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A comparative study of reciprocity in two rural social networks in Tamil Nadu, India

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In this paper a comparative social network analysis is provided of the villages of Ayyanapuram and Sankarapandiapuram in the district of Virudhunagar of Tamil Nadu province in India. Social network data on three different types of links (monetary help, advice and companionship) reveal that, while the villages are situated close to each other geographically, they differ considerably in the structure of their social networks. The paper also illustrates a few common community detection algorithms.

1. Objectives and main contributions of paper

This paper contributes to our understanding of rural India from the social network perspective by analyzing two unique data sets on three types of social networks (monetary help, advice and companionship) collected from households in two villages of Tamil Nadu in southern India. Arumugam et al. (2014) investigated the social network properties of the village of Sankarapandiapuram; this paper proposes an extension via a study of the village of Ayyanapuram, geographically located close to Sankarapandiapuram but remarkably different in the structure of its social networks, as will be evidenced here.

In addition, this paper utilizes the network of monetary help in crisis times to illustrate a few common community detection algorithms.

2. Background

Ayyanapuram is a village situated in the eastern side of Sankarapandiapuram village in Southern Tami Nadu, India (see Figures 1, 2 and 3); it is administered by the Melarajakularaman Gram Panchayat (Village Council; there are about 265,000 Gram Panchayats in India). Three different communities, Yadhava, Devar and Pillai live in harmony in this village. The total population of the village is around 3,500 with 450 families belonging to the Yadhava community, 250 families belonging to the Devar community and 550 families belonging to the Pillai community. The streets in the village are typically named using the name of the community. This study is based on data collected from 91 families of the Yadhava community through an interview and questionnaire. The 91 households were selected as follows.

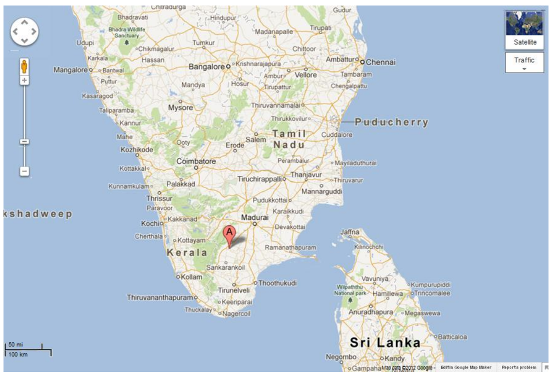


Figure 1: Location of Ayyanapuram and Sankarapandiapuram (Map data ©2012 Google)

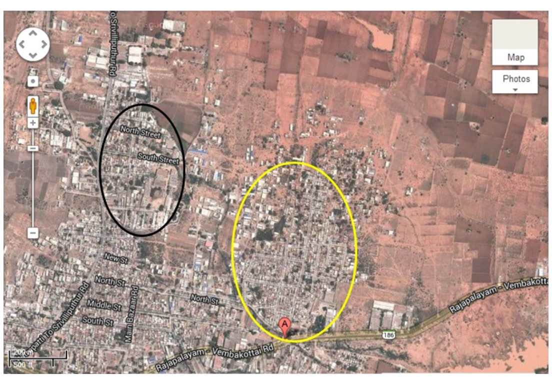


Figure 2: Satellite view of Ayyanapuram (yellow) and Sankarapandiapuram (black) (Imagery ©2014 DigitalGlobe, Map Data ©2014 Google)

We first choose one family arbitrarily and collect data from that family. If this family has stated that they approach, for example, families 50, 60 and 72 for any type of help or companionship, we collect data from families 50, 60 and 72 (where numbers such as 50 are labels for each of the 450 families in the Yadhava community). We then continue collecting data from new families mentioned by these families and so on. We stop this process when the number of new families coming up in the process is very small (in a few rare cases, it was logistically impossible to contact a particular household).

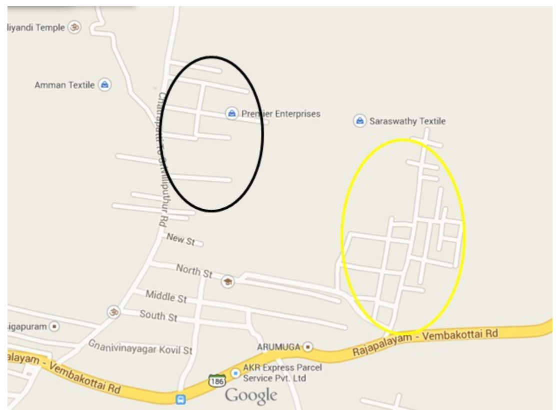


Figure 3: Map of Ayyanapuram (yellow) and Sankarapandiapuram (black) (Map data ©2012 Google)

We recall that in the village of Sankarapandiapuram, all 100 families in the village were interviewed and that, quite interestingly (Arumugam et al., 2014), no family was an isolate in all 6 networks: the only 4 isolates in the companionship networks were connected to other families through the remaining 4 networks (financial help and advice, in both crisis and normal periods).

The main occupation of people from the Yadhava community is work as laborers in cotton mills, in surgical cotton industries, in the field of communication or agriculture, and work rearing cattle and selling milk. Thus most of the workers are daily wage laborers. A very small number of them work in other countries such as Singapore, Malaysia or the United Arab Emirates, in the information technology and construction fields.

Table 1: Rituals and social behavior in the Yadhava and Saliyar communities

Events	**Behavior of Yadhava Community**	**Behavior of Saliyar Community**
Child birth	Gold ring or Cash or dress from relatives	Optional as per the interest of the individual
Removal of hair for the first time from the head of the child and piercing a hole in the ears in the case of a girl child for wearing gold stud in future. (This is conducted as a ritual in a temple)	Minimum Rs. 1000 in cash or gold stud or silver anklets or bracelets or any other ornament for the child	Optional as per the interest of the individual
Puberty function for girl child normally organized at house	Silk saree or gold/silver ornaments or household electronic goods such as television, mixer, grinder, refrigerators etc.	Optional as per the interest of the individual
Higher studies, Marriage engagement, housewarming function, medical care etc	Monetary help assured from relatives.	Optional as per the interest of the individual
Death rituals	5k grice+2 coconuts +vegetables+new dress +cash (MinimumRs.50) from relatives who are close to the concerned family	New dress +cash from close relatives to the concerned family

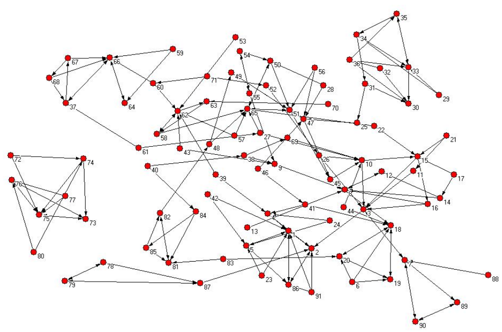
Most members of this community are illiterate and cannot read or write even in local language, namely, Tamil. In fact among the ninety one houses of our sample, only five households have graduates in commerce or arts and science disciplines. According to the classification of the Government of India the Yadhava community is in the category of Most Backward Community (MBC category). In spite of these disadvantages, the living standards of the Yadhava community are higher than those of the Saliyar community which we investigated in our earlier paper (Arumugam et al., 2014). While no quantitative data (such as for example household expenditure per capita) are available to measure the living standards of both communities, we note that in Ayyanapuram:

(i). All 91 families in our data have their own house to live in.

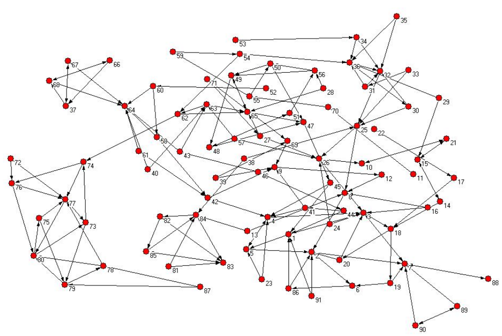
(ii). Most families have at their disposal a large area of land which can be cultivated.

(iii). Almost all individuals in any family earn personal income. It is common to see even healthy elderly persons work and earn income. Also adolescents who have no interest in studies earn their share of income by working in the construction field or the cotton industry.

Before undertaking the comparison of social network data from the Saliyar and Yadhava communities, we discuss prominent differences in the social behavior of these two communities. In Indian Hindu culture several rituals are conducted, starting from child birth to death. Close relatives and friends participate in most of the rituals and give a contribution, which is invariably reciprocated. In Table 1 we list some of the rituals and the social behavior of the two communities.



(a) Network of monetary help during periods of crisis



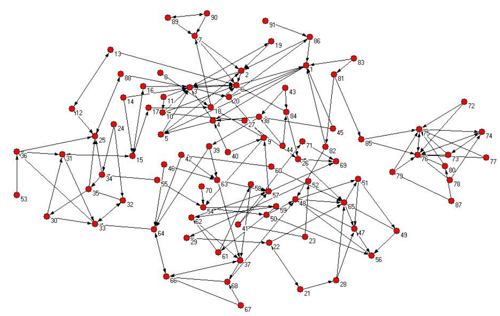
(b) Network of monetary help during normal periods

Figure 4: Network of monetary help

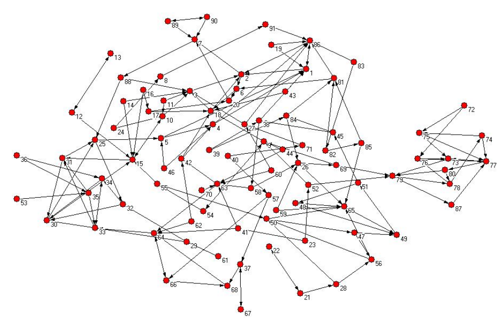
3. Visual investigation of the six networks

We now proceed to investigate the six networks, namely, the network of monetary help during crisis periods (Figure 4a), the network of monetary help during normal periods (Figure 4b), the network of advisory help during crisis periods (Figure 5a), the network of advisory help during normal periods (Figure 5b), the network of companionship during crisis periods (Figure 6a) and the network of companionship during normal periods (Figure 6b) constructed from the Yadhava community data. We compare these networks with the corresponding networks of the Saliyar community discussed in our earlier paper (Arumugam et al., 2014).

In this paper, as in Arumugam et al. (2014), a crisis is defined as an accident or death or any unforeseen expenses occurring in the family. We note here that the data were collected only at one point of time, mostly through personal interviews. This made it possible to obtain during one interview information from respondents about whom they turned to for financial help, advisory help and companionship in both normal and crisis situations.



(a) Network of advisory help during periods of crisis

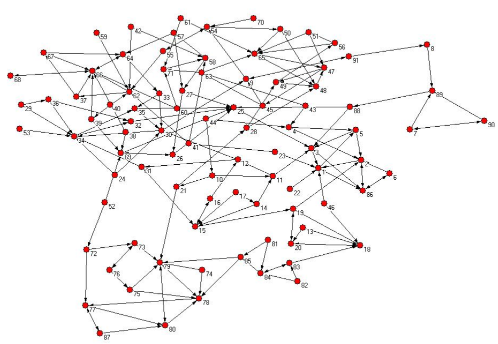


(b) Network of advisory help during normal periods

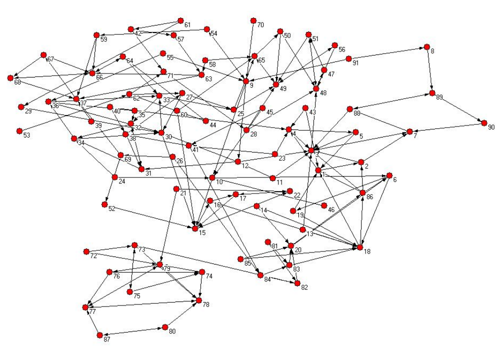
Figure 5: Network of advisory help

All six graphs were constructed with Pajek (2014) using a Fruchterman and Reingold (1991) algorithm, a force-directed graph drawing method which aims to provide an aesthetic display of the graph. This kind of algorithm implements a trade-off between attractive forces (associated with edges and similar to springs) and repulsive forces (associated with all pairs of nodes and similar to electrical forces).

We note that all six networks representing Yadhava community data have no isolated vertices whereas many isolated vertices are observed in some of the networks of the other community (Saliyar), although, as mentioned earlier, no vertex is an isolate in all 6 networks in the Saliyar community. There are two main reasons for this. In the Yadhava community in the village of Ayyanapuram when boys or girls are ready for marriage, they invariably choose a bride or bridegroom from the same village. As a consequence any two families are related or closely related. Furthermore, all relatives invariably attend all rituals in a family, and give a contribution, which is always reciprocated. Hence nice reciprocity is built in the system and there are no isolated vertices in any of the 6 networks.



(a) Network of companionship during periods of crisis



(b) Network of companionship during normal periods

Figure 6: Network of companionship

In the monetary help network during crisis and normal periods (Figures 4a and 4b) respondents 1, 3, 65 and 64 have the maximum in-degree 7 (this holds for the normal monetary help network as far as 64 is concerned). Thus they provide financial help to 7 households. Respondents 1 and 3 are involved in agriculture, 64 is a mill worker and 65 is involved in business. Four respondents, 6, 7, 87 and 91 have maximum out-degree 3: they are daily wage laborers who often need monetary help. The number of reciprocal pairs in the network of monetary help is 26 during crisis times and 15 during normal times. Only two reciprocal pairs (3, 7) and (89, 90) appear in both networks.

It is quite interesting to note that the monetary help network during normal times is denser than that during crisis times. One component, consisting of respondents 72, 73, 74, 75, 76, 77 and 80, becomes disconnected in crisis times, and its connection in normal times hangs on one key respondent, 74 (who is a cooli worker). Respondent 87, who is involved in business, connects the triad with respondents 78, 79 and 87 to the main component in crisis times; however this triad connects to the group with 72, 73, 74, 75, 76, 77 and 80 during normal times.

In the network of advisory help (Figures 5a and 5b), respondent 3, a worker in the cotton mill industry and respondent 76, a small scale industry businessman have maximum in-degree 9 (9 households reach out to them for advice) in the crisis time network (Figure 5a) and respondent 86, a small scale industry business man, has maximum in-degree 7 (7 households reach out to him for advice) in the normal time network (Figure 5b). All 91 households seek advice (the minimum out-degree is one in both normal and crisis times). Respondents 9 and 15 have maximum out-degree 3. Furthermore out of the 91 respondents, 81 have out-degree 2. There are 16 reciprocal pairs in each of these networks and 4 pairs are common to both networks.

In the network of advisory help in crisis times, it appears that respondent 3 holds a central position in the main part of the network, while respondent 76 plays an important role in the smaller subsection consisting of respondents 72, 73, 74, 75, 77, 78, 79 and 80. This subsection behaves quite differently in crisis and normal times, with different respondents playing the role of maintaining connection between the subsection and the main group.

In the network of companionship (Figures 6a and 6b), respondent 66, involved in business, has maximum in-degree 8 in the crisis network and respondent 3, a mill worker, has maximum in-degree 9 in the normal network. Respondent 86, involved in business, has maximum out-degree 4 in both networks. The number of reciprocal pairs in the two networks is respectively 21 and 19; only two pairs are common to both networks. Overall the image of the network is one of a tightknit community, tighter in normal than in crisis times, with members such as 79 (a cooli worker) and 86 playing an important role in keeping all subgroups connected.

4. Numerical summaries for the six networks

We now present tables comparing the parameters obtained from Ayyanapuram data and Sankarapandiapuram data. Since any two families in the Ayyanapuram data are related to each other, for purpose of comparison we have taken only the network of relatives in the Sankarapandiapuram data. We first recall definitions of terms used in the tables.

Let G be a network with vertex set V and arc set A. For any vertex v in V, the number of arcs of the form (u, v) in A is called the in-degree of v. The number of arcs of the form (v, u) in A is called the out-degree of v. A vertex with both in-degree and out-degree 0 is called an isolated vertex. A vertex with in-degree 0 and out-degree greater than 0 is called a transmitter. A vertex with out-degree 0 and in-degree greater than 0 is called a receiver. A vertex with both in-degree and out-degree greater than 0 is called a carrier.

If (u, v) is an arc but (v, u) is not an arc in the network, then (u, v) is called asymmetric. If both (u, v) and (v, u) are arcs, then the pair of arcs is called a symmetric pair or a reciprocal pair.

Table 2a gives the number of reciprocal pairs in both communities for all 6 networks (CMH and NMH denote the crisis and normal monetary help networks, CAH and NAH denote the crisis and normal advisory networks, and CCH and NCH denote the crisis and normal companionship help networks).

Table 2a: Comparison of the number of reciprocal pairs

		CRISIS			NORMAL			
		CMH	**CAH**	**CCH**	**NMH**	**NAH**	**NCH**	**Total**
Ayyanapuram	reciprocal pairs	27	16	21	15	16	19	113
Sankarapandiapuram	reciprocal ties within relatives	6	10	21	5	10	25	77

Table 2b: Comparison of the reciprocity measures (number of reciprocal ties divided by the total number of ties)

	Monetary		**Companionship Advice**		**Companionship**	
	Crisis	**Normal**	**Crisis**	**Normal**	**Crisis**	**Normal**
Ayyanapuram	.31	.19	.18	.19	.24	.21
Sankarapandiapuram	.15	.14	.16	.16	.20	.23

Table 3: Comparison of in-degrees and out-degrees

		CRISIS			NORMAL		
		CMH	**CAH**	**CCH**	**NMH**	**NAH**	**NCH**
Ayyanapuram data	max in-degree	7	9	8	7	7	9
Sankarapandiapuram data	max in-degree	5	8	8	4	7	8
Ayyanapuram data	min in-degree	0	0	0	0	0	0
Sankarapandiapuram data	min in-degree	0	0	0	0	0	0
Ayyanapuram data	max out-degree	3	3	4	2	2	4
Sankarapandiapuram data	max out-degree	3	3	6	3	4	6
Ayyanapuram data	min out-degree	1	1	1	1	1	1
Sankarapandiapuram data	min out-degree	0	0	0	0	0	0

Table 4: Comparison of the number of isolates and other types of vertices

		CRISIS			NORMAL		
		CMH	**CAH**	**CCH**	**NMH**	**NAH**	**NCH**
Ayyanapuram data	isolates I=O=0	0	0	0	0	0	0
Sankarapandiapuram data	isolates I=O=0	42	23	4	45	19	4
Ayyanapuram data	transmitter I=0 O>0	29	22	21	22	20	24
Sankarapandiapuram data	transmitter I=0 O>0	23	25	14	23	25	13
Ayyanapuram data	receiver I>0 O=0	0	0	0	0	0	0
Sankarapandiapuram data	receiver I>0 O=0	17	19	4	18	21	4
Ayyanapuram data	carrier I >O >0	62	69	70	69	71	67
Sankarapandiapuram data	carrier I >O >0	18	33	78	14	35	79

Table 5: Comparison of the number of isolates and other types of vertices

		CRISIS			NORMAL		
		CMH	**CAH**	**CCH**	**NMH**	**NAH**	**NCH**
Ayyanapuram data	asym ties	119	144	135	138	140	140
Sankarapandiapuram data	asym ties	35	53	83	30	52	86
Ayyanapuram data	reciprocal ties	54	32	42	30	32	38
Sankarapandiapuram data	reciprocal ties	6	10	21	5	10	25
Ayyanapuram data	sym and asym ties total	173	176	177	168	172	178
Sankarapandiapuram data	sym and asym ties total	41	63	104	35	62	111

Table 2b gives a measure of reciprocity (equal to the proportion of ties which are reciprocated) in all 6 networks in both communities. Interestingly, apart from the crisis monetary help network in Ayyanapuram, the reciprocity measures are fairly similar across the two communities.

Table 3, 4 and 5 give the maximum and minimum values of the in-degrees and out-degrees for all six networks in both communities, and compare the numbers of isolates, transmitters and receivers as well as symmetric and asymmetric ties in the networks.

5. Community detection: an illustration of a few common algorithms

We now turn our attention to a description of the clusters (communities) present in the network. A visual inspection of the graphs earlier in the paper tentatively identifies a major and a few minor groups in the monetary help networks (and to some extent in the other networks). We examine this issue further by comparing on the crisis monetary network the results of four common community detection algorithms.

The problem of identifying communities in a graph in such a way as to maximize the number of links inside the communities and minimize the number of links between the communities is a difficult problem which has spawned a sizeable literature. Fortunato (2010), gives an extensive review of methods for extracting communities, pointing out that the matter of defining what a community is is not always settled in the literature and that communities are sometimes defined as the outcome of a particular algorithm rather than in an a-priori fashion. In particular some attention has been given to algorithms which can identify communities in very large graphs.

An examination of Figure 7 reveals that four commonly used algorithms (Edge betweenness, Fast greedy, Leading Eigenvector and Walktrap) tend to yield a central core, itself made-up of about 3 subgroups, and a few small peripheral clusters. The algorithms differ to some extent on how they treat the central core. The R package *igraph* was used to construct the solutions; the code and data are available with this paper.

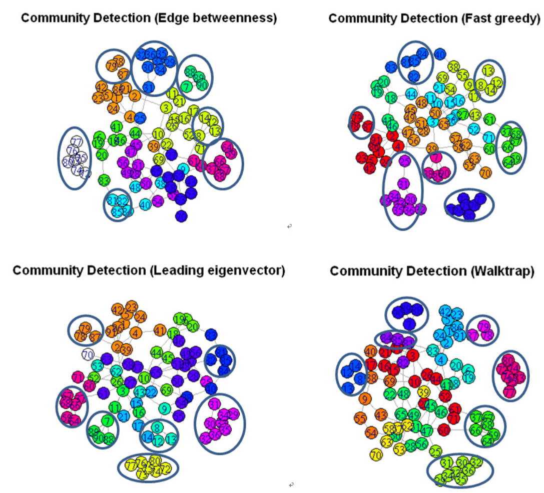


Figure 7: Communities within the crisis monetary help network: igraph algorithms

To get an idea of the quality of the different algorithms for community extraction, a rather intuitive method consists in computing, for each algorithm and each cluster, the intra- and inter-cluster density (Fortunato, 2010, p.84). The intra-cluster density is defined as the number of edges internal to the cluster divided by the number of possible internal edges in the cluster. The inter-cluster density is the ratio of the number of edges between vertices inside the cluster and vertices outside of the cluster to the number of possible such edges. A natural measure of the quality of a partition into communities is the sum of differences between the intra- and inter-densities over all clusters. All computations are performed ignoring the direction of edges. These measures are equal to 3.65 (Edge betweenness), 3.81 (Fast greedy), 3.31 (Leading Eigenvector) and 6.80 (Walktrap). By that measure Walktrap is the best algorithm.

In Figure 7, in order to facilitate the comparison of results across the four algorithms, we circle the peripheral clusters identified by the Walktrap algorithm, and circle those same groups in the graphs produced by the other three algorithms. Essentially, all algorithms agree on the identification of the small peripheral groups, but differ in how they treat the central core. A more exhaustive comparison of community detection algorithms applied to the networks in this paper would be very interesting, and lies outside the scope of the current article.

6. Discussion and related work

This paper has investigated the structure of a rural community in Southern Tamil Nadu, the Yadhava group in the village of Ayyanapuram, and has compared it with that of a previously investigated community in a very similar geographical location, the Saliyar group in the village of Sankarapandiapuram. The analysis in the paper has revealed that the social network structures of the two communities are quite different, on all three dimensions of monetary help, advisory help and companionship.

The social network in the Yadhava community is much tighter than in the Saliyar community and it is qualitatively clear that the Yadhava community enjoys higher living standards. This raises the question of whether tightknit networks, where members help each other, yield benefits to members in the form of higher living standards. The case we have presented here leads credence to the notion that social capital is important in communities such as the Yadhava and Saliyar groups.

We mention here related work in the area of rural development, notably in India. Matuschke (2008) suggests that a combination of social network analysis and econometrics could help establish which network characteristics have the greatest impact on the adoption of innovative technologies among small farm holders in rural areas and presents a case study on the adoption of hybrid wheat in India. Spielman et al. (2011) also investigate innovation systems and networks in rural areas, this time in Ethiopia. The emphasis is on understanding how networks facilitate the transfer of knowledge among various actors, such the innovators themselves, farm holders, cooperatives, non-governmental organizations etc.

Vanneman et al. (2006) using a nationwide survey of 40,000 households in India, examine variation in social capital across caste, tribe and religion. The networks examined here involve ties between households and persons in medical, educational and governmental institutions. The authors find that social capital does vary across hierarchies of caste, tribe and religion in India, but that these differences are mitigated to some extent by wealth and education, indicating some success of the "reservation" (affirmative action) system.

Bichir and Marques (2012) investigate the role of personal networks in the reproduction of urban poverty in Brazil, focusing on the cities of São Paulo and Salvador. The emphasis here is on the size of personal networks, with a finding that poor people's networks tend to be smaller and less diversified in their sociability profiles.

While these studies focus on different aspects of social networks, a common theme is that social networks are an integral and important part of living standards studies. We hope and expect that the data and analysis in this paper will be of use to further research in this direction.

In this paper, we extracted communities from the crisis monetary network using common community extraction algorithms. The idea of extracting communities in such a way that intra-community links are many but inter-community links are few is quite classical and is described for example in Newman (2004). The algorithms compared in this paper yield similar sets of peripheral smaller clusters but treat the central core differently (Figure 7).

A recent discussion of algorithms for implementing divisive edge (and vertex) cutting processes can be found in Kim and Candan (2012). A very interesting future perspective would be a more exhaustive comparison of community detection algorithms in the context of the networks in this paper.

7. Acknowledgements

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