

# Cyclic motifs in the Sardex monetary network

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**From decentralized banking systems to digital community currencies, the way humans perceive and use money is changing<sup>1-3</sup>, thus creating novel opportunities for solving important economic and social problems. Here, we study Sardex, a fast-growing community currency in Sardinia (involving 1,477 businesses arrayed in a network with 48,170 transactions) using network analysis to shed light on its operation. Based on our experience with its day-to-day operations, we propose performance metrics tailored for Sardex but also to similar economic systems, introduce criteria for identifying prominent economic actors and investigate the interplay between network structure and economic robustness. Leveraging new methods for quantifying network 'cyclic density' and 'k-cycle centrality,' we show that geodesic transaction cycles, where money flows in a circle through the network, are prevalent and that certain nodes have a pivotal role in them. We analyse the transactions within cycles and find that the economic turnover of the involved firms is higher, and that excessive currency and debt accumulations are lower. We also measure a similar, but secondary, effect for nodes and edges that serve as intermediaries to many transactions. These metrics are strong indicators of the success of such mutual credit systems at individual and collective levels.**

From new transaction technologies, such as blockchain and mobile payment mechanisms<sup>1,2</sup>, to novel implementations of alternative currencies and decentralized mutual credit systems<sup>3</sup>, a plethora of new instruments allow people to trade without using legal tender money. Of special interest are 'complementary currencies' (also known as community currencies) that have recently resurfaced and that aspire to stimulate depressed local economies by addressing the money liquidity problem. While this concept can be traced back to the nineteenth century, the penetration of the (mobile) Internet and the emergence of sophisticated digital credit management platforms (<http://www.cyclos.org/>) render modern complementary currency systems particularly attractive, as they can be used to support business-to-business trading (<http://www.wir.ch/>), promote sustainable and local consumption (<http://bristolpound.org/>) and even facilitate cooperation in sharing-economy applications<sup>4</sup>.

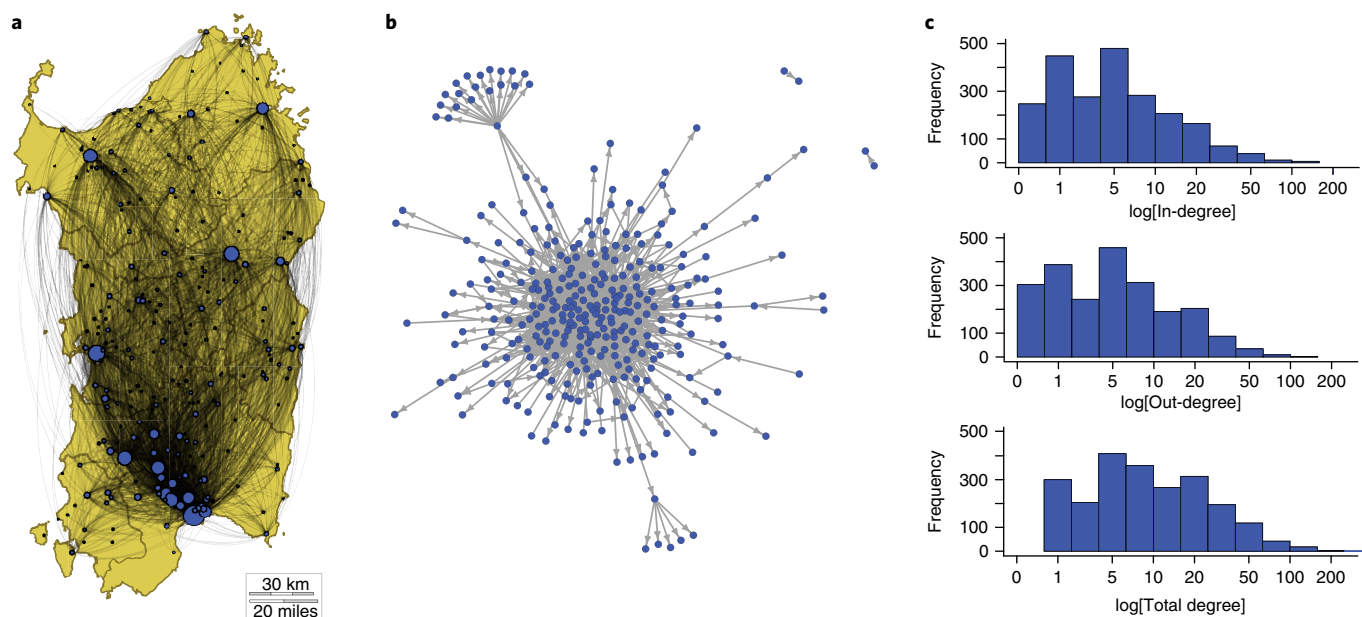
Despite their importance for the economy and society, we currently lack a clear understanding of the operation of such systems. For instance, what are their salient economic and structural features? How can we quantify the performance of these closed economies as a whole, or characterize the individual performance of their members? Which of the members play a crucial role in the system's endurance and wealth-creation capacity? How can we assess the

trust that permits use of the currency beyond bilateral-only trading (and that contributes to functional economies)? What are the network properties of such systems and are there any network effects such as those observed in other economic systems? The answers to these questions cannot rely solely on stylized theoretical models but require an in-depth analysis of a real alternative economy. Hence, we investigate these issues using a novel and complete data set from Sardex (<http://www.sardex.net/>), a community currency launched in Sardinia in 2010 as a response to the financial crisis and currently considered one of the most successful in the world<sup>5,6</sup>.

Sardex uses an electronic-only complementary currency, is based on a decentralized system implementation without a bank, and aims to serve as a means of exchange. It is a 'closed' economy in the sense that the currency is not directly exchangeable with the official currency in Italy (that is, the euro), and cannot be used outside of Sardinia. For instance, a company that is located (or, moves subsequently) outside of Sardinia is not allowed to participate in the network. However, Sardex is pegged to the euro with a ratio of 1:1 to avoid the need for price discovery. This is essentially a 'mutual credit' (or, zero-sum) system in the sense that every transaction induces a credit surplus for the seller and an equal debt for the buyer, while the aggregate credit accumulation across all members is zero; that is, there is no credit deficit or surplus in the economy at any given time. This creates network externalities among ostensibly independent transactions that involve different (even distant) actors.

Sardex Spa is the legal entity that monitors the market and ensures the secure operation of the electronic ledger. The system includes businesses representing almost all sectors of the Sardinian economy, spanning the entire island. When a business joins Sardex it obtains a credit line based on the committed capacity of resources it brings into the system. This commitment is expressed in euros and is noted in the contract signed by the business. The goal of the commitment is twofold. It ensures the businesses will not have unwanted Sardex credits, and that there will be enough commodities and services to render Sardex an attractive market place. While the businesses can trade also in euros (outside the network) and are free to decide to what extent they will be involved in Sardex transactions, they must abide by certain trading rules. For instance, the prices they charge in Sardex should be equal to the respective charged prices in euros. Each Sardex member can leave the network, as there are no exit barriers, under the condition that it brings its balance to zero, namely by selling (if it is negative) or buying (if positive) commodities. Finally, it is important to emphasize that there is no interest rate, positive or negative, a design decision aiming to increase the

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**Fig. 1 | A representation of the Sardex transaction network from 1 January 2013 to 31 December 2014. a**, Each super-node represents the collection of Sardex nodes located within a city or town. The node size is proportional to the number of traders in that city, and edges capture transactions between different locations;  $N=276$  cities;  $E=48,170$  transactions. **b**, The Sardex transaction network within the capital city of Cagliari ( $N=137$  businesses;  $E=498$  partnerships). **c**, In-, out- and total degree distribution of the Sardex network on a log-log scale ( $N=1,477$  businesses;  $E=13,753$  partnerships). Map in **a** adapted from <http://d-maps.com>.

circulation of Sardex credit. Additional information is provided in Supplementary Note 1.

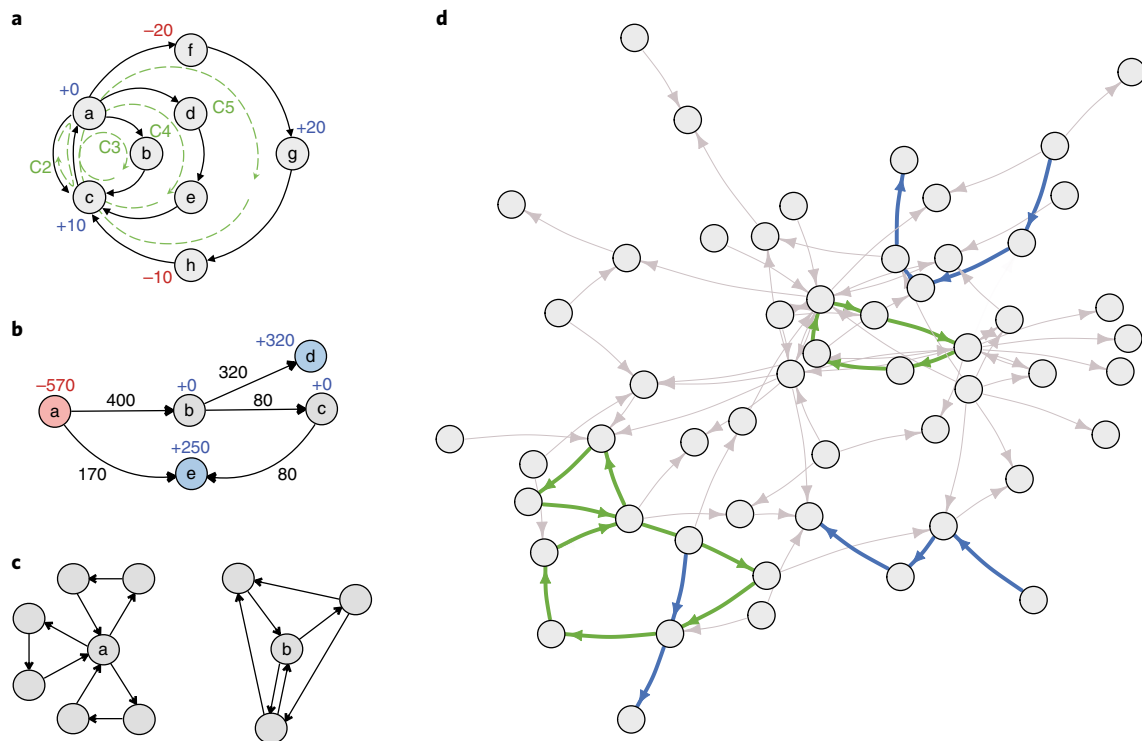
We model the Sardex economy as a network where the nodes are businesses and the edges the currency flow among them. We perform a thorough network analysis that sheds light on the operation of this large-scale digital economic system. We also introduce analytic performance and robustness metrics for the economy, and centrality metrics for identifying prominent nodes. We particularly focus on cyclical geodesic transaction motifs, namely ‘cycles’—where the beginning and end of a series of transactions is the same entity. Such cycles are necessary to sustain the continuing flow of money and also to suppress excessive debt or credit accumulation (which is one of the major causes of failures of these systems). We also perform a secondary analysis, focusing on ‘betweenness’ of nodes and edges, which measures the extent to which they act as transaction intermediaries in Sardex. The insights we obtain are not only relevant to complementary currencies, but also to a range of collaborative platforms with similar operational principles. Our analysis thus sheds light on possible network-related mechanisms pertaining to how humans adopt and use novel monetary instruments.

The spatial characteristics of the Sardex network and the trading relations across different cities can be seen in Fig. 1a, while a network instance for the capital city of Cagliari is shown in Fig. 1b. In our analysis, each individual trader is modelled as a node, where the node degree represents the number of its trading partners, while the weighted directed edges capture the aggregate currency flow from each buyer to each seller in the time interval of interest. The Sardex network has a skewed degree distribution, as depicted in Fig. 1c, with an average degree equal to 18.6 partners (median=10; s.d.=26.9) and a maximum of 259. After the fast-growing phase of Sardex in the first three months of this two-year period, several graph properties remained relatively unchanged. For example, the average directed path length (that is, the average length of the sequence of pair-wise directed ties between any two nodes) was approximately 3.5 (median=3; s.d.=0.9), and the diameter

of the network stabilized at 10. Similarly, the clustering coefficient was 0.14 and the transitivity was approximately constant and equal to 0.10. Sardex has a single network component and low average path length, similar to small-world<sup>7</sup> and scale-free networks<sup>8</sup>, but has a high clustering coefficient (12 times higher than Erdos-Renyi networks<sup>9</sup> but 5 times lower than small-world graphs). A detailed descriptive analysis can be found in Supplementary Note 1.

Our network analysis here focuses on cycles and cyclic transactions; that is, sets of transactions where a group of traders buy and sell from each other in a cyclic fashion. The length  $k$  of a cycle is defined as the number of edges that it comprises (see Fig. 2a). A reciprocal (bilateral-only) transaction is a cycle of length  $k=2$ , while lengthier cycles involve more participants. Obviously, a lack of cycles in dynamic flow (here, credit) networks with no sink or source nodes results in high accumulations of surpluses and debts, disrupting in practice the credit balance (see Fig. 2b). Moreover, the existence of cycles is crucial to distinguish economically healthy mutual credit systems from speculative pyramid or Ponzi schemes that result in isolated and exploited nodes. Besides, there is an intuitive relationship between the system’s overall performance on the one hand, and the existence of transaction cycles, especially the lengthier ones, on the other. That is, lengthier cycles need more time to be completed (counting the time the currency needs to return to, and be redeemed by, the initial seller), meaning, in practice, that they involve a higher trust of the participants towards the currency; this enables the solution of a larger set of ‘double coincidence of wants’ problems and helps to yield a functional economy (Supplementary Fig. 5).

The idea of cyclic network motifs, and procedures for identifying cycles, have been previously described<sup>10,11</sup>, but here we propose and implement a set of analytical metrics for assessing the presence of cycles at the network level, and for quantifying the contribution of each node to cyclic transactions. We first introduce the cyclic density, which captures the extent to which the network overall contains cycles. This metric is defined as the ratio of the total number of cycles in the trading graph over the expected number of cycles in a



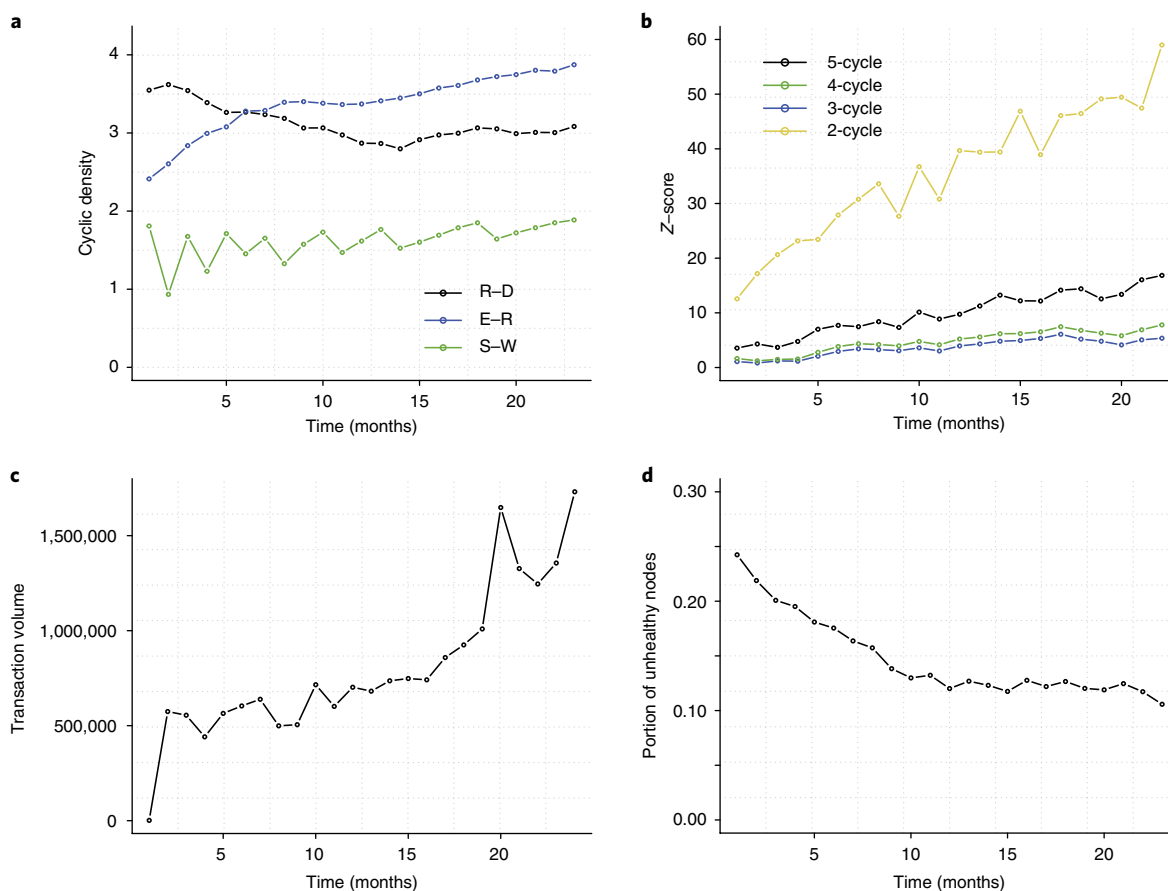
**Fig. 2 | The concept and importance of cycle transactions.** Edges indicate money flow from buyers to sellers. **a**, Graph with 4 transaction cycles of lengths 2, 3, 4 and 5. Illustrative positive and negative balances shown in red and blue. For example, node d has 4-cycle centrality equal to 1, but 3-cycle centrality equal to 0. **b**, An economic network with no cycles; node d lies at the end of the transaction path (a, b, d), and node e at the end of the path (a, b, c, e). Nodes d and e accumulate credit that they will not be able to spend, while node a builds up a debt that it cannot service. **c**, An example of  $k$ -cycle centrality and  $k$ -cycle coverage. Nodes a and b both have 3-cycle centrality equal to 1, but node a has 3-cycle coverage of 1 (6/6), while for b this value is 0.5 (3/6). **d**, Cycles of length 3 and 5 (green) and paths of length 2, 3 and 4 (blue) in the Sardex network of the city of Sassari (2013,  $N = 54$  businesses;  $E = 91$  partnerships).

properly defined null model. The higher the value of the cyclic density, the higher the potential performance of the trading network in all likelihood. Building on earlier work<sup>10</sup>, we also introduce the notion of  $k$ -cycle node centrality, which quantifies the portion of the network's trading cycles of length  $k \geq 2$  in which a node participates. The larger the value of the  $k$ -cycle centrality, the more important that node probably is for the performance of the system. For example, removing a node with a 5-cycle centrality value of 0.5 will break down 50% of the cycles of length 5 in the whole network, and this will increase the likelihood of having isolated nodes with high debts or surpluses. Note that it is known that severed trading relationships are often difficult and time consuming to replace<sup>12</sup>, even more so in closed economic systems such as Sardex. Finally, we introduce the  $k$ -cycle node coverage metric, which quantifies, for each node, the overlap of its cycles, and hence how many different nodes appear in its cycles. Two nodes may have the same  $k$ -cycle centrality but different  $k$ -cycle coverage, as shown in Fig. 2c.

To assess the performance of this mutual credit system, we propose and quantify two metrics: the aggregate volume of transactions (or turnover) of the system and the credit healthiness for each of its members. The first metric has been used by practitioners to describe the system-level performance of various community currencies. The second, node-level metric captures excessive and prolonged credit (positive) or debt (negative) accumulations by traders. In particular, nodes that have had a high credit or debt for many days during the time interval of interest are those with undesirable credit healthiness (examples are provided in Supplementary Note 2). Such accumulations indicate inactive members who pose a threat to the robustness of the system, either because they immobilize credit surpluses or because they are incapable of reducing their debts.

Leveraging our approaches to identifying and quantifying trading cycles, we then explore two fundamental questions. At the network level: does Sardex have many cycles, and are there nodes with a pivotal role in them? At the cycle level: are cycles associated with the above performance metrics, and what is the economic activity within the cycles? Moreover, we investigate these questions for cycles of different length: is it preferable in such local economies to have small trading relations, involving two or three nodes, or lengthier cycles, involving transactions among four or five nodes in cycles involving 'unseen' others?

First, we examine cyclic density and credit healthiness at the overall network level, across time. Based on our experience from the day-to-day management of the system, we consider as unhealthy the state of having debt or credit higher than 90% of a node's capacity (its credit line). Figure 3a depicts the network's cyclic density for different sizes of the Sardex graph, which has a higher number of cycles compared to different null models. For the latter, we have used an analytical formula that quantifies the expected number of cycles in a graph built by randomizing the edges of the observed Sardex network while preserving its in/out-degree distribution (henceforth referred to as reshuffled-degree graphs)<sup>13–15</sup>. We have also used an Erdos–Renyi<sup>9</sup> graph and a small-world<sup>7</sup> graph as null models, and further verified the results by a Z-test using a population of 100 reshuffled-degree graphs, as shown in Fig. 3b. Regarding the performance metrics, the aggregate volume of new transactions conducted in every month increases with time, as shown in Fig. 3c. Moreover, Fig. 3d depicts the portion of unhealthy nodes at the end of each month; interestingly, we observe a 50% reduction of this quantity during the two-year operation of the market. In other words, as the network grows, Sardex traders not only manage to



**Fig. 3 | Overall performance of the Sardex exchange.** **a**, Sardex cyclic density calculated with respect to the expected number of cycles in a population of 200 reshuffled-degree graphs (using the formula in ref. <sup>13</sup>; denoted R-D), a population of 200 Erdos-Renyi graphs with the same number of nodes and edges (denoted E-R) and a population of 200 small-world graphs (denoted S-W). **b**, Z-test scores for Sardex comparing the number of observed cycles with the cycles in a population of 100 random graphs preserving the Sardex in-/out-degree distribution (R-D graphs). **c**, Volume of new transactions per month. **d**, Credit ‘unhealthiness’ in Sardex; that is, portion of nodes with average absolute balance greater than 90% of their capacity, at the end of each month. Figure 3a has been created with Supplementary Codes 4, 5 and 6.

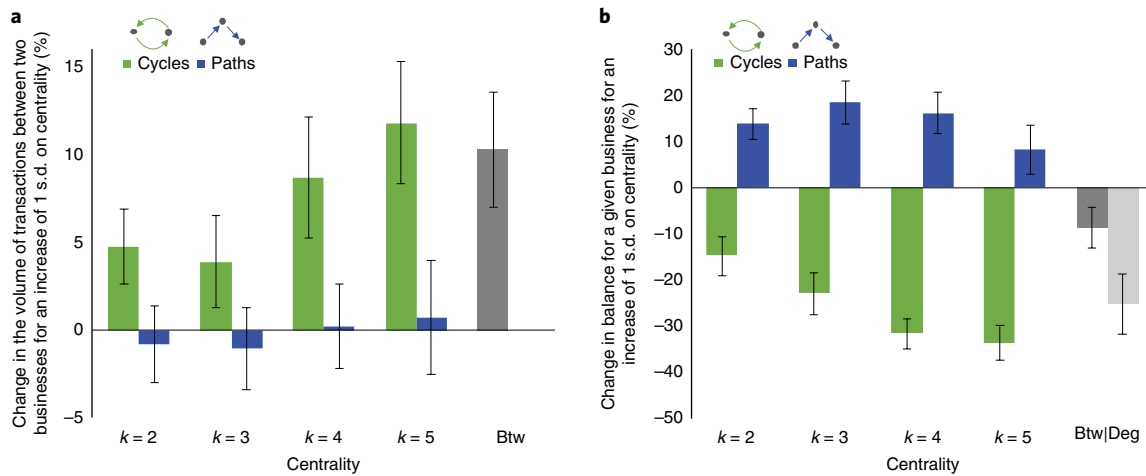
increase the volume of their transactions, but they do so in a fashion that avoids prolonged, excessive debt or credit accumulations.

Regarding the role of nodes in Sardex cycles, we see that the distribution of the  $k$ -cycle centrality has a heavy tail, with a few nodes participating in a large percentage of cycles, while many nodes do not participate in any cycle. These results depart substantially from the cycle centrality distribution in the null models and reveal that a small subset of nodes plays a crucial role in the economy as, for example, their removal would increase idle currency accumulations (prolonged surpluses or debts). We also correlated the cycle centrality with other node centrality metrics—that is, the degree and betweenness centrality<sup>16</sup>—to assess the information load of this new metric. We find that the correlation of cycle centrality with betweenness centrality ( $r=0.70$ ,  $P<0.001$ ) is comparable to the correlation of betweenness with degree centrality ( $r=0.77$ ,  $P<0.001$ ). Additionally, we find that the correlation of the cycle centrality with degree centrality can be high ( $r=0.92$ ,  $P<0.001$ ) for certain ranges of values of these centralities. Interestingly, however, a closer look at the scatter plots (Supplementary Fig. 9) reveals that nodes with small-to-medium values of cycle centrality have a large range of betweenness and degree centrality. This suggests that cycle centrality does carry additional information. Finally, we calculated the  $k$ -cycle coverage distribution in Sardex and found substantial variation and non-redundancy (see Supplementary Fig. 10).

Next, we turn our focus to the transactions within cycles to assess the association of a firm’s being in cycles with its economic performance. First, we explore the role of cycles at the edge level using a dyadic generalized linear regression model<sup>17</sup>. The construction of the transaction graph and the enumeration of cycles is performed for each year separately, and the analysis is conducted jointly on both samples with proper adjustments. Figure 4a shows the model estimates. We observe that an increase of 1 s.d. of the number of cycles of length  $k=2$  is associated with an increase of 5% in the edge transaction volume ( $b=0.05$ ; 95% confidence interval (95% CI), 0.03, 0.07;  $P<0.001$ ), and that this increases up to 12% for cycles of length  $k=5$  ( $b=0.10$ ; 95% CI, 0.07, 0.14;  $P<0.001$ ). Interestingly, we find also that the betweenness centrality of the edges has a comparably positive impact on their transaction volume, meaning that edges participating in many chains of transactions (of any length, open or closed) have higher performance ( $b=0.09$ ; 95% CI, 0.06, 0.12;  $P<0.001$ ). Note that the impact of cycles of length  $k=5$  was comparable to that of betweenness. As shown in Fig. 4a, a similar association was not observed for paths (that is, unclosed cycles) of the same respective length. The latter are defined as sequences of connected nodes where no node appears more than one time, and we have used only the paths that are non-nested, and, thus, independent of cycles and longer paths.

Finally, we explore the credit healthiness of the nodes that are involved in many cycles. We used an ordinary least-squares (OLS)





**Fig. 4 | Statistical models' coefficients with 95% CIs ( $N = 1,477$  businesses;  $E = 13,753$  partnerships).** **a**, Relationship between cycles and paths of length  $k$ , and edge betweenness (Btw) centrality and the edge transaction weight (dyadic generalized linear models with a random effect at the node level). **b**, Relationship between cycles and paths of length  $k$ , degree (Deg) and node betweenness (Btw) centrality and the node credit healthiness (OLS model). The figure has been created with Supplementary Code 7.

model with the credit healthiness of each business as the dependent variable (see Methods). Figure 4b shows the estimates of these models. We observe that businesses with many trading partners (degree) have a lower average absolute balance; that is, better credit healthiness. Businesses that are part of longer cycles also have lower average balance. While an increase of 1 s.d. in the number of cycles of length  $k=2$  is associated with an improvement of 14% in the trader's credit healthiness (by lowering the average absolute balance;  $b = -0.17$ ; 95% CI,  $-0.21, -0.12$ ;  $P < 0.001$ ), this impact increases to 30% for cycles of size  $k=4$  ( $b = -0.38$ ; 95% CI,  $-0.44, -0.33$ ;  $P < 0.001$ ) and size  $k=5$  ( $b = -0.41$ ; 95% CI,  $-0.47, -0.35$ ;  $P < 0.001$ ). Similar to the edge-level analysis, we find that the betweenness centrality of the nodes improves substantially their credit healthiness ( $b = -0.09$ ; 95% CI,  $-0.14, -0.03$ ;  $P = 0.003$ ). However, the betweenness effect is smaller than the impact of cycles; that is, nodes that are involved in many (and lengthier) cycles are healthier even compared to nodes with high betweenness centrality. As hypothesized, and shown in Fig. 2b, the number of non-closed paths passing through a node is associated with an increase in its average absolute balance; that is, a decrease in its healthiness.

The findings at the edge and node level resisted a long battery of robustness analyses accounting for dependencies and alternative modelling approaches (see Supplementary Note 3). In addition, we indirectly compared the impact of cycles of different lengths by using a stepwise statistical analysis (gradually adding the different cycles), and observed an increase in model fit that supports the importance of lengthier cycles. Identical conclusions are reached if we compare the coefficients and the fit of the different independent models. We also compared the cycles and the paths by considering the respective aggregate metrics—that is, number of cycles of all lengths and number of paths of all lengths that an edge belongs to—and the results were aligned with the above findings. Finally, we explored whether the observations about performance within cycles relate to the geographic proximity of the transacting nodes. Interestingly, we found that traders within cycles are not more frequently co-located than traders that participate in non-nested paths; and, more important, we found that edges across different cities (both for cycles and paths) have slightly higher weights (see Supplementary Note 2). Therefore, the association of cycle length and economic performance that we observe is not rooted in geographic co-location of the traders.

Alternative financial services are of increasing importance. They leverage recent technological advances and aspire to address

fundamental economic needs, especially in rural and under-developed areas where affordable banking services are often lacking. At the same time, they constitute promising laboratories for the study of salient aspects of social and economic life, such as how humans perceive and use money, or trade and collaborate with each other<sup>2,18</sup>. And studying such monetary systems allows us to revisit fundamental questions regarding the emergence and performance of various monetary instruments<sup>19,20</sup> using quantitative analysis of detailed digital transaction traces<sup>21</sup>. Furthermore, credit systems such as Sardex are increasingly relevant for emerging sharing-economy services<sup>4</sup> that rely on decentralized trading and cooperation platforms. In these systems, more often than not, the exchange of goods and services takes place using some kind of a coupon-based system. In all of these cases there is a need for (and already use of) an accounting mechanism similar to Sardex, so as to facilitate the participants' interactions. Hence, the ideas and metrics proposed here are applicable elsewhere too.

Information from monetary instruments that trace out paths through an economy is not commonly available<sup>22</sup>. But the availability of data such as ours, with a panopticon view of a complete and defined economic system, which is increasingly possible<sup>21</sup>, allows us to examine the flow of money in a new way. We find that Sardex shares common features, such as the small-world property, with social or technological networks; but it also has distinct properties such as the prevalence of cycles. We show that cyclic motifs are increasingly over-represented in the Sardex economic network and that a subset of nodes plays a central role in the existence of cycles. This result verifies the common intuition about the importance of circular transactions in an economy, which is even more crucial (and structurally necessary) in these closed mutual-credit economies. We then quantified important economic metrics, namely edge weight (the transaction volume between traders) and node credit healthiness (a measure of net balances), for the traders involved in many cycles. Our findings suggest that cycles are positively associated with system performance at both global and individual levels and that these associations are larger for the longer cycles. Besides, such associations are not seen (or are much smaller) for linear paths of equal length to such cycles.

These findings resisted a battery of robustness checks. Nevertheless, we do not make any formal causality claim about the effects of cycles on economic performance because, from a statistical point of view, this cannot be strictly proved. Namely, a proper

randomized controlled trial is unfeasible in this setting and hence we would need to rely on either observational studies or natural experiments for leveraging instruments. With either of these methodological approaches, valid causal inference could be pursued at the level of granularity of the economy (having whole economies as units of analyses) or at the level of businesses (within a single economy). Unfortunately, there is only one economy of this type at this stage of development, and analysis at the business level raises treatment interference issues for which there are no straightforward solutions, though we use spatial regression models and other analytic tools here (see Supplementary Note 3).

Still, our network modelling and analysis approach reveals that complex types of embeddedness in economic systems—and not just dyadic (or even triadic) interactions between two traders engaged in direct exchange—are associated both with individual actors' economic performance and with the economic success of the system as a whole. Previous experimental work has shown that the structure of networks can affect the value individuals can extract from networks, whether their interactions are cooperative or monetary<sup>19,23–25</sup>. In the economy, such studies have focused on the topological properties of the world trade web<sup>26</sup>, or of interbank payment networks<sup>27</sup>. Our data involve different types of economic actors, a much smaller geographic scale, and include detailed temporal and geodesic information. Of course, it is important to emphasize that fully disentangling the Sardex flows is practically impossible because the currency units do not have identification numbers<sup>22</sup>.

The significance of diverse motifs in complex systems has been evaluated in various situations in recent decades, and several techniques for quantifying them have been devised<sup>15</sup>. Cyclic motifs are of crucial importance in a variety of settings that range from bartering- and sharing-economy applications<sup>4</sup> to gift exchange networks or even to kidney exchange systems<sup>28</sup>. Nevertheless, cycles are uncommonly investigated, especially in directed graphs such as ours. One earlier study provided a closed-form expression that relates the number of expected cycles in a directed graph with its in/out-degree distribution, and it showed that cycles in food web, power grid, metabolic and other networks are under-represented compared with respective random graphs<sup>10,13</sup>. Our analysis builds on these earlier works and provides a systematic approach not only for assessing the prevalence of cycles in observed networks, but also for quantifying which nodes contribute to this phenomenon, using the new  $k$ -cycle centrality and  $k$ -cycle coverage metrics.

The existence of cycles has been, mainly, associated with negative effects such as instability in dynamic systems. It has been shown that short or long feedback loops can destabilize systems by reinforcing oscillations and amplifying undesirable perturbations. For example, a study of biological and technological networks found that directed cycles are under-represented, and it hypothesized that this property emerged through an evolutionary process rewarding stable structures; extensive simulations supported this argument<sup>11</sup>. Similarly, another study used an analytical model to prove that cyclic network motifs can amplify risk contagion effects in financial systems such as the interbank loan networks<sup>29</sup>. In this case, a small asset devaluation in a bank might trigger a cascade of equity reassessments to its lenders, and, through a cyclic path of successive interbank links, further deteriorate the equity of this bank. Contrary to these results, we show here (using actual data) that the system's performance is improved within the cyclic transactions. This is not surprising if one realizes that Sardex cycles capture cooperative relationships, and the credit obligations are not bilateral but rather towards the community. Namely, each debtor can pay its debt by selling products and services to any other Sardex member, and, similarly, each creditor can spend its credit buying from any other member. Hence, perturbations and node failures can be amortized and accommodated by the system.

Furthermore, Sardex cycles perhaps reflect trust in the currency and in the ability of Sardex members to sustain this complementary

market, and hence the cycles reinforce this positive effect. It is possible to see the positive effect of cycles as due to the fact that money in Sardex is essentially a cooperation-fostering medium, while, in other financial networks, it is treated as a commodity. Finally, it is interesting to note that our findings suggest also that betweenness centrality plays a very important role in both of the considered performance metrics and mainly in increasing the edge weight. Intuitively, this might be related to the fact that, in such closed systems, the economic activity can be improved if certain links act as strong conduits transferring credit among distant groups of nodes, and this is, by definition, the role of these high-betweenness edges.

The existence and relevance of cycles also suggests possible strategies for policy makers to evaluate, for example, strategically fostering cycles by brokering introductions to trading partners. While outsiders to a system intervening in it may not be able, for example, to change the betweenness centrality of actors, they might be able to change cycle centrality to similar effect by brokering a few introductions to foster the creation of cycles. Moreover, with respect to the credit healthiness of firms, for nodes with the same turnover (that is, weighted degree), increasing the number of trading partners (degree) improves healthiness since it splits the load more evenly (more, smaller transactions are creating the same wealth). On the other hand, if we want to actually increase the turnover in the system, adding more transactions over the existing trading relationships (that is, the existing edges) deteriorates the balance unless these transactions are part of cycles.

Trust of the users towards a complementary currency such as Sardex is probably the most important element for its function, as it enables the currency's adoption and utilization beyond bilateral-only trading. The notion of trust here is more intricate than in classical macroeconomic models<sup>30</sup> as it includes the trust of the traders towards the Sardex network itself (which is not backed by any official state), the trust that there will be enough resources of interest to buy in the future in this closed economy and the trust that the other traders will repay their debts. Cycles in networks may be relevant to economic success in part because the existence of many—and, in particular, lengthy—cycles indicates the trust of the traders in this closed economy with respect to all of these factors. Hence, money itself may not be enough to induce trust or robustness of exchange among strangers in groups<sup>31</sup> and cycles may also be needed. Indeed, from a structural, geodesic point-of-view, cycles play a crucial role in the flow of money in a mutual credit system. Moreover, and more generally, cycles may be relevant to other phenomena within graphs, such as the flow of germs or information, beneficially retarding the flow of the former and harmfully suppressing the flow of the latter. Cycles are also surely relevant to the controllability of a graph<sup>32</sup>. Understanding the practical relevance of cyclic motifs is an opportunity for further work. While individuals might control their bilateral economic ties, they have less control over their long-range interactions. Yet, such unseen network features may matter, both for individuals themselves and for their group as a whole.

## Methods

**Data sets and network model.** Our data set includes detailed information for all Sardex transactions conducted from 1 January, 2013 until 31 December, 2014 (see Supplementary Note 1). Additionally, the data set includes information about each firm's category, capital commitment, location and date of joining the system. This time interval constitutes the fastest expansion period of Sardex, which, by the end of 2014, yielded an aggregate turnover of 38.81 million euros. We do not have data about the businesses' transactions in euros, nor about their overall economic activities (in euros). We have removed the transactions among businesses and their own employees since the latter have different qualitative and quantitative features. Namely, employees conduct much smaller transactions than businesses and, most importantly, they cannot have debt since they are not assigned a credit line. The entire population of the businesses in Sardex has been used, and therefore no statistical methods were employed to predetermine sample. The authors have the necessary approval to analyse and publish these data.

We have defined the Sardex network as follows: each node represents a Sardex business, and each directed weighted edge captures the aggregate flow of currency from the buyer business (source node) to the seller business (destination node) during the time period of interest. This currency flow can be the result of one or more transactions. We construct and analyse the Sardex network on a yearly basis. That is, we split the network into two distinct networks; one for the first year, and one for the second year. The reason for following this approach is twofold. First, we do not assume that the effect of transaction edges persists forever, and hence we consider only cycles within a certain time interval (12 months). Second, we have found that the cycles of length  $k=5$  are created, on average, in approximately 230 d, which renders the annual separation more representative (Supplementary Fig. 5). Following this methodology, the Sardex network had 877 nodes and 5,962 edges in 2013, 1,353 nodes and 9,916 edges in 2014 and 1,477 nodes and 13,753 edges for the overall period of two years (2013–2014). Mathematically, Sardex is modelled as a weighted directed graph  $G=(N,E)$ , where  $N$  is the set of Sardex businesses and  $E$  the set of edges representing their transactions during the time period of interest. Every edge  $(i,j) \in E$  with weight  $e_{ij}$  captures the total amount of currency that  $i$  has paid to  $j$ .

**Formulae.** Following previous modelling approaches<sup>33</sup>, we define an elementary path  $p_{uv}$  of length  $k$  as an ordered set of nodes  $p_{uv}=(u=u_1, u_2, \dots, u_{k+1}=v)$ , such that  $(u_i, u_{i+1}) \in E$  for  $i \in [1, k]$ . Next, we define an elementary cycle  $c_{uv}$  as an elementary path in which the first and the last nodes are identical. A cycle of length  $|c_{uv}|=k$  contains  $k$  edges and  $k$  different nodes. Two elementary cycles are considered distinct if the one is not a cyclic permutation of the other, and we have considered only such cycles in our study. We define the set of cycles of length  $k$  that include nodes as  $P_k(n)=\{c_{uv}: n \in c_{uv}, u \in N, |c_{uv}|=k\}$ , and we also define the set of all cycles of length  $k$  in the graph  $P_k(G)=\{c_{uv}: u \in N, |c_{uv}|=k\}$ . We introduce the  $k$ -cycle centrality of node  $n$  as the portion of  $k$ -cycles that node belongs to; that is,  $C_k(n)=|P_k(n)|/|P_k(G)|$ . By definition,  $k$ -cycle centralities, for all nodes and all values of  $k$ , lie in the interval  $[0,1]$ . If a graph does not have any cycles of length  $k$ , we set the  $k$ -cycle centrality equal to zero for all nodes. Finally, we define the  $k$ -cycle coverage  $Cv_k(n)=M_k(n)/|P_k(G)|(k-1)$ , where  $M_k(n)$  is the number of different nodes in the  $k$ -cycles that traverse node  $n$ .

The  $k$ -cyclic density and (overall) cyclic density for a network  $G=(N,E)$  are defined as follows:

$$C_k(G) = \log \left[ \frac{P_k(G)}{\max\{1, E(|P_k(G_N)|)\}} \right], \quad k=2, \dots, N,$$

$$\text{and } C(G) = \sum_{k=2}^T \frac{1}{T} \log \left[ \frac{P_k(G)}{\max\{1, E(|P_k(G_N)|)\}} \right]$$

where  $T$  is the upper bound of the length of cycles we enumerate, and its value depends on the context. In this study, we use  $T=5$ ; that is, we count up to 5 cycles, as the average creation delay of longer cycles expands beyond the duration of the data set. The cyclic density metric takes a negative value when the observed cycles are less than in the null model, a zero value when it is exactly the same and positive values for graphs that exhibit more cycles. Note that we use a logarithmic scale as the number of cycles grows exponentially with the number of nodes. Also, the 'max' operator in the denominator ensures the metric is properly defined even for small-sized graphs. The enumeration of cycles can be implemented using previous methods<sup>33</sup>.

**Models.** For the edge-level analysis in Fig. 4a, we have used dyadic generalized linear models with a random effect at the node level<sup>17</sup> predicting the volume of transactions between two businesses (that is, over a certain edge). Due to skewness of distribution, volume was log transformed and treated as a normal distribution. Confidence intervals were measured using two-tailed tests. We controlled for the type of businesses involved (using the business category) as well as for their lifespan (that is, the duration since they joined the network), and we compared the results with the number of paths of the same length crossing that edge. Our analysis is on an annual basis. That is, the construction of the transaction graph and the enumeration of cycles is performed for each year separately, and the statistical analysis is conducted jointly on both samples with proper adjustments. For the node-level analysis in Fig. 4b, we have used an OLS model with the credit healthiness of each business as the dependent variable. Due to skewness of distribution, credit healthiness was log transformed and treated as a normal distribution. Confidence intervals were measured using two-tailed tests. We controlled for the business type, its weighted degree (turnover) and its lifespan; and we again compared the results with the impact of paths of the respective length.

Several alternative modelling approaches have been employed, including a random effects model for the node-level analysis, that account for relational and temporal node dependencies with appropriate corrections for the standard errors (Supplementary Note 3). We have also implemented various measures for assessing and reducing multicollinearity issues. We repeated our study for each year separately, so as to consider the time dimension, and we also employed a lagged model that studies the impact of cycles created in year one on the performance metrics in year two, and reached the same conclusions about the transactions and credit conditions within cycles. We also tested the robustness of the above findings

when we employ only the time-sequential cycles; that is, those cycles with edges that are created in strict time sequence. We controlled for the  $k$ -cycle coverage of nodes and edges and did not observe any qualitative difference in our findings. Finally, we also employed a set of non-parametric, non-linear models, such as random forest and support vector machine models, which, however, did not produce interpretable results. Details for all models and methods are available in Supplementary Note 3.

**Reporting Summary.** Further information on research design is available in the Nature Research Reporting Summary linked to this article.

**Code availability.** Code for the main models and figures that are presented in the paper and the Supplementary Information is provided at the Supplementary Software report, and also available upon request from the corresponding author.

## Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to approval by Sardex Spa and based on the confidentiality agreement of Sardex Spa with its clients.

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### Author contributions

G.I., Y.C., L.T. and N.A.C. designed the project. G.I. and G.L. prepared the data. G.I. and Y.C. performed the statistical analyses. G.I., Y.C., E.M.A., L.T. and N.A.C. analysed the findings. G.I., Y.C., E.M.A., G.L., L.T. and N.A.C. wrote the manuscript.

### Competing Interests

G.L. is one of the founders and currently an employee of Sardex Spa.

### Additional information

**Supplementary information** is available for this paper at <https://doi.org/10.1038/s41562-018-0450-0>.

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Research sample	The analysis has been conducted in the entire population of Businesses in the Sardex Network active from 1/1/2013 to 31/12/2014.
Sampling strategy	Samples were not used; entire population of the B2B transactions has been analyzed
Data collection	The data has been collected from the computer database of Sardex, which keeps records in real time of all Sardex transactions and has additional information about the features of the participating businesses (such as location, date joined the system, etc.). The files were extracted in the ".csv" format and were made available to the authors. The data were extracted and prepared for statistical analysis by GI and GL.
Timing	The data were registered in Sardex ltd in real time, i.e., during the interval from 1/1/2013 to 31/12/2014; their extraction was made in 3/2015.
Data exclusions	This study analyzes the entire dataset of transactions among businesses in Sardex (B2B network). Note that we do not consider the transactions among businesses and employees since the latter have different qualitative and quantitative features. Namely, employees conduct smaller transactions than businesses and, most importantly, they cannot have debt since they are not assigned a credit line.
Non-participation	As it is a retrospective study based on administrative data, no participants dropped out.
Randomization	Participants were not allocated into experimental groups.

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