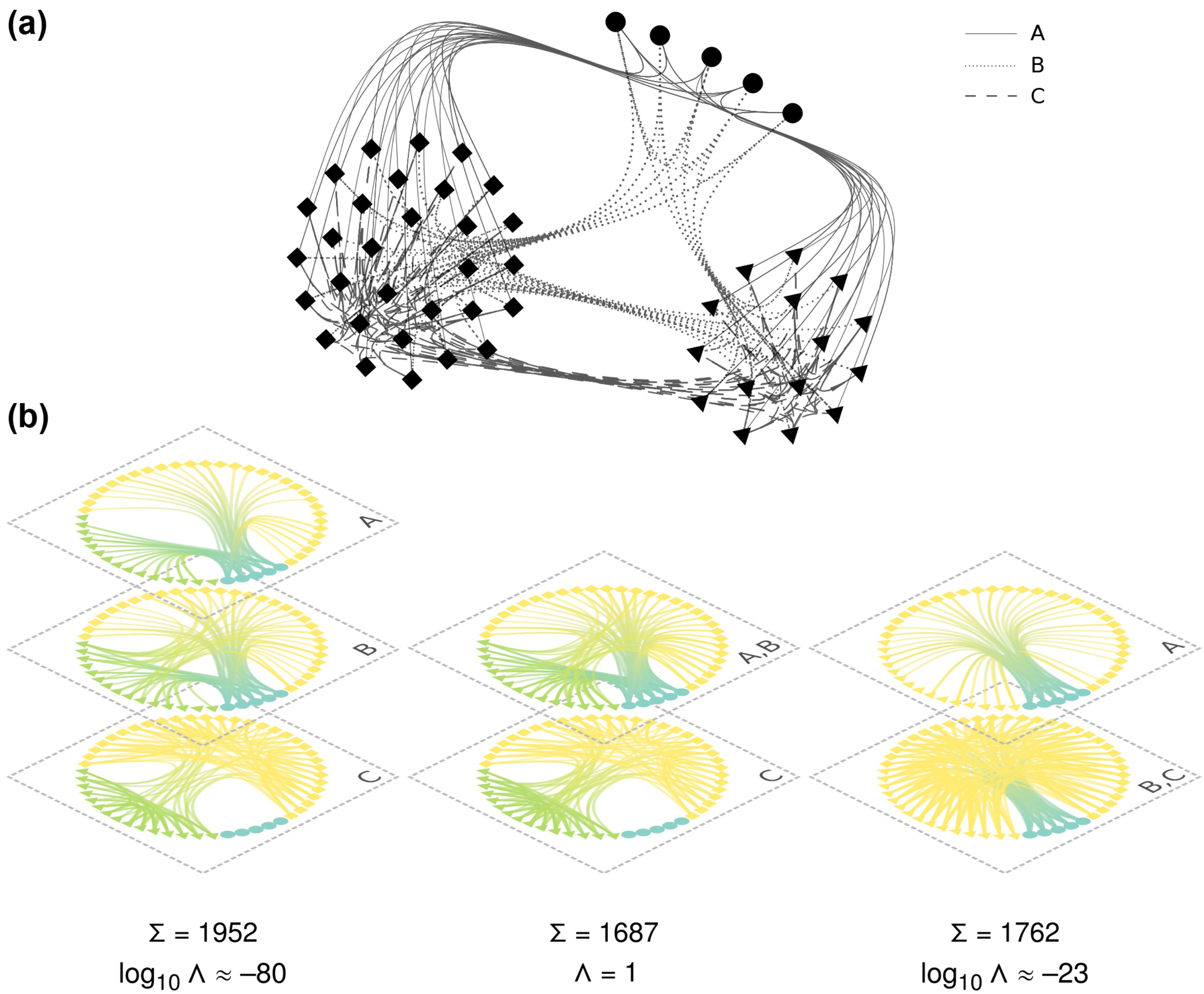

Figure 2. Illustration of inferring the optimal granularity (OG) for a small network with the coarse-grained layered SBM. Images created with the graph-tool Python library[50]. **(a)** An undirected and unweighted network with three types of edges (representing three generic interactions of type A, B, C) and three types of nodes (circle, square, and triangle). The interaction types define the network layers. Their network structure can be described as: perfect core-periphery (CP) (layer A), imperfect CP (B), and community structure (C). **(b)** The network is shown with three levels of granularity. From left to right, these are: complete differentation $\{A, B, C\}$; merging of layers A and B with a lonestanding C $\{\{A, B\}, C\}$; and the merging of layers B and C with a lonestanding A $\{A, \{B, C\}\}$. The nodes are coloured according to the group index b_i inferred by the coarse-grained layered SBM. The description length Σ [bits] and posterior odds ratio Λ relative to the OG for each representation are also indicated. The OG for this network is $\{\{A, B\}, C\}$. This can be understood by realising that both layers A and B have CP structure so that the merged layer $\{A, B\}$ can be described more efficiently by just one CP model.

two squares and between two triangles. Interaction A gives rise to circle-triangle and circle-square interactions. There are no circle-circle interactions of the C type, and circle-circle interactions of the types A and B are sparse. This is the kind of higher-level organisation into groups of nodes that SBMs can infer.

The results of the fits with the coarse-grained layered SBM for three levels of granularity are displayed in Fig. 2(b). Comparing the DL Σ for the three fits, the preferred model is the OG $\{\{A, B\}, C\}$ with $\Sigma = 1687$ bits ≈ 211 bytes. The network

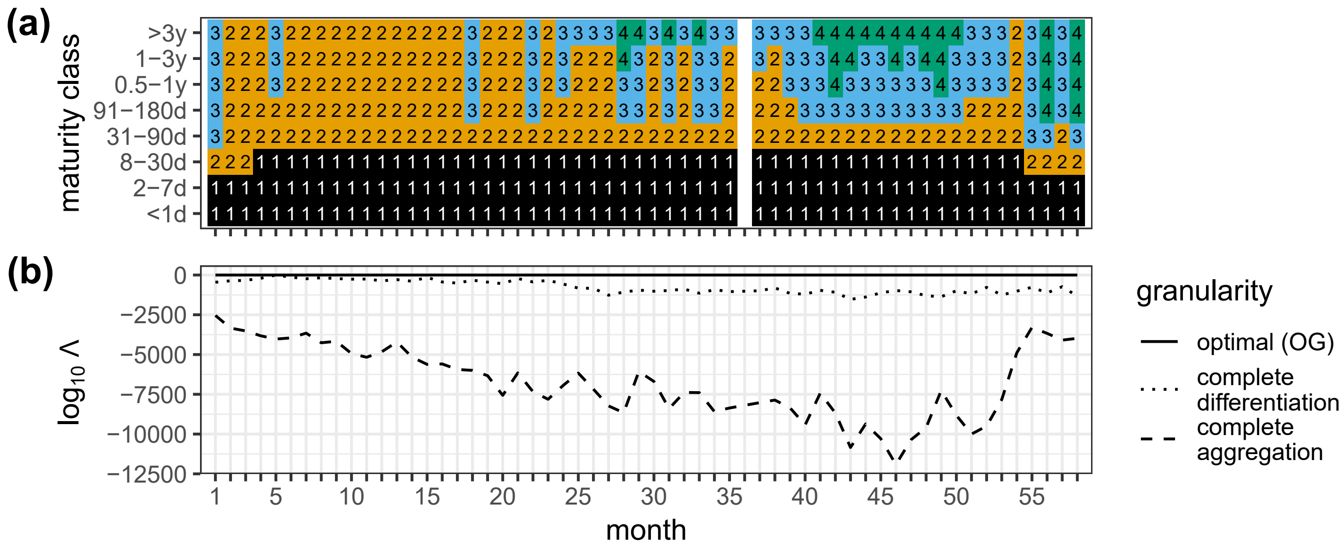

Figure 3. The optimal granularity (OG) with respect to the loan maturity classes for the Russian interbank lending network. The OG corresponds to the maturity bin set $\{\ell\}$ parameter of the best-fit coarse-grained layered SBM. **(a)** Monthly time series of the OG inferred from the monthly interbank lending network. Each OG bin (OGB) holds one or more maturity classes and is labelled by an OGB index $1,2,3,4$ and indicated by a colour. The OGB index runs from short to long maturities. The OGBs correspond to lending patterns between the bank groups that differ from each other in a statistically significant way. **(b)** Temporal evolution of the $\log_{10}$ of the posterior odds ratio Λ (for its definition see Eq. 3) of the layered SBM for three different granularities: (i) the OG; (ii) complete loan maturity differentiation; (iii) complete loan maturity aggregation. Complete aggregation is decisively rejected as an optimal representation of the mesoscale of the monthly interbank lending network. The largest $\log_{10}\Lambda$-value different from zero is $\log_{10}\Lambda = -6.33$ and occurs for complete differentiation at $t = 5$.

in Fig. 2(a) can be saved to disk in graph-tool's[50] native binary format as a file with a size of approximately 3,400 bytes, while the OG coarse-grained layered SBM can compress this (e.g. using arithmetic coding) down to $\Sigma \approx 211$ bytes (excluding the bytes needed for storage of practicalities[51] such as the file header). We use the POR Λ of Eq. 3 to determine the confidence levels. The model $\{\mathrm{A},\mathrm{B},\mathrm{C}\}$ that stands for complete differentiation is rejected with $\log_{10}\Lambda \approx -80$, indicating that it is an overly complicated model of the group structure. Indeed, the wiring patterns in layers A and B can be summarised neatly by merging them, since the inferred groups in $\{\mathrm{A},\mathrm{B},\mathrm{C}\}$ and $\{\{\mathrm{A},\mathrm{B}\},\mathrm{C}\}$ are identical. In contrast, merging layers B and C induces a change in group structure where the distinction between the squares and triangles is lost and these two groups are aggregated into one with many internal interactions. It is worth mentioning that the $\{\mathrm{A},\{\mathrm{B},\mathrm{C}\}\}$ model is still a more appropriate description of the network than the $\{\mathrm{A},\mathrm{B},\mathrm{C}\}$ one.

Fitting the coarse-grained layered SBM to the monthly ILNs

For each monthly ILN $\{G_l\}$ we fit the coarse-grained layered SBM by the MAP estimate of its parameters $(\{\theta\},\{\ell\})$. From this we obtain a time series of the OGs and the bank groups $\{b_i\}$.

The monthly OGs

Fig. 3 shows the monthly OGs together with the PORs relative to complete differentiation and complete aggregation. As noted before, each OG consists of a set of bins numbered from short to long maturity by the OG bin index (OGB index). The most important result is that complete aggregation is always rejected as the appropriate level of granularity for $\{G_\ell\}$. The maturity layers are thus informative of the monthly ILN's network structure in the sense that including them in a layered SBM yields an improved description compared to an SBM of the collapsed monthly ILN $\{G_c\}$. In other words, the lending patterns in the monthly ILNs $\{G_l\}$ correlate with the maturity classes in a way that cannot be captured completely by just considering the loans alone, i.e. without maturity information. This is also indicated by the fact that complete differentiation is seen to yield substantially better fits to $\{G_l\}$ than complete aggregation. The $\log_{10}\Lambda$ of Eq. 3 that measures the degree of rejection, tends to increase until roughly month 50 (February 2004), after which the degree of rejection becomes weaker. This aligns with the timing rumours surfaced about a large scale government investigation into money laundering by banks. This eventually caused several bank licenses to be withdrawn, see Appendix F for a time line.

The eight maturity classes reflect the Central Bank of Russia (CBR)'s reporting standards. One may therefore ask whether all eight classes also have an economic function in the actual lending and borrowing between banks. Interestingly, the OGs are always different from complete differentiation, which means that the maturity classes are partly redundant and that the lending patterns may be described more effectively by merging maturity layers into bins according to the OG. The OGBs are indicative of the fact that lending patterns between the bank groups can be combined in a more comprehensive form. For example, the short layers ($G_{\text{<1d}}$, $G_{\text{2-7d}}$, $G_{\text{8-30d}}$) which are characterised by the ILN stylised features in Table 1 are almost always merged together. We emphasise that this does not necessarily indicate pointwise similarity between these layers; rather the merging of the layers in the OGB induce a new lending pattern between the bank groups that is significantly different from the other OGBs.

Figure 3(a) shows that the number of OGBs increases with time, which points to a developing interbank money market as more significantly differing lending patterns emerge between the bank groups. An additional argument is that the OGs differ more and more from the complete aggregation (see Fig. 3(b)). Indeed, the monthly number of bins in the OG correlate with the known two phases in the Russian money market's development: early development (before month 35) and emerging maturity (from month 35 onward) (see Methods). This indicates that the market's emerging maturity phase is characterised by a more complex layered SBM with up to four statistically significantly lending patterns between the bank groups. This is in contrast with the early development phase, where mostly only two lending patterns are discerned (maturities up to 30 days and maturities longer than 30 days). In other words, the interbank market can be characterised during the early development phase by the existence of only two distinct lending strategies between the bank groups.

The bank groups

In Fig. 4(a) we display the number of groups B $(1 \leq b_i \leq B)$ inferred for each monthly ILN. As $B > 1$ across time, the monthly ILNs do contain group structure. Second, B follows the same upward trend as in Figs. 1(a),(b); 3(b), indicating that the increase in the number of groups goes hand in hand with the development of the Russian ILN into a more mature phase as the months in our dataset pass.

We now look at time correlations between the inferred monthly group structure. Fig. 4(b) shows the normalised mutual information (NMI) between the inferred bank groups in given month t and the previous month $t-1$. In the Russian ILN, one

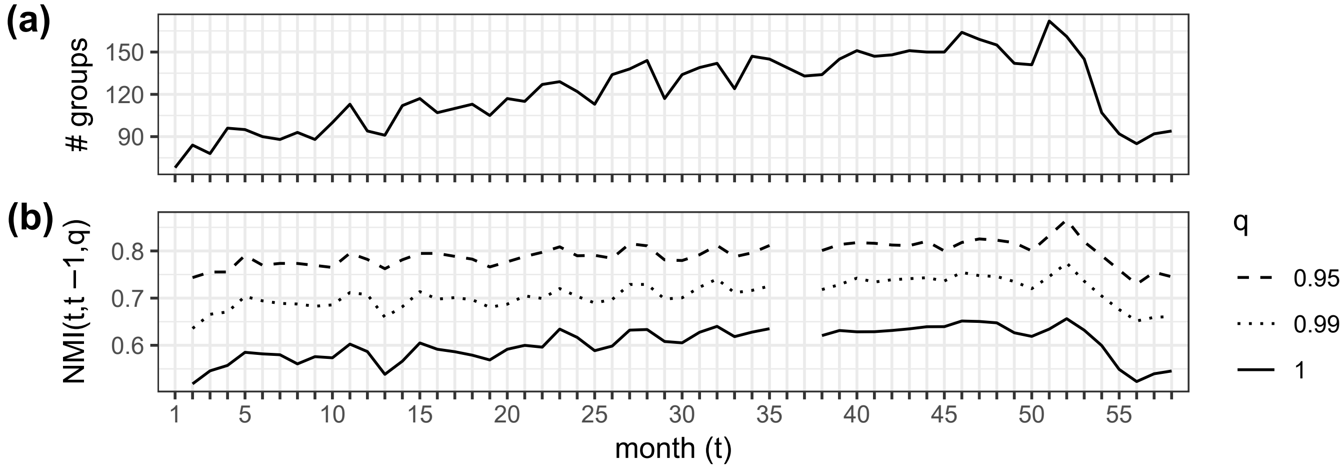

Figure 4. Information about the bank groups $\{b_i\}$ for the monthly Russian interbank lending networks as inferred from the optimal granularity (OG). **(a)** Temporal evolution of the number of different bank groups. The number of groups roughly increases until $t = 50$. This indicates that the mesoscale structure of the monthly interbank lending networks becomes progressively more complex as more bank groups are needed to fit the lending patterns. **(b)** The temporal evolution of the normalised mutual information (NMI) between the OG group memberships of the set of banks active in two consecutive months $(t, t-1)$ for three strength fractions q. For example, for $q = 0.95$, banks responsible for 95% of the network's lending and borrowing are included. In many fields, including community detection, the NMI is a popular quantity to measure the similarity between two partitions of a set[53].

discerns non-important banks. They display little activity over time and volume, and accordingly they are inclined to fluctuate between groups. To account for this, we condition the NMI on q, a measure to control which bank strengths[52] are included. The strength s_i^l of a bank i is defined by the total amount it borrows and lends in a layer l during a certain month:

$$s_i^l = s_i^{l,\mathrm{in}} + s_i^{l,\mathrm{out}} = \sum_{j,k} x_{jik}^l + \sum_{j,k} x_{ijk}^l \,. \tag{4}$$

We also define the size of a maturity layer $S^l = \sum_{i<j,k} x_{ijk}^l$ as the total amount borrowed or lent during a certain month. The size of the monthly ILN is given by $S = \sum_l S^l$. To construct Fig. 4(b), we calculate for each month t the relative strength of each active bank $s_i = \sum_l s_i^l / 2S$. Then we create a list of banks by adding one bank at a time, *starting out with the strongest bank and proceeding in order of decreasing bank strength*. We then include those banks with a cumulative relative strength closest but larger than q. In this way, we exclude banks that are only responsible for an insignificant amount of lending and borrowing in the network. We intersect the included banks with those at time $t-1$ and calculate the NMI from the two intersected bank group memberships for $q = 0.95, 0.99, 1$. Figure 4(b) shows that with decreasing q the NMI grows, pointing to increasing similarity between the inferred bank groups at consecutive months. It is hard to draw conclusions from the NMI without a reference. By excluding the "5% least important banks by strength" ($q = 1 \longrightarrow q = 0.95$) a considerable increase in correlations between the inferred bank groups in consecutive months is observed. This is indicative of the temporal stability of the inferred groups.

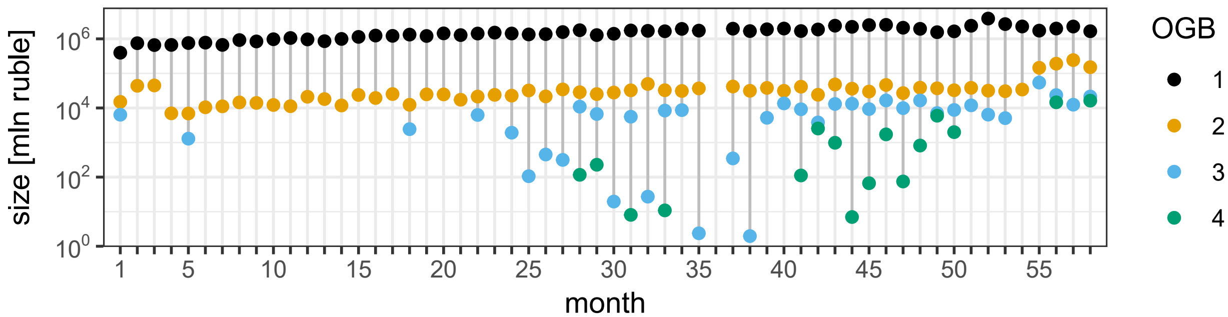

Figure 5. Correlations between aggregate loan sizes and lending patterns: the size of the optimal granularity bins (OGBs) through time. The size of an OGB is defined as the total amount of issued money in the interbank lending network defined by the OGB. The OGB indices and colours correspond to those of Fig. 3(a).

Characterisation of the OGBs

The OGBs can be interpreted as corresponding with statistically significant differing lending patterns between the bank groups. For consistency, we numbered the bins in the OG with an OG bin index (OGB index) from short to long maturity. Even though their actual content can vary considerably through time, we find that this numbering scheme reveals surprisingly consistent patterns.

At the network level, Fig. 5 displays the OGB sizes $S^\ell = \sum_{l\in\ell} S^l$ throughout time. We see that the order of magnitude of the OGBs corresponding with the shorter maturities stays consistent across time, even though the composition of the OGBs (i.e. the maturity layers in the OGBs) changes considerably through time. This is especially so for OGB 2 (see Fig. 3(a)): it contains the long maturity layers during the early development phase but not during the emerging maturity phase. It is interesting to note that while the sizes of the "longer" OGBs are much smaller than the short ones, these are not merged in the emerging maturity phase of the Russian ILN. This points to lending patterns that are sufficiently different from those in the short OGBs. (This still holds, except in one month, for the non-contiguous binning in Appendix B.)

Finally, we look at the bank level, i.e. the lending behaviour of individual banks. Again we use the bank strength to single out the "important" banks. In Fig. 6 we have shown the time-integrated distribution of $s_i^{\mathrm{in},\ell}/s_i^\ell$ of the top 10% most important banks of each month, separately for each OGB ℓ. (Note that the conclusions hold for other cutoffs – see Appendix E.) The instrength of a bank i in maturity bin ℓ during a certain month is $s_i^{\ell,\mathrm{in}} = \sum_{l\in\ell}\sum_{j,k} x^l_{jik}$, and the strength s_i^ℓ is defined analogously as in Eq. 4. At monthly time scales the important banks in "short" bins tend to both lend and borrow equal amounts of cash, while the important banks in the "long" bins tend to either lend or borrow. Together with the indications for CP structure in the short layers, this suggests that the economic function of the important banks changes from financial intermediation (short bins) to financing (long bins). The apparent patterns in the short bins are indeed reminiscent of the functions in CP structures, while those in the long bins have, to the best of our knowledge, not often been included in the literature. Thus our coarse-grained layered SBM of the ILN uncovers a correlation between statistically significant lending patterns between the bank groups, the economic functions of the important banks, and the maturity classes of the loans involved.

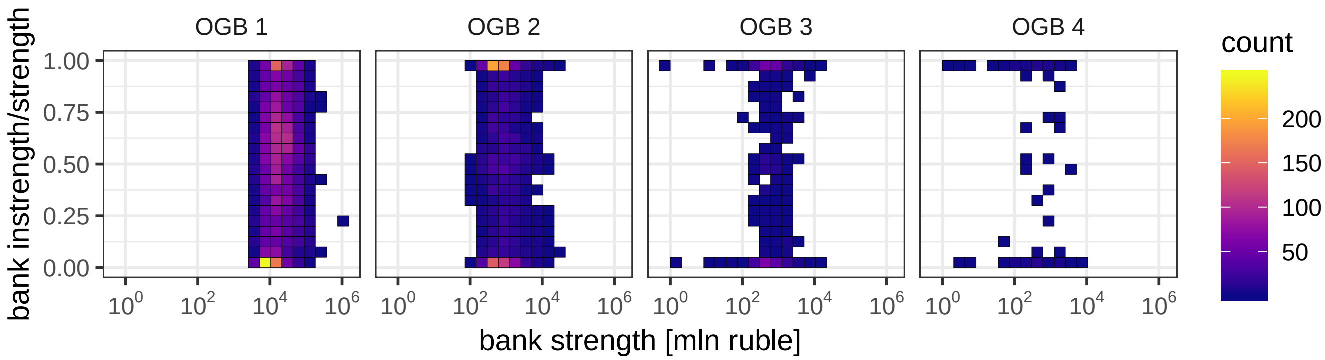

Figure 6. The time-integrated distribution of the strength and the instrength/strength ratio of the monthly "important banks" for the four optimal granularity bins (OGBs). As in Fig. 4(b) we gauge a bank's importance by its strength: For a given month a bank is deemed important if its strength lies in the top 10%. With growing OGB index, the important banks increasingly tend to either lend or borrow. Banks in OGB 1 and OGB 2 tend to balance lending and borrowing. This suggests that the economic function of the important banks in the various OGBs changes from financial intermediation (short maturity bins) to financing (long maturity bins) on a monthly time scale.

Discussion

In this paper, we investigate the importance of loan maturity information in interbank lending networks towards understanding its mesoscale structure. We do this to better understand the possible diversity in lending and borrowing patterns in ILNs and their accompanying economic functions. We employ the complete population of all Russian interbank lending contracts over a 55 months period (January 2000–October 2004) containing uniquely granular loan maturity layers. Descriptive statistics on the different maturity layers uncover non-homogeneity in network measures along loan maturity layers. This non-homogeneity indicates that complete maturity aggregation, as is common in ILN literature, is not capable of fully capturing the diversity in lending and borrowing patterns present. To investigate the optimal and most informative granularity of maturities, we apply a coarse-grained layered stochastic block model[1] to the data. We find that complete maturity aggregation obscures the existence of, in our data four, maturity layer bins that show distinctly different lending- and borrowing patterns per layer, encoded in their structure, that have a functional economic interpretation. We find, for example, a consistent shorter term maturity layer that behaves in line with the theory around tiered banking, with important banks intermediating liquidity. We also detect another layer that aligns with long-term financing of bank activities, with the important banks acting as sources or sinks of liquidity.

These findings immediately imply that the common practice of complete maturity collapse, by choice or for data limitations, obscures important information about the functions banks perform in an ILN. This leads potentially to unrealistic ILN models and misguided policy conclusions about systemic stability, especially so in times of liquidity crunches when the short term layer of the ILN issuance network collapses. The structure to which loans belong not only depends on the maturity of the loan itself but also on the phase of development of the interbank money market. The longest maturity loans, for example, only show structure related to interbank financing at later phases of market development. This makes economic sense since long-term loans entail greater counter-party risk and counter-party trust is only established over time through engagement in long term relationships.

All in all this implies that theoretical and empirical research can neither adequately grasp the generative process of ILNs nor arrive at reliable policy conclusions from ILN modelling and simulation in the absence of appropriate granular maturity information. This underlines the importance for policy and regulatory bodies to collect maturity information on interbank loans if they desire to arrive at reliable insights into the health and systemic stability of the interbank lending market. It should also stimulate further theoretical and empirical research that incorporates loan maturity in modelling of the ILN generative process, its dynamics and its occasional transition to phases of instability or collapse.

Methods

Dataset

Overview

The interbank data analyzed in this work offers a rich and unique account of Russian commercial bank activities over a six-year timeline (August 1998–October 2004). The data is provided by Schoors and Karas[15] and has been painstakingly assembled from public and private sources. The dataset used in this paper can be retrieved on demand from the authors. To the best of our knowledge the dataset is unique[54] in quite a number of aspects. We mention the availability of information about the issuance months of loans (most often only the derived exposure is available) and rather detailed granular information about the maturity (see Appendix G). The fact that the Russian interbank market went through many stages of development during 1998-2004 adds an additional layer of dynamics. Note that the CBR is not included as a node and that we do not have information about any of its transactions. A classification of the banks together with a recent description of the money market can be found in[43]. On average, about half of the Russian banks are active on the interbank market[21]. The dataset starts a few weeks before the so-called “1998 Russian default”[55], which caused a complete collapse of the interbank money market. In response the CBR imposed to little avail several extraordinary measures to stabilise the market. These exceptional circumstances greatly disrupted the workings of the interbank market and because of this we have restricted our analysis to the period of 55 months from January 2000 until October 2004. As can be inferred from Fig. 1, during months 1-35 the market is developing. We refer to this period as the early development phase. Roughly starting from month 35 (December 2003) the interbank market enters an emergent maturity phase: the amount of active banks stabilises and the share of overnight loans declines in favour of longer-maturity loans. The emergent maturity phase includes the trust crises in the second half of 2003 and the summer of 2004 caused by a money laundering scandal (see Appendix F in the Supplementary Material for more details). As compared to the Russian default of 1998, the crises of 2003 and 2004 were less disruptive for the interbank lending market.

Contents

The data consists of the issuance of domestic unsecured interbank loans, annotated by lender bank ID, borrower bank ID, month of issuance, loan size, interest rate and maturity class. The loan issuances are reported to the legislator on the first day of each month throughout August 1998 up until November 2004 in one of the following eight maturity classes: overnight (less than one day, <1d), 2-7 days (2-7d), 8-30 days (8-30d), 31-90 days (31-90d), 91-180 days (91-180d), 0.5-1 year (0.5-1y), 1-3 years (1-3y), more than 3 years (>3y). Because of this reporting standard, the precise issuance month of the loans is known. For January 2003 (month 36) there is no data available. Whenever possible, we interpolate the missing month in the time series. For some variables (Figs. 3(a) and 4(b)) this is not feasible and this is at the origin of the missing data point in the time series.

Aggregation window

Loans are aggregated by issuance month into monthly ILNs (as in[21]) for two reasons. First, monthly aggregation is the most granular time scale available in the data. Second, monthly compliance with regulatory requirements for banks (e.g. for liquidity and capital) induces a monthly periodicity in the data.

Availability

The dataset as well as the inferred bank groups are available on request.

Implementation

Inference algorithm with agglomerative hierarchical clustering

We infer the OG for a layered network using an agglomerative hierarchical clustering heuristic as suggested in[1]. At the start of procedure each layer is put in its own bin. In the next steps, bins are merged so as to reduce the overall DL. The overall DL consists of the DL of the layered SBM plus a "SBM extension term" that accounts for the model comparison between the possible levels of granularity (Eq. 17 in[1]). With contiguous binning only contiguous bins are merged, while for non-contiguous binning any pair of bins may be merged at each step. In this way a series of layered networks is generated, starting with the original layered network and ending with the collapsed network. The layered network with the smallest overall DL defines the OG.

We use the efficient inference algorithm[56] implemented in the graph-tool library[50] to fit the layered SBMs to the monthly ILNs. The algorithm employs an agglomerative heuristic to fit the layered SBM and a multilevel Markov Chain Monte Carlo to sample the posterior distribution. We used High Performance Computing resources to perform four runs of numerical calculations: two of those used contiguous binning and two of those used non-contiguous binning for the maturity layers. In each run we used agglomerative hierarchical clustering to fit the layered SBM and to sample the posterior for the levels of granularity generated for each of the monthly ILNs. The number of samples were set to 10,000 and 25,000 for both the contiguous and non-contiguous runs. All runs (including the test runs) yielded similar results for each monthly ILN which alludes to the stability of the posteriors. The layered SBMs with smallest DLs were gathered from both runs.

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Author contributions statement

Author contributions: M.V.S., M.v.d.H, J.R, and K.S. designed research; M.V.S., and M.v.d.H performed research; M.V.S. analysed and processed results; and M.V.S., M.v.d.H, J.R, and K.S. wrote the paper.

Additional information

Competing interests: The authors declare no competing interests.

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