

Shareholder Networks

Qing Yao^{1,2}, Tim S. Evans^{1,3}, Kim Christensen^{1,2},

- (1) Centre for Complexity Science, Imperial College London, London, SW7 2AZ, U.K.
- (2) Condensed Matter Theory Group, Imperial College London, London, SW7 2AZ, U.K.
- (3) Theoretical Physics Group, Imperial College London, London, SW7 2AZ, U.K.

Key Words: Complex Network, Shareholder Network, Company Investors, Centrality

Abstract

We construct two examples of shareholder networks in which shareholders are connected if they have shares in the same company. We do this for the shareholders in Turkish companies and we compare this against the network formed from the shareholdings in Dutch companies. We analyse the properties of these two networks in terms of the different types of shareholder. We create a suitable randomised version of these networks to enable us to find significant features in our networks. For that we find the roles played by different types of shareholder in these networks, and also show how these roles differ in the two countries we study.

1 Introduction

Complex networks capture information about the bilateral relations between pairs of objects [1]. As pairwise relationship are so fundamental to many processes, the networks approach has proved to be a powerful tool for many different areas, see for instance Newman [2] for an overview.

This paper looks at some networks in an economics context which is one area where networks have proved useful [3, 4, 5]. In our work we focus on the networks representing the interactions between companies, a topic that has already received some attention. Vitali, Glattfelder and Battiston used network science to show that the world is in control of a few important shareholders [6, 7]. Takayasu and her collaborators have studied the flow of money from suppliers to consumers over long time periods [8, 9, 10]. Viegas *et al.* successfully applied the complex systems theory to Mergers and Acquisitions markets (M&A), studying the scaling relationship between the companies ancestry and the number of M&A to predict mergers [11]; Huajiao Li, Pengli An, Haizhong An and *et al.* has studied the common shareholdings and give implications particularly using Chinese listed energy companies [12, 13, 14, 15, 16].

In our work, we use complex network methods to study the investment characteristics of different types of shareholders. To do this we build a network of shareholders linked if they have invested in the same company. The topological structures of this network have been quantified and analyzed. Furthermore, to provide some insights of organization choices: Measures of the complex network is compared with some empirical analysis.

Before that, we will first summarize some relevant concepts from finance and economics since this paper is not intended to deal with the legal issues of corporate formation and corporate governance.

1.1 Owners of companies

The earliest and profound work of Adolf Berle and Gardiner Means, pictures the image of ownership of the modern firm, by the time 1930s [17]. It is generalised into the concepts that corporations were widely held in US. After 60 years, the story is different. In the work of Rafael La Porta, Florencio Lopez-De-Silanes and Andrei Shleifer [18], with the information of large corporates in 27 wealthy economies, they identified the ultimate controlling shareholders of these firms. They come to the conclusion that the controlling shareholders typically have power over firms significantly in excess of their cash flow, primarily through the use of pyramids and participation in management. However, the equity control by financial institutions was far less common. Although Berle and Means were aware of the role of financial institutions, they did not predict the huge participation today of institutional investors and the power they possess - the growing financial institutions desire to participate in decision making.

On the other hand, the 1960s contingency theory by Lawrence and Lorsch addressed the environment that affected the organisational behaviour [19]. It inspired the scholar to consider the way that an organisation is viewed as interacting with its environment. In 1974, Zeitlin's work of "corporate ownership and control" [20], as a turning point for managerial theory - it is necessary to study the environmental constraint large corporations suited. These concepts are aligned with the concept in complex system that most of the emergent phenomena can not be explained by studying a single part in isolation [21, 22].

1.2 Networks Representations of Companies and Shareholders

The recent interest in complex networks has led to new approaches in this area. A network is made up of two parts: the nodes (vertices or actors), and the bilateral relationship between pairs of nodes which are represented as pairs of nodes known as edges (links or ties). Nodes can be any appropriate unit while edges can represent any type of relationship between any the units; for example, kinship, material transactions, flow of resources or support.

In our context, a natural way to capture the information about shareholdings is to make use the nodes to represent the companies and shareholders. The edges are directed with an edge from a shareholder to the company invested in.

Several studies of shareholders and companies start from this network perspective. For instance, Vitali, Glattfelder and Battiston [6] use a version of this shareholder-company weighted directed network to capture both the influence by a shareholder through direct shareholdings along with the influence implied by chains of ownership and shareholdings. This investigation first confirms that ownership tends to be parsed among numerous shareholders, while control is found to be in the hands of few important shareholders globally. They discovered a structure of bow-tie, revealing the control flowing to small tightly connected financial institutions.

This highly connected concentrated status may give power to the financial institutions. Gai and Kapadia [23] look at financial contagion through the network of financial institutions, using this as a possible explanation of the financial crisis.

2 Materials and Methods

2.1 Data Sources

The data used in this research is extracted from the Amadeus, a product of Bureau Van Dijk (BvD) [24]. This provides data on around 21 million companies across Europe, including the names of shareholders, the percentage of a company's shares held by each shareholder. We have focused on the data for one year, 2012, and two exemplary countries within this data: Turkey

and the Netherlands. We found fifty thousand Turkish companies and over a million Dutch companies.

The data we use for macroeconomic statistics is retrieved from the World Bank [25] and CEIC Data [26].

2.2 Network Representation

Our data on the shareholders in companies has a natural representation as a network. In our “shareholder-company network”, each distinct shareholder and each distinct company is represented by a node. A directed edge is placed from shareholder to each company in which they have invested, see Fig. 1. Note that the network is only approximately bipartite, some companies can be shareholders of other companies. Also, we do not have the value of each investment, nor can we be sure that all investors are present in our databases. For those reasons we chose not to try to represent the size of investments e.g. through a weight added to the edges.

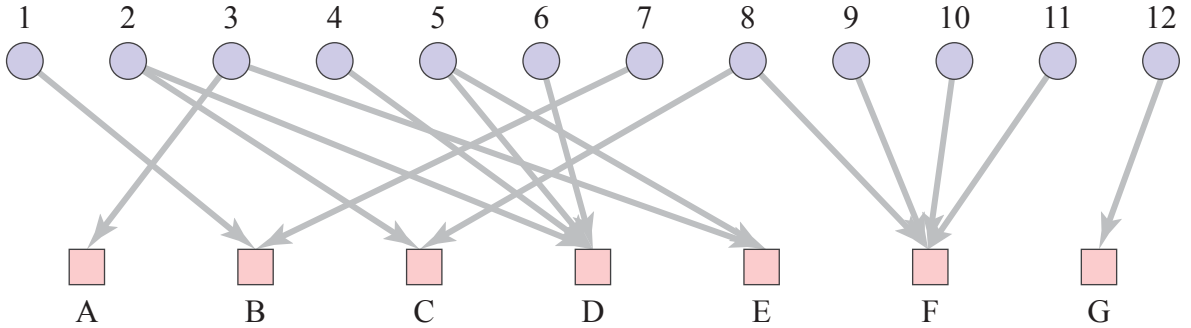


Figure 1. An example of our shareholder-company network, which illustrates the relationships between shareholders, the upper blue circles numbered 1 to 12 and companies, the lower red squares labelled A to G. An edge indicates that there is an investment from the shareholder represented by the source node in the company represented by the target node. For example, shareholders 3 and 5 have both invested in company E, and an arrow represents this relation. In addition, shareholder 3 has invested in company A, but no other shareholder.

The boundary of each network is defined by the nationality of the companies; here we study two examples: Turkish companies and Dutch companies. We consider all the shareholders of each company which means that we consider both domestic and overseas shareholders. We will highlight this when analysing the data for companies in the Netherlands.

We are particularly interested in the relationships between investors implied by their investments. That is, if two investors have invested in the same company they have a common interest and are likely to have similar wider commercial interests. So we will focus most of our work on the analysis of these investor-investor relationships and we do this through a representation of our data in terms of a projection onto just the shareholder nodes. Our “shareholder network” has one node for each shareholder, and two different shareholders are connected by an undirected edge if they have both invested in the same company. An example of the shareholder network is shown in Fig. 2 which is a representation of same data shown in the shareholder-company network of Fig. 1.

An important aspect of our work is that our data also classifies the shareholders to be one of 13 different types of owner, as listed in Table 1. We will use this classification to study how the structure of the shareholder networks depends on the type of owner. It is immediately clear from the numbers of each type that companies in different countries can have very different

ID	Shareholder Type	Description	Turkey	Netherlands
1	Venture Cap.	Venture capital	6 (0.01%)	143 (0.07%)
2	Financial Co.	Financial company	133 (0.23%)	7028 (3.6%)
3	Families	One or more named individuals or families	53360 (92.29%)	663 (0.34%)
4	Public Co.	Publicly listed companies	1 (0.002%)	1 (0.001%)
5	State	Public authority State Government	26 (0.04%)	162 (0.083%)
6	Hedge Funds	Hedge funds	1 (0.002%)	16 (0.0082%)
7	Insurance Co.	Insurance company	34 (0.06%)	235 (0.12%)
8	Self Owned	Self Owned	1 (0.002%)	1 (0.001%)
9	Private Equity	Private Equity firms	18 (0.03%)	282 (0.14%)
10	Corporates	Industrial company	4007 (6.93%)	156644 (80.25%)
11	Mutuals	Mutual, Pension Fund, Nominee, Trust, Trustee	91 (0.16%)	9563 (4.90%)
12	Banks	Banks	127 (0.22%)	363 (0.19%)
13	Foundations	Foundation, Research Institute	15 (0.02%)	20059 (10.27%)
TOTALS			57820 (100%)	195199 (100%)

Table 1. The different types of shareholder recorded in our data as retrieved from the BvD database. The numbers found in our different data sets are in the righthand columns.

3 Results

In this section we will look at the results of our analysis of the shareholder network. We will start with some general characteristics of the network before moving on to focus on how the different types of shareholder play different roles in the network as revealed by various measurements.

3.1 General Network Analysis

Some key facts for our two data sets and for the shareholder networks derived from them are summarised in Table 2.

Country of Companies	Turkey	Netherlands
No. of Companies	45,831	1,157,672
No. of Companies with Information Available	22,445	259,249
No. of Nodes in Shareholder Network	57,820	195,199
No. of Edges in Shareholder Network	93,439	133,276
Degree distribution power-law slope γ	2.6	2.7
No. of nodes in LCC	1,807	3,152
No. of edges in LCC	14,459	120,935
Clustering Coefficients	0.87	0.64
Diameter	12	19
Average Shortest Path	4.50	4.47

Table 2. Basic information on the two data sets used in this study. Each data set looks at the companies registered in one country and their shareholders from any country for the year 2012. There is no information on many of the Companies as the numbers above indicate. The number of edges in our shareholder network is based on the information available on the shareholding information. The slope γ of an equivalent power-law degree distribution, $P(k) \sim k^{-\gamma}$, is obtained from a simple fit to the data. ‘LCC’ is the largest connected component.

An important characteristic of any network is the degree distribution, $P(k)$. This may be defined as the probability that a node selected uniformly at random has degree k , where the degree of a node refers to the number of edges connected to a node. The degree distribution for the shareholder networks are shown in Fig. 4. The distributions are generally fat-tailed and parts of the degree distributions can be described, roughly, using a powerlaw $P(k) \sim k^{-\gamma}$.

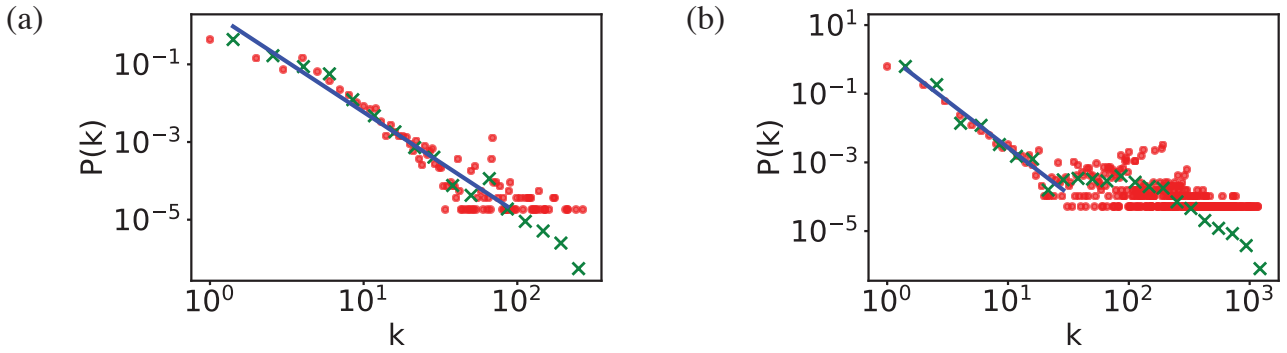


Figure 4. The degree distributions $P(k)$ (the frequency of nodes with degree k) against degree k edges on a log-log scale for shareholder networks where the holdings are in (a) Turkish companies, (b) Dutch companies. The red dots are the raw data, the green crosses represent the same data in logarithmic bins, and the blue lines are the best linear fits ($P(k) \sim k^{-\gamma}$) to ranges of k values where we see approximately linear behaviour. The slope of the blue lines, $-\gamma$, is 2.6 and 2.7 for Turkey and the Netherlands respectively. A summary of the general statistics of these shareholder networks can be found in Table 2.

It can be seen from Fig. 4, that the distribution of the degrees of the network roughly follows a power-law. The large k tail implies that typically there are a small number of shareholders who have investments in common with large numbers of other shareholders. On the other hand, the small degree part of the distribution indicates that most shareholders have investment in common with only very few others.

The distributions show other interesting features. For the Netherlands there is a distinctive ‘bump’ in shareholders who are related to between twenty and a hundred other shareholders. These appear to be far more common than the trend shown for small degree would suggest. One explanation for this is that some companies have lots of overseas shareholding relationships, for example the French shareholder of the Turkish Tobam Holding Co. With foreign shareholders, it seems likely that most would be large investors who are looking to diversify their holdings by looking outside their home company. Including these shareholders has two effects. First including them increases the total number of nodes in our shareholder network which lowers the distribution $P(k)$ for shareholders investing in companies based in their home country. Secondly, it seems likely that if a foreign shareholder has gone to the trouble of making one investment across borders, it is likely they have made several, so that they are the bump. Put another way this is a boundary effect. Our large foreign investors will also be linked through foreign firms to small foreign shareholders who only invest in foreign firms, part of the low degree part of the distribution. Those firms are excluded by definition from our data. The fact that the bump is much less pronounced in the Turkish shareholder network suggests that Foreign investment does not play such a big role in this case. As the macroeconomic data suggests that Netherlands has high FDI (International trade and foreign direct investment) indexes both outward and inward, 13.37% net inflows of GDP. It ranks 9th in the world.

3.2 Analysis by Shareholder Type

One of the major features of our data set is that we can distinguish between 13 different types of shareholder as shown Table 1. So we will have a look at how various network measures reveal the different roles of different types of shareholder and how that depends on the two countries we are studying.

3.2.1 Degree

The degree of a node is one of most important and simplest centrality measurements. In our shareholder networks, a high degree of a shareholder may indicate that that shareholder has better contacts within the business community. To evaluate the different role of different types of shareholders in Section 2, the violin plots for the degree of different types of shareholders are shown in Fig. 5. Violin plots are similar to box plots indicating ranges and additionally show the estimated probability densities of the data at different values and include a marker for the median of the data.

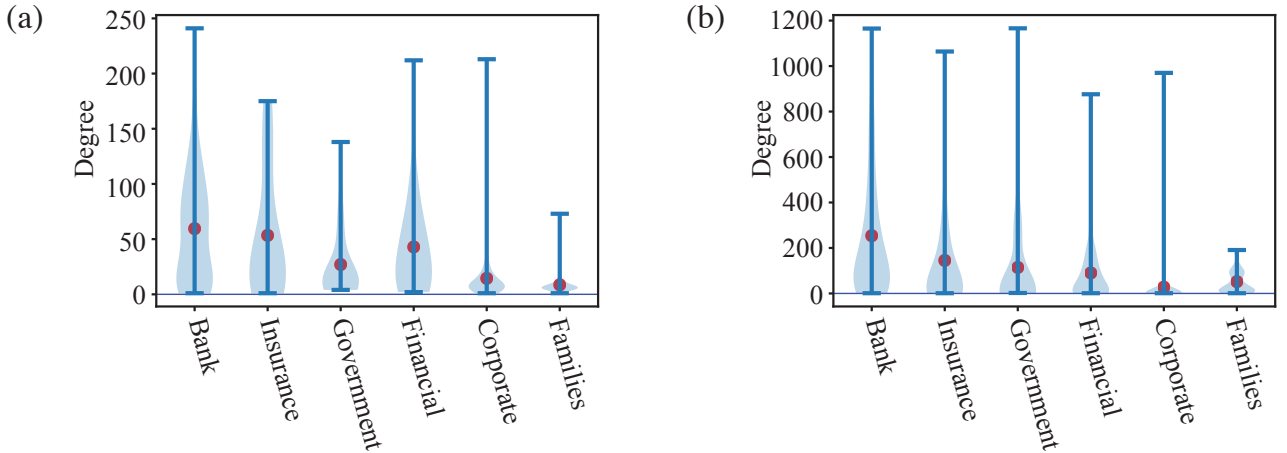


Figure 5. Violin plots of the degree of the most common types of shareholders for the largest connected component of shareholder network of (a) Turkish and (b) Dutch companies. There are too few shareholders for other types of investor. This figure breaks down degree distributions into different types of shareholders. We note that in Turkey, the large degrees are contributed by the banks and insurance while in Netherlands, banks' average degree is higher than the other types of shareholders. It means Netherlands' banks co-invested a lot with other shareholders.

This degree centrality is straightforward to find from the data, but does full complex network provide more information? We consider several other topological measurements but we start with one of the simplest. We look at the effect on the largest connected component of removing nodes one at a time, choosing the remaining nodes uniformly at random from those of just one type. The effect of removing different types of shareholder on the largest connected component of the Turkey shareholder network is shown in Fig. 6.

3.2.2 Percolation

In our percolation analysis, we focus on one type of shareholder. Starting from a given shareholder network, $G(r)$, we choose one node, uniformly at random from the set of shareholders of the given type, and we remove that node and any edges attached to it. This leaves us with the next network $G(r - 1)$ with one less node. We then repeat the process. In our case we will start from the the largest connected component of one of our shareholder networks, and then we will remove the nodes corresponding to one of the more common shareholder types. We will look at the number of components of the sequence of networks $G(r)$ as a function of the number of nodes removed, r .

Results are shown in Fig. 6. For both countries, we see that the change in the number of components is roughly linear, at least for a relatively large rank of r values, but the slopes are very different. These differences in the percolation analysis give us an insight into the roles of different types of shareholders within the network.

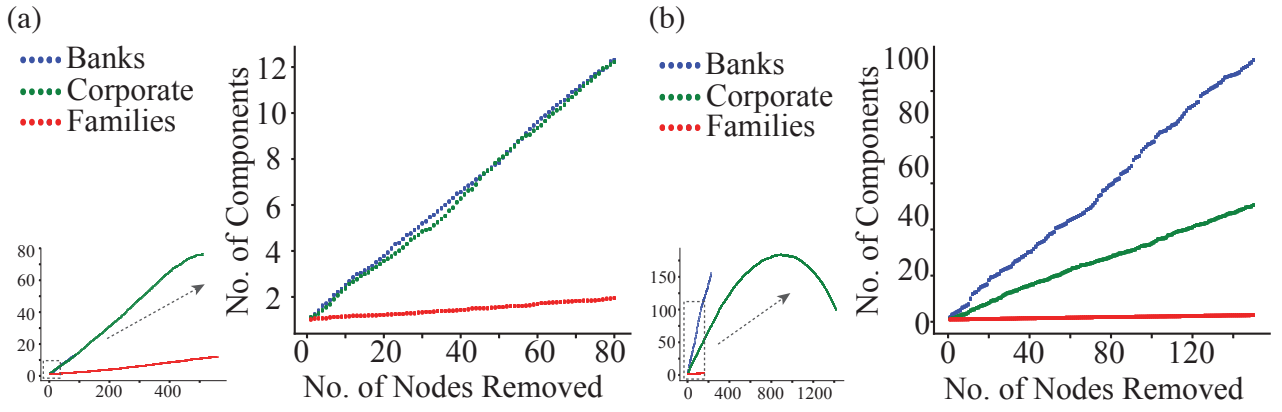


Figure 6. The number of components increases as the number of nodes removed. (a) Turkish and (b) Dutch companies. Nodes of one shareholder type are chosen at random and removed one by one from the largest connected component of the shareholder network. Blue represents Bank shareholders being removed, green represents Corporate and red represents Families. The larger scale plots show the behaviour for small numbers of nodes, the regions in the dashed boxes of the smaller scale plots. Note in particular the different role of banks in the two countries.

Individual and Family investors, which are 92% of the nodes in Turkish shareholder network while 0.34% in Dutch shareholder network, seem to have a limited effect on the connectivity of the largest component. This can be understood by the nature of Individual and Family investors whom we would expect to have investments in a few closely related companies and so would only be linked to a few closely linked shareholders. That is, it is not surprising if Individual and Family investors are poorly connected to other shareholders and are somewhat peripheral to the network.

There are also a large number of nodes corresponding to Corporate shareholders, just under 7% in Turkish shareholder network and 80% in Dutch shareholder network, and their average degree is again not high. Being different from Family investors, removing this type of shareholder breaks up the giant component much more quickly. So Corporate shareholders seem to be important in bringing together smaller components. For instance, in the real world, companies involved in mergers and acquisitions are likely to bring together different bodies of interest.

Since Banks shareholders often invest in a large number of different assets, in terms of the shareholder network they are going to be responsible for providing a path in the shareholder network between many different types of shareholder. This central role is reflected in the fast rate at which their removal breaks up the largest connected component.

3.2.3 Diversity of Neighbours

Interestingly, while Banks and Corporate shareholder nodes are important in maintaining the connectivity of the shareholder network, there is an important difference in their share holding patterns. To see this we turn to a measure of the diversity of the neighbours, $d(i)$, of a node i in terms of the different types of investors. Our measure of diversity of a node i is defined as:

$$d(i) = - \sum_{\tau} \frac{k_i(\tau)}{k_i} \ln \left(\frac{k_i(\tau)}{k_i} \right), \quad \text{where} \quad k_i = \sum_{\tau} k_i(\tau). \quad (1)$$

Here k_i is the degree of node i and $k_i(\tau)$ is the number of neighbours of node i which are of type τ . If the neighbours of a node i are all of the same type, say $k_i(\tau) = \delta_{\tau, \tau_0} k_i$, then $d(i) = 0$. However, if the neighbours of node i are all of a different types, $k_i(\tau) = 1$, then diversity would

be $\ln(k_i)$. To make a suitable comparison, we find the expected measure of diversity d_{null} given the distribution of labels in each data set, that is

$$d_{\text{null}} = - \sum_{\tau} \frac{N(\tau)}{N} \ln \left(\frac{N(\tau)}{N} \right) \quad (2)$$

where $N(\tau)$ is the total number of nodes of type τ and we have $N = \sum_{\tau} N(\tau)$. The null model diversity measurements indicates the global diversification of different types of investors within one country. Here we see that at in terms of the classification scheme used in our data, the Netherlands has a much more diverse set of investors than Turkey. If a node's diversity is lower than this expected diversity value, this indicates attraction of certain types of shareholder to the same investments. On the other hand, if a node's diversity is higher than might be expected at random, this indicates that some shareholders repel each other and they actively avoid investing in a company if particular shareholder types are present.

Diversity indices for Turkey correlate roughly with degree for different types of investors. The exception is the Family shareholder type whose diversity index is the lowest and below the global average model, indicating these investors tend to invest with a very limited range of co-investor types. One explanation is that many Family type shareholders only invest in other Family type investors and perhaps, in many cases, these connections reflect real social and family ties. We will see further evidence for this view in other measures. The Netherlands' diversity index is interesting as most of the shareholder types have mean diversity measures below the global diversity measure, showing some tendency for Dutch shareholders to invest with a limited set shareholder types. Overall though the values of diversity measurement of the same type in two countries are similar, implying that in terms of diversity, the behaviour of different types of shareholder is similar in different countries, except the type Families.

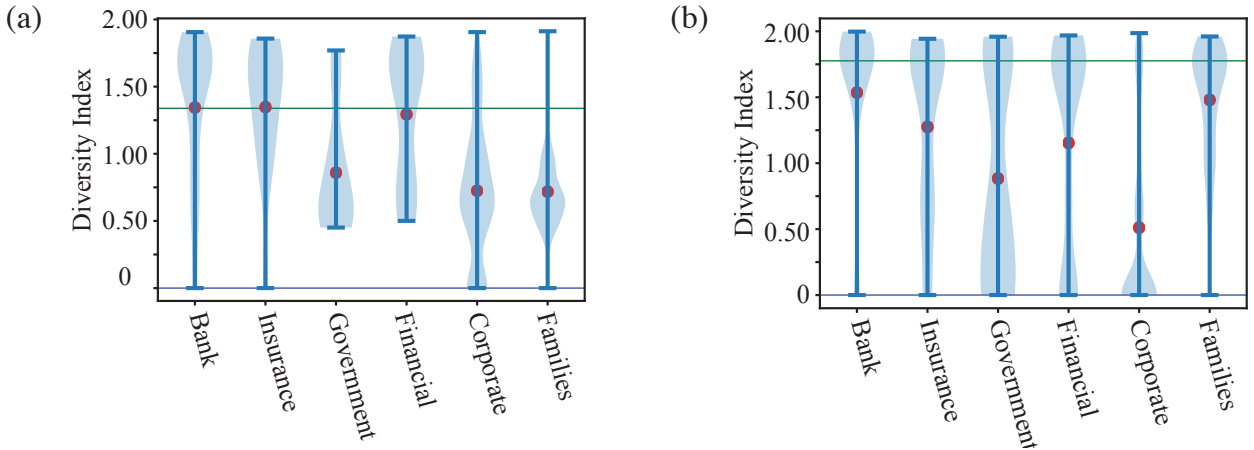


Figure 7. The violin plot of diversity index of selected types of shareholders for (a) Turkey and (b) Netherlands. The information of other type is not listed here because due to the limited information available and the limited amount of the data. The blue space is the diversity index density estimation and compared with a null index (indicated by a green line) which is define as d^{null} in Eq. (2).

3.2.4 Betweenness Centrality

Another way to study how the roles of different types of shareholders vary in our network, it is useful to look at how *betweenness centrality* values vary. Betweenness centrality measures the number of shortest paths passing through a node. In the context of our shareholder network, the shortest path can be interpreted as the the minimum number of common assets that connect

other two shareholders as each edge represents a shared asset between a pair of shareholders. The interpretation is that the higher the betweenness the more likely they will be central to the process of connecting other shareholders making them more important to other shareholders.

In order to see if these betweenness values are significantly high or low, and so to see if this measure gives different information from the degree, we compare our values against those in our null model in which the edges are swapped but the degree of each node is unchanged. We create 100 different null models and use these values to create the boxes in Fig. 8 alongside the results obtained from our data.

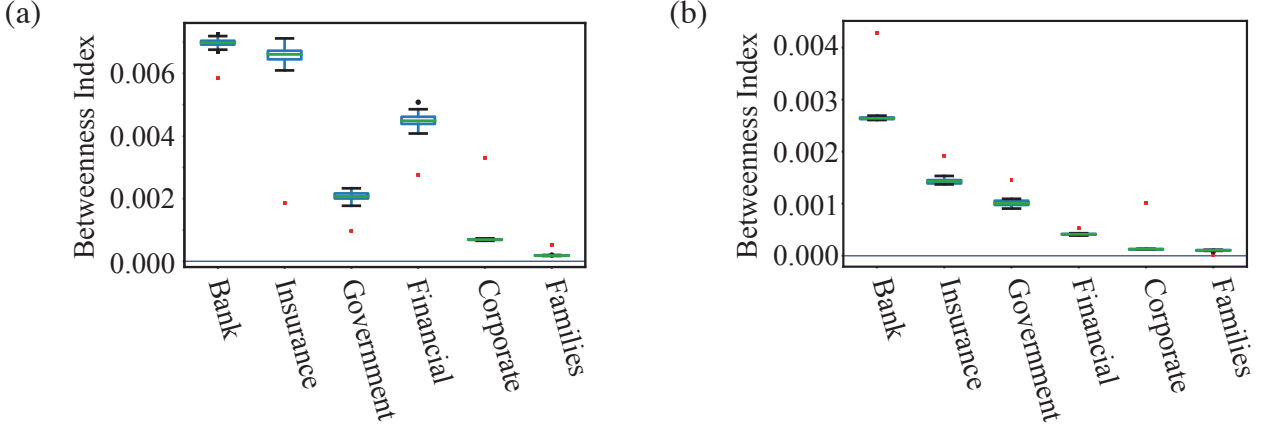


Figure 8. The mean betweenness values for different types of shareholders in the largest connected component of shareholder networks, (a) for Turkey and (b) for the Netherlands. The red dots are the real data and the box plots for the results obtained from 100 degree preserving null models as illustrated in Fig. 3. We note that most betweenness values for Turkey and Netherlands are significantly different from the randomised networks, some types are lower and some types are higher. That means that there is significant network structure on larger scales and the properties are not just controlled by the degree.

In Fig. 8(a) we show the betweenness centrality values for each type of shareholder in the Turkish shareholder network, as well as the results from our null model. In this case, Banks always have the highest average betweenness and highest maximum betweenness. This implies that a high percentage of shortest paths go through Banks which in turn means that Banks can play a pivotal role in linking other shareholders. As these are key instruments for providing investments in firms, this is not surprising. However, this network measure confirms our intuition and hence we see these companies are fulfilling their role in the economy.

However, nodes representing Banks, Financial and Insurance companies are much less central than you expect from the null model. These companies have a high degree yet their betweenness is lower than one might expect. So Banks, Insurance and Financial companies are still very central in the network but they are much less effective in brokering connections than we would expect from their degree value, the message from their betweenness values in the null model. What this suggests is that in Turkey, Banks, Insurance and Financial companies are investing in a narrower range of companies than they could. This picture is slightly different in a different year as discussed in Appendix A.

The State organisations in Turkey are also less central than expected, suggesting their involvement is constrained by some issues, e.g. political or legal constraints limiting involvement to certain key sectors or to just a few larger firms.

On the other hand while the largest number of shareholders in Turkish companies are the Family type shareholders, this type of shareholder has the lowest average betweenness. This is consistent with what we found from both the low degree of most Family shareholders but also

from the diversity measures that the focus of many Family type investors may be framed within a social and family setting. Another explanation may be that the size of these investments may be smaller, again biasing their involvement to smaller firms. The picture is that the investments made by Family type shareholders are peripheral to the large scale shareholding structure in Turkey. Our results on community detection in section 3.2.6 will support this view.

When we compare the results for Turkey against those for the Netherlands, we see two big differences as the Banks and Insurance companies investing in Dutch companies are much more central than found in the null model, the opposite of our result for Turkey.

Betweenness centrality measurement can be related to one index in the real world, the Capital Adequacy Ratio (CAR) of a bank is a measure of a Bank's capacity to absorb potential losses. The CAR is defined as the ratio of Bank capital and reserves to a bank's risk. The higher the ratio means more capability and more liquidity to undertake credit risk (much higher than randomised model betweenness index of a node may imply the negative impact may quickly transfer to it and they do not have enough liquidity to absorb the risk). The Netherlands banks had a CAR of 14.50% in Dec 2014 (CEIC data) and bank capital and reserves to total assets ratio is 5.37%(World Bank data). On the other hand the Turkish banks had a CAR of 15.3% in Dec 2014 (CEIC data) and bank capital and reserves to total assets ratio is 11.59%(World Bank data). These are CAR calculated according to the Basel II accords, which require all banks to have least 10%. So the too much higher than expected centrality may be reflecting their lack ability to take on a wider range of risk and that translates to an investment in a wider range of companies which puts them more central than their high degree suggests. The opposite argument is then suggested for Turkey. From 2008 until 2013, Dutch banks received criticism for the poor performance with high leverage. Until 2013 Dutch banks have done deleverage and their performance have increased. On the other hands, Turkey's banking sector is well regulated and well capitalised only went through a hard time in 2012.

However, this argument needs to be further validated using other countries' data.

3.2.5 Closeness Centrality

While betweenness centrality indicates how a node may control the important communication pathways between shareholders, closeness centrality indicates how easy it is for each shareholder to reach any other shareholder. The closeness of a node is the inverse of the sum of the shortest path distances from that node to all other nodes, though this is usually rescaled or normalised in some way. The larger the closeness of a node, the shorter the distances to other nodes and so in general fewer message transmissions, less loss of information, shorter time to communicate and lower costs.

In the context of our shareholder network, information can be related to opportunities to buy new assets or to sell existing ones. Since the network is highly interconnected, a failure in one sector can have repercussions in another so the earlier a shareholder hears about potential problems, the more successful they are likely to be.

To see how the closeness varies for the different types of shareholders, we use the same edge swapping techniques of our null model Fig. 3 to make comparisons. In Fig. 9 and Fig. 10, we see that for the both shareholder network that the average closeness of each shareholder type is lower and that this shift is similar for all types of shareholder. This tells us two things.

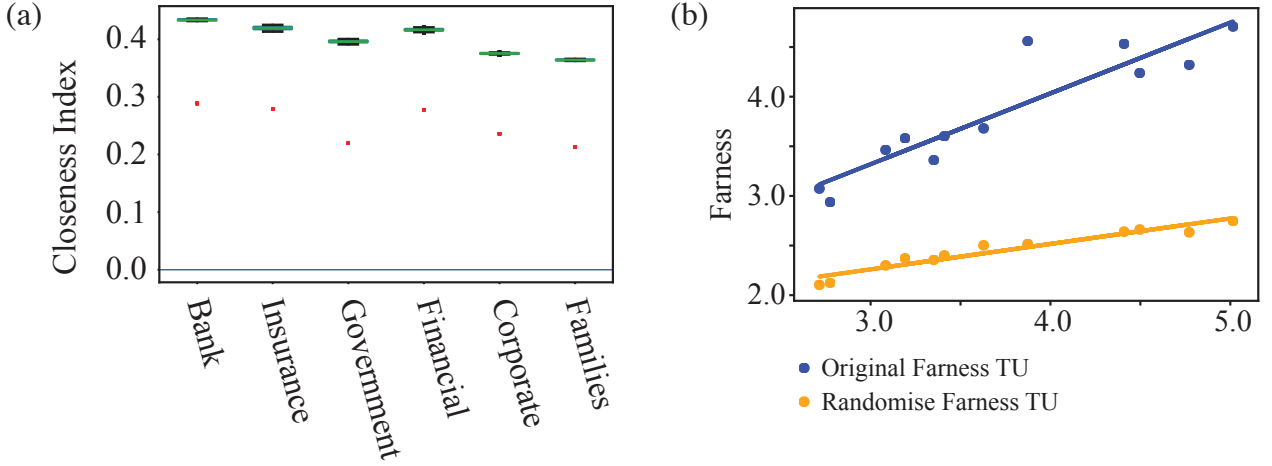


Figure 9. The average closeness indices for different types of shareholders in the LCC of Turkish shareholder network. The red dots are the original data and the box plots for the randomised data. In Figure (a) we show the results for each shareholder while in (b) we plot the average ‘Farness’ (the inverse of closeness) against $\log(N/k)$. The lines are fitted between Farness and $\log(N/k)$ and the Pearson correlation coefficients are 0.80 for the original data and 0.91 for the random null model. The slope for original data is 0.71. For the random null model is 0.26 and the theoretical value of a random branching model is 0.24.

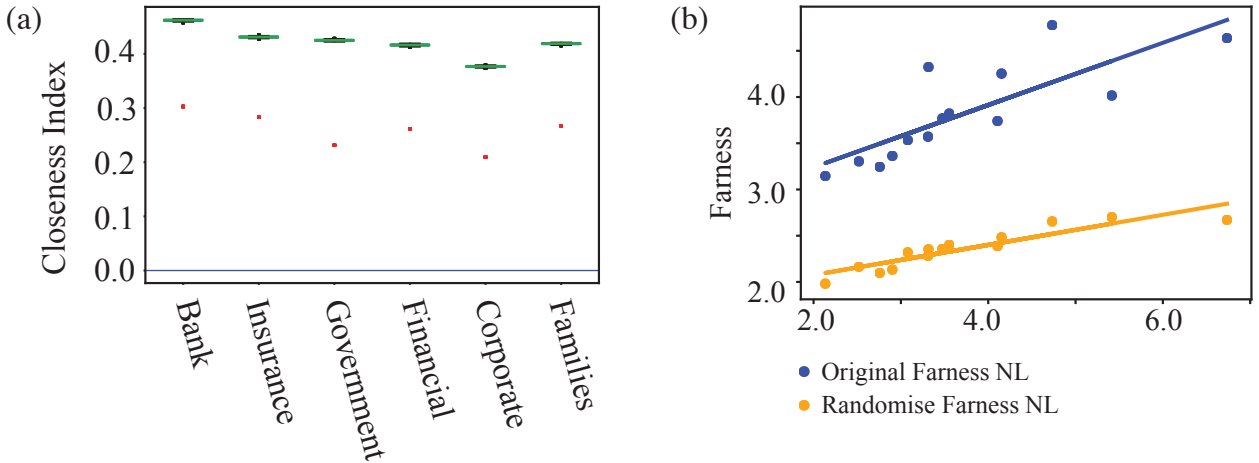


Figure 10. The average closeness indices for different types of shareholders in the LCC of Dutch shareholder network. The red dots are the original data and the box plots for the randomised data. In Figure (a) we show the results for each shareholder while in (b) we plot the average ‘Farness’ (the inverse of closeness) against $\log(N/k)$. The Pearson correlation coefficients between Farness and $\log(N/k)$ are 0.80 and 0.91 in the original data and in the random null model. The slope for original data is 0.34. For the random null model is 0.16 and the theoretical value of a random branching model is 0.17.

First that there is additional structure in the real world over the null model. In particular, connections in the real network lead to longer paths between shareholders, so that the communication in the real world to all parts of the network is not as efficient as it could be. As Turkey is dominated by the Family and Individual shareholder types, it is paths to and from these nodes which dominate the closeness values for all types of shareholder. The Family type of shareholder has the lowest average value of closeness of all our shareholder types which again shows they are very peripheral and poorly connected despite having an average degree of around a dozen. Our null model will bring in lots of ‘short cuts’ to/from these peripheral

nodes so the null model closeness values are higher. If the Family shareholders dominate the closeness measurements, it is not surprising if the rise in closeness is similar for all shareholder types. The similar argument can be applied to Corporate shareholders in Dutch network.

The second feature of the shareholder network in Fig. 9 and Fig. 10 is that there is a small but statistically significant variation in closeness between the different shareholder types. However, a large part of this variation can be understood as coming from the different typical degree of each type of shareholder node. If we look at the Pearson correlation of farness (the inverse of closeness) and $\log(N/k)$ (see Eq.(15) in the appendix), we find values of 0.80 for the original data, and 0.91 for our null model which has the same degree distribution. Again the fact the real data has a significantly lower value of the Pearson correlation indicates that real world processes have added significant structure as compared to a randomised network.

This dependence of closeness on degree can be understood by looking at a random tree. Suppose we start from a node in a tree of degree k . At each step we move along an edge to find nodes one step further away from our starting point. In general assume we find \bar{z} new neighbours (the branching factor), we can show that in such a tree structure with N total nodes, the sum of the distances, the farness (inverse closeness) is expected to scale as $\log(N/k)$ (see Appendix A3 for more details). A sparse random graph is often well approximated by a tree with branching factor $\bar{z} = (\langle k^2 \rangle / \langle k \rangle) - 1$ [27, 28] so it is not surprising to find our null model has a strong correlation of farness and $\ln(N/k)$. Even for real data there is still a strong correlation. Real data will not be a tree but it appears that in terms of closeness measurements, the shortest paths which dominate the calculation are to nodes where the structure is statistically similar to a tree or a sparse random graph. That is, once we are one or two steps away from our starting point, the number of new nodes we find one step further away are growing at a roughly constant rate \bar{z} . It is unlikely that this effective branching factor is given by the random graph value of $\langle k^2 \rangle / \langle k \rangle - 1$. However the closeness calculation is likely to be dominated by the paths at distance, say ℓ , where the product of the distance and the number of nodes at that distance, from the starting point, is maximal. Using the effective branching factor at this distance ℓ in our tree approximation will lead to a reasonable estimate for the behaviour of closeness in our data.

Overall, what we see is that the behaviour of our average closeness values for different shareholder types only reveals that on large scales, the shareholders all see a similar global network, one which is less well connected than a randomised version. The only variation between the shareholder types in their average closeness is a reflection of their average degree making the average closeness redundant. That is not to say that closeness is not useful. For individual shareholders, a comparison with the typical behaviour, in terms of degree and closeness, can lead us to find interesting outliers (say low degree, high closeness) worthy of investigation for a given context.

3.2.6 Community Detection

The shareholder network can also show us if the common shareholdings reveal large scale ‘communities’ within the shareholders, more than the labels in the data record. Such communities in the projected network show us groups with common interests. Looking at these groups can tell us something about the diversity of shareholders for each corporate or the centrality of shareholders of the whole economy, which has been discussed in Section 1.1.

To do this we use community detection methods to look for groups of nodes which typically have more connections between themselves than one might expect, and/or fewer connections to nodes outside a community. Two popular algorithms have been used here to detect the communities: the Louvian method [29] and Infomap [30], see Appendix A.4 for more details on these methods. We construct a distribution for the size of the communities we find. Using

two approaches gives us a handle on the uncertainties in this process and we look to see to which community each node belongs to for the two methodologies separately. Some statistics are listed in Table 3.

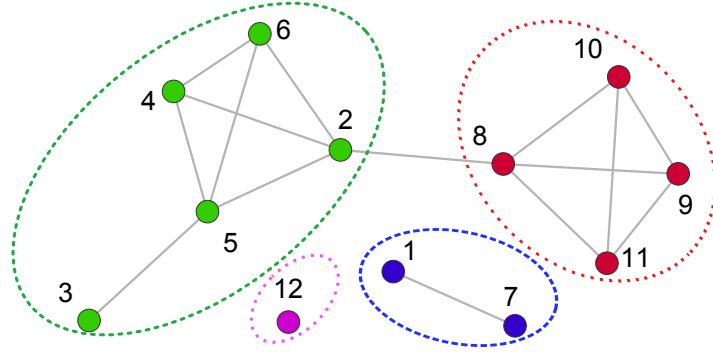


Figure 11. The same projected graph as in Fig. 2 from the network graph shown in Fig. 1. The different colours label them as different communities which are the structural characteristics in the network science context. As in the graph, 1-12 shareholders are categorised into 4 communities, 12 belongs to one community, 2,3,4,5,6 belong to another community, 8,9,10,11 are in the third community and 1,7 are in the fourth community.

Country	Turkey		Netherlands	
Methodology	L	I	L	I
No. of communities	21,175	21,270	182,263	182,375
Avg. community size	2.73	2.71	1.07	1.07
Max. community size	1169	190	1532	1384

Table 3. Statistics of the communities found in the shareholder networks derived from the two data sets using the two different methodologies, Louvain (L) and Infomap (I). ‘Avg. community size’ is the average number of shareholders in one community. The average community size is defined by as the number of shareholders divided by the number of communities, where the number of communities include the communities whose community size is 1.

In Fig. 12, we show the community size distribution on a log-log plot for Louvain and Infomap method for each country

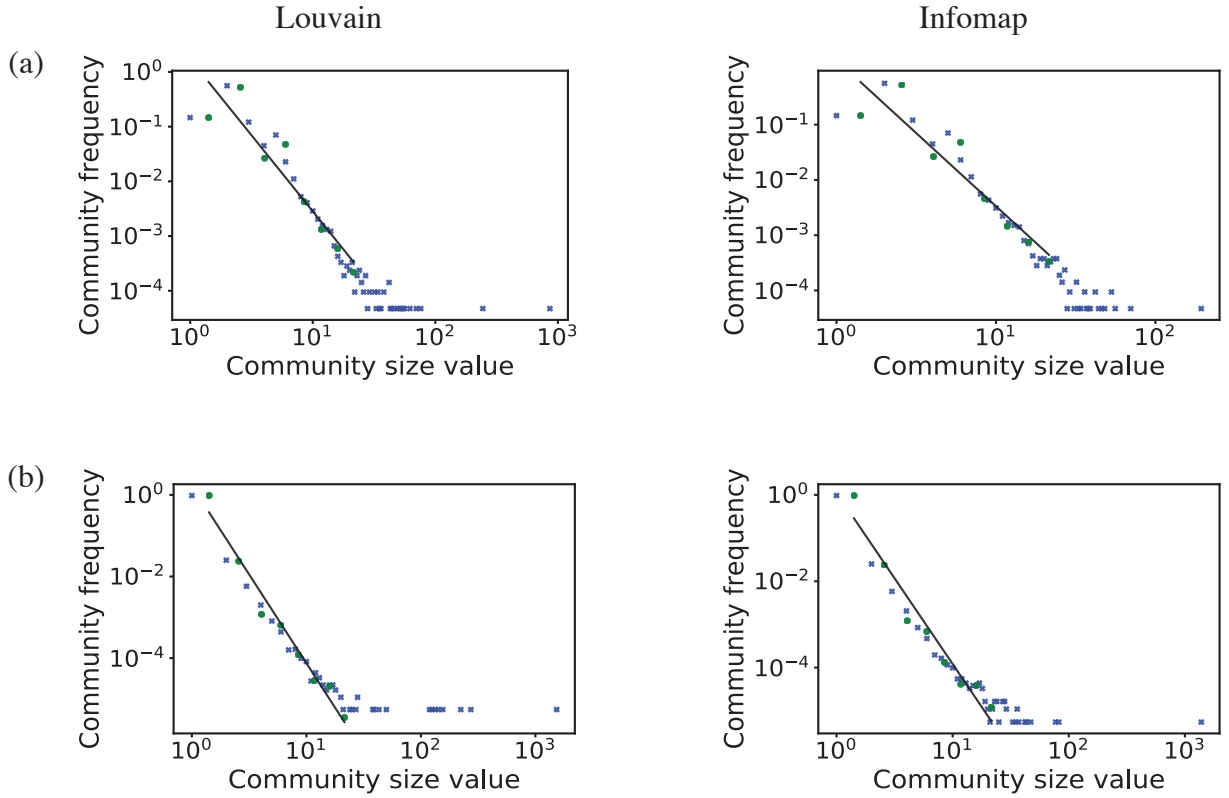


Figure 12. Community size frequency distribution for (from top to bottom): (a) Turkey and (b) the Netherlands. The figures are plotted on log-log scale. For each country we show the results from two methods; Louvain on the left and Infomap on the right. The blue cross represents the data, the green dot represents the data binned using a logarithmic binning, and the black line is a linear fit to the binned data.

The community size distributions are clearly fat-tailed and power-laws, indicated by the straight lines on the plots, capture most of the behaviour. These distributions show that the vast majority of communities are small, typically three or four shareholders. These are simply disconnected components of the shareholder graph created when a small number of shareholders invest in the same one or two companies. Their shared connections mean these investors form a strong community.

The tail of these community size distributions in Fig. 12 shows that there are a small number of large communities representing shareholders have cross-invested in each other's investment portfolio but in a way that is highly correlated. Comparing against our null model, we find that such correlated cross investment, the fat-tail of the community size distribution, disappears after our edge swapping. This again shows that the shareholder network is not like a random graph, it has significant structure which reflects a non-trivial way in which these connections are made.

To see what we can learn from these community structures we look at the kind of shareholder we find in each community using the classification of our 13 type of shareholders shown in Table 1. We will take Turkey as an example. In this case two types of shareholder dominate: the Industrial investor (Industrial companies) and the Family investor ('one or more named individuals or families'). In any one community, we look at the fraction of shareholders of these two common types in the different communities. The distribution for each of the two common types of shareholder are shown Fig. 13.

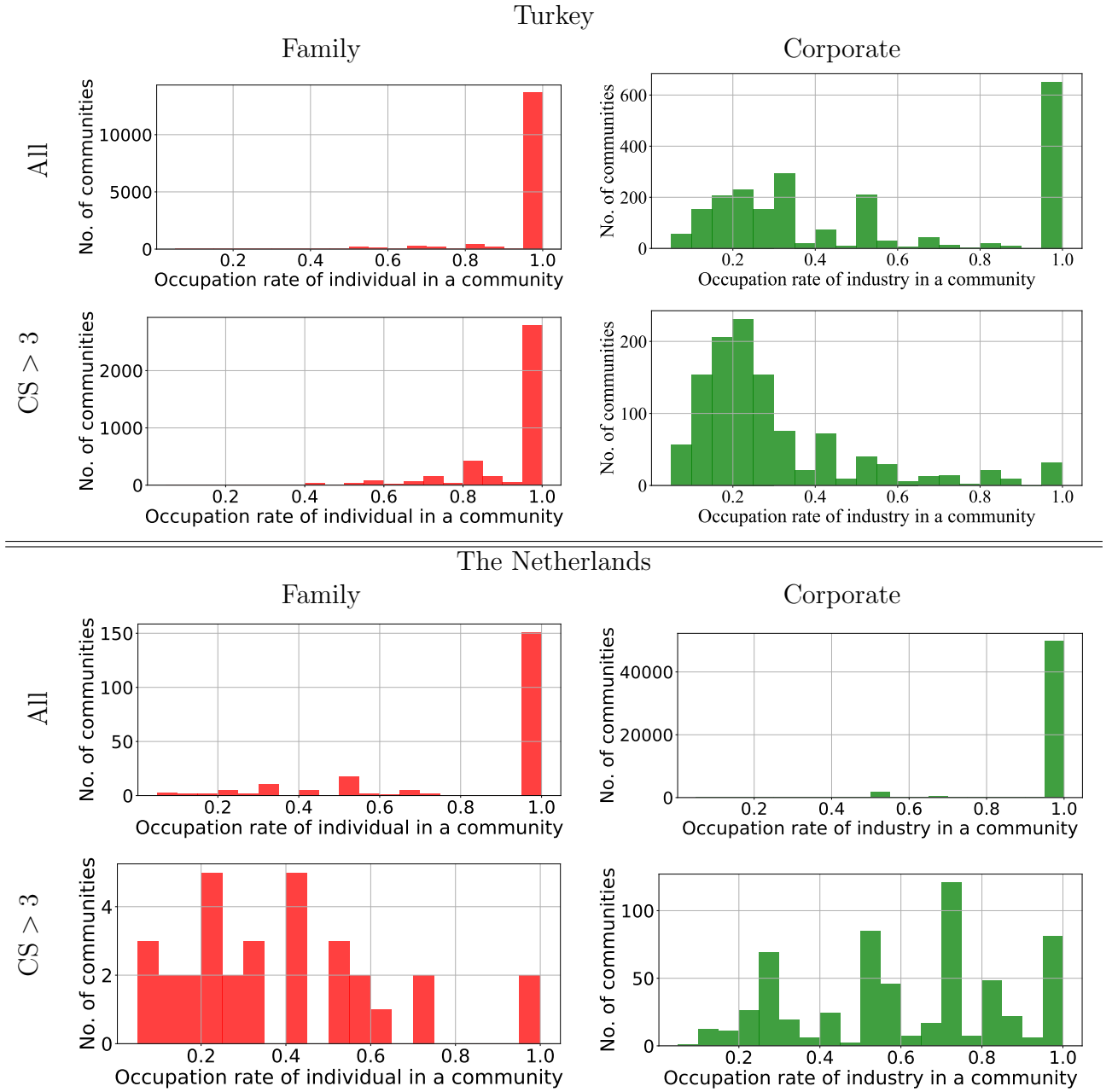


Figure 13. The number of communities found with a given fraction of one type of shareholder. The communities are found with Infomap in the shareholder network for Turkey and Netherlands. On the left we have the fraction of Family shareholders in different communities while on the right we have the fraction of Corporate shareholders in each community. The figures in first row includes community of all sizes. The fat-tailed distribution means this is dominated by the large number of small communities, and these are almost always of a single type of shareholder, hence the peak at 1.0. The second row shows the same analysis done when we exclude small communities which have three or less nodes ($CS = \text{community size}$). Similar analysis for the Louvain community detection method is given in the appendix.

It can be seen from Fig. 13 that Individual or Family shareholders behave quite differently from the Corporate shareholders in these two countries. Individual and Family investors prefer overwhelmingly to invest in companies with the same type of shareholder. One explanation is that this preference for other Family type owners reflects genuine family ties in the social sense. In general though, individual or family shareholders tend to bond together and exclude other types of investors. By way of contrast, we can see that Corporate shareholders are much more

happy to share control with other types of shareholders.

However, if we exclude the large number of small communities, those of size one, two and three shareholders, the number of communities we do not see much change in the pattern of ownership for those with family type shareholders in Turkey, there is not much change in the types of shareholder in these larger communities, Family type investors prefer to share control with other Family type shareholders. On the other hand, we do see that larger communities containing industrial companies are far more likely to have mixed types of investor. This phenomenon can be explained by the fact that individual or family shareholders are mainly in small isolated communities which is created by few common investments. In contrast, the corporate shareholders in Turkey and Netherlands appear in both large and small communities. In small communities, they do not invest with other types of shareholders, while in large communities, they have relatively low occupation rate. Further detailed comparison of largest connected component has been provided in appendix A.5.

The co-invested structures of individual or family are small simple and pure and this supports a picture of the controlling power of family social unit as discussed in the work of Villalonga and Amit [31] and that of Yurtoglu [32].

4 Conclusion

A core strength of network science is its ability to model relationships between individuals while allowing us to capture the structure of the network on bigger scales and to find the impact of this structure on the individuals within the group. Here we have used this approach to build a network of shareholders and their relationships, as defined by common share holdings. The key to this is to be able to construct the network from real data sources which are difficult and expensive to obtain and require extensive cleaning. We have shown this can be done by producing networks for two different countries. An important aspect of our networks is that we retain information on the types of shareholder involved so that we provide a new perspective on the roles of these different types of shareholder.

One network feature of note is the way that closeness centrality is found to be of little use as it is highly correlated with degree. This stems from the fact that much of its behaviour is dominated by the network at large distances from any node where the network, at least statistically and in terms of the shortest path routes, acts like a random graph and so like a random tree.

Our network analysis has highlighted several features in the data. One particular one is that the role of the individual or family investor in Turkey is far more peripheral than found in the data for the Netherlands. We have seen this in percolation, diversity, and betweenness measurements and in the makeup of the network communities. Another observation has been the way what are termed Bank shareholders seem to have a different role in the two countries, more important than other types shareholders in the Netherlands and Turkey.

Looking ahead, one application of our methods in the context of finance would be to evaluate the risk in such networks. Our percolation measurement illustrates the principle. By removing nodes at random we see how the network has different vulnerabilities to random failures in different types of shareholder. We could also use our network to see how the loss of confidence of one shareholder might spread through the network, effecting the price of different companies in different ways. This would illustrate how negative (or positive) effects travel through the networks which will give rise to the systematic risk.

Another future direction is to look at similar data sets from different time periods and to see how the network changes over time. Can we find a model of the behaviour of shareholders at the microscopic scale which shows the macroscopic evolution of the network such as the phenomenon of takeovers?

Acknowledgment

The authors would like to thank Eduardo Viegas, Henrik Jensen, Tarun Ramadorai, Yangshen Yang and Nanxin Wei for useful comments.

A Appendix

A.1 Network Definition

We will set up the basic notation and definitions of the networks used in this work. We have a set of SHAREHOLDERS \mathcal{S} , labelled s_i , who hold shares in one or more COMPANIES, the set \mathcal{C} labelled c_j etc. In addition, each shareholder $s \in \mathcal{S}$ carries a TYPE label $\tau(s) \in \mathcal{T}$ where \mathcal{T} is the set of fifteen different labels given in Table 1. It is sometimes convenient to indicate the subset of shareholders of one particular type so we use \mathcal{S}_α to indicate the set of shareholders of type $\tau \in \mathcal{T}$

$$\mathcal{S}_\alpha = \{s | s \in \mathcal{S}, \tau(s) = \alpha\}. \quad (3)$$

We can use our data to define a CORPORATION-SHAREHOLDER NETWORK, \mathcal{B} in which the set of nodes, \mathcal{V}_B , are the union of the set of shareholders and companies, $\mathcal{V} = \mathcal{S} \cup \mathcal{C}$. An edge is present in this network between a shareholder and a company if the shareholder has shares in that company.

In practice our work focusses on a projection of the corporation-shareholder network onto just the shareholder nodes. That is we define the SHAREHOLDER NETWORK \mathcal{P} to have a set of nodes \mathcal{S} , the set of shareholders. An edge between two shareholders, say s_i and s_j , exists in this network if both s_i and s_j have invested in the same company (at a level above our threshold). In terms of an adjacency matrix \mathbf{P} for this network, we have that

$$P_{s_i s_j} = \begin{cases} 1 & \text{if } \sum_c B_{s_i c} B_{s_j c} > 0 \text{ and } s_i \neq s_j \\ 0 & \text{if } \sum_c B_{s_i c} B_{s_j c} = 0 \text{ or } s_i = s_j \end{cases}. \quad (4)$$

This ensures the shareholder network \mathcal{P} is a simple network.

A.2 Betweenness Centrality

A WALK is a sequence of vertices in which each node is connected by an edge to the next node in the sequence. A PATH is a walk in which no node appears twice. The LENGTH OF THE PATH is the number of vertices minus one, i.e. the number of edges traversed as one moves through the sequence of vertices.

For many centrality measures we consider the shortest path from an initial source node s and ending with a target node t . The number of shortest paths from s to t is denoted by σ_{st} as there can be more than one path of the same length between any pair of vertices. Given these shortest paths, we define $\sigma_{st}(v)$ to be the number of these shortest paths which pass through some v other than s or t . Then, the BETWEENNESS [33, 2] $b(v)$ of a node $v \in \mathcal{S}$ is defined to be

$$b(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}. \quad (5)$$

A.3 Closeness centrality

We will define CLOSENESS CENTRALITY $c(v)$ [34, 2] of a vertex v to be

$$c(v) = \frac{n-1}{\sum_{u=1}^{n-1} d(u, v)}, \quad (6)$$

where $d(u, v)$ is the shortest path distance between u and v and n is the number nodes in the component connected to node n .

A.3.1 Estimating Closeness

Consider first a general random graph, that is, one with a specific degree distribution but otherwise unconstrained, working in large sparse graph regime, $N \rightarrow \infty$, $\langle k \rangle \sim O(1)$. This type of configuration model graph can be constructed using edge rewiring. Suppose we start at a node of degree k . Then we might estimate that the number of nodes ℓ steps away from our starting node is

$$n_\ell = \bar{z}^{\ell-1} k, \quad \ell \geq 1, \quad (7)$$

where \bar{z} is some effective BRANCHING RATIO. That is we expect each node we arrive at ℓ steps away from our starting node, in some breadth first search out from the initial node, to be connected to an average of \bar{z} new vertices which are then $(\ell+1)$ steps away. The approximation here is that all nodes look the same as they must in a true random graph. The exception is the first node where we know that that has k neighbours if that node has degree k . However we note that statistically, all we are really saying in this approximation is that for most networks, taking a few steps is sufficient to allow us to sample any part of the network so statistically many networks will appear to be homogeneous on larger scales.

If we are being more precise, for a random graph near its phase transition, where we can assume a tree like structure, we know that \bar{z} will be the average degree of a neighbouring node minus one — we arrive on one edge going into a neighbour, leave on the remaining edges. Because the current degree of a neighbour $\sum_k k \frac{kp(k)}{\langle k \rangle} = \frac{\langle k^2 \rangle}{\langle k \rangle}$. So

$$\bar{z} = \frac{\langle k^2 \rangle}{\langle k \rangle} - 1. \quad (8)$$

However, for any given large network, we do not need to assume (8) is true, merely that there is some effective branching ratio such that (7) still works well.

To estimate closeness, we first estimate the maximum distance ℓ_{\max} by demanding that the total number of nodes connected to our starting node is the number in the Largest Connected Component N_{LCC} as we assume we are studying nodes in this component. This may be estimated as

$$N_{\text{LCC}} \approx \sum_{\ell=0}^{\ell_{\max}} n_\ell = 1 + k \frac{(\bar{z}^{\ell_{\max}} - 1)}{(\bar{z} - 1)} \quad (9)$$

Rearranging for $N_{\text{LCC}} \gg 1$, we find that

$$\ell_{\max}(k) \approx \frac{\ln(1 + N_{\text{LCC}}(\bar{z} - 1)/k)}{\ln(\bar{z})}. \quad (10)$$

Not surprisingly, if you start from a high degree node, a high k , your first step will reveal far more of the network and so take you closer to the remaining parts. Thus the maximum distance in a random graph drops as the degree k of the node increases.

Now we can use this to find the closeness $c(v)$ of a node v since this is defined to be the inverse of FARNES, $f(v)$, the average distance from a node to all other nodes. For the random graphs, or graphs which appear homogeneous on larger scales, we can estimate farness using (7) as

$$f(v) = \frac{1}{(N_{\text{LCC}} - 1)} \sum_{\ell=1}^{\ell_v} \ell n_\ell \approx \frac{1}{N_{\text{LCC}}} k_v \left(\frac{(\ell_v + 1) \bar{z}^{\ell_v}}{\bar{z} - 1} - \frac{\bar{z}^{\ell_v+1} - 1}{(\bar{z} - 1)^2} \right) \quad (11)$$

where we have used (9) and we write $\ell_v = \ell_{\max}(k_v)$ as the largest of the shortest path lengths from vertex v which has degree k_v . Not surprisingly this is dominated by the distance to the further nodes as in the tree they are the dominant contribution. We see that if $(\bar{z} - 1) \gg k/N$, i.e. if we are not close to the transition and we have a large N , then this result for farness gives us that $f(v) \approx \ell(v)$ so that

$$f(v) \approx \frac{\ln(N_{\text{LCC}}(\bar{z} - 1)/k_v)}{\ln \bar{z}}. \quad (12)$$

While in this limit a random graph, let alone a real graph, is not a tree, it shows that we should expect the closeness centrality measure to be correlated with the degree of a node. Indeed the prediction is that the inverse closeness (farness) should show a linear dependence on the logarithm of the degree of a node, $\ln(k)$, with a slope that is the inverse of the log of the branching ration minus one, $1/\ln \bar{z}$, that is

$$\frac{1}{c(v)} = f(v) = -\frac{1}{\ln \bar{z}} \ln(k_v) + a. \quad (13)$$

Since this expression is true where we do not have a tree, we do not expect the slope to match a the value of \bar{z} in a random tree (8). Rather, if we do find a linear relationship for the farness and logarithm of degree, then the slope is a way of defining an effective branching ratio.

A.4 Community detection algorithms

Louvain Modularity, is a scale value between -1 and 1 that measures the density of edges inside communities to edges outside communities and mathematically

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i c_j), \quad (14)$$

where A_{ij} represents the adjacency matrix between nodes i and j ; k_i and k_j are the sum of the weights of the edges attached to nodes i and j , respectively; m is the total number of edges in the graph. c_i and c_j are the communities of the nodes. The Louvain algorithm minimise the modularity effectively by first small communities are found by optimizing modularity locally on all nodes, then each small community is grouped into one node and the first step is repeated.

The Infomap community detection is based on the random walker's movements, which minimize the map equation. Map equation can be expressed in the form following Shannon's source coding theorem:

$$L(M) = q_{\curvearrowright} H(Q) + \sum_{i=1}^m p_{i\curvearrowleft} H(P_i), \quad (15)$$

where M is the modules or partitions of the network and each node is assigned to a module i . $L(M)$ is the description length of the trajectory of a random walker walking along the links of the networks. q_{\curvearrowright} and $q_{i\curvearrowleft}$ represent that the random walker enters and exits each module i , respectively. The detailed see the original work of Martin Rosvall and Carl T. Bergstrom [30].

A.5 Comparison of community detection results for largest component of Turkey

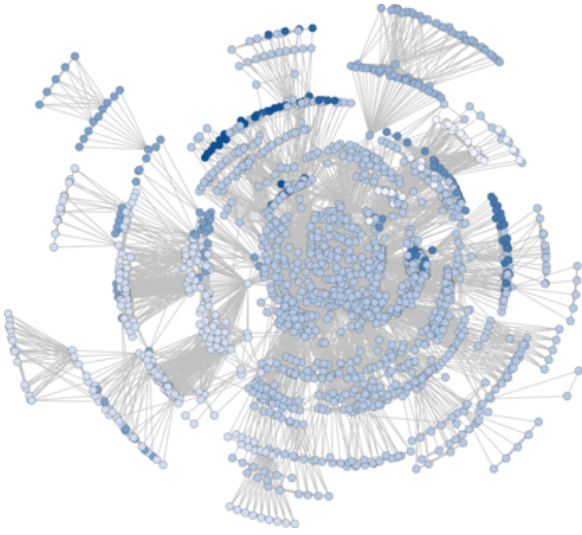
If the structure of communities is established well enough, the two should be able to give similar results [35]. After detecting the communities of the graphs using the two algorithms for 2 countries, we found that the percentage of nodes whose two communities containing the

same nodes is about 75% in Turkey. However, it is noticed from Fig. 12 that Louvain has a very large community size, while Infomap does not have this large one. In fact, Infomap takes the advantages of the modularity (network structures) together with the shortest description length partitions.

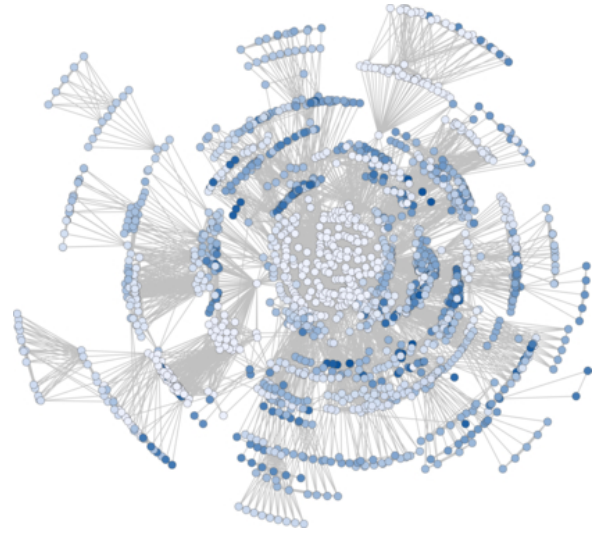
If we looking at the largest giant component, the two different methods are separating this component in different ways, see Figure 14. We can see from Fig. 14, most outside parts of the circles are drawn the same shape of nodes in the same colours which means the these nodes are in one community in both methods. In the center of the graphs, that nodes are coloured differently show these square nodes are in same community in Louvain but in different communities in Infomap method. In Table 4 we give out the statistics of the comparison of communities.

		Infomap	Percentage	Louvain	Identical	Ranking of Louvain
1st Largest	Size Community	130	100%	1199		1st
	Types	9		15		
2nd Largest	Size Community	65	100%	93		3rd
	Types	5		5		
3rd Largest	Size Community	58	100%	58	yes	6th
	Types	4		4		
4th Largest	Size Community	58	100%	75		4th
	Types	4		4		
5th Largest	Size Community	56	100%	56	yes	7th
	Types	5		5		
6th Largest	Size Community	51	100%	1199		1st
	Types	5		15		
7th Largest	Size Community	41	100%	41	yes	13th
	Types	4		4		
8th Largest	Size Community	38	100%	132		2nd
	Types	4		6		
9th Largest	Size Community	38	100%	38	yes	15th
	Types	4		4		
10th Largest	Size Community	37	100%	37	yes	17th
	Types	4		4		

Table 4. Table for comparison between the consisting companies in large community for Louvain and Infomap algorithms applied to Turkish network. It is ordered by the community size of the results of Infomap, the percentage 100% means this Infomap community is the subset of Louvain community in this row. The ranking of Louvain reveals the size ranking of this Louvain community.



(a) Louvain method



(b) Infomap method

Figure 14. This is the comparison between the two detection methods, the left one is for Louvain method and the right one is for Infomap method. The layout style is based on force-directed graph drawing. The number of unique communities for Louvain method is 9 and for Infomap is 124. Each colours represents a community and the colour schemes of the two methods are the same.

A.6 Louvain analysis of Individuals and Industrial in Turkey

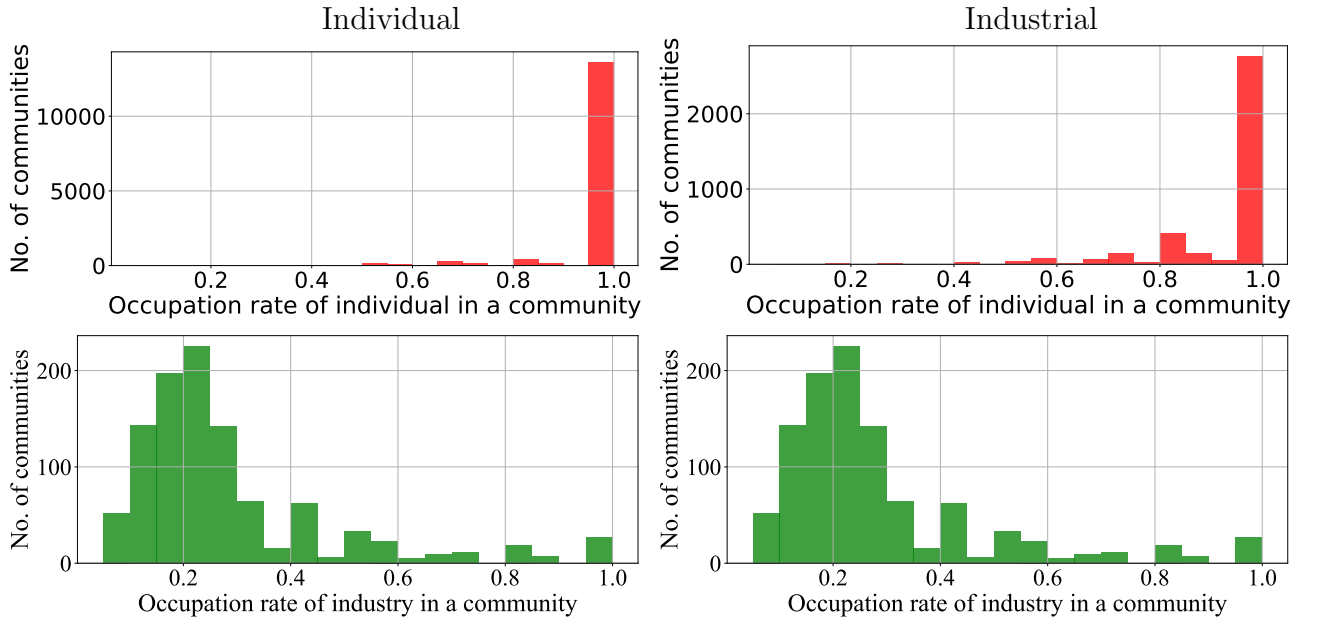


Figure 15. The bar plots of frequency analysis for One or more named individuals or families (upper ones), Corporate company (lower ones) in Turkey: Comparison between the frequencies of percentages of this type of owners within one community. The method used is Louvain. The figures in first row analyses all the community sizes while those in second row excludes small communities(including $CS \geq 3$)

A.7 Capital to Assets Ratio and Capital Adequacy Ratio

The capital to assets ratio is $\frac{\text{Capital and Reserves}}{\text{Assets}}$, where Capital and reserves include funds contributed by owners, retained earnings, general and special reserves, provisions, and valuation adjustments. Capital includes tier 1 capital (paid-up shares and common stock), which is a common feature in all countries' banking systems, and total regulatory capital, which includes several specified types of subordinated debt instruments that need not be repaid if the funds are required to maintain minimum capital levels (these comprise tier 2 and tier 3 capital). Total assets include all nonfinancial and financial assets. This information is from the data source The World Bank [25]

The Capital Adequacy Ratio is defined as

$$CAR = \frac{\text{Capital and Reserves}}{\text{Risk Weighted Assets}}, \quad (16)$$

and is the ratio of a bank's capital to its risk. To ensure its banks can absorb a reasonable amount of loss, national regulators can track a bank's CAR and comply banks with some capital requirements. The data for this paper is from CEIC Data [26].

A.8 Update of Data Base

The data of two countries is retrieved from BvD [24], which will be updated every year. New data sources will be added to the data base. The total number of known companies in a certain year changes. For example, 4% difference is observed from 2017 to 2018. However, the authors have downloaded the data and done the analysis at different years from 2016, 2017 and 2018. The results have no noticeable changes.

References

- [1] Brandes U, Robins G, McCranie A, Wasserman S. What is network science? *Net. Sci.* 2013;1(01):1–15. doi:10.1017/nws.2013.2.
- [2] Newman M. *Networks: an introduction*. OUP Oxford; 2010.
- [3] Arthur WB. Complexity and the economy. *Science*. 1999;284(5411):107–109.
- [4] Farmer JD, Gallegati M, Hommes C, Kirman A, Ormerod P, Cincotti S, et al. A complex systems approach to constructing better models for managing financial markets and the economy. *Eur. Phys. J. Spec. Top.* 2012;214:295–324. doi:10.1140/epjst/e2012-01696-9.
- [5] Acemoglu D, Akcigit U, Kerr W. Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*. 2016;30(1):273–335.
- [6] Vitali S, Glattfelder JB, Battiston S. The network of global corporate control. *PLOS One*. 2011;6(10):e25995.
- [7] Glattfelder JB, Battiston S. Backbone of complex networks of corporations: The flow of control. *Physical Review E*. 2009;80(3):036104.
- [8] Ohnishi T, Takayasu H, Takayasu M. Network motifs in an inter-firm network. *Journal of Economic Interaction and Coordination*. 2010;5(2):171–180.
- [9] Ohnishi T, Takayasu H, Takayasu M. Hubs and authorities on Japanese inter-firm network: Characterization of nodes in very large directed networks. *Progress of Theoretical Physics Supplement*. 2009;179:157–166.
- [10] Iino T, Kamehama K, Iyetomia H, Ikeda Y, Ohnishi T, Takayasu H, et al. Community Structure in a Large-Scale Transaction Network and Visualization. In: *Journal of Physics: Conference Series*. vol. 221; 2010. p. 012012.
- [11] Viegas E, Cockburn SP, Jensen HJ, West GB. The dynamics of mergers and acquisitions: ancestry as the seminal determinant. In: *Proc. R. Soc. A*. vol. 470. The Royal Society; 2014. p. 20140370.
- [12] Li H, An H, Huang J, Huang X, Mou S, Shi Y. The evolutionary stability of shareholders' co-holding behavior for China's listed energy companies based on associated maximal connected sub-graphs of derivative holding-based networks. *Applied Energy*. 2016;162:1601–1607.
- [13] Li H, Fang W, An H, Gao X, Yan L. Holding-based network of nations based on listed energy companies: An empirical study on two-mode affiliation network of two sets of actors. *Physica A*. 2016;449:224–232.
- [14] An P, Li H, Zhou J, Chen F. The evolution analysis of listed companies co-holding non-listed financial companies based on two-mode heterogeneous networks. *Physica A*. 2017;484:558–568.
- [15] Li H, Fang W, An H, Yan L. The shareholding similarity of the shareholders of the worldwide listed energy companies based on a two-mode primitive network and a one-mode derivative holding-based network. *Physica A*. 2014;415:525–532.
- [16] Guan Q, An H, Liu N, An F, Jiang M. Information Connections among Multiple Investors: Evolutionary Local Patterns Revealed by Motifs. *Scientific Reports*. 2017;7(1):14034.

- [17] Berle AA, Means GGC. The modern corporation and private property. Transaction publishers; 1991.
- [18] Porta R, Lopez-de Silanes F, Shleifer A. Corporate ownership around the world. *The Journal of Finance*. 1999;54(2):471–517.
- [19] Lawrence PR, Lorsch JW. Differentiation and integration in complex organizations. *Administrative Science Quarterly*. 1967; p. 1–47.
- [20] Zeitlin M. Corporate ownership and control: The large corporation and the capitalist class. In: *Classes, Power, and Conflict*. Springer; 1982. p. 196–223.
- [21] Simon HA. The architecture of complexity. In: *Facets of systems science*. Springer; 1991. p. 457–476.
- [22] Christensen K, Moloney NR. Complexity and criticality. vol. 1. Imperial College Press; 2005.
- [23] Gai P, Kapadia S, et al. Contagion in financial networks. 2010;.
- [24] Dijk BV; 2017. Available from: <https://www.bvdinfo.com/en-gb/home>.
- [25] Bank TW; 2018. Available from: <http://www.worldbank.org/>.
- [26] CEIC, D (2018) Global Economic Data, Indicators, Charts and Forecasts <https://www.ceicdata.com/en/>
- [27] Aldous D, Lyons R, et al. Processes on unimodular random networks. *Electron J Probab.* 2007;12(54):1454–1508.
- [28] Benjamini I, Schramm O, et al. Recurrence of distributional limits of finite planar graphs. *Electronic Journal of Probability*. 2001;6.
- [29] Blondel VD, Guillaume JL, Lambiotte R, Lefebvre E. Fast unfolding of community hierarchies in large networks. *J.Stat.Mech* 2008; p. P10008. doi:10.1088/1742-5468/2008/10/P10008.
- [30] Rosvall M, Bergstrom CT. Maps of random walks on complex networks reveal community structure. *Proceedings of the National Academy of Sciences*. 2008;105(4):1118–1123.
- [31] Villalonga B, Amit R. Family control of firms and industries. *Financial Management*. 2010;39(3):863–904.
- [32] Yurtoğlu BB. Corporate Governance and Implications For Minority Shareholders In Turkey. 2003;.
- [33] Freeman LC. Centrality in social networks conceptual clarification. *Social Networks*. 1978;1(3):215–239.
- [34] Bavelas A. Communication patterns in task-oriented groups. *The Journal of the Acoustical Society of America*. 1950;22(6):725–730.
- [35] Lancichinetti A, Fortunato S, Radicchi F. Benchmark graphs for testing community detection algorithms. *Physical Review E*. 2008;78(4):046110.