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Interpersonal versus interbank lending networks: The role of intermediation in risk-sharing

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ABSTRACT

Analyzing the interpersonal lending network of a Hungarian village in a disadvantaged region, we find strong intermediary activity and a tiered core-periphery structure. We show that the main motive behind lending is not altruism or profit-seeking, but risk-sharing which is the most accentuated in poor-to-poor and Roma-to-Roma relations. Comparing this informal lending market to a formal interbank market, we find more similarities than differences. In both markets, intermediation is a key element in risk-sharing and an effective tool to cope with liquidity risk. Regulatory and development policies should respect the existing institutions of risk-sharing.

1. Introduction

Lending networks can differ according to the nature of the players (banks, firms, households, etc.) and the interlinkages between them (payment, ownership, derivative transactions, debt exposures, etc.). *Debt transactions* (secured or unsecured) may serve different purposes such as entrepreneurship, project financing, smoothing of the life-cycle consumption, or *liquidity management*.

In this paper, we investigate two lending networks: (i) an interpersonal lending market within a small village in a disadvantaged region and (ii) an interbank deposit market - both operating in Hungary in 2015. Thus, we compare an *informal* and a *formal* financial market serving basically the same fundamental purpose (liquidity management with no collateral), where players, protocols, institutions, and mechanisms are different. We complement the analysis of the interpersonal market with in-depth interviews. In this way, we get insight into the operation of this specific informal market and reveal causes and consequences of financial exclusion.

While interbank markets have been extensively analyzed in the finance literature (Csóka and Herings, 2018, 2021; Craig and von Peter, 2014; Eisenberg and Noe, 2001; Rogers and Veraart, 2013; Silva et al., 2016), informal lending networks are a much less researched area, which is mainly due to the lack of reliable data. We have access to a comprehensive database representing the informal lending activity of a whole village where a significant part of families lives in extreme poverty, discrimination, and financial exclusion as defined by Allen et al. (2016). We gathered these data as a part of a participatory action research. The whole research project lasted more than a year to complete, with the actual data collection taking 3 months (Gosztonyi, 2017). The novelty of our

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paper is the characterization of this interpersonal lending network employing the analytical tools developed for formal financial networks. Specifically, we detect hierarchy and approximate a (continuous and asymmetric) core-periphery model to the informal lending network of the villagers. The corresponding formal network, the interbank network, serves as a benchmark for this analysis.

The main contribution of our research is a thorough analysis of a village's interpersonal lending network relative to an interbank network. We have a snapshot of all lending relationships of the entire population reported voluntarily in a three-month period in 2015. Up to our knowledge, we are the first to describe the core-periphery structure of an informal risk-sharing network in detail. Our findings highlight the importance and interaction of intermediation, reciprocity, and risk-sharing.

Seminal empirical papers demonstrated that financial networks exhibit a special core-periphery structure where peripherical banks do not transact with each other directly, only through the intermediation of core banks (Craig and von Peter, 2014; Fricke and Lux, 2015; Langfield et al., 2014; Lelyveld and Veld, 2014; León et al., 2018; Silva et al., 2016). A core-periphery model can be defined in different ways (discrete/continuous, symmetric/asymmetric) and its calibration to real data can rely on different optimization algorithms (Borgatti and Everett, 2000; Boyd et al., 2010). The essence is that some players serve as intermediaries, who take offsetting positions in their balance sheet to help others trade. Clearly, they have "skin in the game" and run significant partner risk.

There are several explanations in the finance literature why intermediation is necessary in financial networks, in other words, why a core-periphery structure emerges. These explanations relate to market frictions such as asymmetric information (Lux, 2015), transactional costs (Hojman and Szeidl, 2008), illiquidity (Aldasoro et al., 2017; In't Veld et al., 2020), and other risks and uncertainties (Chang and Zhang, 2018). When managing liquidity shocks, low-educated poor people face these problems similar to highly educated professional traders working on the interbank market. Consequently, strategies, hence network structures, can be similar as well.

When comparing the interpersonal and interbank markets, we find some obvious differences (players, loan amounts, maturities, interest rates, regulation, emotional effects, etc.) and surprisingly many similarities. Most of all, the share of intermediaries among players is significant both in the interpersonal and the interbank markets (44% and 61% respectively). Investigating the core-periphery structures, the interpersonal market is found to be more hierarchical in the sense that more hierarchy levels coexist, while the interbank market is more bipolar from this perspective. Interviews reveal that, in the interpersonal market, lenders use sophisticated risk management techniques (rating, screening, monitoring, partner limits, etc.), just like professionals (see Appendix).

Moreover, the main motive behind trading shows similarities as well. In principle, motivations can be altruism, profit-seeking, and risk-sharing. Caudell et al. (2015) collected interpersonal lending data among Sidama population in southwestern Ethiopia and investigated the effects of large exogenous (weather) shocks. They found that lending was motivated mainly by altruism as rich farmers helped out the poor. Contrary to this, according to our data, under normal economic conditions, lending is not purely driven by altruism as the dominant relationship is not rich-to-poor, but overwhelmingly poor-to-poor. Surprisingly, not even profit-seeking is the motivation. In the interpersonal market, the interest rate is 0%, so there is no direct financial benefit from the intermediation activity. We also show that, in the interbank market, although the interest rate is positive, the intermediary profit is negligible even for the largest intermediators, which contradicts In't Veld et al. (2020). We conclude, therefore, that both markets are mainly driven by risk-sharing (Dubois et al., 2008; Fafchamps and Lund, 2003; Laczó, 2015). Basically, poor villagers lend to each other practically for the same reasons as treasury traders: they operate a mutual insurance scheme to deal with liquidity shocks.

Our results indicate that risk-sharing cannot work without intermediaries who are willing to lend anyway, even if they know that they themselves will need to borrow at the end of the day (or month) to settle their own position. The main feature of intermediaries is that they are more attractive partners in the eyes of others, get credit more easily and use this personal capital to operate the risk-sharing system (Craig and von Peter, 2014; Fricke and Lux, 2015; In't Veld et al., 2020). Thus, social capital replaces physical capital in both markets, but especially in the interpersonal market (Guiso et al., 2004; Portes and Landolt, 2000).

When zooming into the interpersonal network, we investigate to what extent income, ethnicity, kinship, friendship, and geographical distance determine the lending activity. We find evidence for strong poor-to-poor and Roma-to-Roma homophily and reciprocity. Poor Roma families accumulate an especially large amount of social capital via family ties, friendship, and (less significantly) neighborhood. In-depth interviews also strengthen the view that financially excluded poor families operate effective risk management systems employing a wide range of sophisticated tools and following rational decision-making rules (Banerjee and Duflo, 2011).

In most of the empirical literature on risk-sharing, the income smoothing effect is tested. If consumption is more stable over time than income, it is considered to be the result of risk-sharing. Dubois et al. (2008) and Laczó (2015) found strong evidence for risk-sharing with limited commitment in Pakistanian and Indian villages, respectively. De Weerdt and Dercon (2006) showed that in a small village of Tanzania, for food consumption, risk-sharing is extended for the whole village with full commitment, whilst it is only partial for non-food consumption. Bold and Broer (2021) found in Indian villages that income shocks are smoothed out symmetrically and the risk-sharing community is smaller than the whole population of the village. Lam and Paul (2013) pointed out that a displacement of a community in Nepal seriously eroded the informal risk-coping mechanisms and created a vicious cycle of poverty.

There are relatively few papers examining the inner structure of risk-sharing networks, which can be due to the lack of reliable data. Caudell et al. (2015) analyzed lending network data for a village in Ethiopia focusing on the effects of a large exogeneous weather shock and found evidence for rich-to-poor altruism. Our research setting is different as in the investigated period, the Hungarian economy was prospering and there was no major macro shock. We find that poor Roma-to-Roma households are the most active in lending each other with zero interest rate. In-depth interviews strengthen that risk-sharing is the main motive behind lending (see Appendix). Basically, kinship and friendship shape the network structure, which is consistent with the findings of Fafchamps and Lund (2003). This also means that risk-sharing is not perfect in the sense that not all liquidity schocks can be diversified within the community. Fafchamps and Gubert (2007) investigated the interlinkages in a risk-sharing network in the Philippines. On the one hand, risk-sharing is expected to be more beneficial if the income profiles of the participants are different. On the other hand, social and geographical distance increases the costs of developing and maintaining the linkages. Fafchamps and Gubert (2007) found that occupations had no significant effects, while the geographical closeness (probably through kinship) increased the likelihood of a lending relationship. In our sample, we have no information on occupations, but kinship and friendship are significant in all settings and take over the effects of the other variables (ethnicity, income, and geographical closeness).

Empirical papers on village economy and informal risk-sharing systems concentrate on developing countries in the third world, whereas our paper investigates the informal lending market of a Hungarian village in the middle of the European Union. Durst (2015) and Szőke (2018) examined informal intra-village lending in the same region of Hungary, but they relied on qualitative research methods (interviews, case studies) from a sociological perspective. Durst (2015) focused on the local power structures and the role of informal lending (especially usury). Szőke (2018) found that interpersonal lending is an essential tool for "rescaling insecurities" and the mayor of the village is actively involved in the operation of the local informal credit market. Our research, the first quantitative study in the field using detailed network data, confirms and complements the findings of the existing social science literature on Hungarian villages.

The paper's structure is the following. In Section 2, a comparative network analysis is presented with a special emphasis on the core-periphery structure; in Section 3, the interpersonal and interbank networks are examined separately in more detail focusing on the possible motives behind trading; in Section 4, results are discussed, and finally, in Section 5, we set out the policy implications and identify possible directions for further research.

2. Comparative network analysis

We compare the networks of interpersonal and interbank markets. When managing their liquidity shocks, players must overcome market inefficiencies by developing effective lending protocols (selection of their partners, loan structures, monitoring, etc.) which shape the networks' structures. On the one hand, the two markets are similar in many respects (liquidity management without collateral). On the other hand, there are differences as well. Most importantly, traders are either low-educated, financially excluded poor people managing their own money (interpersonal lending) or highly educated, well-suited professionals managing the bank's money (interbank lending). Borrowing is an uncomfortable situation in the interpersonal market (see Appendix) while it is completely neutral for a trader in the interbank market. To assess the effects of these factors, we investigate similarities and differences in the corresponding network structures.

First, we describe network data, then we compare the basic characteristics of the two networks, and finally, we analyze the hierarchical core-periphery structure of the networks in detail.

2.1. Data

A participatory action research took place in the period between June 2014 and September 2015 during which researchers lived in a small rural village in a disadvantaged region of Hungary and developed a close relationship of trust with local people. The aim of the research was to investigate the financial survival strategies of low-income households (Gosztonyi, 2018). All procedures were carried out in compliance with relevant laws and institutional guidelines and have been approved by the Doctoral School of Sociology of Corvinus University of Budapest.

The research included 171 structured surveys related to 158 households covering approximately 2/3 of the population (in some cases, more than one person in a family completed the questionnaire). Households were defined as people living at the same address. In the investigated period, researchers identified 260 addresses in the village, and all the corresponding households were approached. However, only 164 of them were willing to answer the survey, and only 158 of them reported at least one lending relationship with other households in the village. Thus, we have access to the full lending network of the whole population based on voluntary reporting. Non-respondents tend to be richer, non-Roma, and living on the main road. We can assume that they are financially more included, and they do not participate in the intra-village lending activities.

The survey contained the following questions related to interpersonal lending:

(Q1) To whom do you *lend* a smaller amount (cash, transportation, food)?

(Q2) From whom do you *borrow* a smaller amount (cash, transportation, food)?

(Q3) From whom do you *borrow* a larger amount?

The survey was conducted between 15 May and 24 June of 2015 and the typical maturity of the loan was around 2–4 weeks. Given that people tend to overweight recent events (recency effect), the loans in question are supposed to be disbursed in March, April, and May of 2015.

A significant part of the lending activity is within nuclear families living under the same roof, so when we transformed our data into households, the average number of links dropped significantly. During the survey, respondents mentioned several partners who did not live in the village but in the neighboring villages (70%), other cities in the county (25%), or outside the county (5%). These partners, who were not directly involved in the survey, had 38 in-degrees (borrowing) and 0 out-degrees (lending) in total. For the sake of consistency, however, they were excluded from the analysis. As Q1 had a different direction (*lending*) than Q2 and Q3 (*borrowing*), when aggregating data, we transposed the adjacency matrix of Q1, then took the maximal value of the three adjacency matrices corresponding to Q1, Q2, and Q3. Thus, we got the intra-village network represented by an aggregate adjacency matrix $H_{i,j}$ (containing 1 if household i borrows from household j, and zero otherwise) for 158 households (nodes) and 281 transactions (edges) between them.

For the sake of comparison, we use a comprehensive database of the interbank deposit market from the National Bank of Hungary

Table 1
Typical loan conditions (mode of distribution).

	Interpersonal	Interbank
Amount	2 thousand HUF	2 billion HUF
Maturity	2 weeks	1 day
Interest rate (annualized)	0%	1.80%

Source: participatory action research (interpersonal market), National Bank of Hungary (interbank market).

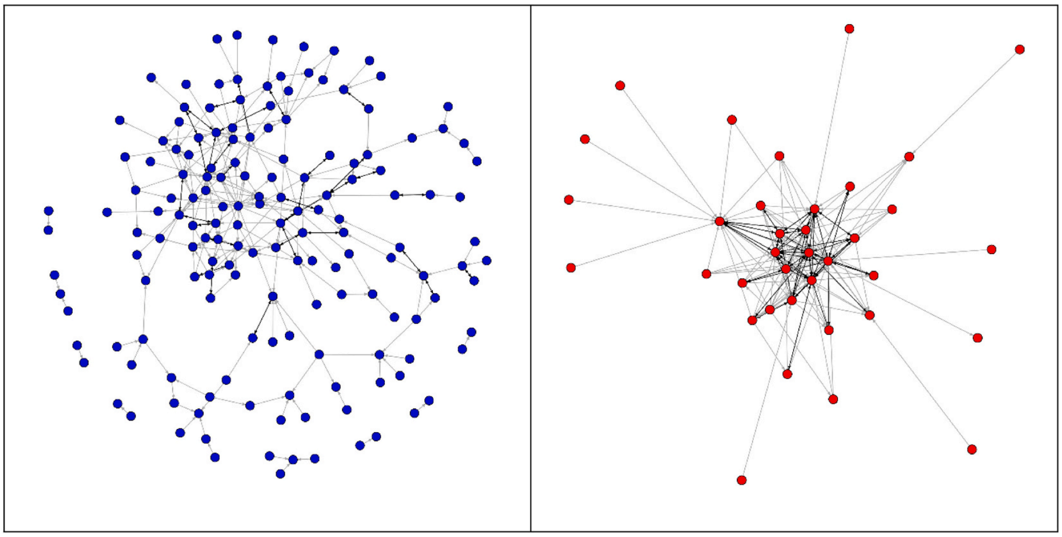

Fig. 1. Interpersonal and interbank networks (March, April, and May 2015).
Note: Bidirectional (one-way) edges are colored in black (grey). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

which is built up from the "*Daily report on interbank HUF lending and borrowing interest rates*" containing overnight (one-day-long) and longer transactions. The database consists of the codes of the data provider (borrower) and the partner (lender) banks, the loan amount, the maturity, and the interest rate for each transaction. The vertices of the network represent all Hungarian or international banks active in Hungary (regulated by the National Bank of Hungary), and the edges are transactions, that is HUF-denominated, mostly (91%) overnight loans/deposits between the banks. Data are anonymous, banks cannot be identified, hence vertex characteristics (size of the balance sheet, ownership structure etc.) are not available. Aggregating all reported transactions initiated in March, April, and May of 2015, we produce an adjacency matrix for the interbank deposit market $B_{i,j}$ (containing 1 if bank i borrows from bank j, and zero otherwise) which comprehends 36 banks (nodes) and 198 transactions (edges).

As a result, we have two directed adjacency matrices representing the interpersonal and interbank lending markets, $H_{i,j}$ and $B_{i,j}$, respectively, which are parallel snapshots reflecting comparable market structures. Typical loan conditions are presented in Table 1.

In the interpersonal market, loan amounts are one million times lower, maturities go typically until the next month, and there is no interest rate at all.

One caveat of the interpersonal market data is that reporting is voluntary; whereas in the case of the interbank network, it is mandatory. Consequently, data in the interpersonal market can be missing and biased. Nevertheless, there is no other research methodology that would allow for a better exploration of the whole network than the long-lasting participatory action research building on mutual trust. It is also notable that a lending relationship can be reported either by the lender or the borrower, or both; therefore, the detection rate can be high, which also contributes to reducing reporting bias. The two-dimensional representations of the two lending networks can be seen in Fig. 1.

The interpersonal network's density is much lower than that of the interbank market (0.01 versus 0.16, respectively). Probably, the difference in the densities can also be due to the difference in the data collection processes (voluntary versus mandatory data provision). The interpersonal network seems to be in the so-called "supercritical range" characterized by a giant component and smaller islands (like the internet, electricity, scientific co-authors, and protein molecules); while the interbank market is composed of a strongly interlinked unique super-component (like actors' network) (Barabási, 2016, Figs. 3.7 and 3.9). The large difference in the densities may have long-reaching consequences on the applicability of methods and on the interpretation of the results. For example, densities have effect on the reciprocity, the clustering coefficient, and core-periphery models can be fitted only to an interconnected component.

Table 2
Basic network characteristics.

2.A Descriptive statistics		Interpersonal		Interbank	
	Number of nodes	158		36	
	Number of edges	281		198	
	Density[1]	0.01		0.16	
	Reciprocity[2]	0.24		0.52	
	Clustering (average local)[3]	0.12		0.52	
	Diameter[4]	14		5	
	Average path length	5.14		2.04	
2.B Degree analysis		Interpersonal		Interbank	
	Maximum of in-degrees	10		24	
	Maximum of out-degrees	19		14	
	Average of in and out-degrees	1.8		5.5	
	Mode of in-degrees	0		0	
	Mode of out-degrees	1		1	
	Median of in-degrees	1		2	
	Median of out-degrees	1		4	
	HHI of in-degrees	149		707	
	HHI of out-degrees	147		460	
2.C Share of different types of players		Interpersonal		Interbank	
		number	share	number	share
	Borrowers	29	19%	2	6%
	Lenders	59	37%	12	33%
	Intermediaries	70	44%	22	61%
	Sum	158	100%	36	100%

[1] Number of actual edges divided by the number of possible edges.
[2] Probability that two connected nodes are linked in both directions.
[3] Probability that two neighbors of a given node are also neighbors.
[4] The shortest distance between the two most distant nodes.

The giant component of the interpersonal network and the entire interbank network seem to exhibit a core-periphery structure, although this is less obvious for the interpersonal network. Reciprocal relationships (indicated by black arrows) are mainly concentrated at the core, which is more accentuated in the case of the banking network.

In the interpersonal network, the mayor of the village is the central lender as he lends needy households out of his pocket on a regular basis (19 households in this period). The central borrower is a poor Roma family (having 10 in-degrees). In the interbank network, there are no central points like these (the National Bank of Hungary is the lender of last resort, but it is not included in the network). Here, an exclusive club of the biggest and most reliable banks plays the central role in the middle of the graph as they are the most attractive trading partners for the others (Craig and von Peter, 2014; Fricke and Lux, 2015; In't Veld et al., 2020).

2.2. Basic network characteristics

The interpersonal network is less reciprocal and clustered; however, it can be due to its lower density. The interpersonal network is also more extended, the diameter (the distance between the two farthest nodes in the largest component) is 14 (versus 5), and the average path length is 5.14 (versus 2.04) which is a typical value in social networks (Barabási, 2016, Table 3.2).

In directed graphs, it is worth analyzing out- (lending) and in- (borrowing) degrees separately (see Table 2.B). In the interpersonal market, the HHI (Herfindahl–Hirschman index) measures of concentration for borrowers (in) and lenders (out) are at a low level and are close to each other; while in the interbank market, concentration is higher, and borrowers are more concentrated than lenders. Thus, in the interbank market, more lenders are financing less borrowers. In this sense, the interpersonal market is more equilibrated and reciprocity is more prevalent.

We categorize nodes into three disjoint groups: borrowers who only borrow; lenders who only lend; and intermediaries who borrow and lend during the same period. The shares of different players are presented in Table 2.C for both markets. It is notable that, in both markets, most players are intermediaries while borrowers are relatively few, which reflects the importance of intermediation and risk-sharing in shaping the networks.

2.3. Network structures

First, we detect the hierarchy in the networks, then we calibrate an asymmetric core-periphery model to data.

Networks may have different structures. (A) In the Erdős-Rényi model of a random network, vertices are given, and edges are

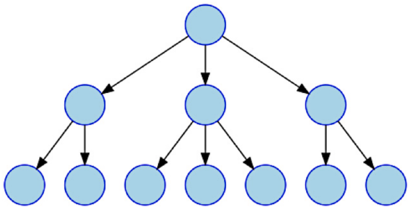

Fig. 2. A hierarchical network.

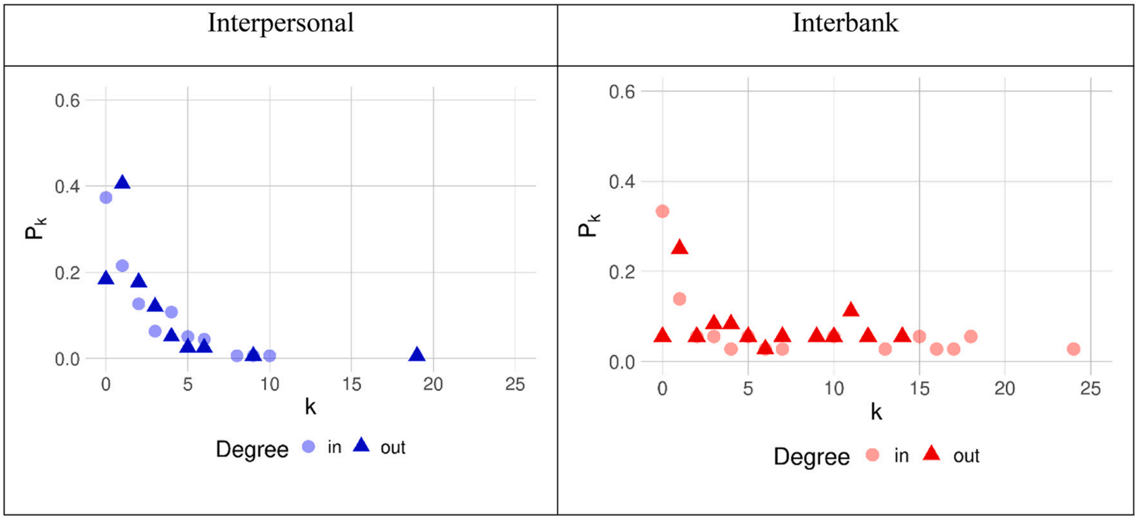

Fig. 3. Degree distributions.
Note: Dots represent a group of players having the same number of degrees. k is the number of degrees (in or out) and P_k is their relative frequency.

created randomly with probability p. Clearly, in such a network, any structures emerge randomly. (B) In the Barabási-Albert model of scale-free small worlds, new vertices are born and connected to existing ones with a probability which is a positive function of the nodes' degree (preferential attachment). As a result, some nodes may have an extremely large number of edges. (C) Hierarchical networks are also scale-free, but nodes and links are generated in an iterative and self-replicating way. In theses networks, central nodes tend to interconnect other nodes that are not connected directly.

In a non-hierarchical small world (B), there are several dense hubs linked by players that are not necessarily central. In a hierarchical network (C), however, hubs are interlinked by the central players. In a hierarchical network, higher-level players are interlinked with more and more players (all their inferiors and their counterparts), and they tend to interlink separate hubs. For example, in a large corporation, employees in the marketing and the finance departments do not communicate directly, only via their directors connected by the CEO. The more this feature holds for a network, the more it is considered as hierarchical, see Fig. 2.

These basic structures are qualitatively different. Networks are comparable quantitatively only if they exhibit the same basic structure. To differentiate between the basic structures, we examine (i) the degree distribution and (ii) the clustering coefficients the of the nodes as a function of their degrees (Barabási and Oltvai, 2004).

Scale-free networks (small world and/or hierarchical) differ from random networks in their degree distribution; the former follow a power law instead of a Poisson (or normal) distribution, therefore, nodes with an extreme large degree are much more probable. Representing the degree distribution on a log-log scale, scale-free networks fit to a straight line (see Barabási and Oltvai, 2004, Box2, Bb and Cb). A Babarási-Albert network is scale-free, but not hierarchical. A hierarchical structure can be detected by investigating the relationship between the clustering coefficient and the number of degrees on a log-log plot. The most important sign of hierarchical modularity is if we get a straight line of slope -1 (see Barabási and Oltvai, 2004, Box2, Cc). The intuition behind this is that in a hierarchical structure, central players with more degrees tend to interconnect those ones who are not communicating with each other directly.

We investigate the interpersonal and the interbank networks from this perspective. Fig. 3 presents degree distributions where out- and in-degrees (k) of different vertices are on the x axis and their relative frequency (P_k) is on the y axis.

Fig. 3 shows that out- and in-degrees tend to be lower and less dispersed in the interpersonal market, which again, can be due to its

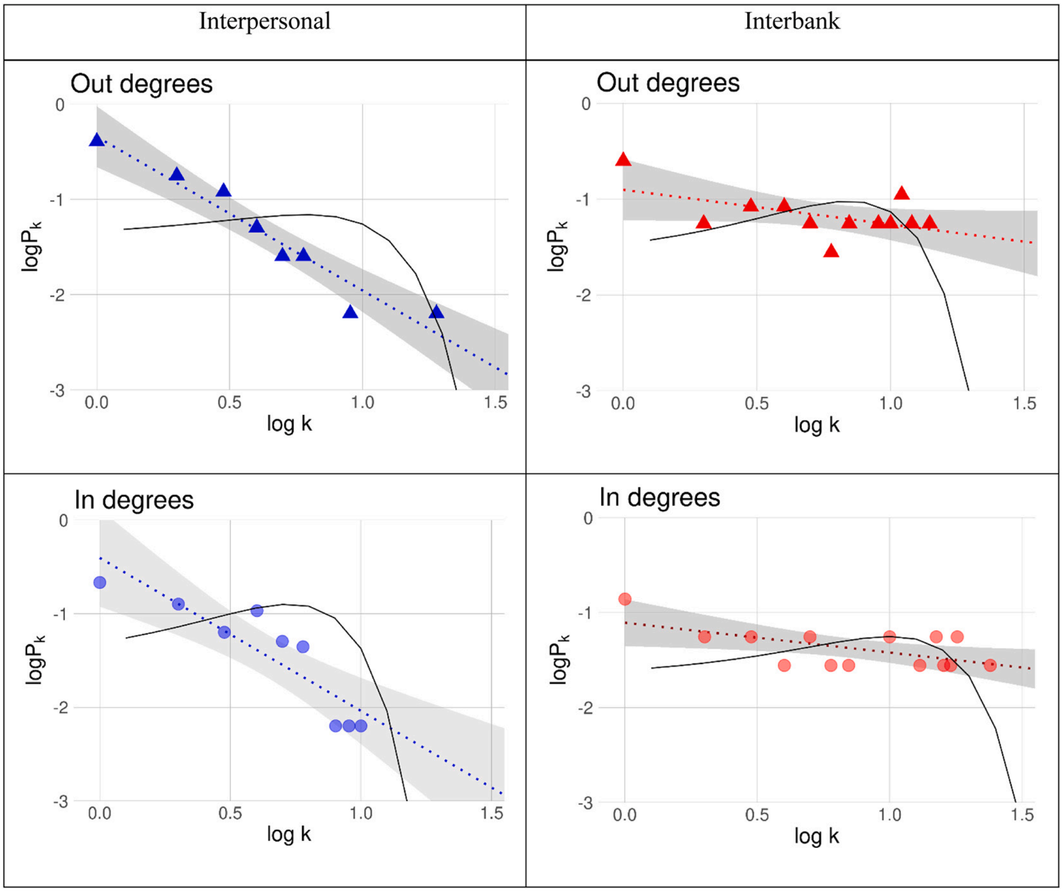

Fig. 4. Degree distributions relative to the normal distribution on a log-log scale.
Note: Dots represent a group of players having the number of (in or out) degrees. k is the number of degrees and P_k is their relative frequency. Grey areas indicate the confidence interval of 95% corresponding to the linear regression. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

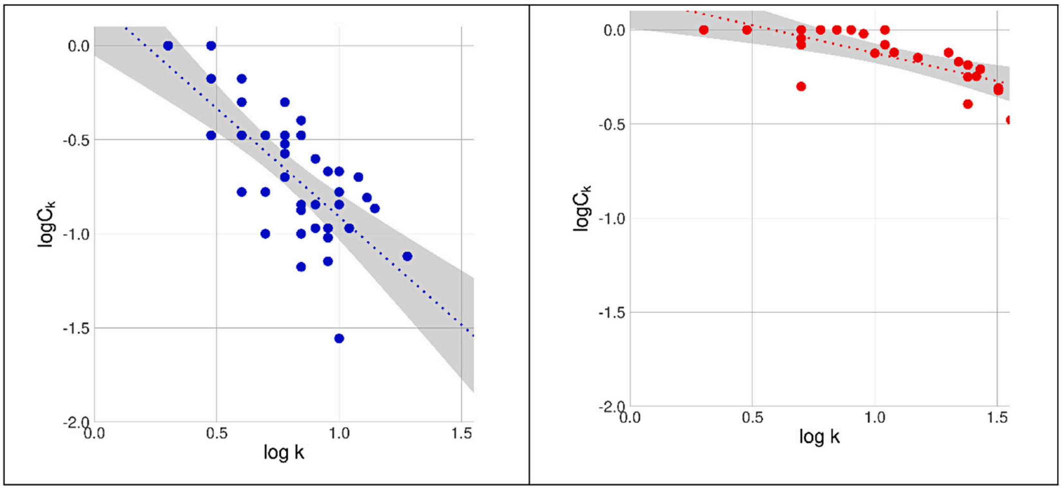

Fig. 5. Clustering coefficients and degrees on a log-log scale.
Note: Dots represent a group of players having the same number of degrees. k is the number of degrees and C_k is the clustering coefficient (probability that two neighbors of a given node are also neighbors).

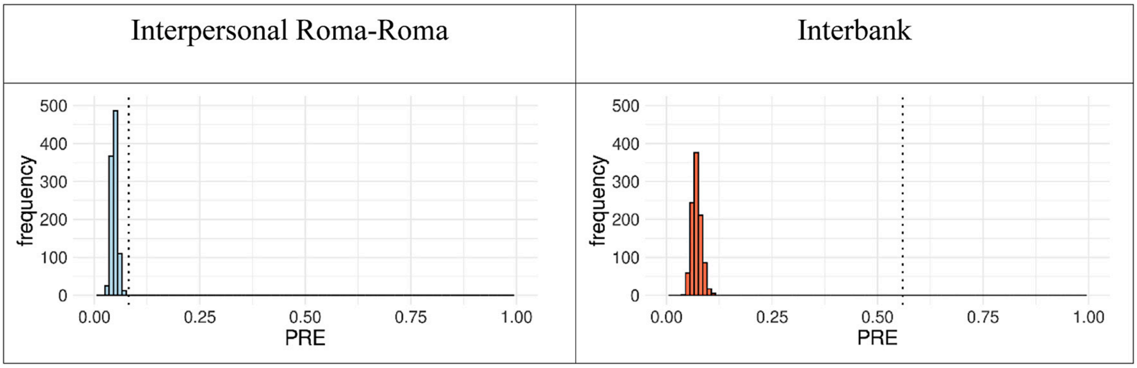

Fig. 6. Goodness of fit of a core-periphery model in Erdős-Rényi and empirical networks.
Note: Blue columns represent the frequencies of the proportional reduction of errors (PRE) measures in line with Boyd et al. (2010) resulting from the calibration of a core-periphery model for 1000 simulated Erdős-Rényi random networks of similar size and density. The dotted line indicates the PRE measure of the empirical network.

lower density. In Fig. 4, we can compare the normal distribution with the same mean and standard deviation (black line) to the empirical distribution of degrees separately by markets and directions.

Fig. 4 suggests that the dots lie on a straight line, thus degree distributions have fat tails, so both networks seem to be scale-free which is consistent with our expectation based on the literature of interbank networks (Craig and von Peter, 2014; Fricke and Lux, 2015; In't Veld et al., 2020;). However, we must be careful with the interpretation of these results as we have too few observations to test hypotheses or calibrate distributions.

Now, let us check hierarchy in line with (Barabási and Oltvai, 2004, Box2, Ca, Cb, and Cc). Calculating local clustering coefficients for all the vertices and plotting them against the total degree on a log-log scale, we get Fig. 5.

Fig. 5 shows that the interpersonal market is more hierarchical as the slopes of the lines are −1.15 (interpersonal) and − 0.29 (interbank) (p values are 0.000). Note that this result cannot be explained simply by the difference in the densities because, ceteris paribus, a higher density increases both the clustering coefficient and the number of degrees.

Thus, both networks seem to belong to the third basic category (C) showing the signs of a scale-free degree distribution and a certain level of hierarchy, see Fig. 2. In the interpersonal network we investigate, hubs are mainly constituted by families (for example, cousins, grandparents living at different addresses) communicating via their "leaders", for example by active and caring housewives (interviews highlight the central role of women, see Appendix) having lots of connections both within the family and outside. Friendship and neighborhood may also shape the hierarchical structure. Section 3 provides a deeper analysis on the role of kinship, friendship, and neighborhood.

2.4. Core-periphery models

As some hierarchy is detected for both markets, it is meaningful to analyze their core-periphery structure. Core-periphery models are based on the observation that interbank networks are characterized by a so called "disassortative mixing", meaning that small banks tend to trade with large banks but rarely among themselves. Most banks do not lend to each other directly but through core banks acting as "intermediaries of intermediaries", which leads to a hierarchical structure where core banks can be considered as systemically important financial institutions (Craig and von Peter, 2014; Fricke and Lux, 2015).

From a methodological point of view, we start from Borgatti and Everett (2000). A core-periphery network can be interpreted as a partition of the nodes into two distinct sets, a core in which nodes are connected to each other densely and a sparse periphery in which the connections between nodes are rare. Craig and von Peter (2014) applied this approach to the German interbank data, In't Veld et al. (2020) followed suit on the Dutch market, and Fricke and Lux (2015) improved the method and examined Italian interbank data (e-mid platform).

Borgatti and Everett (2000) described a continuous core-periphery model where the elements of the coreness vector can be real numbers – typically normalized between zero and one – and can be interpreted as a measure of a node's "coreness". In more general and interesting applications, adjacency matrices are asymmetric (directed graphs), and two vectors are calculated: the "in-coreness" (u) and "out-coreness" (v) of the players.

For the calibration of the asymmetric and continuous model, Boyd et al. (2010) proposed an algorithm called MINRES/SVD (minimal residual/singular value decomposition) based on the approximation of the adjacency matrix $\boldsymbol{A}$ by its singular value decomposition (SVD) udv^T where u and v are right and left singular vectors and d is the largest singular value (we constrain it to 1). Thus, we minimize the sum of squared residuals between the data matrix and the candidate approximation udv^T but ignore the diagonal elements with respect to u and v:

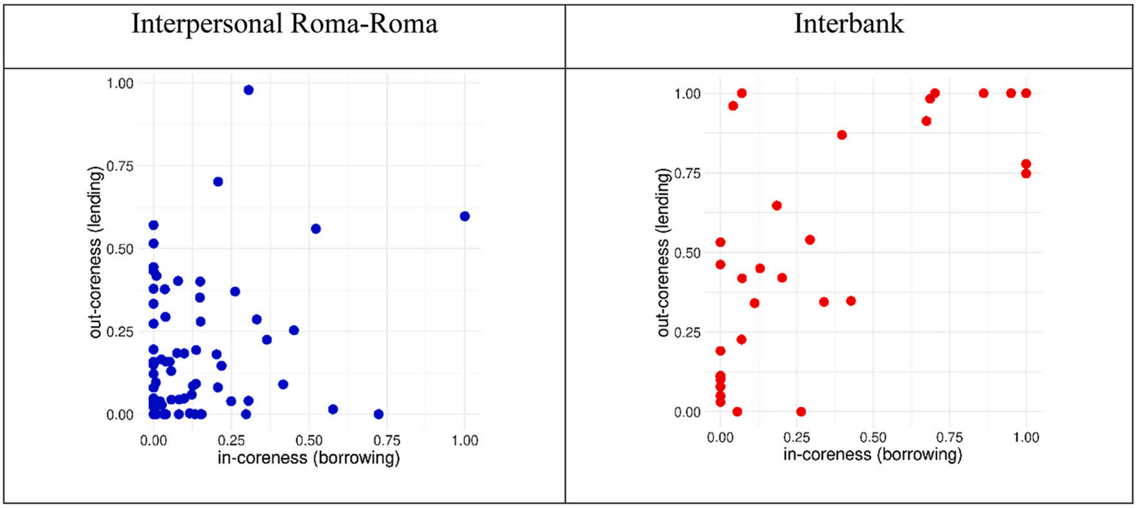

Fig. 7. Coreness measures of the two markets.
Note: Dots represent players in the plane of the in-coreness and out-coreness measures.

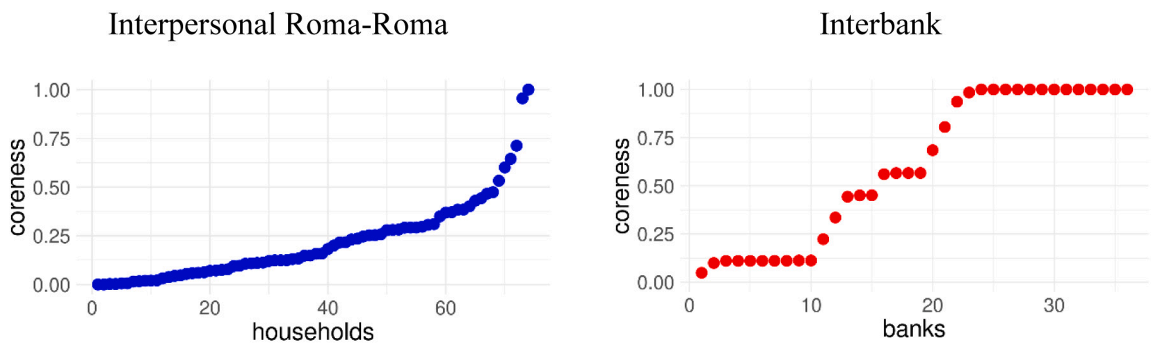

Fig. 8. Symmetric core-periphery structure.
Note: Dots represent players and their coreness measures. Assuming a perfect reciprocity, in-coreness equals out-coreness.

$$\min_{u,v} \sum_i \sum_{j \neq i} \left(A_{ij} - u_i d v_j\right)^2 \quad (1)$$

Due to the low density of the interpersonal market with a giant component and several islands, the optimization program cannot give any meaningful result. Therefore, we focus only on the Roma-Roma subgraph composed of 76 Roma families lending to each other actively. This is a highly interconnected subgraph with sufficiently high density (see Section 3.1. for more details) to calibrate a core-periphery model.

Based on the literature, we formulate a hypothesis related to the interpersonal (Roma-Roma) and the interbank markets:

H1. *core-periphery structure*: both markets exhibit a tiered core-periphery rather than an Erdős-Rényi random structure.

The core-periphery structure is a specific hierarchical structure in which core players act as intermediaries connecting peripheral actors. Over the last decade, several studies have shown that *formal* financial networks can be described along this structure the best (Craig and von Peter, 2014; Fricke and Lux, 2015; In't Veld et al., 2020). Moreover, key players, the so-called systemically important financial institutions, can be identified by their coreness measure. It is assumed that the higher the coreness measure, the more important the player is from the perspective of network stability. This naturally leads to the research question of whether *informal* financial networks share this characteristic or not. If yes, the coreness measure may play a role in informal networks as well, for example, in selecting which actors to target in a given development program."

Core-periphery models can be calibrated to any (interconnected) random graphs. Therefore, we test the goodness of the fit in the empirical network and compare it to that of simulated random graphs in which a core-periphery structure emerges only by chance.

To test H1, we follow the method of Craig and von Peter (2014) and simulate 1000 Erdős-Rényi random networks with the same number of nodes and vertices as we have in the interpersonal (Roma-Roma) network. Then we calibrate an asymmetric and continuous

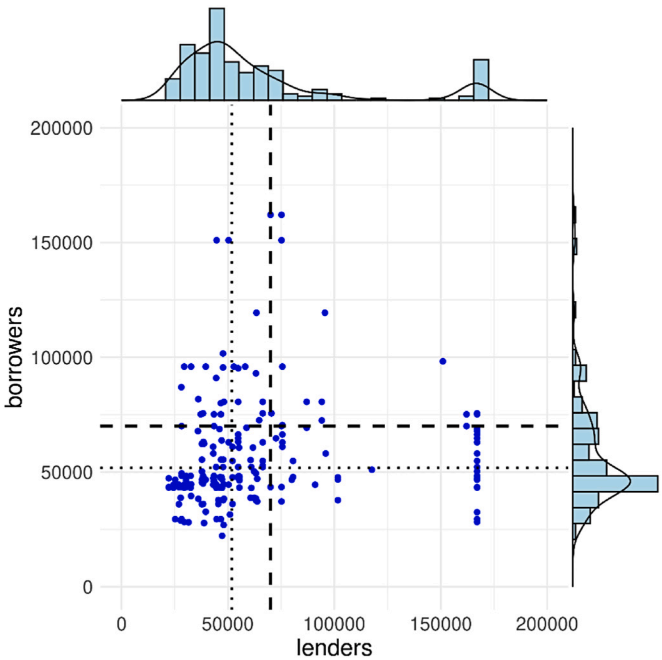

Fig. 9. Income per capita (OECD1) of lenders and borrowers, 2015, HUF.
Note: Income per capita is given in Hungarian forint (HUF). The official relative poverty threshold was around 70,000 HUF (~200 EUR) in 2015 (dashed line). The net wage for public workers was 51,847 HUF in 2015 (dotted line).

core-periphery model using the MINRES/SVD algorithm. We calculate the goodness of fit, that is the proportional reduction of error (PRE) measure (Boyd et al., 2010) for each realization, and compare these to the PRE measure of the empirical network. We repeat the process for the interbank market, see Fig. 6.

Comparing the PRE measures in the hypothetical and the empirical networks, we can be sure at a significance level of 99.9% that both the interpersonal and the interbank empirical networks have a core-periphery rather than an Erdős-Rényi random structure (the goodness of fit of 1000 random graphs never exceeds that of the empirical network). The core-periphery structure of both formal and informal lending markets is, therefore, a common characteristics from which fundamental implications can be derived: (i) core players are key in operating the network by connecting the peripherical players; (ii) for peripherical players, the access to the core is crucial; (iii) coreness and intermediation are inherently the same concept; (iv) there is a strong reciprocity among core players.

Fig. 7 presents the coreness measures for the two markets.

The core-periphery structures of the two investigated markets are different. In the Roma-Roma interpersonal market, most households have low coreness both in borrowing and lending, and there are no households in the upper-right corner of the box at all. In the interbank market, however, almost as many banks have very high in- and out-corenesses as very low ones. Moreover, here, the distribution is asymmetric as out-coreness tends to be much higher than in-coreness, meaning that core lending banks do not need (or do not get) that much financing.

If we assume that links become reciprocal sooner or later, we can examine the corresponding undirected symmetric networks and their coreness structures as well, see Fig. 8.

Although both networks exhibit a core-periphery structure, coreness measures are different. In the interbank network, banks are more bipolar in the sense that they take more extreme positions, they are mostly either deeply in the core or in the periphery. Thus, it is more straightforward to select the systemically important players (SIFIs). However, in the Roma-Roma interpersonal market, the transition between the two poles is much smoother and most of the coreness measures are well below 1. In the interpersonal market, more hierarchical levels coexist, but there are smaller differences between the hierarchy levels. Hence, here, it is more difficult to select the systemically most important players; all households are almost equally important. Thus, in the interpersonal market, it is not worth singling out some well-defined players, but rather treating the community as a whole.

3. Granular network analysis

In this section, we provide a more detailed analysis of the two markets exploring market-specific characteristics. In the interpersonal network, we know the basic attributes of the households while in the interbank network, nodes are completely anonymous, hence, banks cannot be identified. The interbank market, however, provides rich additional information on the loan conditions (loan amount, maturity, and interest rates) which in turn are not available for the interpersonal lending market. In Section 3.1, we analyze

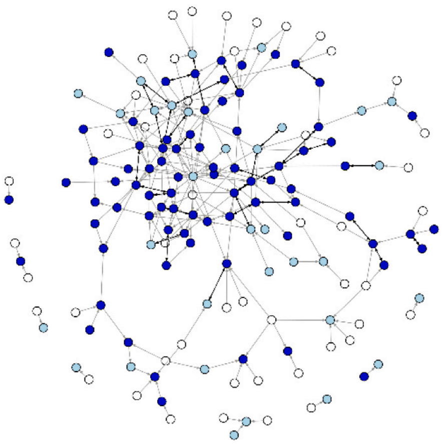

Fig. 10. Poor (dark blue), rich (light blue), and non-defined (white) households in the interpersonal network.
Note: Dark (light) blue dots represent households living under (above) the relative poverty threshold (RPT). White dots represent households where incomes are not known. Bidirectional (one-way) way edges are colored in black (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

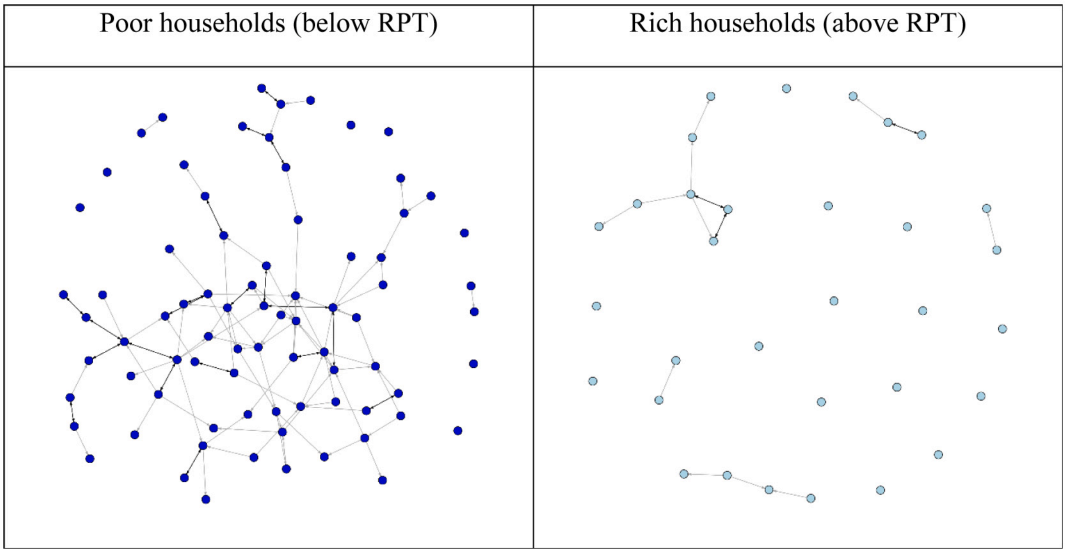

Fig. 11. Subgraphs of poor (dark blue) and rich (light blue) households.
Note: Dark (light) dots represent households living under (above) the relative poverty threshold (RPT). Bidirectional (one-way) edges are colored in black (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the relationship between households' attributes and their network positions; and in Section 3.2, we have a closer look at intermediary profits in the interbank network.

3.1. Interpersonal network in detail

From a lending and borrowing perspective, the most important household characteristics are income, size of the family, ethnicity, and location. Age, gender, and financial literacy can also play a role in lending. The interview excerpts in the Appendix show that children are of primary importance, women have a decisive say in household finances, people take care of the elderly, and in many respects, they are quite conscious of their financial planning. However, these categories cannot be meaningfully aggregated for households. Therefore, we formulate the following hypotheses:

Table 3
Poor-to-poor homophily.

	Dependent variable: Lending relationship				
	(1)	(2)	(3)	(4)	(5)
Poor to poor		0.008***			
		(0.002)			
Poor to rich			−0.004		
			(0.003)		
Rich to poor				−0.007***	
				(0.003)	
Rich to rich					−0.001
					(0.004)
Intercept	0.015***	0.012***	0.016***	0.017***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	13,110	13,110	13,110	13,110	13,110
R^2	0.000	0.001	0.0002	0.001	0.00001
Adjusted R^2	0.000	0.001	0.0001	0.001	−0.0001
Residual Std. Error	0.123 (df = 13,109)	0.123 (df = 13,108)	0.123 (df = 13,108)	0.123 (df = 13,108)	0.123 (df = 13,108)
F Statistic (df = 1; 13,108)		13.230***	1.985	7.804***	0.109

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
The sample contains all households (115) where income was known. The number of observations equals the number of possible interlinks (114x115 = 13,110).

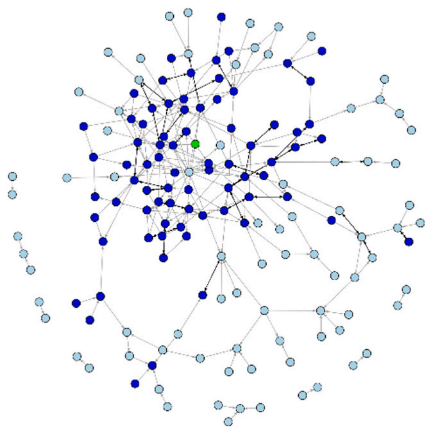

Fig. 12. Roma (dark blue), non-Roma (light blue), and mixed (green) households in the interpersonal network.
Note: Dark (light) blue dots represent Roma (non-Roma) households. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

H2. *income and family size*: richer households lend the poorer ones.

H3. *ethnicities*: there is an ethnical-based separation between Roma and non-Roma households.

H4. *kinship*: households transact more if they are related.

H5. *friendship*: households transact more if they are friends.

H6. *geographical distance*: people transact more if they live close to each other.

For each household, we calculate the income per capita according to the OECD1 standard conferring different weights to different family members (the first adult in the family gets 1, further family members with employment get 0.7, while unemployed adults and children get 0.5). The relative poverty threshold (RPT) in Hungary was around 70,000 HUF (~200 EUR) in 2015 (dotted line in Fig. 9).

Fig. 9 shows that the lending and borrowing activity is concentrated in the poor-to-poor section. Below a certain income threshold, people may be excluded from formal banking, hence they rely mostly on informal lending, but once financially excluded, the exact level of income per capita does not matter anymore. Similarly, above a certain income threshold, households are financially more included, hence do not need to participate in the informal lending market (except for the mayor of the village who is a central lender) and income has no effect on this. It is also notable that the income per capita of several borrowers is just below 50,000 HUF. These families are likely to rely heavily on public work, which, although very low, provides a predictable fixed income in the next month that can be used as a guarantee for loan repayments.

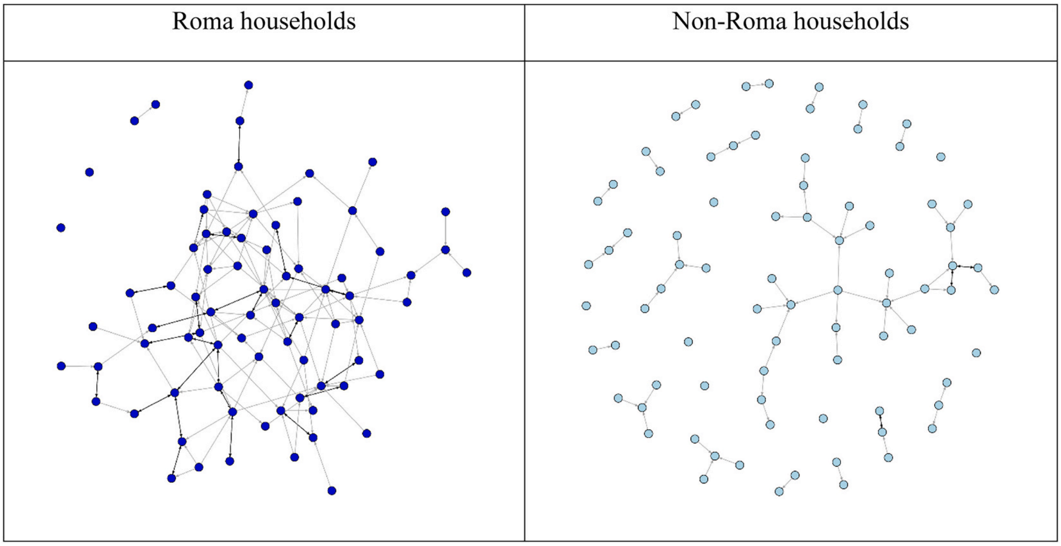

Fig. 13. Subgraphs of Roma (dark blue) and non-Roma (light blue) households.
Note: Dark (light) blue dots represent non-Roma (Roma) households. Bidirectional (one-way) edges are colored in black (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Roma-to-Roma homophily.

	Dependent variable: Lending relationship				
	(6)	(7)	(8)	(9)	(10)
Roma to Roma		0.022***			
		(0.001)			
Roma to non-Roma			−0.007***		
			(0.001)		
non-Roma to Roma				−0.010***	
				(0.001)	
non-Roma to non-Roma					−0.003**
					(0.001)
Intercept	0.011***	0.005***	0.012***	0.013***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	26,732	26,732	26,732	26,732	26,732
R^2	0.000	0.008	0.001	0.002	0.0002
Adjusted R^2	0.000	0.008	0.001	0.002	0.0002
Residual Std. Error	0.102 (df = 26,731)	0.102 (df = 26,730)	0.102 (df = 26,730)	0.102 (df = 26,730)	0.102 (df = 26,730)
F Statistic (df = 1; 26,730)		225.325***	24.038***	50.761***	5.135**

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
The sample contains all households having at least one transaction (164). The number of observations equals the number of possible interlinks (163x164 = 26,732).

Based on households' distribution, we classify families with income per capita below the RPT (70,000 HUF = ~200 EUR) as poor (72%) or above the RPT as rich (28%). Most people in this village live in an extreme poverty, and only few households can be considered as medium- or high-income. Fig. 10 illustrates the relative positions of poor and rich households in the lending network (for empty circles, income per capita data were not available).

Fig. 10 shows that households in central positions are typically living below the RPT (except for the mayor of the village classified as rich and being in the center), poor households maintain a denser network among them, and lending relationships are based more on reciprocity. Fig. 11 visualizes it more explicitly by dissecting the network of the poor and the rich.

In Table 3, we can have a closer look at the poor-to-poor homophily by examining to what extent the income level of the families determines the likelihood of a lending relationship among them.

As it is reflected by the intercept in model specification (1) in Table 3, only 1.5% of the potential interlinks exist. According to model specification (2), if two households live both below the poverty threshold, the probability of a lending relationship is 2% (1.2% + 0.08%), which is only 1.2% otherwise, hence, in a poor-to-poor relationship, lending is 66% more probable. It is notable that a rich-to-poor relationship reduces the probability of lending, thus altruism does not seem to play a role. Other relationships (poor-to-rich and

Table 5
Average degrees in different subgraphs.

	Non-Roma - Poor	Non-Roma - Rich	Roma - Poor	Roma - Rich	Anyone
Non-Roma - Poor	0.348	0.228	0.164	0.127	0.310
Non-Roma - Rich	0.190	0.244	0.196	0.290	0.307
Roma - Poor	0.164	0.416	1.876	0.694	0.747
Roma - Rich	0.127	0.406	0.858	0.543	0.433
anyone	0.135	0.214	0.578	0.283	0.318

Note: Degrees show borrowing from row i to column *j*.

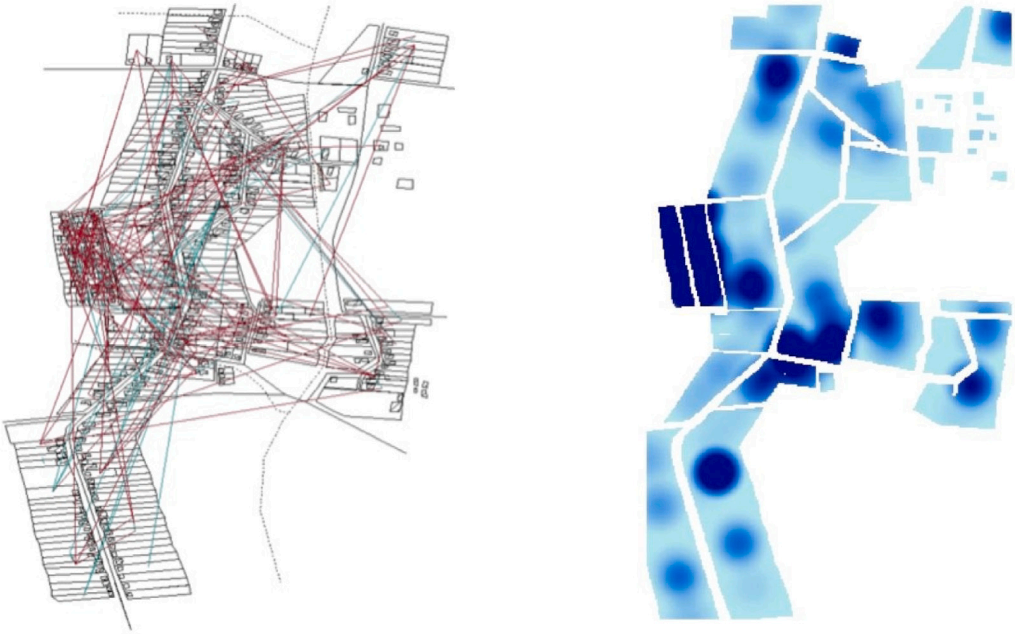

Fig. 14. Geographical visualization of the interpersonal network (based on the local map of the village).
Source: (Gosztonyi, 2018).

rich-to-rich) are not significant either. We can conclude, therefore, that poor families operate a strong informal insurance (risk-sharing) system helping each other in cases of liquidity shocks, which is supported also by the interviews (see Appendix), so, we reject H2.

Let us turn to another important dimension: ethnicity. Ethnical classification is based upon self-assessment. 48.6% of the households are Roma, 51.3% are non-Roma, and only one household is mixed (0.006%). The Spearman-correlation of Roma ethnicity with the size of the family is +0.31 and with the income per capita (OECD1) is −0.30 and with the classification of rich is −0.19. Therefore, Roma households are larger, have lower income per capita, and consequently, have a larger probability of living under RPT in this village. Fig. 12 depicts the ethnic structure of the network.

Fig. 12 indicates that Roma households produce a more interlinked network while non-Romas are rather in the periphery in a more fragmented structure (except for the mayor of the village again). Although, there is a strong Roma-to-Roma homophily in the network, there are several interethnic relations as well. Fig. 12 reveals that Roma households play a crucial role in the lending network maintaining a high number of in- and out-degrees. Fig. 13 presents the Roma and non-Roma subgraphs separately (interethnic links are deleted).

Subgraphs in Fig. 13 emphasize the large difference in Roma and non-Roma relationships (subgraph densities are $D_R = 0.029$ and $D_{NR} = 0.009$). Deprived Roma households are effectively operating a risk-sharing system by helping each other in a liquidity need. From this perspective, non-Roma households can be in a worse situation lacking such safeguards in difficult situations unless they have access to other formal or informal financial markets (as it is also reflected in the interviews, see Appendix).

Roma-to-Roma homophily is further examined in Table 4.

As Table 4 indicates, a strong Roma-to-Roma homophily exists in our sample. According to model specification (7), if two households are Roma, the probability of a lending relationship is 2.7% (0.5% + 2.2%), which is only 0.5% if at least one of the parties is non-Roma. Hence, lending is 54 times more probable in a Roma-to-Roma relationshipthan in other relationships. Thus, H3 is accepted.

To have a closer look at lending relationships, we calculate average degrees for subgraphs in the dimensions of ethnicity (Roma

Table 6
Kinship, friendship, and geographical distance.

	Dependent variable: Lending relationship										
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
kinship	0.288***					0.277***	0.276***	0.276***	0.276***	0.276***	0.284***
	(0.004)					(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
friendship		0.224***				0.189***	0.189***	0.189***	0.212***	0.157***	0.190***
		(0.006)				(0.006)	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)
E distance			−1.030***			−0.144			−0.092		
			(0.178)			(0.159)			(0.161)		
p30 distance				0.010***			0.002*			0.001	
				(0.001)			(0.001)			(0.001)	
same street					0.006***			0.002			0.003**
					(0.001)			(0.001)			(0.001)
kinship x E distance									0.209		
									(1.188)		
friendship x E distance									−4.612***		
									(1.451)		
kinship x p30 distance										−0.0001	
										(0.008)	
friendship x p30 distance										0.080***	
										(0.011)	
kinship x same street											−0.023***
											(0.008)
friendship x same street											−0.002
											(0.011)
Intercept	0.004***	0.008***	0.016***	0.008***	0.009***	0.003***	0.002***	0.002***	0.003***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	26,732	26,732	26,406	26,406	26,732	26,406	26,406	26,732	26,406	26,406	26,732
R^2	0.170	0.049	0.001	0.002	0.001	0.204	0.204	0.205	0.205	0.206	0.205
Adjusted R^2	0.170	0.049	0.001	0.002	0.001	0.204	0.204	0.205	0.204	0.206	0.205
Residual Std. Error	0.093 (df = 26,730)	0.099 (df = 26,730)	0.102 (df = 26,404)	0.102 (df = 26,404)	0.102 (df = 26,730)	0.091 (df = 26,402)	0.091 (df = 26,402)	0.091 (df = 26,728)	0.091 (df = 26,400)	0.091 (df = 26,400)	0.091 (df = 26,726)
F Statistic	5461.689*** (df = 1; 26,730)	1381.765*** (df = 1; 26,730)	33.639*** (df = 1; 26,404)	49.737*** (df = 1; 26,404)	17.149*** (df = 1; 26,730)	2260.126*** (df = 3; 26,402)	2261.202*** (df = 3; 26,402)	2292.606*** (df = 3; 26,728)	1358.518*** (df = 5; 26,400)	1369.481*** (df = 5; 26,400)	1377.519*** (df = 5; 26,726)

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

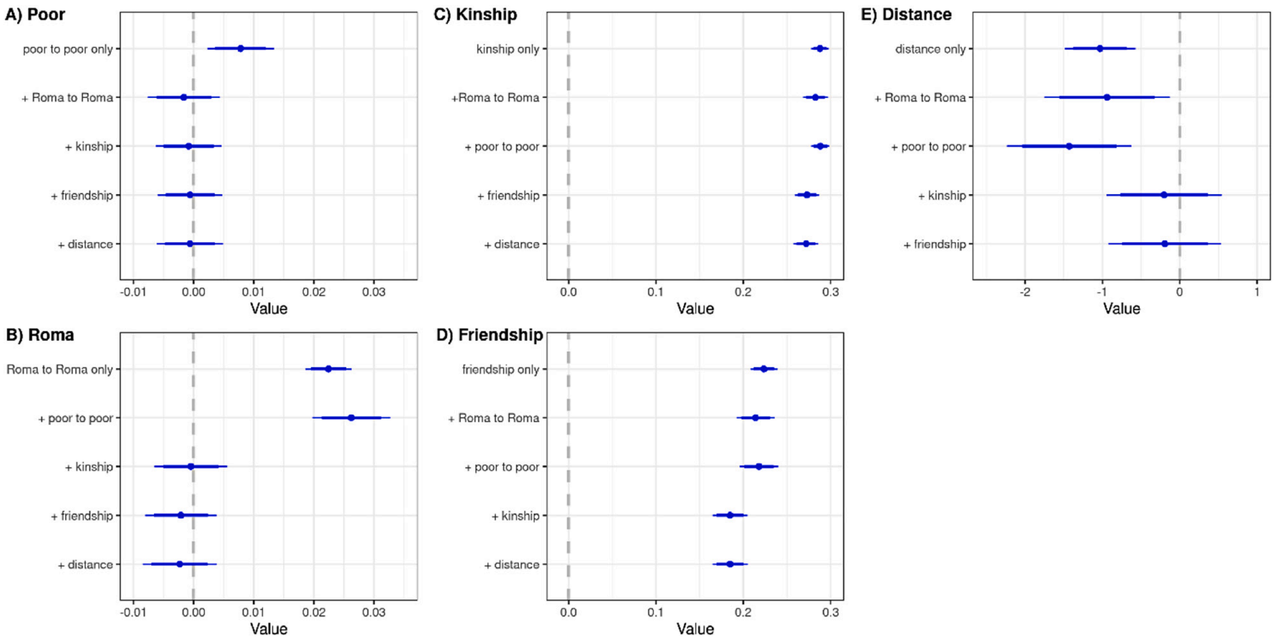

Fig. 15. Income, ethnicity, kinship, friendship, and geographical distance.

Table 7
Largest intermediary profits in the interbank market (March, April, and May of 2015, in M HUF).

Bank code	Intermediary profit (M HUF)	Cumulative share of profit	Intermediation volume (M HUF)	Profit rate
10	4.2	51%	892,075	0.0005%
14	1.8	72%	326,590	0.0005%
224	0.9	83%	76,800	0.0012%
8	0.6	90%	46,923	0.0013%
5	0.3	94%	49,100	0.0007%
27	0.2	96%	31,000	0.0008%
9	0.2	99%	118,200	0.0002%
4	0.1	100%	78,250	0.0001%
17	0.0	100%	131,650	0.0000%
6	0.0	100%	52,400	0.0000%

Note: Profit rates are calculated as the three-month intermediary profit in HUF divided by the three-month intermediation volume in HUF.

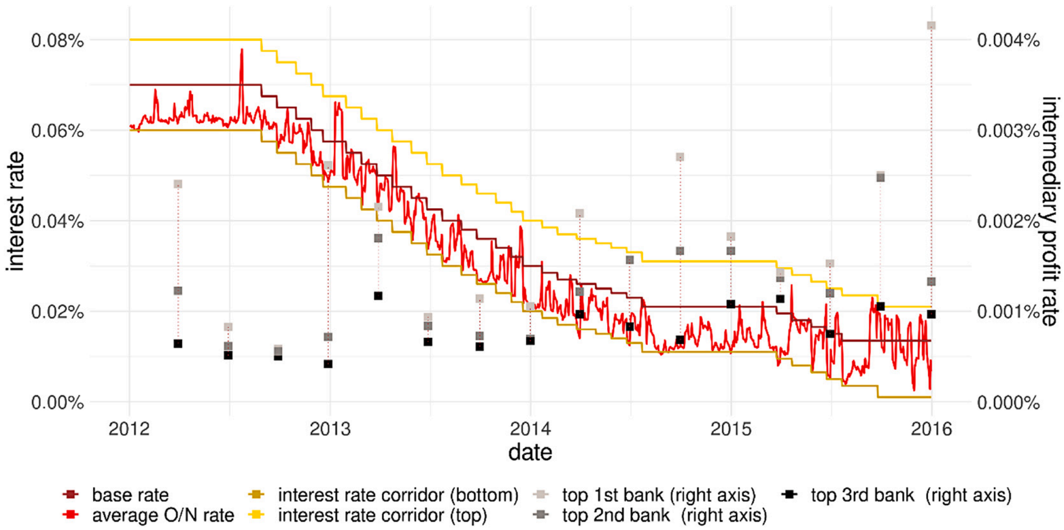

Fig. 16. Intermediary profits and interest rates.

versus non-Roma) and income per capita of the households (poor versus rich), see Table 5.

Table 5 demonstrates that poor Roma families interact the most, the average degree on this subsample (1.876) is nearly 6 times higher than in the total sample (0.318) strengthening that the most deprived families are the most active in informal lending (Guiso et al., 2004; Portes and Landolt, 2000). It is notable, however, that most of the poor non-Roma families can be excluded not only from the formal, but also from the informal financial markets. Policymakers should pay particular attention to this segment.

Finally, the location (family address) is the third important variable of our analysis. For visualization purposes, we use space informatics techniques to match the local map of the village and the lending network. We complement this tool with the Kernel heatmap of the transactions, see Fig. 14.

Fig. 14 discovers the strong geographical determination of the lending network. The densest (dark blue) parts of the village called “Gypsy settlement”, “Ring”, and “Upper-Ring” are lived mainly by poor Roma families. At the same time, there are some darker blue areas in the main street, as well, lived by wealthier (sometimes Roma) families or those intermediating between Roma and non-Roma. To disentangle the effects of kinship, friendship, and geographical distance, we run several regression models as presented in Table 6.

Geographical distance is proxied in several ways: i) the Euclidean distance calculated from the geolocation (E distance); ii) dummy = 1 if the Euclidean distance between the two households is among the lowest 30% of all possible distances, or 0 otherwise (p30 distance); iii) dummy = 1 if households live in the same street, or 0 otherwise (same street).

Table 6 suggests that in one-dimensional settings (model specifications (11)–(15)), kinship and friendship increase, while geographical distance decreases the likelihood of a lending relationship. In multivariate models (model specifications (16)–(18)), the coefficients of kinship and friendship (27.7% and 18.9%, respectively) remain stable, but distance measures lose their significance. Examining interactions (model specifications (19)–(21)), we find that if people are friends, Euclidean distance has a negative effect on lending, which can be due to higher transactional costs. However, if people are relatives, then living in the same street has a negative effect on lending. Had they known other relatives farther from their houses, people might prefer to borrow from them, perhaps because they feel less pressure.

Thus, H4 (kinship) and H5 (friendship) are accepted, but H6 (geographical distance) is rejected.

According to Fig. 15, poor-to-poor homophily disappears if we take ethnicity into account (A). Roma-to-Roma homophily disappears if we take kinship and friendship into account (B). The effects of kinship and friendship are so strong that their coefficients remain significant even if we control for all the other variables (C and D). Kinship and friendship take over the effect of the Euclidean distance as well (D). People are hence selective about who they are willing to transact with; risk-sharing is not perfect. Due to endogeneity (for example, measurement error, reverse causality, omitted variables), we cannot prove causality in the above models. Nevertheless, we can conclude that a large amount of social capital is accumulated via family ties and friendship which can be used effectively in sharing the liquidity risk. The more socially excluded (Romas) and poor someone is, the more they rely on this social capital.

3.2. Interbank network in detail

Robust empirical evidence proves that financial markets exhibit a core-periphery structure where core banks intermediate between banks in the periphery (Craig and von Peter, 2014; Fricke and Lux, 2015; Langfield et al., 2014; Lelyveld and Veld, 2014; León et al., 2018; Silva et al., 2016). Core banks are believed to take advantage of their central position in the form of intermediary profits (In't Veld et al., 2020). Thus, we formulate our next hypothesis accordingly:

H7. *intermediary profit*: the main motive behind intermediation in the interbank market is the profit coming from interest rate margins.

The daily volume of intermediation for bank i is defined as the minimum of the total lending $x_{i,t}$ and the total borrowing $y_{i,t}$ on day t. Considering the lending and borrowing interest rates, we can estimate the intermediary profit (π) for bank i on day t as

$$\pi_{i,t} = intermediation_{i,t} \bullet interest\ margin_{i,t} = min\left(y_{i,t}; x_{i,t}\right) \bullet \frac{r^{L}{}_{i,t} - r^{B}{}_{i,t}}{360} \tag{2}$$

where $r^{L}{}_{i,t}$ and $r^{B}{}_{i,t}$ are the weighted average (annual) lending and borrowing interest rates, respectively. Table 7 presents the top 10 banks according to their profits from intermediation over the three months in question (summing up daily profits over the three months).

The total volume of intermediation was significant relative to the total volume of transactions (over 25%). However, monetary gains from this activity proved to be extremely small (practically zero) even for the top 10 intermediary banks, see profit rates in Table 7. For some large intermediaries, the intermediary "profit" was even negative. Fig. 16 proves that low intermediary profits cannot be explained by the interest rate environment.

Fig. 16 shows that low intermediary profits are not the result of the low interest rate environment, as profit rates were insignificant even when interest rates were high in 2012–2013. In fact, as interest rates have fallen, intermediary profits slightly increased. This leads to the conclusion that banks' interbank activity is motivated rather by mutual risk-sharing than by profit-seeking similar to the interpersonal market. Thus, H7 is rejected.

Finger and Lux (2017) analyzed the interbank trading network by a stochastic actor-oriented model and found traits of "relationship banking" which means that banks heavily rely on their long-lasting relations even if they had an opportunity to form economically more profitable new connections. In this aspect, too, the two lending markets investigated in this study operate in a similar way where risk-sharing is the key motive.

4. Discussion

Both the interpersonal and the interbank markets are used to manage liquidity risk, players employ sophisticated techniques (rating, screening, monitoring, partner limits, etc.), and social collateral tends to replace physical collateral. Performing a comparative network analysis, we find that the two networks are strikingly similar to each other. In particular, there is a strongly interlinked giant component; degree distributions seem to exhibit a fat tail; structures are hierarchical, fitting well to a continuous asymmetric core-periphery model; there are well-defined central players serving as intermediaries, while intermediary profits are marginal or zero.

We show that the main motive shaping the network structure is risk-sharing; and basically, the interpersonal market operates like the interbank market even if trade amounts are a million times smaller and the trading activity is not regulated and monitored. Thus, we find that poor low-educated villagers manage their liquidity risk basically upon the same principles as highly educated professional traders.

The main difference in the networks can be rooted in the difference in the data collection procedure (voluntary surveys versus mandatory reports) resulting in an incomplete and less dense interpersonal network where there is a giant super-component but also many small islands around it. Contrary to this, the interbank network is totally interlinked. Thus, analytical tools were applied carefully for the interpersonal network (for example, taking only the densest Roma-Roma subgraph for calibrating a core-periphery model). We find some other distinctive features related mainly to the concentration of in- and out-degrees, the extent of hierarchy, and the coreness structure. In the interpersonal market, the concentration of lending and borrowing are lower; there are more hierarchical levels; while coreness is not so high and the transition between the core and the periphery is smoother. The interbank network seems more sharp-edged in this aspect: the systemically important players can be distinguished more easily.

Zooming into the interpersonal market, we analyze the relationship between households' basic attributes (income level and ethnicity) and their network position. We find all these attributes essential for the network topology: poor Romas lend to each other the most actively; while Romas and non-Romas are separated even if there are some well-defined intermediaries between them. We also investigate the role of kinship, friendship, and geographical distance in the formation of lending relationships, and find that kinship and friendship are of high importance, whilst geographical distance also matters, but is less significant in a multivariate model. The most interconnected and densest part of the network is formed by poor Roma households. Although risk-sharing is not perfect, the interpersonal lending network operates as a sophisticated multi-player and multi-level social insurance system. Non-Roma households are more isolated and fragmented, so poor non-Roma households might be in a more difficult situation in cases of liquidity shocks unless other formal or informal financial markets are available for them.

5. Conclusions

Despite the many differences between the formal and informal financial networks, we find a surprising result that the two markets have many common features such as intermediation, reciprocity, risk-sharing, and the reliance on social capital. We conclude that intermediation manifested in a core-periphery structure plays a crucial role in risk-sharing in both the interpersonal and interbank markets.

Implications for development policies may be twofold. First, poor people are able to operate an effective risk-sharing system to manage their month-to-month large-scale liquidity shocks employing a variety of sophisticated tools similar to professional traders. Second, development policies should understand and respect existing informal risk-sharing mechanisms that are based on cooperation and social capital. Our research may contribute to the design of community-based social development programs as suggested by Bhattamishra and Barrett (2010). Further theoretical and empirical research is needed to find the right policy mix. As far as formal financial markets are concerned, regulators should understand the risk-sharing nature of the interbank markets and balance carefully between individual (micro-prudential) and collective (macro-prudential) risk management objectives.

CRediT authorship contribution statement

Edina Berlinger: Conceptualization, Methodology, Validation, Writing – original draft, Supervision. **Márton Gosztonyi:** Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing – review & editing, Visualization. **Dániel Havran:** Methodology, Software, Validation, Formal analysis, Data curation, Writing – review & editing, Visualization. **Zoltán Pollák:** Methodology, Software, Validation, Formal analysis, Data curation, Writing – review & editing, Visualization.

Declaration of Competing Interest

The authors declare no competing interests.

Data availability

Anonimyzed interpersonal lending data will be shared in Data in Brief. Interbank dataare confidential, hence cannot be shared.

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Appendix A. Interview excerpts

The below table summarizes the findings of the in-depth interviews with the villagers. The highlighted sections introduce the key concepts. The linked illustrative sentences are taken verbatim from the in-depth interviews.

A) Rating, screening, and monitoring

- Trustworthy borrowers have priority.
- Alcoholics and gamblers are refused.
- The needs of the family and children are the main consideration.
- Most supported credit purposes: food, fuel, funeral.
- People monitor each other to see who is spending what.
- If someone does not pay back the loan, they are not given it next time, they are "blocklisted".

I/4: "Well, it depends how they behave with you. We do not help strangers. Usually, we help relatives... Well, because they say they can't buy something, for example, they don't have enough money for firewood. And then I usually give them some money. And if they can't go shopping because they don't have enough money, I tell them to come, and I'll give some money to them… Here is my brother who comes to ask money for nappies, I always help him."

I/5: "Usually I lend to someone who I know will pay me back, and I know how much he needs my help, and what he usually asks for, I know all that... Lending to a relative is good, because we know why the relative is like that, for example, we know that the woman is raising five children alone because her husband left her, and she has no money. She won't squander it, no going to the pub, no slot machines - thank God we don't have any of that.... For example, if someone can't buy the public transport pass to go to work, which is 25,000 forints, we help him, because it's a big amount and it's important for him to be able to do his job. Or, for funerals the biggest amount we gave was 80,000 forints, we lend it only as a favor, there is no interest on it."

I/6: "You hear there are people. I know the village very well. I was born here, I worked here, I lived here. If, say, a family man would come to me, a father or a mother I know, that they are debauched, they drink, and he would ask. I wouldn't give them, Marci (note: the nickname of one of the authors). I wouldn't give money to them, because I know that they're not giving it to their kids, they're not giving it to their family, they need it to get drunk or to forget their troubles, well, no. Then I'd say, I'll either leave that little money or give it to someone else. To my kids, for food."

I/10: "Yes, people ask for money in this street all the time, but the truth is that not everyone can be trusted, because some people don't give it back... Of course, you hear here and there people giving each other money, this one gives it back, that one doesn't."

I/11: "Well, we know many people who have screwed up by not giving back and they don't get money anymore."

I/12: "I give it to whoever deserves it... Well, I would only give it to someone I trust."

B) Partner limits

- People have in mind the maximum amount they would give to a given partner.
- The partner limit depends on the current financial situation of the lender, the borrower, and the purpose of the loan.

I/4: "So, if everything is okay here at home, then no problem, I'll go up till 20... Well, it happened when we've given 50." (*Note: 20 and 50 thousand forints*)

I/5: "For those who don't get large sums, but 2–3 thousand forints, it is for 1 month. Usually, we help my wife's sister this way, as they get the paychecks later, than we, …, then I know whom I have to give, because I know that 5 or 3–4 thousand forints mean a lot to her, because I know that she won't be able to put anything on the table that day."

I/11: "I can give him 2000 forints, or if he goes to the hospital, up to 5000."

C) Reciprocity, risk-sharing, social capital

- People do favor each other in a reciprocal way.
- Lending can be non-monetary as well.
- The better people live, the less they help each other.
- Extended relationships function like a safety net.

I/4: "He just comes over and he is my good mate, so if I need him, he'll help me. And if he needs something, I'll go over and help him."

I/5: "Sometimes it is not money that we give. For example, my mother-in-law says she'll get the pension in two weeks, so when I get my paycheck and go to the Metro supermarket, I bring her few things. ... Helps like that occur sometimes, or when their boots are too tight, or when they need some firewood or when I go with a saw, because they can't cut it."

I/6: "People are living better, even though they work less or don't work at all, and still live well, but of what? Decades ago, everybody worked, and they didn't live so well. There was a stronger cohesion. Even now they live better than we who work. They don't work but they live better, some people have 2–3 cars, and they don't work. They have more houses, listen, how?... Well, I'm poorer, but my neighbor can ask me to help her at least once a month."

I/9: "Well, I have a very good relationship with more than 10 people, so if they need something, I will give them money."

D) Preferential lending

- Family members have priority.
- Kinship is understood broadly: parents, children, siblings, cousins, etc.
- Secondarily, other people in the neighborhood and friends can also get credit.

I/4: "Usually the relatives come. They come, they come over, we talk a bit, and then they say they don't have money, and then I ask them how much they need, and then they say the sum, and if it's possible, if I can give, I will give it.... Yes. He has been in a tight spot, he came to me, and I helped him. That's how we help each other in troubles."

I/12: "Only for family members. I wouldn't lend to a stranger even if I could... No. So we don't lend to strangers only like this to brother-in-law, sister-in-law."

I/13: "Yes, to brothers and sisters, relatives, or if you are from here and from the neighborhood, or just a nice person, sometimes."

E) Nonpayment, enforcement

- In case of non-payment, physical violence is sometimes used, but most of the time it is simply left at that.
- The risk of non-payment is controlled by the partner limits.
- There is a list of bad borrowers, a common knowledge throughout the village.
- Non-payment is shameful.

I/4: "Everybody knows, and then they can't get money next time. Well, it was about 2 months ago, a girl had a toothache, and her mother asked my son to give a ride to the dentist in Miskolc. He took her, but she didn't pay back the 3000. And she had the nerve to stand in our doorway, she needed medicine, she was shouting ... well, I said, get out while you still can.... This game is over for the rest of her life. It's hard to lose the honor, but she has lost it."

I/5: "I helped him, though he was a non-Roma. We used to bike to the forest to get some firewood. I go to him, and I see the child, the little child was eating the newspaper, basically there was nothing for the child to eat. And they say, T., help me with a few thousand forints, there's nothing for the child to eat. I went home and collected pasta, bread, potatoes, and everything else, and I wrote it all down and said you pay it to me from your pension. And when he got the pension, I told him what was going on, and things didn't come out right, even the child started to bark at me, they attacked me, and I hit him on the ear. I told him, listen, not this was the deal. His brother came, I knew him, his mother came too. As soon as his mother fell down, she broke her finger and I was reported to the police, and I got suspended prison of 8 months. So, I couldn't go to work when I graduated from the security service school."

I/6: "Marci, whoever didn't give it back to me or won't give it back to me, I can't be angry with him. Okay if he has some self-esteem or has some skin on his face, then he looks me in the eye, but I'm not mad at him. … If he wants, he'll return it, if he doesn't want, he won't, but then he shouldn't ask anymore."

I/14: (*And what do you do if he doesn't return it?*) "Nothing. I tell him, be happy with it. He wouldn't get anymore, and he'd be ashamed anyway."

F) Protocols and administration

- Decisions are usually made jointly by the family.
- The housewife plays a central role in the decision.
- Loans are not kept written.
- Debts are usually kept in the head.

I/4: "We always discuss it. Without that I won't even give money to my brother. We'll talk whether to help someone, and then we'll say, okay, let's give him... We keep it in mind. We don't give to many, just to one or two."

I/11: "Women are the ones who tell it.... Well, I have a booklet. And I write everything down in it...Well, for example, I write down that debts, right on the page from whom it is, and that's how chaos usually happens."

I/12: "I know it by heart."

I/14: "No, we are... we are with my mother-in-law so that this is theirs and that is ours, so everything is common, and we eat it together or share or so, this is how we are separate... My mother-in-law is the big brain, so to speak. She's the head of the family, of course, so things go through her. If something works out for us, it works out through her.... We sit down and talk together about how to make it better for everyone. You know? And then we discuss everything, and everybody acts in a way to be good."

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