Methodological and Ideological Options

Transaction network analysis for studying Local Exchange Trading Systems (LETS): Research potentials and limitations

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ABSTRACT

The numerous studies of Local Exchange Trading Systems (LETS) have so far been based mostly on qualitative approaches. The aim of this paper is to introduce the method of transaction network analysis as an important complement to these studies, enabling one to quantitatively describe functioning of LETS in terms of the actual flows of currency, materialized transactions and topology of the exchange network, the types of information markedly missing in most of the existing LETS studies. We demonstrate the potentials of the method on the case of the LETS initiative "RozLEŤSe" based in Brno, Czech Republic. Looking at the transaction flows using the network analysis approach, we identify the key members of the group, network characteristics of the exchange system and its development over time. This allows us not only to provide a complex description of the system, but also to simulate certain scenarios (e.g. removal of a key person from the network). Within the discussion of potentials and limitations of applying transaction network analysis for studying LETS and other community currency initiatives (e.g. time banks) on a larger scale, we also provide a free accessible software tool for doing so and invite other researchers to cooperate on the task.

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1. Introduction

The last decade has witnessed another wave of both practitioners' and academic interests in alternative or heterodox economic practices (Gibson-Graham, 2008; Healy, 2008), including a variety of community currency initiatives (CCs) such as local currencies, time banks, and Local Exchange Trading Systems (LETS).[1] This upsurge could partly be interpreted as a result of the 2008 economic crisis (see Conil et al., 2012); however, the quest for more democratic, community-based, socially and environmentally beneficial models of creation and use of money has a much longer tradition (see Gesell and Pye, 1958; Kennedy, 1995; Mellor, 2010; North, 2007). Although there are serious doubts expressed in the literature about the potential of community currency schemes to transform the current socio-economic system on a larger scale (Dittmer, 2013; North, 2005), a significant number of

CCs have evolved within the eco-social, or new economic grass-roots movements.

According to Blanc and Fare (2012), we can find more than 4000 initiatives of complementary, community, or local currencies in 50 countries all around the world. The latest estimate comes from Seyfang and Longhurst (2013:69), who reported 1412 systems of mutual exchange, predominantly having the form of LETS, in 14 countries extending over five continents.[2] After the collapse of the Eastern Block, some LETS schemes and time banks have also appeared in Central and Eastern Europe (CEE), namely Hungary, Poland, Slovakia and the Czech Republic (Jelínek et al., 2012; Zagata, 2005).[3]

In contrast to this remarkable occurrence and diversity, the studies of LETS initiatives seem to be limited — not necessarily by their number or scope, but more by the lack of variety of approaches employed. There are numerous studies describing specific LETS initiatives in qualitative terms — looking at their history, motivation of the members for participation and the various complications arising during their development

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[1] Following Seyfang and Longhurst (2013), we define Local Exchange Trading Systems (LETS) as a specific form of community-based exchange networks using virtual currency for exchange among a defined group of people. Community currencies represent a broader category including (printed) local currencies, time banks and other monetary alternatives still specifically employed with the aim of creating more sustainable forms of exchange (Lietaer, 2001) which are explicitly intended to serve the needs of a specific community, often limited to one locality/region (Douthwaite, 1996). The term complementary currencies is then the broadest category including any money system parallel to the national formal currency, i.e. also profit-oriented ones such as loyalty point systems and business barter schemes (Seyfang and Longhurst, 2013:65).

[2] These numbers are only estimates, though; complete reliable data on the number of various CC types are not available. For example, within the voluntary self-reporting Online Database of Complementary Currencies Worldwide, there are about 250 Local Exchange Systems registered, including, however, also non-local schemes. For details see http://www.complementarycurrency.org/ccDatabase/les (2013-06-02).

[3] Besides current (even if partially) formalized systems such as LETS, there have been numerous informal ways of exchange and gift-giving found in post-communist societies, although they were rarely reflected by researchers. For exceptions, see Acheson (2007) or Jehlička et al. (2013).

and decline (Douthwaite, 1996: chapter 3; Lee, 1996; North, 2002; Seyfang and Smith, 2002). To study the discourses around LETS, some statistical mixed methods were also used such as the Q methodology[4] applied by Barry and Proops (1999, 2000). Recently, several broader studies have tried to categorize the existing community currency schemes (e.g. Blanc, 2011), map their historical and geographical development (North, 2007), count their numbers (Seyfang and Longhurst, 2013), and assess their (potential) impacts (Dittmer, 2013).

However, it still applies that these LETS studies are either qualitative, or quantitative but based mainly on self-reporting of the practitioners, which is necessarily limited, both in terms of their ability to recall their own activities within the network, and their overview of the functioning of the group as a whole (Collom, 2012:19). Hence, there is a lack of data (reported by the above-mentioned authors themselves) on such issues as the extent of individual initiatives, the nature, volume and frequency of the realized transactions and the following social, environmental and economic impacts, as well as on understanding the dynamics of the overall developments of the LETS networks.

During the last decade, more CC groups started to use software tools for the administration of their transactions, thus their detailed transaction data are potentially available.[5] Indeed, a few researchers have recently turned to electronic transaction records as a valuable source of information about CC initiatives, particularly Collom (2008, 2011, 2012), Panther (2012) and Nakazato and Hiramoto (2012). We have engaged in this line of research and have tried to develop it further. We believe that the above-mentioned lack of empirical data on real transactions within LETS can at least partly be explained by the missing methodological tools that have not been easily available to LETS researchers. The network analysis can be effectively used to fill this gap.

The aims of this paper are thus the following: 1) to introduce the network analysis as a useful tool for analysing LETS and other CCs; 2) to demonstrate its potential on a pilot study of a LETS initiative in Brno, Czech Republic; 3) to discuss further possible developments and the scaling-up of the method; and 4) to provide an accessible software tool for others to cooperate and advance the work.

The paper is divided into six parts. After introducing the context and scope of the study (Part 1), the method of network analysis and its relevance for LETS studies are explained (Part 2). Its specific application to the case study of LETS initiative RozLETŠe in Brno, Czech Republic is then described. Both the methodological chapter (Part 3) and the summary of results (Part 4) are focused on the transaction network analysis and its outcomes; the method is explained in enough detail to make it possible for others to replicate it. Broader interpretation of the results and further application possibilities of the transaction network analysis are then discussed (Part 5). The main contributions of the paper are summarized (Part 6), including a link to the open-source online tool available for other researchers (see Footnote 23 for the link).

2. Network Analysis, Graph Analysis and LETS

With the advent of new tools for the analysis of large datasets and complex systems over the last decade, network analysis has found applications in many fields (Albert and Barabási, 2002; Strogatz, 2001). It provides researchers with tools for the description and analysis of complex systems comprising many entities and their relationships.

Economic systems on various scales represent good examples of such complex systems with network characteristics: the entities represented as nodes can range from individuals or companies to countries, and the links may represent a broad spectrum of economic relationships such as monetary or material flows. One of the well-studied economic networks is the International Trade Network (ITN), capturing trade among countries using annual data reaching back more than fifty years. Among other insights, the network approach revealed the core-periphery structure (Bhattacharya et al., 2008), the role of geographical distance (Fagiolo, 2010), commodity flow relations (Barigozzi et al., 2011), the stability of the network (Foti et al., 2013) and various models of ITN development over time (De Benedictis and Tajoli, 2011).

LETS initiatives operate on a small, local or maximally regional scale. However, they also embody network properties analogical to larger-scale systems such as ITN.[6] LETS can thus be seen as a network of a defined number of people (nodes) connected together via individual transactions (edges) with defined direction (from node A-seller to node B-buyer). Approaching the transaction data as a network enables one to employ the well-established mathematical methods and tools of graph theory, which are effective for the quantification of network structure, visualization, and the modelling of network generation and development dynamics (Batagelj and Mrvar, 1998; Börner et al., 2007).

Fig. 1 shows how a graph is constructed from the transaction data. The left part (A) shows the original sequence of transactions (horizontal arrows) between accounts (vertical lines) in time. To create the graph representation, the individual transactions are collapsed across the time dimension whilst the edge (a,b) becomes present in the graph only if there is at least one transfer from account a to account b. As already noted, the edges (i.e. transactions) can be directed and weighted: the source and target nodes can be distinguished, and the edge can be associated with a distinct value. Two weighting functions are typically considered: 1) the sum of the currency units sent from account a to account b, and 2) the number of transactions between a and b (regardless of the amount of money exchanged in the transactions). An example graph constructed from the sequence of example transactions (A) is shown in Fig. 1(B). For an example of the full graph derived from our data, see Fig. 6.

Equipped with the network analysis framework, it is possible to pose new questions about LETS (and provide novel answers to the old ones), such as the following: 1) Are all the LETS members equally active in the transactions? 2) Is the group compact, or is it divided into distinct trading groups? 3) Is it possible to identify the important members contributing most to the currency flows? 4) Is there some identifiable core group, or are the more active members separated? 5) What happens to the rest of the group if an active member leaves? Does it pose a threat to its functioning, or to the account balance of some specific members? With the network analysis, it is possible to translate these questions about LETS communities into the language of graph-theoretical metrics and distill the answers from the transaction data.[7]

For the LETS initiatives using software tools (such as Cyclos), all the transaction data are potentially available, and there are already researchers engaged in their analysis. Collom (2008) made use of the framework of social network analysis to investigate the engagement of the elderly in a time bank community. He also used the transaction records of a time bank sorted into categories to relate the trade activity with self-reported motivations obtained from a questionnaire (Collom,

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[4] The Q methodology combines qualitative and quantitative approaches to investigate views and attitudes (i.e. discourses) within particular groups; Barry and Proops (1999, 2000) demonstrated this method on participants from several LETS initiatives in the UK.

[5] For time bank initiatives e.g. the Community Weaver or Time and Talents software tools are available (see Collom, 2012:19). Many LETS initiatives use Cyclos, open source on-line banking software, see http://www.cyclos.org/ (2013-07-31). Currently there are about 40 user initiatives listed on the Cyclos website, see http://www.cyclos.org/cyclos-users (2013-06-06), and very probably there are more.

[6] Technically speaking, LETS represent "membership clubs using a virtual currency created at the moment of transaction as a credit for the seller of a good or service and a debit for the buyer. All participants start their accounts at zero, and can spend before they have earned any currency. [...] Printed directories or online databases are used to communicate supply and demand, and a centralized accounting system, usually managed by volunteers, registers all transactions." (Dittmer, 2013:3).

[7] Note that the numbers of the questions relate to the numbering of Sections 4.1–4.5 of the Results, which provide answers to these questions using the transaction network analysis.
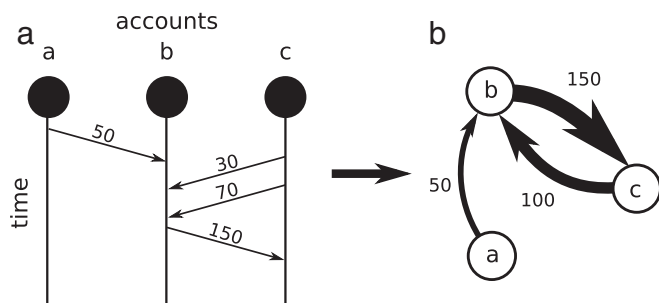
Fig. 1. Creation of the graph from the transaction data. On the left (A): individual transactions between nodes (i.e. accounts) a, b and c in time; on the right (B): the corresponding graph with distinguished direction of transactions, weighted by the sum of the value of transactions.

2011)[8]; both methods are summarized in Collom (2012). Collom's transaction analyses are, however, limited to node-local metrics: the number of (reciprocated) trading partners, the number of services exchanged and the metrics of ego-network density.[9]

Nonetheless, the main benefit of treating the transaction records as a network is the possibility to pose questions about the system as a whole. Nakazato and Hiramoto (2012) moved in this direction and used a combination of various metrics quantifying the transaction network with a self-reported questionnaire about the types of social support received from the local currency community. However, the whole-network metrics are used in their analysis only as correlation factors; very little detail is given to the motivations and interpretations of these measures in the context of transaction network analysis (accompanying methodological article is unfortunately available only in Japanese). Panther (2012) combined the field work (questionnaires, interviews) with a network analysis in her study of two community currency systems (LETS and a time bank). She used the transaction network analysis to investigate her concepts of social cohesion and reach, to inspect the reciprocity of the ties, and to guide her fieldwork.

We would like to join these authors and promote the utilization of electronic transaction records in the analysis of community currency systems. As an extension of existing studies, we have introduced specific network-wide metrics such as the centrality analysis and rich-club coefficient (see further) to explore the full potential of transaction network analysis applied to LETS and other CCs.

3. Materials and Methods

During spring 2013, several interviews with key contact persons from our case study LETS initiative RozLEŤSe were conducted regarding the history, organizational structure, decision-making processes and activities of the group. Our research project was presented to the group at one of its regular meetings, and then access to the transaction data from Cyclos (see below) was granted by the group.[10]

The data comprise all the transactions of the RozLEŤSe members made from March 2011 to mid-April 2013 (i.e. the whole 2-year period available from the beginning of using the Cyclos software by RozLEŤSe). The primary data for the analysis were tables from the database of the

Cyclos software.[11] The scripts for graph generation, basic manipulation and metrics computation were written in Python using the NetworkX package (Hagberg et al., 2008). The interactive visualization and graph inspection were performed using Gephi software (Bastian et al., 2009).

To gain insight into the composition of the traded goods and services, all the transactions were coded according to their character and divided into 24 categories (see the Supplementary materials, Table 1), with four super-ordinate categories: food, other goods, services, and others. The division was based on the description field of the transaction entry. The same categories were also used for coding the supply and demand adverts, also available from Cyclos.

From the transaction data, a graph was constructed following the procedure described above (Section 2).[12] In the first step, we inspected the basic topological property of the network, the presence of connected components. A sub-graph of a directed network is considered to be a strongly connected component if there is a path – sequence of edges respecting the direction – connecting any pair of its nodes. In the second step, we counted the node and edge statistics as part of inspecting the basic properties of the network: the distribution and median of node degree and strength, and the distribution and median of edge weight.

In the third step, we identified nodes with an important position in the context of the topology of the network. There is a whole family of metrics within the graph theory dealing with the importance of a node. In the transactional context we chose the centrality of a node as it can capture both the diversity of the member's trade partners, and their influence on the exchange network. We evaluated and compared four centrality metrics: degree, strength, Eigenvector centrality and PageRank.

The degree and strength centralities are the simpler measures, as they ignore the neighbourhood of the node. Node degree is defined as the number of edges connecting the node to the rest of the graph and denotes the number of trade partners. Node strength is an extension of node degree to a weighted network and is defined as the sum of the weights of incident edges; it corresponds either to the cash flow in the case of weighting by value, or to the total trade activity of the corresponding account in the case of weighting by number of transactions.[13] See an example of the node degree and strength in Fig. 2.

The more complex metrics of centrality are Eigenvector centrality and PageRank, which both rank nodes with central neighbours higher than nodes with the same number of peripheral neighbours (Fig. 3). The Eigenvector centrality (Bonacich, 1972) is defined on a binary network for a particular node as the sum of centralities of its direct neighbours:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij} x_j \qquad (1)$$

where A is the binarized adjacency matrix, $x = (x_1, x_2, \dots x_n)$ is the vector of node centralities and λ is constant. It can be shown that the ratio of the node centralities converges to the principal eigenvector of the adjacency matrix. In this form, the metric ignores the weights on the edges. On the other hand, the edge weights are taken into account by the PageRank metric (Page et al., 1999). It modifies the weighted adjacency matrix to column-stochastic (sum of every column is 1) and

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[8] We provide similar categorized statistics in the Supplementary materials (Table 1). In our case, the majority of transactions comprised of food, in contrast to case studies of LETS and time banks by both Collom (2011) and Panther (2012), where most transactions were related to social activities and events. This further illustrates how valuable the transaction data are for systematic comparison between various CC initiatives.

[9] The ego-network density of a node is the ratio between the actual number of edges between pairs of neighbours of a node, and the number of all its potential neighbours' edges.

[10] Questionnaire information was also gathered during June and July 2013 regarding the socio-economic profile of the members, their history and interaction within RozLEŤSe, their motivations for participation, and their views about the functioning of their LETS system. We acknowledge that to understand the transactional data (see further), it is necessary to combine them with the insights of the members. For the results of the questionnaire and the qualitative part of our research, see Kala et al. (2013).

[11] According to interviews with key persons from RozLEŤSe, we can assume that a vast majority of all the realized transactions were recorded by the RozLEŤSe members in Cyclos. However, it is possible that there are a few which were not; these are not included in the analysis. All the transactions associated with the system accounts that served for special purposes (paying fees, etc.) were removed, as well as all the accounts which were not associated with any transfer. All the data were then made anonymous.

[12] We used the transaction volume as edge weight. Mathematically, the weighted directed graph is a tuple $G = (V, E, l)$, where V is a set of nodes, E is a set of edges (such as $E \subseteq (V \times V)$ and l is the weighting function on edges. It is often convenient to represent the edges in the form of adjacency matrix A — the square matrix of the dimension $|V|$ where A_{ij} is 0 if there is no edge between nodes i and j; otherwise, it is equal to edge weight $l(i, j)$.)

[13] If $E_a \subseteq E$ is the set of edges adjacent to node a, then node degree is $|E_a|$ and node strength is $\sum l(e)$, $e \in E_a$.
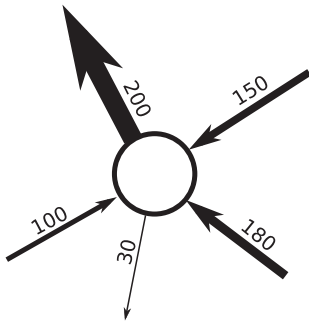
Fig. 2. Local centrality measures: the node strength is 660 (total cash flow); the degree is 5 (number of transactions, i.e. number of edges).
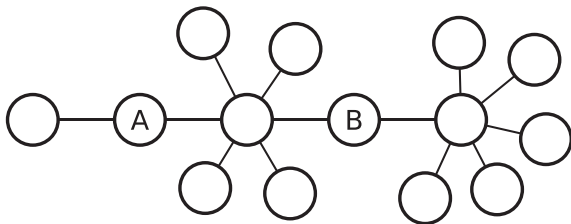

Fig. 4. Rich-club example: the size of nodes marks their importance; the thickness of edges marks their weight. Important nodes are distributed in network (a), or form a tightly interconnected rich-club in network (b).

then computes the first eigenvalue and the corresponding eigenvector, as in the case of Eigenvector centrality. The difference between Eigenvector and PageRank centrality is analogous to the one between the degree and strength of a node: the degree-based variants capture the importance of an account solely in terms of the number of trade partners, whilst the weight-sensitive variants also take the activity of the partners into consideration.

To describe the topology of the network with the various centrality levels of the nodes in more detail, we searched in the fourth step for a backbone in the network concentrating the most important nodes that were highly connected to each other. We quantified this property with the help of the rich-club coefficient (Opsahl et al., 2008) for weighted undirected networks (meaning we ignore the direction of the edges). In short, the coefficient ϕ for given importance r (in our case, node strength based on transaction volume or number) is a ratio between the weight of the edges connecting the nodes that are at least as important as r, and the hypothetical case when these nodes are connected with the most weighted edges of the network. High values of the coefficient ϕ then imply strong connectivity between important nodes; low values imply the important nodes to be distributed throughout the network without any increased interconnection, as illustrated in Fig. 4.

More rigorously, the rich-club coefficient is defined as follows:

$$\phi^w(r) = \frac{W_{>r}}{\sum_{l=1}^{E_{>r}} w_l^{rank}} \qquad (2)$$

where r is the importance metric of the nodes, W_r is the sum of weights connecting the nodes with the importance of at least r, E_r is the number of such edges and w^{rank} are the weights from the whole graph ordered by their importance. The absolute value of the rich-club coefficient was normalized against the randomized network to contrast the presence of a rich-club against a null model. The randomization of the network was performed by shuffling the weights on the outgoing edges of every node. Thus, the importance of the node and distribution of the outgoing edge weight was kept constant and only the targets of the prominent edges were randomized (Opsahl et al., 2008). The

Fig. 3. Illustration of the difference between degree- and eigenvector-based centralities. Both nodes A and B have the same degree of two. However, node B has many more central neighbours and thus will be ranked much higher in Eigenvector centrality than node A.
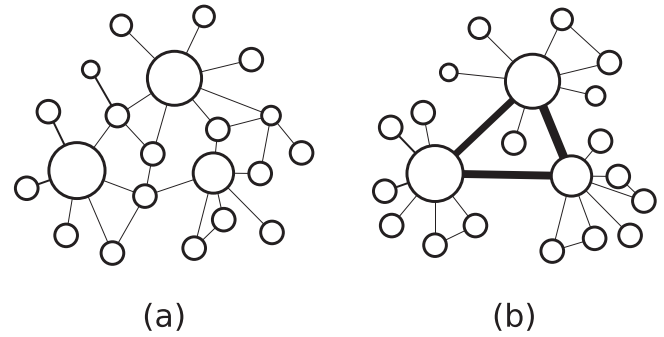
randomization was repeated 1000 times and the average value of the rich-club coefficient was used for normalization.

As the last step of the analysis, we examined the resilience of the network to changes, that is, the capability of the network to maintain connectedness and function after the removal of some edges or nodes. We focused on evaluating the impact of the removal of one and two central nodes on the account balance of the remaining nodes to measure the distribution of the removed cash-flows, and to identify the nodes threatened by the removal of their important trade partner(s) (see Figs. 10 and 11). We simulated the failure of the node(s) by removing all its (their) transactions from the database and recalculating the time development of the remaining account balances.
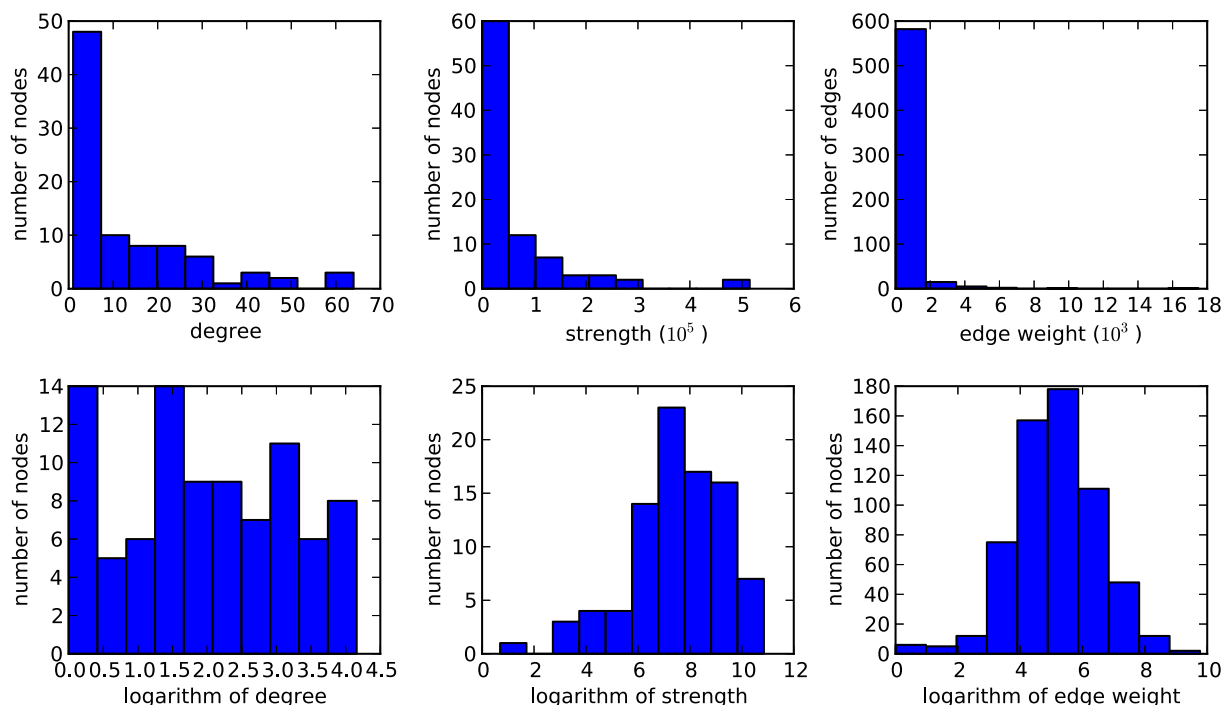
4. Results

The origin of RozLEŤSe dates back to 1999. At that time its predecessor, the ROZLET system, was founded as the social activity of a permaculture group in Brno, inspired by other LETSystems from abroad. The exchange of goods (mostly seasonal fruits and vegetables) and mutual help (mostly babysitting) took place during the regular meetings of the group. At its peak, there were 48 members, although not all of them traded actively. Due to various complications, the group dissolved during the switch to the online accounting system (Cyclos) in 2006. RozLEŤSe was established in November 2010, reassuming the inspiration of ROZLET. Several initial members started meeting at that time and the group has been slowly growing since, becoming much more heterogeneous both in personal and trading scope than its progenitor ROZLET (Jelínek et al., 2012). The group soon chose its name and the name of its currency (BRK), agreed on the basic rules, adopted the Cyclos software (February 2011) and started regular trading.[14] Since June 2011, the group has been organizing regular meetings almost every month to advance personal contacts within the group, facilitate exchanges, discuss organizational issues, and sometimes also share additional activities such as film screenings, debates and singing.

Regarding the basic characteristics of the group derived from the transactional data, there were 134 member accounts in Cyclos in April 2013, of which 89 made at least one transaction during the research period. For the whole research period, the number of transactions was 1347, and the overall volume of transactions was 263,036 BRKs. The number of trade partner pairs was 606, yielding a network density[15] of 0.077 (a rather sparse network). The number of active members

Fig. 5. Distributions of the basic network properties: node degree (number of trade partners), node strength (total volume of transactions) and edge weight (volume of transactions between two members). The horizontal axes show quantities; the vertical axes indicate frequencies. All three distributions are skewed to the right (as can be seen in the figures in the first row); the node strength and edge weight follow log-normal distribution.

grew from 10 to 15 transacting members per month in the second half of 2011 to 15–25 transacting members per month in 2012, peaking at 41 in March 2013. Similarly, the number of transactions grew from 20–50 per month in 2011 to 50–100 during 2012, peaking at 166 transactions per month in February 2013. Finally, the volume of transactions also grew from 5000–10,000 BRKs per month in 2011[16] to 7000–15,000 BRKs during 2012, peaking at almost 26,000 BRKs in February 2013.

The following sub-chapters introduce the already advanced network-wide characteristics of the LETS derived from the application of the transaction network analysis as described in five steps in Materials and Methods.

4.1. Connected Components

In terms of network topology, the network comprised of one connected component, meaning that there were no isolated groups of trading partners independent of the rest of the group. When the directionality of the trade was taken into account, several peripheral nodes would break off to single-node strongly connected components, as they were connected to the rest of the graph by only one or two edges with the same direction. These represent either inactive members, who only tried to trade once and left the network, or new members, who did not have time to make more transactions. However, apart from these isolated cases, the remaining sub-graph comprised of only one strongly connected component.

4.2. Node and Edge Statistics

The average degree of the nodes (i.e. the average number of trade partners) was 14, which was evenly split into in- and out-degree (i.e. incoming and outgoing transactions), both equal to 7 on average. The average node strength (i.e. the volume of all transactions performed by an account) was 5793 BRKs; the median was 1975 BRKs. The average

edge weight (i.e. the volume of transactions between two accounts) was 412 BRKs; the median, 150 BRKs. The distributions of node degree, strength and edge weight are plotted in Fig. 5. As we can see from the distributions, the network was heterogeneous in terms of both degree and node weight. This means that a few nodes were much more connected (both in degree and strength) than the majority, and a few edges were far heavier than the average. The fact that activity in the network was not evenly distributed shows two things: that there were a few considerably more active members than the majority of the community, and that the volume of the transactions between a few pairs
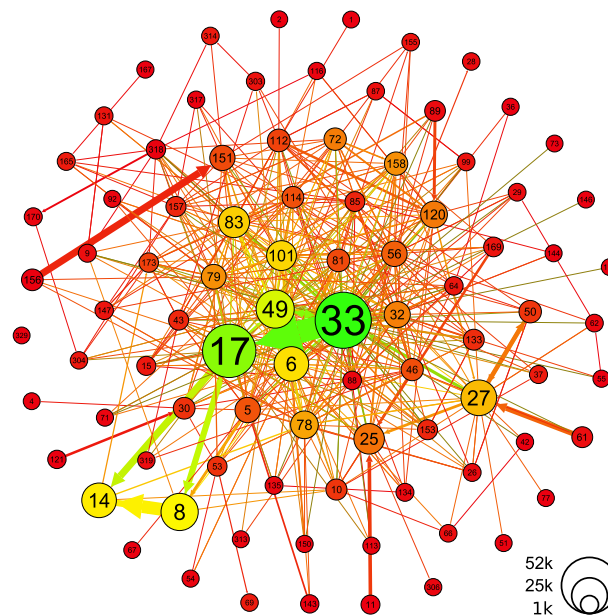
Fig. 6. Centrality of the nodes in the transaction network. Node size corresponds to its strength; node colour to pagerank centrality; edge thickness scales with its weight. Both metrics take edge weights into account.

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[16] The two largest transactions were both for 5000 BRKs: a second-hand industrial vacuum cleaner in September 2011 and a second-hand car in November 2012.

of members constituted most of the total volume of the trade in the community (see the next section for more details). These findings prompted further questions about network topology, which are addressed below, about who the central and strong nodes were and the level of their importance for the network.

4.3. Centrality Analysis

Fig. 6 visually compares the centralities measured by weight-sensitive measures: node strength and PageRank. Such visualizations are well suited for interactive exploration of the network, as they enable a quick selection of the most important accounts and trade relationships. In the online supplement of the results (see the Supplementary materials, Figs. 1-42), there are also graphs visualizing changes of the network in time. Several time ranges were used: months, trimesters and half-years. Visualization of the development of the network in time enables one to easily see if and how the most important nodes changed during the history of the group, if and when step changes in the number of active nodes or the volume of transactions occurred, etc.

Fig. 7 compares the ordering of the nodes based on the four examined centrality metrics: node degree, node strength, Eigenvector and PageRank centrality. All of the metrics marked node 33 as the most central one, which was followed by nodes 17 and 49, with the exception of degree centrality. Although many of the nodes repeat across the metrics' top ten, the particular order differs. Note the differences between the degree-eigen and strength-pagerank rank orders. Nodes 101 and 6 have high degrees, although ranking lower on the context-aware Eigen-value centrality, whereas node 17 is considered highly centric despite its lower degree. Similarly, in the strength-based metrics, the centrality of nodes 27 and 101 changes when the topological context is taken into account. Also note the differences between the degree- and strength-based metrics: these arise from the fact that the volume and frequency of trades are not necessarily directly proportional for all accounts.

4.4. Rich-Club

A logical question arising from the presence of the few highly central nodes and the few strong edges is whether the network has a rich-club backbone — a core of important nodes interconnected with strong edges. Fig. 8 shows the normalized rich-club coefficient (see Materials and Methods for details) as a function of node strength. The narrow
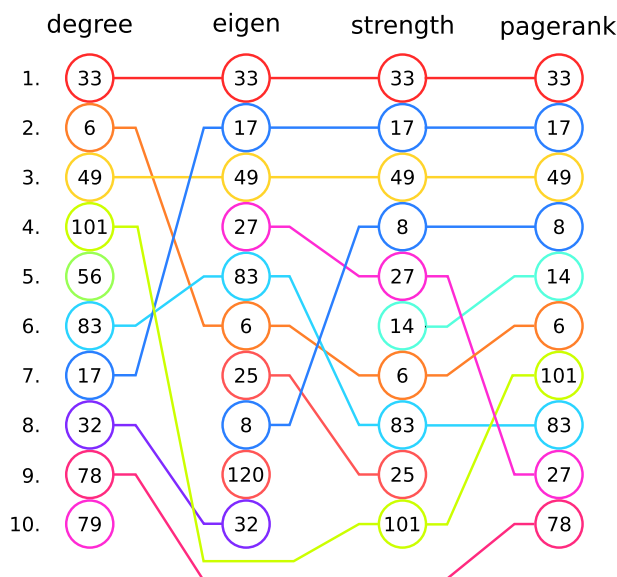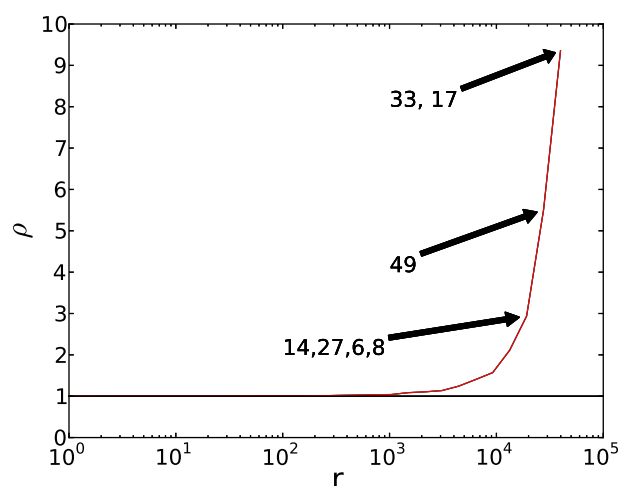
Fig. 8. The rich-club coefficient ρ normalized against null-model, r is the node strength. The nodes differing from the null-model above the strength of 10^4 and their labels are marked on the curve.

majority of the network nodes were not different from the null-model; only a few of the strongest nodes showed large differences. Again, the most distinctive rich-club was comprised of nodes 17 and 33, followed by node 49 and then by nodes 14, 27, 6 and 8 (see Fig. 9 for the corresponding sub-graph). These nodes accounted for more than 85% of the total transaction volume (225,434 of 263,036 BRKs); however, only 28% of this volume was traded between the core nodes. Thus, it is evident that the transaction network does have a rich-club backbone: the few most active members traded intensively with each other. However, at the same time, they were active towards the (peripheral) rest of the community, preventing the creation of a closed, disconnected elite group within the network. We performed the centrality analysis for the network also with the transaction count as edge weight, obtaining very similar results.

4.5. Removal of Important Members

After identifying the structure of the network, we concentrated on the analysis of network resilience by the simulated removal of the important nodes. In the "knock-out" experiment, we first targeted node 33 for removal, due to its most central position in the network (see Fig. 6). The removal of its activity from the transaction history had heterogeneous impacts on the account balances of other members. The most affected was node 17, as 33 was its main source of income in the network. Furthermore, its negative account balance was not matched with any other node, even in the undisturbed network. We then continued with the removal of node 17 (mimicking the cascade effect), because it was the second most central node and also the most endangered one after the removal of node 33. In this case, the removal
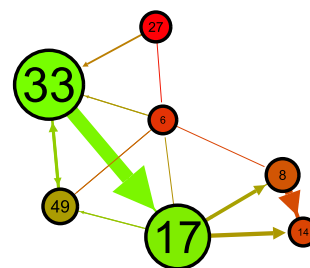
Fig. 9. The rich-club sub-network. Only nodes with a rich-club coefficient higher than the null-model were selected. The thickness of the edges scales with their weight; node size marks the strength, and colour indicates the pagerank centrality. Note the sparseness of the network and the large differences in the overall node importance and in the transaction volumes among the members of the rich-club.

Fig. 7. Comparison of the ten most central nodes as selected by four centrality metrics: degree, eigenvalue, strength and pagerank.
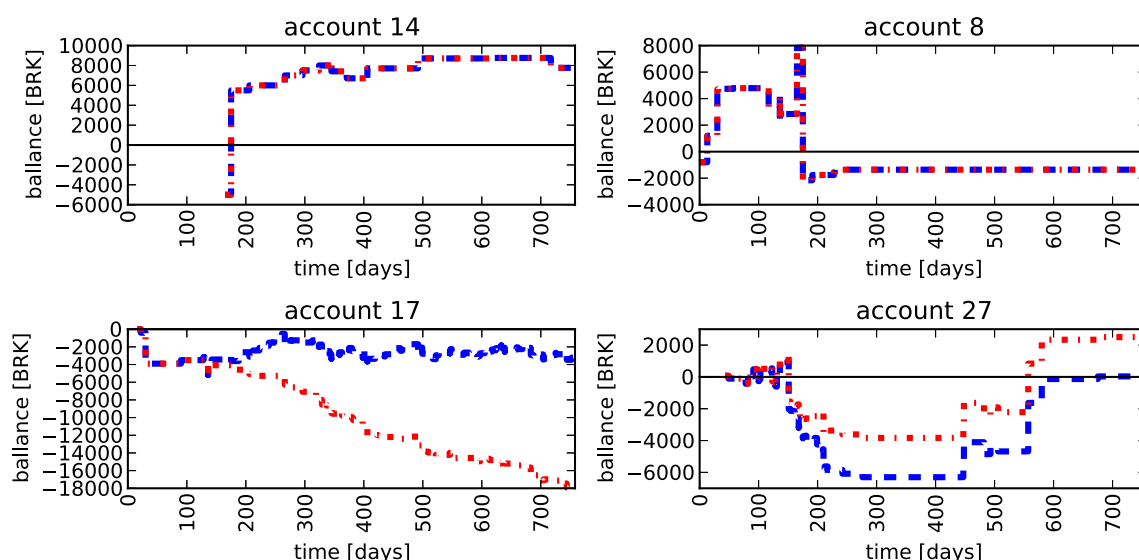
Fig. 10. The account balances of the most affected nodes when removing the transactions of account 33. The account balances before removal are in blue; the ones after removal are in red. As node 17 gets a substantial portion of its income from node 33, it fails to hold the balance around zero after its removal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

affected nodes 8 and 14 most, as they were the most important trade partners of node 17. The account balances for both scenarios (the removal of node 33 and the removal of both nodes 33 and 17) are shown in Figs. 10 and 11.

5. Discussion

Following the aims of the paper, we focused both in the Materials and Methods and Results on the transaction network analysis as we wanted to demonstrate its usability and potential for studies of LETS and other CCs.[17] However, we would like to stress the importance of combining transaction data with other information, both quantitative and qualitative, regarding the particular groups under study. Providing valuable insights about the real volume, composition and structure of the transactions, the network analysis is most useful when applied to confront and complement the self-reported information from CC participants, and related interpretations present in CC literature. In the following discussion, we give examples of such contextual interpretation of transaction analysis results, we compare them with other studies using transaction data, and we discuss further possibilities and limitations for transaction network analysis within LETS and CC studies.

For example, LETS are very often described as reciprocal and inclusive (Williams et al., 2001:126–127; Seyfang and Longhurst, 2013:68; Barry and Proops, 2000:51), reciprocity and inclusiveness also being expressed by LETS practitioners as one of the main motivations for their participation in LETS (Seyfang and Smith, 2002). However, numerous case studies revealed at the same time that it is often only a few most active members who effectively keep the group running (Douthwaite, 1996); thus, doubts were raised about the relevance of such expectations (Bowring, 1998).

For the case of RozLETSe, the analysis of the connected component (see Section 4.1) showed that this group forms a singular trade network which is strongly connected, forming one coherent component. In other words, the members of RozLETSe are not divided into sub-groups and there is no significant imminent threat of such a split.[18] The same

basic structure was observed in most of the systems investigated by Panther (2012), Collom (2012), and Nakazato and Hiramoto (2012). Only the network of the Eco Money (Muraoka, Japan) described by Nakazato and Hiramoto (2012) showed clear division into two clusters; unfortunately, the authors did not comment on this phenomenon further.

For groups larger than RozLETSe, it would be beneficial to supplement the connected component analysis with an analysis of modularity (Newman, 2006), so that one receives much more detailed information about the structure of the possible sub-groups comprising the LETS being studied, and about the differences in the inter- and intra-modular trade relationships. It would also be interesting to gather data from larger LETS groups which split into smaller sub-groups during their life-cycle, determine the roots of these splits and see how long in advance these can be detected. If relevant for the study, it is also possible to specify the groups a priori, regardless of the connectedness of the network derived from the network analysis, as done by Collom (2012). He specified the groups of elderly and younger adults within a time bank, and counted the ratio between the in- and between-group edges. He found the elderly to trade primarily with non-elderly, and interpreted this network heterogeneity as a basis for social integration of the senior participants.

The analysis of the distribution of the basic node and edge properties in our case study (see Section 4.2) revealed that within the singular trade network, there are several extraordinarily active individuals both in terms of the number of trade partners (node degree) and trade activity (node strength). The same phenomena were reported by Panther (2012), who found right-skewed node degree distribution in both of the examined local currency networks (Steelwear Time Bank and Woolgone LETS, UK). Furthermore, some of the bilateral trade relations were far above average. This means that the group comprised of a majority performing very similar average activities, and a handful of very active members with stable repeated trades, forming the central backbone of the network. To find who these core members are, the analysis of centrality was performed (see Section 4.3).[19] Importantly, the choice of the measure of importance (centrality) has partial influence on the composition of the identified central club. The

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[17] In connection to our case study, we refer in the discussion primarily to LETS schemes, however, the same applies to all other CCs using electronic transaction records. Indeed, several researchers (see further) applied transaction analysis both to LETS and time banks.

[18] We suggest that this quality developed at least partly through the regular monthly meetings of the group, which give opportunity to arrange transactions and find new trade partners via direct personal contacts. These meetings also correspond to one of the main motivations of the members for participating in RozLETSe — that of meeting people and experiencing the social spirit within the group (see Kala et al., 2013).

[19] The thresholding of the network can also be applied to filter the more important nodes and remove the weak and uninteresting edges. In our case, the threshold can be twofold: based on the count weight or on the volume weight. Chosen weights can be either arbitrary, or can be guided, for example, by the mean of the weights across the graph.
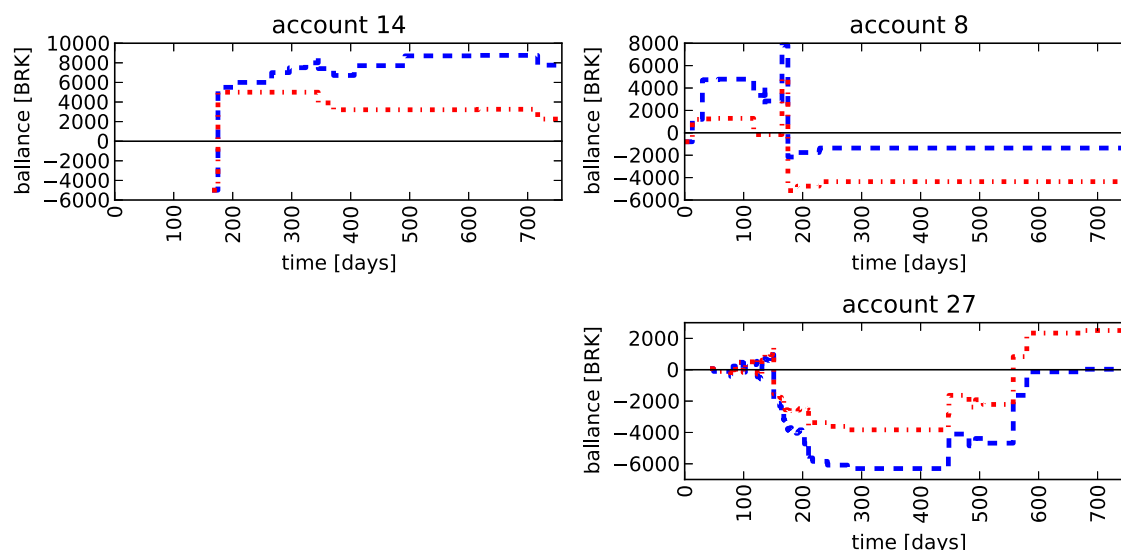
Fig. 11. The account balances of the most affected nodes when removing the transactions of accounts 33 and 17. The account balances before the removal are in blue; the ones after removal are in red. Due to the directional asymmetry of the transactions in the network, both accumulation (account 27) and deficiency (accounts 14 and 8) occur. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

transaction value and count would have the same importance if the pricing mechanism were more homogeneous (such as in time-bank systems, see Cahn (2000)); however, in our case, the pricing mechanism is mixed (see Footnote 14), thus the value of a single transaction ranged from single units to thousands. Whilst in our case the main results of the network analysis were robust as to the choice of edge weight measure, the influence of the edge weight measure should always be checked. Also note that the analysis of a graph without weights does not take the node activity into account and especially in time-aggregated data, this can heighten the importance of nodes with low activity but a large number of trade partners.[20]

The centrality metric can serve as a systematic selection criterion when a qualitative analysis is performed in larger groups to consistently choose the respondents for structured interviews, for example. A particular metric (influencing the results of the selection, see above) can be chosen in accordance with the scope of the analysis (trade partner structure, trade activity, etc.). Similarly, a centrality metric can also serve as a systematic selection criterion when the important members are compared across several LETS systems. In larger systems it would also be possible to extract the profile of a "typical active member" and compare these profiles across systems or over time. Panther (2012) credits network analysis as a valuable tool in this context, both as a guide for her fieldwork and as a means of visualization of the community structure for the discussions with individual members. We fully agree and further stress the importance of confronting several local and network-wide node properties for deeper insight into the transaction network structure.

Nakazato and Hiramoto (2012) also used several network-wide metrics including some centrality metrics, such as effectiveness, betweenness centrality, flow centrality and closeness centrality. Whilst these metrics are mathematically well established in general, they give very little background for the interpretation of these metrics in the context of a transaction network. For example, metrics based on shortest path lengths[21] (closeness and betweenness centrality) make little sense in a network where the edge weight is directly proportional to the importance of the edge (traded value). Great care has to be taken

on the suitability of particular metrics, given the meaning of nodes and edges in the network; this insight is also crucial for the correct interpretation of the computed results.

The rich-club analysis (see Section 4.4) helped us further understand the trade activity of the central members. In the case of RozLETSe, members' activity is not spread evenly throughout the community, but concentrated markedly within the active core.[22] Thus, the system is sensitive to the removal of one or more of them, as shown in the "knock-out" scenarios (Section 4.5). This effect is further intensified by the imbalance in the reciprocal trade relations: if the pairs of the core members were trading with equal intensity in both directions, the removal of one of them would yield zero change to the account balance of the others. However, in our case it can be hypothesized that the removal of one of the core members would bring domino-like changes to the trade frequency and value in the core of the network, if not the actual departure of other members. It should be noted, however, that our "knock-out" scenarios do not take into account the adaptation of the system to change. When data from a longer time-span are available, more complex modelling of the adaptation of the trade network to the removal of one or more important members can be performed, similar to the extinction analysis known from the field of ecology (Foti et al., 2013).

Even within the small group of RozLETSe, the "knockout" analysis illustrates well that the trade relationships are not reciprocally balanced and the currency flows follow more complex loops. The core members correspond to those who found ways to both fulfill their needs in the network and to bring something useful to other members. Although they are responsible for most of the trade volume, they also manage to trade outside the club, as shown in Section 4.4, which can be interpreted as a sign of resilience of the network. However, indirectly, the existence of the rich-club shows the limited activity of the majority of the members, and limited diversity of offered goods and services, both effects reported similarly in many other studies (Aldridge and Patterson, 2002; Crowley, 2004; Douthwaite, 1996; Seyfang, 2002).

Panther (2012) inspects the indirect reciprocity in detail using a different graph-theoretical concept, graph motifs (triads in her case).

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[20]   The difference between the Eigenvector centrality computed without the weights and the PageRank centrality represents a good example of this effect; see Sections 3 and 4.3 for details.

[21]   Path length between two nodes in a weighted graph is equal to the sum of weights of edges connecting these two nodes. The shortest path length is the lowest such sum.

[22]   As with other metrics, it would be fruitful to compare the presence and size of the rich-club across LETS systems of various sizes. Moreover, in LETS functioning over longer time periods, the formation and development of the active core would be an interesting topic for time analysis and for the possible construction of growth models (Garlaschelli and Loffredo, 2005).

Motifs are basic patterns of interconnection which repeat in the graph. In the case of reciprocity triads, these patterns are formed by three nodes and all possible combinations of directed links between them. Panther identified a central, fully bi-directionally connected triad in both analysed systems. This is very close in terms of network structure to our notion of the central backbone quantified by the rich-club metric. The interpretations of network motifs are, however, based on statistical evaluation (counting the present motifs against the expected number given network size and density) and, as such, the precision and significance grows with the network size. Thus, when the transaction networks are quite small in the number of nodes, as in both case studies of Panther (2012), the motif count results are not robust compared to the rich-club metric.

Nakazato and Hiramoto (2012) also dealt with reciprocity in the transaction network; however, they studied only direct reciprocity. They found, somewhat paradoxically, direct reciprocity being negatively correlated with receiving "informational support" from the network. This again shows the importance of a deeper understanding of the studied initiatives, their aims, internal dynamics, etc. for the interpretation of the network analysis results. Although it is tempting for the application of the network analysis, it is important to acknowledge that direct reciprocity is not necessarily a goal in itself either for time banks (see Collom, 2012:25), or for LETS; for both, indeed, the advantage over bartering lies in the possibility of not-directly-reciprocal exchange. Looking for more complex exchange patterns as piloted by Panther (2012) seems thus more promising than studying only direct reciprocity.

5.1. Further Potentials and Limitations for Using Transaction Analysis Within LETS Studies

Transaction network analysis can provide a valuable tool for a deep inspection of the functioning of LETS and other CC networks (see Footnote 17), which can help us understand their developments and critically examine various interpretations of such activities within academic debate. However, these insights can also be helpful for CC practitioners to actively influence the functioning of their groups. By understanding the roles of particular members, the groups can value their specific meaning for the network (either socially or through reward payments within the system). Furthermore, they can actively influence the composition of the members and their supply offers according to the transaction history and members' preferences, also coordinating the pricing mechanism to reflect these preferences. The questions remain, however, as to whether the groups decide to apply these insights and whether they find it desirable to manipulate their functioning in such a manner.

Should the insights from transaction network analysis be useful and interesting for the above-mentioned groups, it would be necessary to expand the number of case studies to see different patterns, developments and experiences of various CC groups. To support such development, we have provided the complete software toolbox online,[23] and invite other researchers to use the tools and/or to cooperate or consult on the topic. Currently, there are at least 40 LETS initiatives using Cyclos software (see Footnote 5), potentially available for transaction network analysis. This number already represents a very interesting pool of data, both in terms of testing the methodology and collecting the empirical experience, valuable both for researchers and practitioners.

Indeed, the main advantages of the transaction network analysis (the potentially easy availability and abundance of transaction data recorded in software tools) entail its main limitations at the same time. First, obviously, those (possibly many) CC schemes not using the electronic tools cannot be involved in the suggested research. Should more CCs be described using the transaction network analysis, any generalization of such results would have to acknowledge that only specific

(e.g. more progressive and IT literate) groups are involved, thus any generalization would necessarily be limited. Also, it is possible that even within groups using software tools, not all transactions are always recorded electronically. It should always be checked with the particular group members what the possible extent of such unrecorded transactions is. Regarding the analyst, processing the transaction data to obtain the suggested network metrics requires rather advanced IT skills, an understanding of network analysis, and knowledge of graph analysis tools. Such equipment cannot be expected to be at the practitioners' side, making CC groups dependent on external expert knowledge once they decide to process the data in the suggested, more elaborate way. However, at least the basic statistical data are easy to get from the software tools (e.g. Cyclos), which already provide useful insights. Moreover, cooperation with outside (potentially perceptive) researchers can make the research participatory and enriching for both sides, as our own experience has shown.

6. Conclusions

Network analysis is typically used for studying complex systems, including the widely interconnected International Trade System (ITS). We have suggested and applied this approach to study Local Exchange Trading Systems (LETS) as a local analogy of ITS, likewise comprising a relatively high number of entities and their trade relations. Network analysis can provide detailed information about the structure of LETS transaction networks, help identify important members of the system, visualize its topology and bring numerous possibilities for the representation and interactive inspection of various properties and relationships within the network. As most studies of LETS and other community currency systems (CCs) have been predominantly based on qualitative approaches, this tool can effectively complement the available data and help us better understand the functioning, dynamics, and impact of CCs. To advance the few previous applications of network analysis to CCs, we propose using suitable network-wide metrics based on node centrality to better quantify and understand the transactional structure in these communities.

The potential of the transaction network analysis has been demonstrated on a case study of the specific LETS system "RozLEŤSe", based in Brno, Czech Republic, revealing several important characteristics of the system. The RozLEŤSe members formed one coherent component, not divided into sub-groups. The group comprised a majority performing very similar average transactions and a central backbone of several very active members. The rich-club analysis showed that 7 members accounted for more than 85% of the total transaction volume; however, only 28% of this was traded among them meaning that they still managed to keep contact with the rest of the group. The "knock-out" experiment illustrated the sensitivity of the group to the removal of the core members. This showed that the trade relationships in RozLEŤSe were not directly reciprocal and the currency flows followed more complex loops.

Transaction network analysis contributes significantly to the understanding of CCs using electronic transaction records by enabling one to follow the actual trading behaviour of their members. To reveal its full potential, more studies are needed of various types of CCs in different contexts. For this purpose, we have provided the complete software toolbox online (see Footnote 23 for the link) and we invite cooperation in taking the work forward.

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[23] The Cyclos Networks package is available at http://www.fi.muni.cz/~xfous/cyclos_networks/.

GA14-33094S "Forms and norms of alternative economic practices in the Czech Republic".

Appendix A. Supplementary Data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2014.09.009.

References

Acheson, J., 2007. Household exchange networks in post-socialist Slovakia. Hum. Organ. 66, 405–413.

Albert, R., Barabási, A.L., 2002. Statistical mechanics of complex networks. Rev. Mod. Phys. 74, 47–97.

Aldridge, T.J., Patterson, A., 2002. LETS get real: constraints on the development of Local Exchange Trading Schemes. Area 34, 370–381.

Barigozzi, M., Fagiolo, G., Mangioni, G., 2011. Identifying the community structure of the international-trade multi-network. Phys. A Stat. Mech. Appl. 390, 2051–2066.

Barry, J., Proops, J., 1999. Seeking sustainability discourses with Q methodology. Ecol. Econ. 28, 337–345.

Barry, J., Proops, J.L., 2000. Citizenship, Sustainability and Environmental Research: Q Methodology and Local Exchange Trading Systems. Edward Elgar Publishing, Chaltenham, UK.

Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: an open source software for exploring and manipulating networks. International AAAI Conference on Weblogs and Social Media.

Batagelj, V., Mrvar, A., 1998. Pajek-program for large network analysis. Connections 21, 47–57.

Bhattacharya, K., Mukherjee, G., Saramäki, J., Kaski, K., Manna, S.S., 2008. The international trade network: weighted network analysis and modelling. J. Stat. Mech. Theory Exp. 2008, P02002.

Blanc, J., 2011. Classifying 'CCs': community, complementary and local currencies' types and generations. Int. J. Community Curr. Res. 15, 4–10.

Blanc, J., Fare, M., 2012. Les monnaies sociales en tant que dispositifs innovants: une évaluation. Innovations 67–84.

Bonacich, P., 1972. Factoring and weighting approaches to status scores and clique identification. J. Math. Sociol. 2, 113–120.

Börner, K., Sanyal, S., Vespignani, A., 2007. Network science. Annu. Rev. Inf. Sci. Technol. 41, 537–607.

Bowring, F., 1998. LETS: an eco-socialist initiative? New Left Rev. 91–111.

Cahn, E.S., 2000. No More Throw-Away People: The Co-Production Imperative. Essential Books, Washington, DC.

Collom, E., 2008. Engagement of the elderly in time banking: the potential for social capital generation in an aging society. J. Aging Soc. Policy 20, 414–436.

Collom, E., 2011. Motivations and differential participation in a community currency system: the dynamics within a local social movement organization. Sociological Forum. Wiley Online Library, pp. 144–168.

Collom, E., 2012. Key indicators of time bank participation: using transaction data for evaluation. Int. J. Community Curr. Res. 16, 18–29.

Conil, J., Castells, M., Cardenas, A., Servon, L., 2012. Beyond the crisis: the emergence of alternative economic practices. In: Castells, M., Caraça, J., Cardoso, G. (Eds.), Aftermath: The Cultures of the Economic Crisis. Oxford University Press, pp. 210–250.

Crowley, E., 2004. Local exchange trading systems: globalising rural communities. Institute for International Integration Studies Discussion Paper No. 37. Trinity College, Dublin.

De Benedictis, L., Tajoli, L., 2011. The world trade network. World Econ. 34, 1417–1454.

Dittmer, K., 2013. Local currencies for purposive degrowth? A quality check of some proposals for changing money-as-usual. J. Clean. Prod. 54, 3–13.

Douthwaite, R.J., 1996. Short Circuit: Strengthening Local Economies for Security in an Unstable World. Lilliput Press, Dublin.

Fagiolo, G., 2010. The international-trade network: gravity equations and topological properties. J. Econ. Interac. Coord. 5, 1–25.

Foti, N., Pauls, S., Rockmore, D.N., 2013. Stability of the World Trade Web over time—an extinction analysis. J. Econ. Dyn. Control. 37, 1889–1910.

Garlaschelli, D., Loffredo, M.I., 2005. Structure and evolution of the world trade network. Phys. A Stat. Mech. Appl. 355, 138–144.

Gesell, S., Pye, P., 1958. The Natural Economic Order. Peter Owen, London.

Gibson-Graham, J.K., 2008. Diverse economies: performative practices for other worlds'. Prog. Hum. Geogr. 32, 613–632.

Hagberg, A.A., Schult, D.A., Swart, P.J., 2008. Exploring network structure, dynamics, and function using NetworkX. Proceedings of the 7th Python in Science Conference (SciPy2008), Pasadena, CA USA, pp. 11–15.

Healy, S., 2008. Alternative economies. International Encyclopedia of Human GeographyManuscript revision version, available at http://www.communityeconomies.org/site/assets/media/stephenhealy/Alternative-Economies.pdf (2014-06-20).

Jehlička, P., Kostelecký, T., Smith, J., 2013. Food self-provisioning in Czechia: beyond coping strategy of the poor: a response to Alber and Kohler's 'Informal food production in the enlarged European Union' (2008). Soc. Indic. Res. 111, 219–234.

Jelínek, P., Szalay, Z., Konečný, A., 2012. Local exchange trade systems in central European post communist countries. Int. J. Community Curr. Res. 16, 116–123.

Kala, L., Fraňková, E., Labohý, J., Fousek, J., 2013. LET's start a new LETS: learning from a case study in Brno, Czech Republic. Envigogika 8, 1–11 (URL: http://www.envigogika.cuni.cz/index.php/Envigogika/article/view/406. [2014-06-20]).

Kennedy, M., 1995. Interest and Inflation Free Money. Seva International.

Lee, R., 1996. Moral money? LETS and the social construction of local economic geographies in Southeast England. Environ. Plann. A 28, 1377–1394.

Lietaer, B., 2001. The Future of Money: Creating New Wealth, Work and a Wiser World Paperback. Century, London.

Mellor, M., 2010. The Future of Money: From Financial Crisis to Public Resource. Pluto Press.

Nakazato, H., Hiramoto, T., 2012. An empirical study of the social effects of community currencies. Int. J. Community Curr. Res. 16, 124–135.

Newman, M.E., 2006. Modularity and community structure in networks. Proc. Natl. Acad. Sci. 103, 8577–8582.

North, P., 2002. LETS in a cold climate: green dollars, self-help and neoliberal welfare in New Zealand. Policy Polit. 30, 483–499.

North, P., 2005. Scaling alternative economic practices? Some lessons from alternative currencies. Trans. Inst. Br. Geogr. 30, 221–233.

North, P., 2007. Money and Liberation: The Micropolitics of Alternative Currency Movements. University of Minnesota Press, Minneapolis.

Opsahl, T., Colizza, V., Panzarasa, P., Ramasco, J.J., 2008. Prominence and control: the weighted rich-club effect. Phys. Rev. Lett. 101, 168702.

Page, L., Brin, S., Motwani, R., Winograd, T., 1999. The PageRank Citation Ranking: bringing order to the web. Technical Report 1999–66. Stanford InfoLab. (URL: http://ilpubs.stanford.edu:8090/422/. [2014-06-20]).

Panther, Julia, U., 2012. 'It Ain't What You Do (It's the Way That You Do It)': Reciprocity, Co-operation and Spheres of Exchange in Two Community Currency Systems in the North of England(Ph.D. thesis) Durham University.

Seyfang, G., 2002. Tackling social exclusion with community currencies: learning from LETS to Time Banks. Int. J. Community Curr. Res. 6.

Seyfang, G., Longhurst, N., 2013. Growing green money? Mapping community currencies for sustainable development. Ecol. Econ. 86, 65–77.

Seyfang, G., Smith, K., 2002. The Time of Our Lives: Using Time Banking for Neighbourhood Renewal and Community Capacity Building. New Economics Foundation.

Strogatz, S.H., 2001. Exploring complex networks. Nature 410, 268–276.

Williams, C.C., Aldridge, T., Lee, R., Leyshon, A., Thrift, N., Tooke, J., 2001. Bridges into work? An evaluation of local exchange and trading schemes (LETS). Policy Stud. 22, 119–132.

Zagata, L., 2005. Czech LETS (empirical study on local complementary currencies in the Czech Republic). Agric. Econ. 51, 271–278.