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ABSTRACT

Political Connections and Firms: Network Dimensions*

Business and politician interaction is pervasive but has mostly been analysed with a binary approach. Yet the network dimensions of such connections are ubiquitous. We use a unique dataset for seven economies that documents politically exposed persons (PEPs) and their links to companies, political parties and other individuals. With this dataset, we can identify networks of connections, including their scale and composition. We find that all country networks are integrated having a Big Island. They also tend to be marked by small-world properties of high clustering and short path length. Matching our data to firm level information, we examine the association between being connected and firm-level attributes. The originality of our analysis is to identify how location in a network, including extent of ties and centrality, are correlated with firm scale and performance. In a binary approach such network characteristics are omitted and the scale and economic impact of politically connected business may be significantly mis/under-estimated. By comparing results of the binary approach with our network approach, we can also assess the biases that result from ignoring network attributes.

JEL Classification: L14, L53, P26

Keywords: connections: PEPs, networks, rents

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NON-TECHNICAL SUMMARY

Politically connected businesses cut across political systems, regions and levels of development. Our paper focusses on economies in East and Central Europe, Russia and, as a comparator, Spain. Using a new and unique dataset that identifies Politically Exposed Persons (PEPs) and their links to companies, politicians and political parties, we identify not only the scale of the phenomenon but also the links between individuals, politicians, political parties and different types of firms, as well as the complex configurations of the resulting networks in each of the countries.

Drawing on the tools of network analysis, we show that each of these countries is characterised by a giant component or Big Island. Nevertheless, we find evidence that their networks have small-world properties, with high clustering and short path length due to a relatively small number of bridging connections. In the network space, however, there are also very different configurations that reflect, inter alia, differences in political and other institutions. Given the region's recent past, it is perhaps not surprising that State-Owned Enterprises (SOEs) are prominent and tend to have positions in the network with relatively high betweenness or centrality. There is a clear difference in this regard when compared with Spain.

Matching the information on connections to firm level data from the Orbis dataset, we demonstrate that there is a positive and robust correlation between the levels of sales, output, wages as well as a performance variable – the return on assets - and being connected. Further, network features can influence these associations. We find clear evidence that the location in a network, the extent of ties and betweenness or centrality is often positively, and significantly, associated with firm level indicators for the scale of activity. Network variables are also seen to be significant when related to performance as measured by the Return on Assets. In other words, not only are networks likely to be important in shaping how connections arise and propagate but they are also important in shaping the returns to connections.

1 Introduction

The interaction of firms and politicians and the outcomes – notably in terms of rent seeking – that result has been documented across a wide range of political and economic systems.[1] State-owned enterprises have been found to be particularly responsive to politicians, although family and other network ties to politicians can deliver advantage to private companies. Regulatory privilege has been found to be an important way in which profits and market share can be boosted. The channels include preferential access to credit, assets and infrastructure (Khwaja and Mian, 2005; Diwan et al., 2015). The flow of transactions may not be one-way, as firms may also favour politicians, including by creating employment at opportune moments in the electoral cycle (Bertrand et al., 2004). These multiple modes through which connections are realised is further qualified by differences across countries in political and other institutions. High corruption levels and weak institutions tend to be associated with more politically connected firms (Faccio, 2006), while, not surprisingly, political connections tend to be endemic in autocratic regimes.

The focus in this paper is on how businesses and politicians interact in a set of transition economies, specifically Bulgaria, Hungary, Romania, Russia, Serbia and Slovakia. Existing studies already indicate that political influence over business and commercial decisions has been – and often continues to be – significant, not least because of the legacy of large public sectors and their subsequent unwinding, including through discretionary asset sales and privatisation (Commander, 2016). In addition, public contracting in the region has tended to be associated with the application of preferential treatment or favouritism. Lack of integrity in public procurement practices not only appears widespread but has also been explicitly linked to the political cycle (Palguta, 2014; Doroftei and Dimulescu, 2015; Koren et al., 2015). As is the case more generally, autocratic regimes in the region appear particularly prone to cronyism with widespread resort to connections in the allocation of assets and contracts.

We also include a Western European comparator, Spain, in the analysis. While the latter sits higher on most rankings of competitiveness and/or governance than the transition economies and has a longer history of democratic institutions, scores for diversion of public funds, favouritism by government officials or irregular payments by firms, show Spain to be comparable to some transition economies (World Economic Forum, 2014).

Existing research on political connections has mostly concentrated on establishing the incidence and consequences of connections, generally at the level of the connected firm. Some papers have also tried to establish the welfare consequences (Cingano and Pinotti, 2013). Yet, it is evident that connections are rarely, if ever, simply binary in nature. Their network

[1] See, inter alia, from a large literature, Faccio (2006, 2010); Fisman (2001); Boubakri et al. (2008); Johnson and Mitton (2003).

properties tend to be important. Indeed, the ubiquity of networks in the social and economic life of humans is now well understood. Networks summarise sets of relationships between agents, often with particular structures. As such, they tend to shape or reflect specific opportunities that link individuals, companies and other entities, such as political parties. Available evidence indicates that network structures vary significantly - some have a large number of ties or edges while others have higher centrality secured by bridges through which those ties or edges pass. Some networks may be more hierarchical than others, maintaining more edges and higher centrality than so-called distributed networks. Dense networks, defined by high clustering and a low number of edges, tend to generate bonding capital that can be useful in leveraging valuable assets or connections and hence in ensuring cooperation.[2] By contrast, more diffuse networks with low clustering and many edges (high degree) tend to be more suited to providing information or access to information; bridging capital, in other words (Granovetter, 1973).[3] A network may also have small world properties where locally dense clusters of nodes are connected to many others through a small number of bridging connections (Humphries and Gurney, 2008). For political connections with firms, dense networks aimed at maximising cooperation with peer pressure might be expected to predominate.

Despite their evident relevance, curiously little attention has been paid to mapping the format and nature of connections between firms, politicians and political parties and to understanding how different types of networks may affect outcomes, including the benefits. Our paper uses a unique dataset that documents politically exposed persons (PEPs) and their links to firms – private and state-owned – as well as to political parties and other individuals. We also are able to match these individuals through ownership and shareholder status to firm level balance sheet and performance data. Not only does this particularly rich dataset document political connections across countries, but it also allows identification of the types of connections that link individuals, parties and companies at a country level. As such, our main objectives are to understand how connections are actually configured, while also analysing how different types of connections may have an impact on firms. The existing literature has concentrated on identifying political connections in a binary manner and then exploring that association – sometimes in a causal way – with outcomes. What is particularly original in our paper is that connections are analysed for their network properties, including the type and location.

The paper is organised as follows. Section 2 reviews the main findings of the large literature on the political connections of companies. Section 3 describes the datasets that

[2]Dense networks can be composed of few agents closely linked or many agents with small average distances between them.

[3]Bonding and bridging capital are terms employed by Putnam (2000).

are used. Section 4 examines the network features of connections picking out differences across countries. Section 5 then examines the association between firm characteristics and performance, using a number of indicators, and being politically connected. Although the base estimates – as is common in the literature – relate variables to whether or not a firm is connected, we augment the analysis by taking account of the nature of those connections and their network properties, such as the extent to which a connection is strategically important as measured by the extent to which a node lies between other nodes. Section 6 concludes.

2 Consequences of connections

Being politically connected has mostly been viewed through the lens of the benefits that such connections confer. The scale of benefits is generally calibrated relative to not having connections. In the broad literature, the focus has mostly been on indicators such as growth in revenues, leverage, taxation, subsidy receipt, productivity and accounting performance, as well as stock market valuation.

When researchers have matched information linking politically connected persons with firm or establishment level data, the evidence across a variety of sectors and economies suggests that political connections can – but not always – support superior financial performance. This may not necessarily be associated with productivity gains. Rather, higher market shares and attenuation of competition can be one outcome (Cingano and Pinotti, 2013). Connections may primarily facilitate survival and employment but not growth in productivity and innovation (Akcigit et al., 2017). Faccio (2010) have argued that although connected firms may have larger market power, they tend to have poorer accounting performance than non-connected firms and this difference is accentuated by the nature of connection. In the case of newly privatized companies, there is some evidence that political connections impede performance relative to non-connected companies (Boubakri et al., 2008).

As regards dynamics, Ben-Nasr et al. (2012) use an event study approach with multi-country observations to argue that firms' performance changes after political connections are secured. Such connections support firm performance and are also associated with an increase in financial leverage, long term debt and liquidity ratios. In general, it appears that connected firms tend to have higher leverage and more exposure to debt financing, measured in terms of long-term debt. Connected firms commonly pay lower taxes but the difference is not always significant. The ability to evade taxes or, for example, to avoid tariffs and non-tariff barriers can be ways in which connected companies achieve preferential status (Rijkers et al., 2015). In most contexts, however, data limitations restrict the scope of analysis, notably in quantifying the benefits flowing to unlisted, privately held entities, while benefits may also be industry-wide rather than firm specific.

The network dimension of connections can be seen in some of the existing research. For example, Bertrand et al. (2004) argue that networks in France get formed around attendance at a common university, prior employment as a civil servant, as well as the political party of the government under which a CEO has served. Companies managed by connected CEOs have lower rates of return on assets than those managed by non-connected CEOs and have particularly weak financial performance and high labour to capital ratios in cases where the companies are located in politically contested areas. Connected firms also tend to make lower tax payments and receive more subsidies. Such firms also tend to reciprocate benefits by taking actions supportive to politicians at opportune moments.

The body of existing research also shows that political connections to firms exist across a wide range of economies, including at different levels of income and institutional development, as well as at differing degrees of de-centralisation. They also cut across political systems, although autocracies seem to select and generate rents for connected parties in rather different ways than more competitive political systems.

Finally, severing, or at least limiting, political connections has motivated the adoption of policies for privatising assets. Boycko et al. (1995), for example, argued that large-scale (and rapid) privatisation in Russia was the principal way to ensure that politicians could no longer influence company decisions. Yet two decades later, evidence from Russia and other transition economies indicates that those objectives have, at best, been partially achieved. In fact, a striking feature has not just been the persistence of state owned enterprises (and even the reversal of policy, as in Russia) but also the persistence of networks tying former SOE managers – subsequently owners – to politicians, as well as to others of their own type. Part of this can be attributed to the way in which privatisation has been engineered (Megginson and Netter, 2001), but also to the deep roots of the networks linking key players.

3 Data description

We use two main data sources in the paper. The first is a database compiled using publicly available information that contains an exhaustive list of Politically Exposed Persons (PEP) in each country. These data will, henceforth, be referred to as *PEPData*. In addition, we use Bureau van Dijk's *Orbis* dataset that provides ownership and shareholder information, along with balance sheet and financial information, for companies in each of the countries.

PEPData classifies PEPs consistent with widely used definitions, such as that provided by the Financial Action Task Force (FATF), but also extends the definition to incorporate the business relationships of PEPs. The dataset has eight categories of PEPs. These comprise individuals in International and Regional Organisations, National, Sub-national and Local Government, State-Owned Enterprises and State-Invested Enterprises, as well as Non-Governmental Organisations. They include all senior political and government leaders and officials but exclude lower level officials. In addition, based on their connection to the primary PEP, links with direct family members and close business associates or advisers are included.

Detailed information for each PEP has been compiled from several sources, including from sanctions, regulatory and legal lists. In addition, a variety of media sources have been used to identify individuals and entities not found on official lists. Consequently, the dataset contains a list of names, aliases and other individual details and evidence on the positions that an individual has held. Each identified individuals links to either a political party, other PEPs or to specific companies or financial institutions are noted, as are links to sources.

For the purposes of our analysis, the data are organised around five main categories. The first two include PEPs, i.e., persons, while the other three comprise entities:

(a) Political Individuals – persons currently holding or having held a political position, including in a political party or having been elected,

(b) Other Individuals – any person appointed (as opposed to elected) to a PEP position or appointed to a government position, as well as immediate relatives or close associates of primary PEPs,

(c) Political Party – any registered and active political party,

(d) State-Owned or Invested Enterprises and,

(e) Private companies or financial institutions.

PEPData also includes links between all of these five categories. This allows us to go beyond the existing literature. The latter has focussed on having, or not having a (0-1 binary-type) link between the first two ((a) and (b)) categories and the latter three ((c), (d) and (e)). However, as our analysis shows, there is a web of relationships, direct and indirect, that matter and which are not captured by this approach.

We additionally link individual PEPs in *PEPData* to firm level information. This is done in the following manner. The first step involves taking the name of the PEP and the explicit link to a company that is directly specified in *PEPData*. We then associate through the name of that company with firm-specific financials and other information (e.g., on employment) contained in Bureau van Dijks *Orbis* dataset. Since firm names are used to match the two datasets, this is referred to throughout the paper as the Firms Name Method (henceforth, FN). In addition, we take the names of the PEPs and then search to see whether they are shareholders or owners of firms, as listed in the *Orbis* dataset for each country. Because of common names and other possible sources of error, each possible match was subsequently reviewed manually to ensure the integrity of the match.[4] A substantial number of matches were discarded as false positives and a revised set of matches adopted.[5] As names of people are used to match the two datasets, this is henceforth referred to as the PEPs' Name Method (PN). Matches from both methods are then used to build the final dataset that contains the total known connections between PEPs and entities.

Table 1 provides some basic descriptive statistics including the number of PEPs identified under each method for each country. Using the FN Method gives a significant amount of variation in the number of companies associated with PEPs. For example, in Bulgaria, Hungary and Serbia only 46-88 firms are identified by this method, as against between 631-800 in Russia and Romania respectively. The number increases significantly when including the PEPs Name Method (PN). For the consolidated measure (FN+PN), the total number ranges between 384 in Serbia and 4568 in Russia.[6]

Using the assets of PEP-connected companies to get an approximation of the aggregate scale of connected companies, Table 1 shows that they account for around 0.8 of GDP in Bulgaria and Hungary, between 2.5-5 percent in Slovakia, Serbia and Romania and >15 percent in Russia in 2013. The massive share for Spain relative to the other countries is due to the fact that in the latter SOEs play a more significant role. In Spain, by contrast, some massive private firms are connected, swelling the share.[7]

Concerning the properties of connected firms depending on the method of identification, applying the size criteria (incorporating revenues, assets and employment) indicated in Appendix Table B1, it appears that the share of small firms among connected firms is far higher when applying the PN Method; 77 percent as against 40 percent for the FN Method. Correspondingly, the share of large and extra-large firms comprises 30 percent for FN identification but only 6 percent when using the PN approach (see Appendix Table B2). This disparity is true for all countries, bar Bulgaria. In addition, regarding the size distribution, Spain looks different as between 27-52 percent of connected firms are large or very large – a

[4]Researchers based in each country and with extensive local knowledge checked each match using a range of complementary sources and documentation. Only verified matches were maintained and false positives and ambiguous matches were discarded.

[5]We explored alternative approaches, such as stochastic matching through location used by Koren et al. (2015), but found that data gaps were too large.

[6]Note that for Russia, when using the FN Method a very large number of firms appeared, attributable to duplication of common firm names (e.g., Sputnik). To avoid this, we use only those firms with a unique name. For the PN Method, each entry was carefully cross-checked to ensure no duplication.

[7]For example, the total assets of just three connected companies amount to over 20% of GDP.

far higher share than for the others where the average is between 4-11 percent.[8] Concerning sector affiliation, there are differences depending on method of identification, but they are not that significant. The share of firms in wholesale and retail trade, as well as professional and scientific, is clearly higher for the PN Method, while the reverse is true for financial and insurance services. Comparing connected and non-connected firms, the former are mostly under-represented in manufacturing, construction and trade while being over-represented in all countries in professional and scientific activity.

Table 2 provides mean and median values for a range of firm characteristics and performance indicators distinguishing between connected – as measured by FN+PN – and non-connected firms. These variables are taken from *Orbis* and comprise levels of assets, capital, sales, employment, wage bill and wage per worker, output per worker, as well as the return on assets (ROA) – defined as the ratio of net income to total assets – leverage (a proxy for access to debt financing) and the tax rate.

For a number of variables, connected firms are consistently larger than non-connected ones. This discrepancy is mostly the case for sales but also for employment and average wages. In the case of ROA, connected firms mostly have lower values than non-connected ones. For leverage, mostly there is little difference although for both Hungary and Romania, connected firms are on average less leveraged. There is no clear pattern for the tax rate. The table also indicates that for both groups of firms, there is a large difference between mean and median values that indicates skewness to the right.

Finally, given that widespread evidence shows that politicians are particularly prone to trying to influence the actions of state owned enterprises (SOEs), such as the amount of hiring, *Orbis* data show that for employment, the SOE share is particularly large in Serbia and Bulgaria (18-21%) and, to a lesser extent in Russia. The employment share for Spain (<6%) is roughly comparable to Hungary and Slovakia. For sales, the SOE share is huge in Russia (>58%) and also substantial (>18%) in Serbia. Elsewhere, the share falls in the range of 4-6%.

4 How are connections configured?

Connections are rarely atomistic tending, rather, to have strong network dimensions. In this section, we try to understand more about the properties of such networks and, in particular, the links running from individuals and/or entities to firms, both private and state-owned. We are interested in identifying the scale of network connections, the factors that appear to sort individuals into networks – such as kinship or allegiance to a political

[8] Country level size and sector breakdowns are available on request.

party – as well as the scope, density and likely robustness of those networks. In a subsequent section, we go on to look at how network attributes correlate with the firm level variables summarised in Tables 1 and 2.

4.1 Some network descriptives

Our objective is to study how firms and political exposed persons (PEPs) are linked and the economic impact of those links. The main innovation in this paper is to look beyond the binary character of the connection, i.e., whether a firm is connected or not, and identify whether connections are direct or, as in most cases, indirect through a network. So for example, in a binary case, some firms may look as if they are not connected, yet in reality they may be connected to PEPs indirectly as through connections to third parties that are, in turn, directly connected to PEPs. These third parties may be other firms, or political parties, or some other entity. In addition, some firms may be connected to multiple PEPs as well as many other firms, and thus be super connected. Likewise, some PEPs may act as hubs with many spokes emanating from them. In a binary approach, all these network characteristics will be lost and the scale and impact of politically connected business may be significantly mis/under-estimated.

By definition, a network is composed of nodes and edges. In our case,[9] the nodes are firms, individuals, and political parties and the edges are the links between these entities. Firms are split into two groups, private and SOEs while individuals can also be separated between political individuals, and others.[10] A network consequently represents relationships between agents, while also providing some form of structure for those relationships.[11] Before deploying all the network analytics – betweenness, clustering, density and so on – it is useful to begin with some simple statistics and to look at the network from the point of view of the firms. In other words, this is to describe the network by looking at how many connections firms have, and with what types of entity.

Table 3 gives the percentage of firms (i.e. nodes) grouped according to the number of connections and whether a firm has connections exclusively with other firms or with firms and/or other entities. It is useful to single out the group of firms that have connections only with other firms, because this is a group where firms are linked with PEPs only by an indirect link (and this indirect link may or may not be intentional). How large is the group

[9]Firms can also be connected through inter and intra-industry trading, but such transactions (as for intermediate goods and services) are not measured in *PEPdata* nor is this dimension being considered in the paper.

[10]*PEPdata* also contain other entities, such as international organizations.

[11]A good review of the wider literature on networks is Ward et al. (2011), see also, inter alia, Do et al. (2015); Goyal et al. (2006).

of firms with only connections to other firms? In Spain, for example, firms with only one link (in network terms with degree 1) are split almost 40-60 between the group of firms that have connections with other entities and those that have connections only with other firms. However, for the other - transition - countries, the share of firms with degree 1 and with connections to other entities is much larger, indicating that indirect connections (of a firm to a PEP via another firm) are less common, except perhaps in Russia.

Interestingly, this split is not constant when considering firms with degree 2, 3, 4 or ≥5. It could be expected that as the number of connections increases, and with it the size of the firm, the proportion of firms with connections with other entities would increase. For example, in Russia, firms with connections with only other firms account for 40 percent of the group of firms with one connection, but only 2 percent for the group of firms with ≥5 connections. A similar pattern is observed for Spain and the other countries.

The rightmost column displays the split at the economy-wide aggregate level. Shares are not uniform across countries. In Russia and Spain, about three quarter of firms belong to the group that have connections with diverse types of entities. In the other countries, this group has a larger share that reaches 97 and 99 percent in Hungary and Slovakia respectively.[12]

What is the distribution of firms in terms of number of connections (or degree)? Figure 1 shows that the distribution is quite left-skewed, with the most common group of firms being that with the smallest number of connections. This skewness parallels that of the size of firms, as large firms to the right of the distribution are both those that have many connections and are much fewer than smaller firms with limited connections.

For firms not exclusively linked with other firms, Table 4 indicates that connections with 'individuals' are the most common type. This table focuses only on the rows of Table 3 that contain firms that have diverse connections, i.e. connections that are not exclusively with other firms. An example may be useful to understand how the percentages in Table 4 are calculated. Consider the 50 percent that represents the share of Russian firms with 2 connections (not exclusively with other firms) that are linked to individuals. This percentage is calculated as the ratio of the number of firms with two connections that are linked to individuals (515 firms) over the number of firms with two connections (with other firms, individuals, political parties and so on; a total of 1,034 firms).[13] Note that the percentages in Table 4 cannot be summed across rows, as they are calculated as the ratio of the number of firms with a fixed number of connections with a specific entity to the total number of

[12]Note that the bottom panel, which includes all countries, does not provide much insight since it basically mirrors Russia, as this country dominates the others in terms of number of firms in the dataset.

[13]Note also that these 1,034 firms are the firms which do not have connections exclusively with other firms, and represent 57 percent of the total number of Russia firms with two connections (as shown in Table 1), which includes both the group of firms with exclusive connections with other firms and the group with diverse connections.

firms with that specific number of connections. Apart from the first column, the rows are not mutually exclusive, as one firm with, say, 3 connections can appear in multiple rows as it may have one connection with an individual, one connection with a political individual, and one with a party.

Table 4 highlights three important features of these networks. First, the largest share of firms with 'diverse' connections have links to individuals, followed by links to other firms, and then to political individuals. Second, the larger the number of connections (remembering that this is a group with fewer firms), the higher is the percentage of connections with individuals (at $\geq$90 percent). This indicates that when firms have multiple connections, it is almost certain that they will have a connection with an individual (a PEP). Third, in no country save Spain, do firms have direct connections with political parties. The latter, most likely, connect people rather than firms.

This descriptive section has highlighted the fact that individuals (PEPs) are indeed the hubs of the network and, further, that they become increasingly important for larger, and more connected, firms. However, the percentages reported in Tables 3 and 4, while informative, do not capture the whole story. To do that, a set of network analytics needs to be deployed.

4.2 Network analytics

Networks are commonly represented in terms of degree (the number of links sent to a node) and density (as indicated by the ratio of ties in a network to the total possible number of ties). In addition, measures of betweenness (the extent to which a node falls between other nodes); closeness (how close nodes are to each other); clustering (the extent of locally dense clusters of nodes); path length or distance (the number of steps to connect a pair of nodes), as well as neighbourhood or proximity measures can be employed.

For the purposes of our analysis, the idea of centrality, or how important particular nodes are in a network, is of particular interest. Centrality is best captured by the betweenness measure. However, there may be significant variation in how centrality is configured. For example, in a small-world network, nodes are located in locally dense clusters but can reach other nodes through a small number of bridging connections (Goyal et al., 2006). In what follows, we apply these measures in order to describe the main features of networks across the selected countries. But, first, some definitions:

For a node i we have

$$Degree_i = Number\ of\ edges\ connected\ to\ i$$

$$Geodesic\ Distance_{ij} = Minimum\ number\ of\ edges\ required\ to\ reach\ node\ j$$

$$Betweenness_i = \sum_{i \neq j \neq k} \frac{Number\ of\ distances\ from\ j\ to\ k,\ through\ i}{Number\ of\ distances\ from\ j\ to\ k}$$

We can take the average for all nodes to get a network-level measure, noting that this will grow with $\log(N)$ where N equals the number of nodes. Moreover, for a network we have:

$$Density = \frac{Number\ of\ edges}{Number\ of\ Nodes * (Number\ of\ Nodes - 1)}$$

$$Clustering\ Coefficient = \frac{Number\ of\ closed\ triplets}{Number\ of\ triplets}$$

A *triplet* is a set of three connected nodes and a *closed triplet* a set of three connected nodes where each one is connected with both others. *Geodesic distance* is also called *shortest path length* and the way the $clustering\ coefficient$ is calculated is called $transitivity$.

In Figure 2 we give a simple illustration for two, stylised examples. On the left hand side, node A has degree 3; the distance to B is 1 (and is the same for C and D). The betweenness of A is 3 (viz., A is between BC, BD and CD). All the others have degree 1, distance to A, 1 and distance to others, 2 with betweenness 0. The network density is 3/12=25% and the clustering coefficient 0. For the right hand example, the betweenness of A becomes 0 (in fact, everyones betweenness becomes 0), the density is 6/12=50%, and the clustering coefficient becomes 1.

4.3 Network properties

We turn to explicit consideration of the characteristics of networks. Specifically, we describe the extent and detail of connections running between individuals, as well as between individuals and institutions in the seven countries. As mentioned above, *PEPData* documents the links that PEPs may have both with other individuals (including other PEPs), as well as with specific firms and political parties. We document the size and composition of the networks, paying particular attention to their components and extent of integration. We consider the extent to which these networks have dense or diffuse features along with evidence of small world properties, where clusters have the ability to link to other parts of the network through a limited number of bridges. The focus also falls on location in the network specifically in the context of centrality. These attributes are subsequently incorporated explicitly in the empirical analysis of Section 5.

4.3.1 Network size

Table 5 provides information about the size of the network, as measured by the number of nodes, in each country. The information is broken down by type of actor, namely; private firm; state-owned enterprise; political party; political individual; other individuals (including relatives). We report an adjusted measure of network size that excludes those family relatives (the overwhelming majority) that have no betweenness – in other words, do not lie between any other nodes and hence are largely irrelevant from a network perspective.

There are significant differences in the size of the network across countries. In absolute terms, Russia has the largest network followed by Spain. Both Hungary and Serbias networks are far larger than neighbouring Slovakia and Bulgaria. Adjusting for population, the network ranking has Russia very clearly at the top followed by Serbia, Hungary, Romania and Slovakia and, lastly, Spain. There are also clear differences in composition: Spain has significantly more political parties and political individuals. In contrast, for Russia not only is there a relatively small number of political parties, but the level and share of SOEs is particularly high. The latter comprise around 9% of the total network, as against an average <3% for the other countries. Romania has a relatively large share of private firms in its network. In all countries, individuals and political individuals comprise between 85-94% of the total network size.

Given our interest in the links to SOEs and private firms, Table 6 reports shares for different types of connections by country. SOE connections are mostly with individuals and, then, politicians[14] (the mean share for both is >5%). In Spain, connections to politicians for both SOEs and private firms comprise particularly high shares. In Bulgaria and Russia there is also a relatively strong connection of SOEs to other SOEs. For private firms, the picture is rather more diverse. Links to politicians are again important in Spain but, elsewhere, the shares of individuals are mostly the largest although that for other firms is also a substantial component; in Romania it is the largest share.

4.3.2 Network components: Big Islands

Aside from the absolute size of the network, it is necessary to look at the constituent parts of the network. A component is composed by taking together all the nodes that are connected to each other (irrespective of their distance) so that the whole network can be divided into components (islands). The issue is whether there exists a component in which the greater part of the network falls, rather than, say, being composed of small fractional

[14]Note that the terms 'political individual' (as per definition (a) on page 6) and 'politician' are used interchangeably.

parts. We call the largest component a 'big island' as its size is much greater than all the others.

Table 7 indicates that for all the countries there is indeed a giant component or big island that comprises up to 76 percent (in Romania) of the adjusted network size. Spains big island holds two thirds of the network; a situation roughly comparable to that in Hungary and Romania. Russias relatively small big island may reflect a difference originating in political systems as in democratic settings, the big island tends to be more prominent. In addition, there is less integration through the network and hence more fragmentation. In Russias case, this may partly be a function of geographical size. Finally, it should be noted that none of the countries have any second level component of significant magnitude, indicating that network activity is concentrated in the big island.

Table 7 also breaks down by category the respective shares contained in the big island. For political parties, there is some – but not massive – cross-country variation. The main outlier is Spain's where only 18 percent of its (many) parties are in the big island (as against an average of 66 percent for the other countries). This may reflect the decentralized nature of Spanish politics. With the exception of political parties, Spain's respective shares are, however, broadly comparable to the others. For political individuals, their inclusion in the big island is everywhere substantial, with the exception of Russia with only 29 percent. For both private firms and SOEs, with the exception of Bulgaria in the latter instance, >60->90 percent fall in the big island.

Appendix Figures C1-C7 also permit visualization of the big island of each country with scaling by degree (or number of edges). It can be seen that in Russia political parties are not only less numerous but also less connected to other entities. The network in Russia is heavily influenced by the SOEs, as also private companies, and the links between the two types of firm. By contrast, in Spain the larger number of political parties stands out, as does the relative absence of SOEs and private firms. Although the scale and location of political parties varies significantly across the other economies, the SOEs' place in the network is clearly significant and, perhaps, the dominant feature. Private firms' place in the respective networks also varies but their presence is more notable when compared with Spain.

4.3.3 Properties of the Big Island

Turning to the properties of the big island, Table 8 shows limited difference in the average degree (or number of links sent to a node) across countries, although Spain, Russia and Romania are somewhat higher. As regards density, both Bulgaria and Slovakia have a higher ratio of ties in the network relative to the total possible number of ties, while Russia and Spain have the lowest ratios. Although there is some clear variation, most of the networks we observe are not that tightly connected, suggesting that diffuse networks are present. Pursuing this point, the clustering coefficient further indicates what share of a person/entitys neighbours are neighbours of each other and hence whether dense clusters of nodes are present in the network. Although there is some variation across countries, with higher clustering in Serbia, in general the clustering coefficient is quite low and especially so in Russia. The complementary indicator of average distance or path-length exhibits less variation across countries.

An obvious question concerns whether these networks have small world properties characterised by high clustering and low path lengths. This is where nodes tend to be concentrated in clusters but with the ability to reach other nodes in the population through a small number of bridging connections. Most generally, such properties exist if the average distance between nodes is very small relative to the size of the population. To assess the 'small-worldness' of the networks, one option is to use the method of Humphries and Gurney (2008) by generating an Erdos-Renyi (E-R) random graph with the same number of nodes and edges, and after calculating their Clustering Coefficient and Average Distance, use them to get the following;

$$S = \frac{\frac{Cluster\ Coeff_{real}}{Cluster\ Coeff_{random}}}{\frac{Average\ Distance_{real}}{Average\ Distance_{random}}}$$

A value of $S > 1$ is evidence of the existence of a small-world network.[15] The intuition lies in the properties that Average Distance will be a bit greater (almost equal) to the random one, whereas the Cluster Coefficient will be much greater than the random one if the network under examination is a small world. Table 8 accordingly reports the clustering coefficient and average distance generated by the random process, as well as the values for S for each country. They show a significantly higher clustering coefficient than those randomly generated alongside a lower average distance. The S values for each country are all >1 implying that small world properties are indeed present.

Several findings emerge from the analysis so far. The first concerns the importance of the big island in all countries. These networks are not a collection of un-integrated small islands. Rather, there is significant integration in the big island. Higher clustering and lower path length relative to the random also provide indications of a small world. This suggests that relatively dense clusters of nodes are able to tie to other nodes in the big island through a small number of bridging connections. Such structure has been noted to be present in many human networks, possibly because the combination of the identity advantages of dense clustering alongside the information advantages of short average distance

[15] Note a key finding in Humphries and Gurney (2008) is that the small-worldness indicator tends to scale linearly with network size and reflects behavioural characteristics.

(Watts, 2003). With this in mind, it is clear that the ways in which nodes are connected, and the role of specific nodes in integrating the network, need more understanding. This brings us to the issue of centrality.

4.3.4 Betweenness and centrality

The extent to which a node lies between other nodes and has, or has not, high betweenness is linked to the broader issue of centrality or the importance of specific nodes in a network. Table 9 reports the betweenness shares - the extent to which nodes lie between other nodes - for each of the components (the columns sum to 100).[16] The betweenness shares are highest for politicians and political parties, as might be expected. Strikingly, betweenness is also high for SOEs; in Hungary and Slovakia the share is higher than for either political parties or politicians. Private firms have low betweenness shares across the board.[17] Russia also looks different. The share for both political parties and political individuals is significantly lower than elsewhere, while the share for SOEs is significantly higher. If we extend this analysis to the neighbours of both SOEs and private firms, the betweenness of both SOE and private firm neighbours is particularly high in Russia (77% and 47% respectively).

4.3.5 Summary

All countries are marked by the presence of a big island. The second largest component is very small in all cases. But the properties of the big island differ significantly across countries. The most obvious difference – reflecting differences in political systems – concerns political parties. These differences relate not only to the number and scale, but also the nature of connections flowing to and from those parties. Mostly, the links are from political individuals to parties. SOEs are in almost all instances a significant component of the big island. In autocratic contexts, such as Russia (but also its neighbours, Belarus and Kazakhstan)[18], SOEs have relatively high betweenness shares. In the case of private firms, betweenness shares are lower than for SOEs but there is also less difference across country. Not surprisingly, betweenness shares for political individuals and political parties

[16]The betweenness share is defined as the ratio of the sum of the betweenness of all nodes in a particular group (parties, SOEs, etc.) over the total network betweenness, i.e. over the sum of the betweenness of all the nodes in the network.

[17]Regarding closeness – which measures how close nodes are to one another and hence of the ability to connect to many, even when not between – shares are higher for both political individuals and other individuals across all countries. For both private firms, and particularly SOEs, the closeness shares are very much higher in Russia than elsewhere.

[18]The betweenness share for Belarus and Kazakhstan is 60% and 50% respectively, while the closeness shares are 17% and 10% - all significantly higher than in either Spain or the other economies covered in this paper.

are relatively high, although lower in the case of Russia. Relative to Spain where networks are more located around political parties and individuals, SOEs, in particular, have a more salient role in all the transition economies. In the following section, in looking at the association between scale and performance and firm level attributes, we explicitly incorporate these network features.

5 Correlates of being connected

We now look at whether being connected and the manner and location of any connection is associated with specific firm level indicators, including sales, output and return on assets. Our measures of being connected may not be exogenous and unobserved factors affecting firm outcomes could also be explanatory factors for having political connections. With the data that we have available, as well as the lack of a significant temporal dimension, instrumentation is problematic. As such, the estimates we report should be viewed as correlates, rather than indicating causality.

We estimate the following:

$$\begin{aligned} Outcome_{ict} = &\beta_0 + \beta_1 Connected_{ic} + \beta_2 SOE_{ic} + \beta_3 Firm\ Size\ dummies_{ict} \\ &+ Sector\ FE + Year\ FE + Country\ FE + u_{ict} \end{aligned} \tag{1}$$

or each firm i, in country c, at year y, where several outcome measures are related to a dummy variable for whether a firm is connected, as indicated by the FN+PN method. We also account for whether the firm is a SOE, using information reported directly in *Orbis*. The reason for including SOEs is that due to their ownership and governance they will, almost by definition, be connected to politicians; features that have, of course, been well documented. The outcome measures include Return on Assets, Leverage, as well as the logarithm of Sales, Output and Wages. We also include fixed effects for firm size, sector, country and year. The definition of firm size (Small/Medium/Large/Very Large) is taken from *Orbis* (see Appendix Table B1).

The results from estimating Equation (1) are reported in Table 10 using a pooled country specification. Note that Russia is excluded due to the severe limitations of coverage in *Orbis*. The same equation has also been estimated separately for each country (see Appendix Table A1). For Log Sales, Log Output and Log Wages, it can be seen that being connected is positively associated across the board and, in most instances, highly significant. For SOEs, the coefficients on sales and wages are positive, large and highly significant but negative and significant for output. With respect to the performance variable – ROA – the coefficient on the connected variable is actually negative, large and significant as is the case for SOEs. For Leverage, being connected is negatively signed but insignificant while for SOEs the sign is also negative but in this instance, significant.

The picture that emerges from the pooled regression reported in Table 10 is that connections tend to be associated with higher levels of sales, output and wages for both connected firms and SOEs. In numerical terms, some of these differences are large. Sales, output and wages are respectively 53, 16, and 24 percent higher for a connected firm than a non-connected firm. In contrast, Leverage and ROA are mostly lower for connected firms. Taking SOEs as a benchmark for politically connected business, apart from Sales, all the other coefficients for SOEs are not only very significant but also larger than those of connected private firms. This is particularly true in the case of ROA where SOEs have a far larger, negative sign.

5.1 Network regressions

The results reported up to this point are part of the standard binary approach of existing analyses of politically connected business. The focus is on the magnitude, sign and significance of the dummy that discriminates connected as against non-connected firms. However, and this is the originality of our study, simply 'being connected' is quite imprecise. A network approach can refine that identification. In a network, a firm can be connected to political power in different ways and with different intensity. We therefore extend the analysis to incorporate the network measures discussed in detail in Section 4 above. We are interested in explicitly testing conjectures relating to the nature of the connection, as well as the impact of variation in network properties. More specifically, we focus on the following measures:

(a) Big Island: whether the firm is in the big island or giant component;

(b) Betweenness – whether betweenness >0, compared to having no betweenness (conditional on being in the Big Island);

(c) Log Degree: the logarithm of the number of connections;

(d) Politician: whether the firm has a shareholder who is a politician.

A common prior for all the above variables is that they should influence the intensity of the connection, and thus the impact on the outcomes from being connected, in a positive way. For example, we would expect that being in the largest component of the network confers a stronger advantage than being connected to some other more peripheral parts of the network. Similarly, having a larger number of connections will be better than having just a few, and so on.

We augment Equation 1 by now including these network measures. Implementation is for the same indicators as reported in the baseline estimates reported in Table 10 and includes country, sector, year and firm size dummies. Since the network variables are defined only for connected firms, all non-connected firms would be excluded from this analysis. As such, we replace all network values with zero for all non-connected firms as well as including a dummy for being connected in all specifications. The table below shows the different specification we estimate.

Network estimations

Variable:	(1)	(2)	(3)	(4)	(5)	(6)
SOE	✓	✓	✓	✓	✓	✓
Connect	✓	✓	✓	✓	✓	✓
Big Island (BI)	✓	✓		✓		
Has Betweenness		✓				✓
Log Degree			✓	✓		
BI × Log Degree				✓		
Politician					✓	✓
Politician × Has Between.						✓
Constant	✓	✓	✓	✓	✓	✓

For example, the estimation of column (1) in equation form is as follows:

$$\begin{aligned} Outcome_{ict} =& \beta_0 + \beta_1 SOE_{ic} + \beta_2 Connect_{ic} + \beta_3 BigIsland_{ic} \\ & + \beta_4 Firm\ Size\ dummies_{ict} + Sector\ FE + Year\ FE \\ & + Country\ FE + u_{ict} \end{aligned} \tag{2}$$

So, it is the same as Equation (1) with the Big Island network variable added to it. Similarly, for the other six columns of the table. Note that these correspond exactly to columns 1 to 7 in Tables 11-15.[19]

The idea behind this set of specifications is to consider the network properties as different layers of the connection. The first layer is simply being connected (examined in equation 1). Then, it is being connected but also being in the Big Island (column (1) in the network specifications). Further the 'location' or centrality matters, so that the betweenness or the

[19] Country-specific estimates are reported in Appendix Tables A2-A6.

number of connections is examined. Finally, we would like to distinguish the impact of the type of the connection, such as whether being connected with a political individual or with another PEP produces different results. Interactions are also considered and these allow us to assess whether the effects of two network properties, for example, being in the Big Island and having multiple connections (degree), reinforce or weaken each other.

Tables 11-15 contain the main results using these different specifications. We provide detailed comments for the results for the outcome 'Log Sales' in Table 11, and then summarize the main differences for the results for the other outcome variables.

For Log Sales, the coefficient for being connected is always large, positive and highly significant. That is also true for the SOE variable. Being in the Big Island yields a positive and significant coefficient (column 1 in Table 11). Indeed, being connected and being in the Big Island (across all countries and years), is associated with a level of sales that is 58 percent higher (viz., exp(0.310+0.148) - 1). Note that this value lies above that identified in Eq. 1 (53 percent) which did not distinguish between being connected and having a presence in the Big Island. In other words, when we control for the network and the locus of the firm in that network, we can distinguish the impact of a connection when a firm is outside of the Big Island, from the impact of being inside it, and we indeed find that there is a difference.

The next specification, column (2) in the table, shows that what really matters is not just being in the Big Island, but having centrality. A firm could be inside the Big Island but this does not produce much of an effect if that firm is located at the periphery, i.e. if the firm has no betweenness. Indeed, in column (2) of Table 11, the coefficient for the Big Island becomes statistically not different from zero, and all of its previous effect (in column (1)) is taken over by the betweenness variable.

A different result is found when comparing columns (3) and (4). The new variable is the log of Degree and this is defined for firms within and outside of the Big Island.[20] Specification (3) illustrates that, without controlling for belonging to the Big Island, the number of connections matters. Specification (4) allows to assess whether the value of connections is the same inside or outside the Big Island. The data tell that with just one connection, there is no difference between having it inside or outside the Big Island. However, starting from two connections onwards, the value of the connections (i.e. the degree) is much higher inside the Big Island than outside. A numerical example can clarify this. Using the coefficients from specification (4), a firm outside of the Big Island with one connection would

[20] Note that log degree for one connection is equal to 0. To avoid this problem, the degree variable has been transformed to into a new variable called degree* which is equal to degree+1. This means that firms with one connection have now degree* = 2 and log degree* = 0.693. Note also that degree is not defined for not connected firms, but with this transformation, we assign degree*=1 to firms with no connection, so that for these firms log degree*=0.

have sales 34% higher (viz. exp(0.223+0.103×0.693)-1) than a non-connected firm. This is similar to the 31% (viz. exp(0.223 - 0.081 + 0.102×0.693 + 0.088×0.693) - 1) increase for a firm with one connection inside the Big Island. But for firms with two connections the difference, with respect to a non-connected firm, is 39.8% when outside of the Big Island, versus 42.0% when inside the Big Island. In sum, the value – in terms of increased volume of sales – of having multiple connections is higher for firms which are already in the main component of the network.

Together, specifications (1) to (4) tell a compelling story. Connections matter, but their importance comes from being in specific locations of the network. In particular, the largest impact of the connections is correlated with firms that not only are in the Big Island, but are there in a central position (with betweenness) and have a high degree.

Specifications (5) and (6) add another layer. Connections with a politician would, a priori, seem important, but a closer look at the data shows a more complex narrative. Without discriminating between groups of firms that have betweenness and those without, specification (5) does not detect any effect of controlling for a connection with a politician. But when the two groups are split, connections with a politician matter for firms with no betweenness, while politicians' relevance is diminished for firms with betweenness, as the interaction term is negative. Politicians can act as 'substitutes' for not having betweenness.

Although there is some variation across the other left-hand side variables that indicate scale of operation – namely Log Average Output and Wage – the results obtained for Log Sales are largely replicated.

Turning to Table 14 that reports estimations for a performance variable – namely Return on Assets – some similar patterns emerge. For ROA, being connected is mostly negatively associated but not always significant, unlike for SOEs where the coefficient is always large, negative and highly significant. In column (3) of Table 14, although being in the Big Island is positive and significant, having betweenness enters negatively and significantly. As in the case of Log Sales of Table 11, this means that for firms that are at the periphery of the Big Island the connection is not so important. Actually, in this case, for firms at the periphery the impact of the connection seems to be diminished, as the coefficient is of the opposite sign compared with firms that are central. This is also true in the estimation that incorporates Politicians. The Politician variable is itself positive and significant, both when entered by itself or along with the betweenness measures.

A clear conclusion can be drawn from these results. Not distinguishing these network attributes may not bias the coefficient of the connected dummy of equation (1), but certainly obscures the large heterogeneity captured in the specifications of Tables 11-15. Taking into account the network dimensions of connections is essential.

6 Conclusion

Politically connected businesses are not a rarity, nor are they limited to SOEs. Their incidence cuts across political systems, regions and levels of development. Our paper has focused primarily on economies in East and Central Europe, Russia and, as a comparator, Spain. Using a new and unique dataset that identifies Politically Exposed Persons (PEPs) and their links to companies, politicians and political parties, we are able to identify the broad scale of the phenomenon in each of the countries. Yet, the originality of the paper lies principally in our ability to identify the links between individuals, politicians, political parties and different types of firms, as well as the complex configurations of the resulting networks in each of the countries. These networks in turn could be expected to shape behaviour.

Drawing on the tools of network analysis, we show that each of these countries is characterized by a giant component or Big Island. The second largest component in all instances is small. Nevertheless, we find evidence that their networks have small-world properties, with high clustering and short path length due to a relatively small number of bridging connections. In the network space, however, there are also very different configurations that reflect, inter alia, differences in political and other institutions. Given the regions recent past, it is perhaps not surprising that State-Owned Enterprises (SOEs) are prominent and tend to have positions in the network with relatively high betweenness or centrality. There is a clear difference in this regard when compared with Spain.

Matching the information on connections to firm level data from *Orbis*, we demonstrate that there is a positive and robust correlation between the levels of sales, output, wages as well as a performance variable – the return on assets – and being connected. We cannot pin down causality, given the limitations in our data, but it seems reasonable to assume that the likely direction of association is from connections to outcomes. However, the principal interest from our data analysis concerns how network features can influence these associations. We find clear evidence that the location in a network, the extent of ties and betweenness or centrality is often positively, and significantly, associated with firm level indicators for the scale of activity. Network variables are also seen to be significant in an estimation that has a performance indicator – Return on Assets – on the left-hand side. In other words, not only are networks likely to be important in shaping how connections arise and propagate (something that we cannot directly measure) but they are also important in shaping the returns to connections. Of course, the configuration of networks, as well as their respective paybacks, is likely to be materially affected by other factors, including political institutions, resource endowments and neighbourhood. We are exploring these features in continuing research for a far larger group of countries and regions using the same dataset.

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Figure 1: Firms with only one connection are the largest group

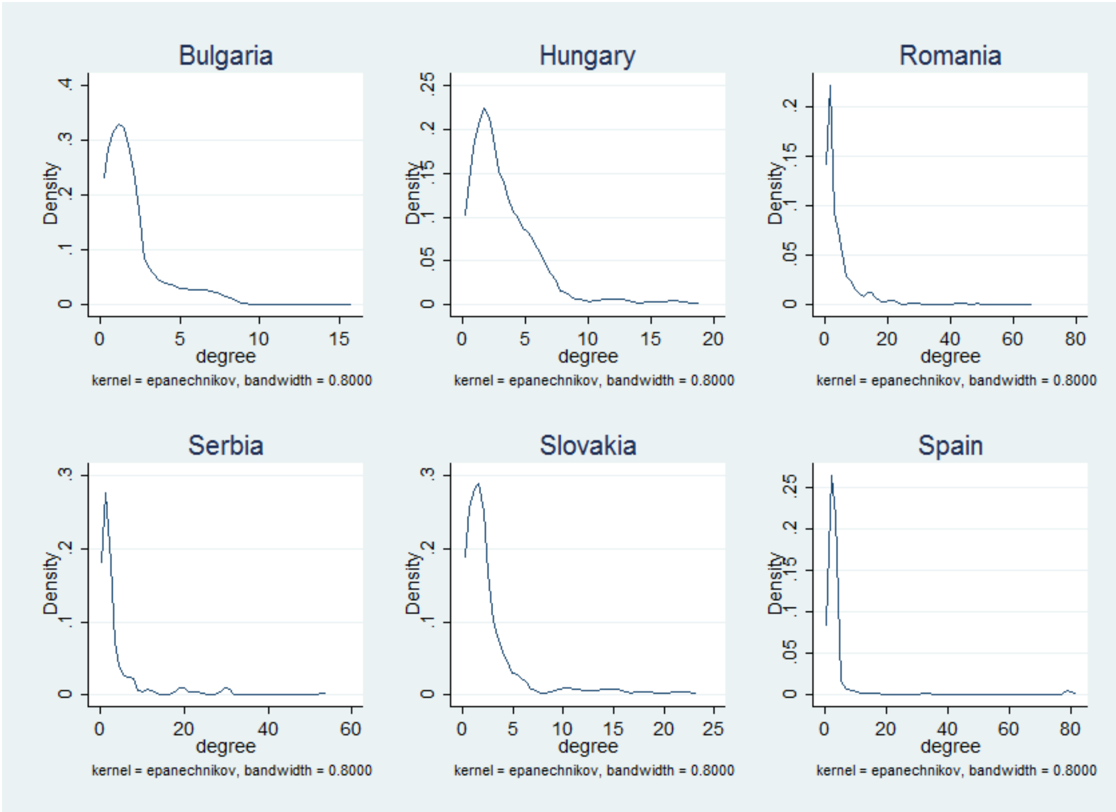

Figure 2: Two stylised networks

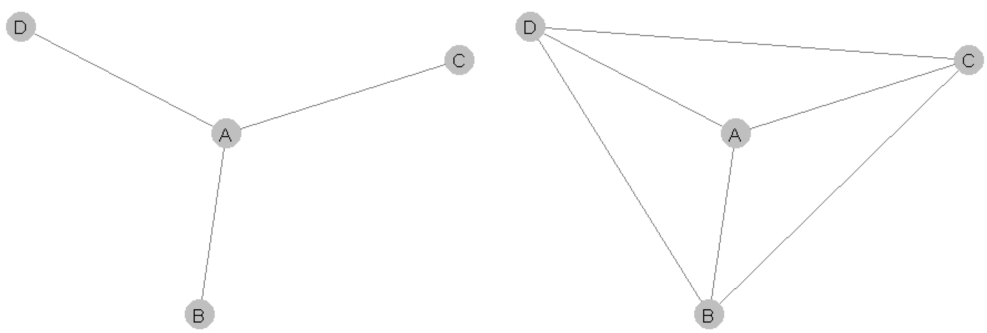

Table 1: Number of Connected Firms and Size/GDP

	Bulgaria	Serbia	Slovakia	Hungary	Romania	Russia	Spain
No. of Connected Firms (FN)	46	88	136	63	851	631	638
No. of Connected Firms (PN)	407	296	1,110	612	1,236	3,937	542
No. of Connected Firms (FN+PN)	453	384	1,246	675	2,087	4,568	1,180
No of All Firms	669,642	110,432	439,497	551,846	837,779	6,194,392	1,181,296
Tot Assets GDP% FN	0.29%	1.92%	1.06%	0.17%	2.12%	4.00%	27.18%
Tot Assets GDP% FN+PN	0.76%	4.61%	1.92%	0.78%	2.59%	15.34%	74.94%
Tot Assets GDP% (All)	397.25%	300.85%	247.67%	461.10%	201.21%	304.90%	494.39%
Tot Assets Ratio FN/All	0.07%	0.64%	0.43%	0.04%	1.05%	1.31%	5.50%
Tot Assets Ratio FNPN/All	0.19%	1.53%	0.78%	0.17%	1.29%	5.03%	15.16%

Calculations are based on 2013.

Table 2: Descriptive Statistics for Connected and Non-Connected: FN+PN

	Bulgaria				Serbia				Slovakia			
	Non-Connected		Connected		Non-Connected		Connected		Non-Connected		Connected	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Employees	7.9	2.0	18.9	3.0	20.7	4.0	116.8	7.0	13.2	2.0	15.8	3.0
Assets	826k	41k	1,510k	165k	3,366k	223k	12,000k	793k	1,685k	63k	1,977k	158k
Sales	464k	20k	762k	62k	2,243k	234k	5,321k	450k	1,500k	57k	1,223k	61k
Capital	143k	4k	123k	4k	1,030k	3k	4,553k	12k	352k	9k	428k	9k
Wage	78k	8k	183k	27k	261k	31k	672k	80k	258k	23k	287k	32k
ROA	10.29	4.35	6.53	2.45	2.49	1.76	3.13	1.33	0.21	0.54	-0.69	0.03
Leverage	0.98	0.42	1.43	0.53	0.63	0.67	0.62	0.69	35.96	0.70	11.05	0.75
Ave Output	48,927	9,866	51,773	18,224	133,527	57,884	167,032	53,033	180,214	51,676	169,088	53,314
Ave Wage	3,938	2,537	6,231	4,201	9,022	6,435	12,292	9,216	15,897	11,228	17,789	14,191
Tax Rate	0.04	0.00	-0.02	0.00	-0.02	0.01	0.03	0.01	0.24	0.00	0.10	0.00
	Hungary				Romania				Spain			
	Non-Connected		Connected		Non-Connected		Connected		Non-Connected		Connected	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Employees	10.1	2.0	27.8	2.0	6.3	1.0	26.3	3.0	16.9	3.0	752.5	17.0
Assets	1,494k	28k	1,864k	56k	624k	23k	4,397k	154k	8,728k	463k	1,110,000k	11,100k
Sales	1,351k	47k	1,329k	52k	527k	16k	5,874k	64k	4,134k	298k	539,000k	4,404k
Capital	171k	2k	367k	14k	104k	0k	689k	0k	1,043k	17k	69,800k	827k
Wage	126k	12k	307k	11k	87k	8k	446k	33k	704k	104k	53,100k	870k
ROA	4.13	2.53	6.29	1.86	1.44	0.00	0.68	0.12	-1.60	0.33	-1.37	0.51
Leverage	16.72	0.53	1.16	0.47	46.64	0.98	5.62	0.76	8.89	0.67	0.79	0.59
Ave Output	151,585	37,678	124,922	47,946	54,977	18,084	124,031	26,353	273,516	102,774	1,513,735	226,204
Ave Wage	12,213	8,009	11,503	8,543	4,082	3,323	6,424	4,731	39,125	33,221	72,459	55,951
Tax Rate	0.09	0.10	0.10	0.10	0.06	0.00	0.18	0.00	0.23	0.25	0.13	0.27

Calculations are based on 2013.

Table 3: Connection types (Share of firms by country, number of connections, and whether they have connections only with other firms, or with firms and other entities)

		Each firm's number of connections:					
	Connection with:	1	2	3	4	>=5	tot
Russia	Diverse entities	60	57	83	90	98	75
	Exclusively other firms	40	43	17	10	2	25
Spain	Diverse entities	43	85	100	75	98	71
	Exclusively other firms	57	15	0	25	2	29
Slovakia	Diverse entities	96	100	100	100	100	99
	Exclusively other firms	4	0	0	0	0	1
Serbia	Diverse entities	94	100	77	100	100	97
	Exclusively other firms	6	0	23	0	0	3
Bulgaria	Diverse entities	63	100	100	100	100	91
	Exclusively other firms	37	0	0	0	0	9
Romania	Diverse entities	89	97	92	100	99	95
	Exclusively other firms	11	3	8	0	1	5
Hungary	Diverse entities	88	98	100	100	99	97
	Exclusively other firms	12	2	0	0	1	3
All countries	Diverse entities	65	60	84	91	98	78
All countries	Exclusively other firms	35	40	16	9	2	22
All countries	All firms	100	100	100	100	100	100

Source: Firm name connected firms database. Note: In the dataset, firms can be connected with diverse entities, which include other firms, individuals, political party, etc., or exclusively with other firms, the second line for each country in the table above.

Table 4: Share of firms with 'diverse' connections by country, entity and number of connections

	Connections with:	Each firm's number of connections:					
		1	2	3	4	>=5	tot
Russia	Corporate	0	74	93	98	88	77
	Individual	39	50	70	73	95	70
	Pol. Individual	23	10	5	7	21	13
	Pol. Party	0	0	0	0	0	0
Spain	Corporate	0	39	33	33	50	34
	Individual	39	74	89	67	97	77
	Pol. Individual	9	22	44	33	43	31
	Pol. Party	0	0	0	33	0	1
Slovakia	Corporate	0	8	17	20	42	22
	Individual	70	92	83	100	100	90
	Pol. Individual	22	24	33	20	28	25
	Pol. Party	0	0	0	0	0	0
Serbia	Corporate	0	42	40	71	28	26
	Individual	69	100	100	100	100	93
	Pol. Individual	25	0	10	0	24	20
	Pol. Party	0	0	0	0	0	0
Bulgaria	Corporate	0	74	40	67	76	59
	Individual	33	63	80	100	76	68
	Pol. Individual	50	42	0	0	52	41
	Pol. Party	0	0	0	0	0	0
Romania	Corporate	0	21	39	47	40	24
	Individual	23	100	96	87	98	72
	Pol. Individual	66	45	48	47	47	53
	Pol. Party	0	0	0	0	0	0
Hungary	Corporate	0	38	81	61	69	56
	Individual	65	98	100	100	100	95
	Pol. Individual	21	11	12	4	34	23
	Pol. Party	0	0	0	0	0	0

Source: *PEPData* with Firm name (FN) listing

Table 5: Network size and components (by country)

	Bulgaria	Serbia	Slovakia	Hungary	Romania	Russia	Spain
Party	31	96	25	38	60	38	319
SOE	218	195	110	349	205	5,660	476
Firm	504	434	1,344	817	2,731	5,802	892
Political Individuals	1,745	2,264	1,092	2,322	5,244	18,066	9,631
Individuals	1,901	5,144	2,130	4,265	7,068	31,445	9,403
Network size	4,399	8,133	4,701	7,791	15,308	61,011	20,721

Table 6: SOE and Firm Connection Shares

	Bulgaria		Serbia		Slovakia		Hungary		Romania		Russia		Spain	
	SOE	Firm	SOE	Firm	SOE	Firm	SOE	Firm	SOE	Firm	SOE	Firm	SOE	Firm
Firm	3%	30%	1%	15%	4%	37%	3%	25%	6%	50%	7%	18%	3%	7%
Individual	56%	39%	71%	59%	68%	47%	73%	48%	56%	33%	49%	45%	45%	43%
Party	1%	1%	1%	1%	0%	0%	0%	1%	0%	0%	0%	0%	1%	1%
Politician	25%	26%	20%	24%	20%	14%	14%	21%	37%	17%	24%	25%	45%	47%
SOE	15%	5%	7%	1%	8%	2%	10%	5%	1%	1%	19%	12%	6%	2%
	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 7: Size of Big Island and components (by country)

	Bulgaria	Serbia	Slovakia	Hungary	Romania	Russia	Spain
Network Size	4,399	8,133	4,701	7,791	15,308	61,011	20,721
Big Island (BI)	1,934	2,499	2,620	5,106	11,593	22,016	13,888
BI (%)	44%	31%	56%	66%	76%	36%	67%
Rest	2,465	5,634	2,081	2,685	3,715	38,995	6,833
Second BI (in rest)	51	1004	27	18	39	51	98
Parties in BI	26	35	19	19	43	24	56
%	84%	36%	76%	50%	72%	63%	18%
SOEs in BI	58	98	69	296	184	4770	303
%	27%	50%	63%	85%	90%	84%	64%
Firms in BI	352	250	982	630	2,480	3,693	666
%	70%	58%	73%	77%	91%	64%	75%
Politicians in BI	997	1,073	748	1,898	4,368	5,270	8,557
%	57%	47%	68%	82%	83%	29%	89%
Individuals in BI	501	1,043	802	2,263	4,518	8,259	4,306
%	26%	20%	38%	53%	64%	26%	46%

Table 8: Network features (by country)

	Bulgaria	Serbia	Slovakia	Hungary	Romania	Russia	Spain
Nodes	1,934	2,499	2,620	5,106	11,593	22,016	13,888
Log(Nodes)	7.6	7.8	7.9	8.5	9.4	10.0	9.5
Edges	4,153	6,811	5,077	13,604	32,923	66,246	46,369
Average Degree	2.1	2.7	1.9	2.7	2.8	3.0	3.3
Density	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
Clustering Coefficient	1.3%	8.6%	1.7%	0.8%	1.7%	0.4%	1.4%
Average Distance	6.3	7.6	6.6	5.9	5.3	5.2	5.1
Random Clust Coeff	0.1%	0.1%	0.2%	0.1%	0.0%	0.0%	0.0%
Random Ave Dist	8	7.8	8.2	7.9	8.2	8.6	7.8
S for small-world	21.65	87.31	13.1	11.3	115.77	47.65	86.26

Table 9: Betweenness by type and country

	Bulgaria	Serbia	Slovakia	Hungary	Romania	Russia	Spain
Betweenness parties	33%	26%	24%	21%	32%	13%	38%
Betweenness SOEs	23%	18%	32%	40%	15%	52%	15%
Betweenness firms	2%	8%	2%	1%	1%	4%	5%
Betweenness politicians	36%	39%	30%	25%	38%	20%	35%
Betweenness Individuals	7%	9%	11%	13%	13%	11%	7%
	100%	100%	100%	100%	100%	100%	100%

Table 10: Baseline Estimates Pooled

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ROA	logSales	logAvOutput	logAvWage	logLev
Connect	-0.616***	0.427***	0.152***	0.221***	-0.031
	(0.230)	(0.028)	(0.023)	(0.013)	(0.020)
SOE	-3.749***	0.175***	-0.335***	0.263***	-0.045***
	(0.135)	(0.019)	(0.016)	(0.007)	(0.014)
Constant	12.331***	10.236***	9.402***	7.700***	-0.932***
	(0.062)	(0.007)	(0.006)	(0.003)	(0.005)
Wald	138.017	55.677	297.127	8.142	.322
p-value	<0.001	<0.001	<0.001	.004	.570
Observations	10,541,077	11,178,831	8,846,434	7,465,385	10,945,643
R-squared	0.039	0.499	0.444	0.660	0.065
Sector Dummies	✓	✓	✓	✓	✓
Size Dummies	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Network regressions: log Sales Pooled

	(1)	(2)	(3)	(4)	(5)	(6)
	logSales	logSales	logSales	logSales	logSales	logSales
SOE	0.175***	0.175***	0.174***	0.174***	0.175***	0.175***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Connect	0.310***	0.310***	0.180***	0.223***	0.392***	0.279***
	(0.052)	(0.052)	(0.054)	(0.070)	(0.040)	(0.050)
BigI	0.148**	0.053		-0.081		
	(0.062)	(0.068)		(0.107)		
HasBetween		0.189***				0.254***
		(0.065)				(0.082)
logDegree			0.167***	0.102*		
			(0.032)	(0.060)		
BigI×logDegree				0.088		
				(0.075)		
Politician					0.075	0.128*
					(0.056)	(0.067)
Politician×HasBetween						-0.082
						(0.119)
Constant	10.236***	10.236***	10.236***	10.236***	10.236***	10.236***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	11,178,831	11,178,831	11,176,694	11,176,694	11,178,831	11,178,831
R-squared	0.499	0.499	0.499	0.499	0.499	0.499
Sector Dummies	✓	✓	✓	✓	✓	✓
Size Dummies	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 12: Network regressions: log Average Output Pooled

	(1)	(2)	(3)	(4)	(5)	(6)
	logAvOut	logAvOut	logAvOut	logAvOut	logAvOut	logAvOut
SOE	-0.335***	-0.335***	-0.335***	-0.335***	-0.335***	-0.335***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Connect	0.079*	0.079*	0.042	-0.008	0.208***	0.110***
	(0.047)	(0.047)	(0.042)	(0.060)	(0.034)	(0.040)
BigI	0.093*	0.047		0.096		
	(0.054)	(0.057)		(0.084)		
HasBetween		0.093*				0.229***
		(0.052)				(0.070)
logDegree			0.075***	.100***		
			(0.025)	(0.049)		
BigI×logDegree				-0.046		
				(0.059)		
Politician					-0.113**	-0.002
					(0.046)	(0.053)
Politician×HasBetween						-0.267***
						(0.097)
Constant	9.402***	9.402***	9.402***	9.402***	9.402***	9.402***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	8,846,434	8,846,434	8,844,757	8,844,757	8,846,434	8,846,434
R-squared	0.444	0.444	0.444	0.444	0.444	0.444
Sector Dummies	✓	✓	✓	✓	✓	✓
Size Dummies	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table 13: Network regressions: log Average Wage Pooled

	(1)	(2)	(3)	(4)	(5)	(6)
	logAvWag	logAvWag	logAvWag	logAvWag	logAvWag	logAvWag
SOE	0.263***	0.263***	0.263***	0.263***	0.263***	0.263***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Connect	0.154***	0.154***	0.073***	0.077*	0.261***	0.176***
	(0.028)	(0.028)	(0.027)	(0.041)	(0.017)	(0.024)
BigI	0.084***	0.008		-0.008		
	(0.031)	(0.035)		(0.054)		
HasBetween		0.146***				0.192***
		(0.028)				(0.034)
logDegree			0.097***	0.098***		
			(0.015)	(0.030)		
BigI×logDegree				0.001		
				(0.035)		
Politician					-0.083***	-0.031
					(0.025)	(0.033)
Politician×HasBetween						-0.104**
						(0.051)
Constant	7.700***	7.700***	7.700***	7.700***	7.700***	7.700***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	7,465,385	7,465,385	7,463,907	7,463,907	7,465,385	7,465,385
R-squared	0.66	0.66	0.66	0.66	0.66	0.66
Sector Dummies	✓	✓	✓	✓	✓	✓
Size Dummies	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table 14: Network regressions: ROA Pooled

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA	(6) ROA
SOE	-3.749***	-3.748***	-3.748***	-3.748***	-3.749***	-3.747***
	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)
Connect	-0.825*	-0.826*	0.574	0.005	-1.334***	-0.602
	(0.481)	(0.481)	(0.460)	(0.665)	(0.307)	(0.411)
BigI	0.263	1.415**		1.197		
	(0.547)	(0.612)		(0.921)		
HasBetween		-2.161***				-1.562**
		(0.521)				(0.615)
logDegree			-0.705***	-1.115**		
			(0.251)	(0.476)		
BigI×logDegree				0.189		
				(0.578)		
Politician					1.610***	1.406**
					(0.462)	(0.597)
Politician×HasBetween						0.126
						(0.945)
Constant	12.331***	12.329***	12.332***	12.332***	12.329***	12.329***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Observations	10,541,077	10,541,077	10,538,873	10,538,873	10,541,077	10,541,077
R-squared	0.039	0.039	0.039	0.039	0.039	0.039
Sector Dummies	✓	✓	✓	✓	✓	✓
Size Dummies	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 15: Network regressions: log Leverage Pooled

	(1)	(2)	(3)	(4)	(5)	(6)
	logLev	logLev	logLev	logLev	logLev	logLev
SOE	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***	-0.045***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Connect	-0.079*	-0.079*	-0.017	0.007	0.006	-0.036
	(0.043)	(0.043)	(0.038)	(0.054)	(0.030)	(0.037)
BigI	0.06	0.036		-0.036		
	(0.048)	(0.052)		(0.077)		
HasBetween		0.046				0.087
		(0.045)				(0.060)
logDegree			-0.012	-0.097**		
			(0.022)	(0.044)		
BigI×logDegree				0.099*		
				(0.053)		
Politician					-0.083**	-0.042
					(0.039)	(0.049)
Politician×HasBetween						-0.086
						(0.080)
Constant	-0.932***	-0.932***	-0.932***	-0.932***	-0.931***	-0.931***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	10,945,643	10,945,643	10,943,381	10,943,381	10,945,643	10,945,643
R-squared	0.065	0.065	0.065	0.065	0.065	0.065
Sector Dummies	✓	✓	✓	✓	✓	✓
Size Dummies	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Appendix A Country-specific regressions

Table A1: Baseline Estimates using Connected Dummy

		ROA	lnSales	lnAvOutput	lnAvWage	lnLev
BG	Connect	-2.804***	0.635***	0.303***	0.229***	0.162**
		(0.996)	(0.08)	(0.063)	(0.045)	(0.067)
	SOE	-14.319***	0.282***	-0.717***	0.458***	0.145***
		(0.522)	(0.047)	(0.042)	(0.019)	(0.04)
SE	Connect	-3.000***	0.024	-0.153*	0.233***	-0.094*
		(0.829)	(0.089)	(0.078)	(0.035)	(0.050)
	SOE	-7.463***	0.099	-0.949***	0.288***	-0.235***
		(0.430)	(0.073)	(0.060)	(0.024)	(0.039)
SL	Connect	-0.904*	-0.039	-0.078	0.061	0.075*
		(0.496)	(0.055)	(0.055)	(0.038)	(0.041)
	SOE	-2.046***	0.336***	0.032	0.402***	-0.043
		(0.771)	(0.089)	(0.09)	(0.05)	(0.067)
HU	Connect	0.708	0.200***	0.084	0.053	-0.267***
		(0.766)	(0.076)	(0.066)	(0.043)	(0.057)
	SOE	-2.829***	0.668***	-0.169	0.529***	-0.095
		(0.717)	(0.103)	(0.111)	(0.050)	(0.067)
RO	Connect	0.259	0.644***	0.220***	0.262***	-0.203***
		(0.376)	(0.037)	(0.027)	(0.017)	(0.027)
	SOE	-5.342***	0.338***	-0.448***	0.496***	-0.284***
		(0.363)	(0.049)	(0.04)	(0.022)	(0.036)
SP	Connect	-0.937***	0.624***	0.237***	0.219***	0.210***
		(0.340)	(0.056)	(0.048)	(0.018)	(0.045)
	SOE	-0.949***	0.111***	-0.101***	0.162***	-0.031*
		(0.140)	(0.021)	(0.020)	(0.008)	(0.019)
Year FE		✓	✓	✓	✓	✓
Sector Dummies		✓	✓	✓	✓	✓
Size Dummies		✓	✓	✓	✓	✓

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Network estimates log Sales

Model	BigI	Big+Big×Betw		Politician	Between×Politician		LogDegree	Big×LogDegree	
Given		Bet=0	Bet=1		Pol=0	Pol=1		B=0	B=1
Effect	BigI	Big	Big	Politician	Bet	Bet	LogDegree	LogDegree	LogDegree
BG	0.525 ***	0.393 **	0.935 ***	-0.091	0.530	0.603 **	0.425***	0.277	0.264
	(0.176)	(0.180)	(0.255)	(0.177)	(0.437)	(0.274)	(0.109)	(0.234)	(0.283)
SE	-0.144	-0.297	0.017	-0.259	0.291	0.282	-0.022	0.024	0.074
	(0.197)	(0.228)	(0.241)	(0.203)	(0.368)	(0.349)	(0.090)	(0.166)	(0.219)
SL	0.334 ***	0.295 **	0.418 ***	0.019	0.327	-0.071	0.074	-0.005	0.017
	(0.114)	(0.123)	(0.151)	(0.108)	(0.201)	(0.202)	(0.066)	(0.117)	(0.153)
HU	-0.207	-0.287	-0.135	-0.158	0.098	0.212	-0.124	0.056	-0.255
	(0.187)	(0.207)	(0.204)	(0.148)	(0.238)	(0.261)	(0.110)	(0.203)	(0.260)
RO	-0.099	-0.241	0.030	-0.136	0.384 *	0.221 *	0.105*	-0.046	0.206
	(0.177)	(0.185)	(0.185)	(0.108)	(0.212)	(0.123)	(0.056)	(0.149)	(0.161)
SP	-0.095	-0.205	-0.033	-0.066	0.130	0.496	0.171**	0.061	0.197
	(0.124)	(0.153)	(0.138)	(0.151)	(0.215)	(0.342)	(0.070)	(0.101)	(0.143)
Year FE	✓	✓		✓	✓		✓	✓	
Sector Dummies	✓	✓		✓	✓		✓	✓	
Size Dummies	✓	✓		✓	✓		✓	✓	

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Network estimates Log Ave Output

Model	BigI	Big+Big×Betw		Politician	Between×Politician		LogDegree	Big×LogDegree	
Given		Bet=0	Bet=1		Pol=0	Pol=1		B=0	B=1
Effect	BigI	Big	Big	Politician	Bet	Bet	LogDegree	LogDegree	LogDegree
BG	0.400 ***	0.313 **	0.667 ***	-0.184	0.081	0.494 ***	0.337***	0.478**	-0.129
	(0.135)	(0.141)	(0.179)	(0.142)	(0.302)	(0.181)	(0.085)	(0.200)	(0.235)
SE	-0.078	-0.154	-0.006	-0.100	0.415	0.156	-0.015	-0.032	0.149
	(0.174)	(0.185)	(0.213)	(0.173)	(0.279)	(0.254)	(0.073)	(0.183)	(0.209)
SL	0.249 ***	0.240 *	0.266 *	-0.161	0.315 *	-0.251	0.064	0.032	-0.069
	(0.122)	(0.127)	(0.159)	(0.110)	(0.19)	(0.204)	(0.072)	(0.102)	(0.153)
HU	-0.170	-0.246	-0.105	-0.212	0.100	0.289	-0.022	-0.018	0.042
	(0.169)	(0.181)	(0.185)	(0.132)	(0.189)	(0.226)	(0.098)	(0.169)	(0.210)
RO	-0.043	-0.051	-0.035	-0.100	-0.002	0.019	-0.01	0.051	-0.054
	(0.117)	(0.122)	(0.123)	(0.073)	(0.133)	(0.087)	(0.045)	(0.091)	(0.104)
SP	-0.054	-0.233 **	0.070	-0.452 ***	0.269 *	-0.057	0.092**	0.099	0.000
	(0.106)	(0.114)	(0.125)	(0.095)	(0.145)	(0.216)	(0.046)	(0.082)	(0.101)
Year FE	✓	✓		✓	✓		✓	✓	
Sector Dummies	✓	✓		✓	✓		✓	✓	
Size Dummies	✓	✓		✓	✓		✓	✓	

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Network estimates Log Ave Wage

Model	BigI	Big+Big×Betw		Politician	Between×Politician		LogDegree	Big×LogDegree	
Given		Bet=0	Bet=1		Pol=0	Pol=1		B=0	B=1
Effect	BigI	Big	Big	Politician	Bet	Bet	LogDegree	LogDegree	LogDegree
BG	0.140	0.127	0.173	-0.230 **	-0.117	0.022	0.154***	0.283**	-0.111
	(0.118)	(0.124)	(0.141)	(0.113)	(0.236)	(0.126)	(0.059)	(0.115)	(0.137)
SE	-0.182**	-0.301 ***	-0.069	-0.175 **	0.221	0.299 ***	0.056*	0.093	0.098
	(0.082)	(0.102)	(0.087)	(0.078)	(0.177)	(0.119)	(0.033)	(0.066)	(0.081)
SL	0.140	0.103	0.211 **	-0.067	0.338 ***	-0.087	0.095**	0.101	-0.053
	(0.093)	(0.100)	(0.103)	(0.081)	(0.121)	(0.131)	(0.047)	(0.074)	(0.100)
HU	0.290 **	0.272 **	0.305 **	-0.170 *	0.140	-0.135	0.119**	0.167	-0.135
	(0.122)	(0.127)	(0.133)	(0.09)	(0.123)	(0.129)	(0.056)	(0.131)	(0.144)
RO	-0.082	-0.150 *	-0.021	-0.162 ***	0.121	0.111 **	0.055**	0.012	0.065
	(0.080)	(0.084)	(0.082)	(0.048)	(0.095)	(0.054)	(0.026)	(0.071)	(0.076)
SP	0.084 **	-0.014	0.150 ***	-0.258 ***	0.064	0.081	0.074***	0.123***	-0.092**
	(0.040)	(0.047)	(0.046)	(0.046)	(0.055)	(0.112)	(0.021)	(0.034)	(0.044)
Year FE	✓	✓		✓	✓		✓	✓	
Sector Dummies	✓	✓		✓	✓		✓	✓	
Size Dummies	✓	✓		✓	✓		✓	✓	

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table A5: Network estimates ROA

Model	BigI	Big+Big×Betw		Politician	Between×Politician		LogDegree	Big×LogDegree	
Given		Bet=0	Bet=1		Pol=0	Pol=1		B=0	B=1
Effect	BigI	Big	Big	Politician	Bet	Bet	LogDegree	LogDegree	LogDegree
BG	4.148 *	4.804 *	2.347	5.798 **	-5.486	-0.671	0.87	2.968	-5.534
	(2.497)	(2.591)	(3.017)	(2.865)	(5.656)	(2.905)	(1.072)	(3.987)	(4.336)
SE	1.490	1.979	1.003	-0.538	-0.062	-0.952	-0.959	-2.931*	1.46
	(1.902)	(2.269)	(2.181)	(1.863)	(3.575)	(3.100)	(0.826)	(1.543)	(1.855)
SL	-0.979	-0.109	-2.613 *	3.106 ***	-2.572	-3.017 *	-1.938***	-3.012***	1.354
	(1.184)	(1.251)	(1.446)	(0.978)	(1.749)	(1.747)	(0.552)	(0.880)	(1.209)
HU	-1.050	1.407	-3.270 *	1.521	-6.498 **	-3.097	-1.508	-1.832	0.338
	(1.769)	(2.064)	(1.953)	(1.600)	(2.599)	(2.719)	(0.978)	(1.507)	(2.086)
RO	-0.386	0.979	-1.576	1.575	-4.283 *	-1.630	-0.979*	1.767	-3.089**
	(1.816)	(1.910)	(1.884)	(1.170)	(2.260)	(1.247)	(0.534)	(1.462)	(1.575)
SP	-0.667	0.385	-1.198	-0.047	-1.497 *	-1.911	-0.635*	-1.184*	0.735
	(0.767)	(0.847)	(0.864)	(0.842)	(0.906)	(2.144)	(0.347)	(0.698)	(0.819)
Year FE	✓	✓		✓	✓		✓	✓	
Sector Dummies	✓	✓		✓	✓		✓	✓	
Size Dummies	✓	✓		✓	✓		✓	✓	

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Table A6: Network estimates Log Leverage

Model	BigI	Big+Big×Betw		Politician	Between×Politician		LogDegree	Big×LogDegree	
Given		Bet=0	Bet=1		Pol=0	Pol=1		B=0	B=1
Effect	BigI	Big	Big	Politician	Bet	Bet	LogDegree	LogDegree	LogDegree
BG	-0.168	-0.248	0.291	-0.530***	0.657*	-0.757*	0.166*	0.202	0.187
	(0.151)	(0.155)	(0.184)	(0.179)	(0.375)	(0.400)	(0.094)	(0.168)	(0.224)
SE	-0.139	-0.02	-0.226*	-0.159	-0.105	-0.21	-0.099*	-0.093	0.005
	(0.111)	(0.115)	(0.127)	(0.105)	(0.159)	(0.235)	(0.057)	(0.117)	(0.142)
SL	0.238**	0.198*	0.113	-0.093	-0.101	0.021	0.035	-0.005	-0.039
	(0.096)	(0.102)	(0.098)	(0.081)	(0.095)	(0.181)	(0.052)	(0.071)	(0.108)
HU	0.029	-0.09	0.222*	0.144	0.302**	-0.327	-0.021	-0.352***	0.526***
	(0.145)	(0.157)	(0.125)	(0.115)	(0.152)	(0.234)	(0.077)	(0.120)	(0.173)
RO	0.185	0.196	-0.021	0.014	-0.144	0.241	0.038	-0.101	0.141
	(0.131)	(0.136)	(0.074)	(0.078)	(0.132)	(0.155)	(0.038)	(0.134)	(0.140)
SP	0.219**	0.208*	0.016	-0.007	0.146	-0.14	0.032	-0.108	0.135
	(0.094)	(0.110)	(0.104)	(0.095)	(0.101)	(0.284)	(0.049)	(0.075)	(0.103)
Year FE	✓	✓		✓	✓		✓	✓	
Sector Dummies	✓	✓		✓	✓		✓	✓	
Size Dummies	✓	✓		✓	✓		✓	✓	

Robust standard errors in parentheses clustered at the level of firm

*** p<0.01, ** p<0.05, * p<0.1

Appendix B Other tables

Table B1: Size firm definitions

	Companies meeting at least one of the criteria are included:
Very large companies*	- Operating revenue (turnover) >= 100 mln EUR; - Total assets >= 200 mln EUR; - Number of employees >= 1 000; - Listed company.
Large companies**	- Operating revenue (turnover) >= 10 mln EUR; - Total assets >= 20 mln EUR; - Number of employees >= 150; - Not related to the category of very large companies.
Medium sized companies***	- Operating revenue (turnover) >= 1 mln EUR; - Total assets >= 2 mln EUR; - Number of employees >= 15; - Not related to the category of large companies.
Small companies	- Companies not classified by any other of the above categories are included.

*Companies with Operating revenue per employee or Total assets of less than 100 EUR, are excluded from this category. Companies with unknown operating revenue, total assets or number of employees, but with capital exceeding 5 mln EUR, are included in this category.

**Companies with Operating revenue per employee or Total assets of less than 100 EUR, are excluded from this category. Companies with unknown operating revenue, total assets or number of employees, but with capital from 500 th. EUR to 5 mln EUR, are included in this category.

***Companies with Operating revenue per employee or Total assets of less than 100 EUR, are excluded from this category. Companies with unknown operating revenue, total assets or number of employees, but with capital from 50 th. EUR to 500 th. EUR, are included in this category.

Table B2: Size by Matching Method (N and %)

	FN	PN	Total (FN+PN)	SOE	FN	PN	SOE
Small	535	2,595	3,130	4,259	40%	77%	31%
Medium	402	574	976	6,749	30%	17%	48%
Large	245	103	348	2,267	18%	3%	16%
Very large	165	94	259	651	12%	3%	5%
Total	1,347	3,366	4,713	13,926	100%	100%	100%

Table B3: Sector Distribution and by Matching Method (N and %)

	FN	PN	Total (FN+PN)	SOE	FN	PN	SOE
A - Agriculture, fore	22	120	142	227	1.6%	3.6%	1.6%
B - Mining and quarry	23	9	32	47	1.7%	0.3%	0.3%
C - Manufacturing	125	301	426	747	9.3%	8.9%	5.4%
D - Electricity, gas	93	21	114	541	6.9%	0.6%	3.9%
E - Water supply, sew	23	19	42	632	1.7%	0.6%	4.5%
F - Construction	133	212	345	984	9.9%	6.3%	7.1%
G - Wholesale	183	632	815	932	13.6%	18.8%	6.7%
H - Transportation	30	53	83	511	2.2%	1.6%	3.7%
I - Accommodation	46	161	207	238	3.4%	4.8%	1.7%
J - Information	99	217	316	372	7.3%	6.4%	2.7%
K - Financial	145	103	248	890	10.8%	3.1%	6.4%
L - Real estate	124	260	384	846	9.2%	7.7%	6.1%
M - Professional	148	784	932	960	11.0%	23.3%	6.9%
N - Administrative	84	209	293	537	6.2%	6.2%	3.9%
O - Public admin	3	2	5	359	0.2%	0.1%	2.6%
P - Education	7	42	49	3,969	0.5%	1.2%	28.5%
Q - Human health	15	121	136	613	1.1%	3.6%	4.4%
R - Arts, entertain	15	64	79	410	1.1%	1.9%	2.9%
S - Other service act	29	36	65	108	2.2%	1.1%	0.8%
Total	1,347	3,366	4,713	13,923	100.0%	100.0%	100.0%

Appendix C Network Mapping by country

Figure C1: Bulgaria Big Island

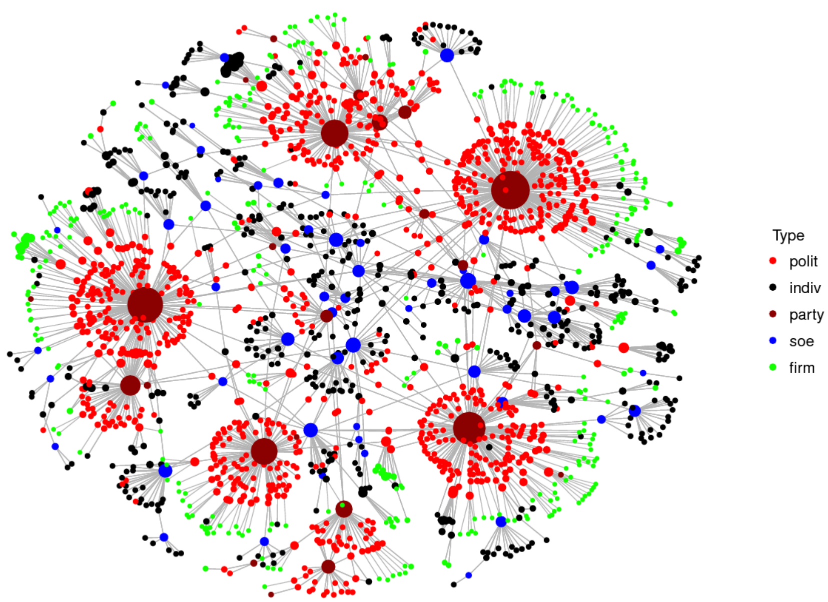

Figure C2: Serbia Big Island

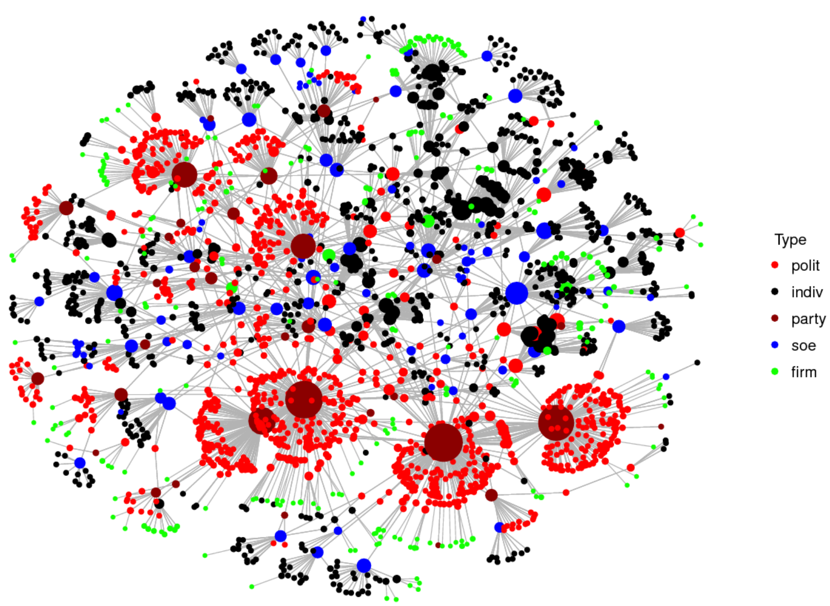

Figure C3: Slovakia Big Island

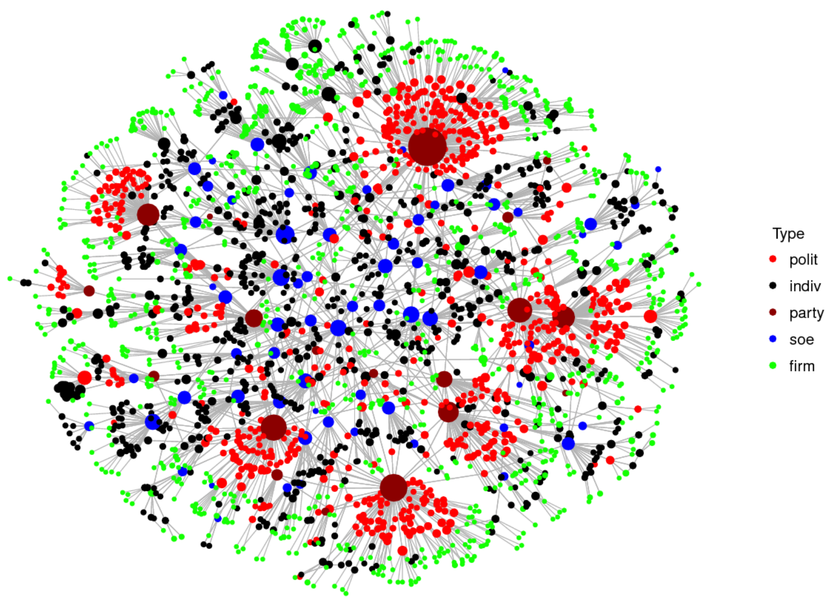

Figure C4: Hungary Big Island

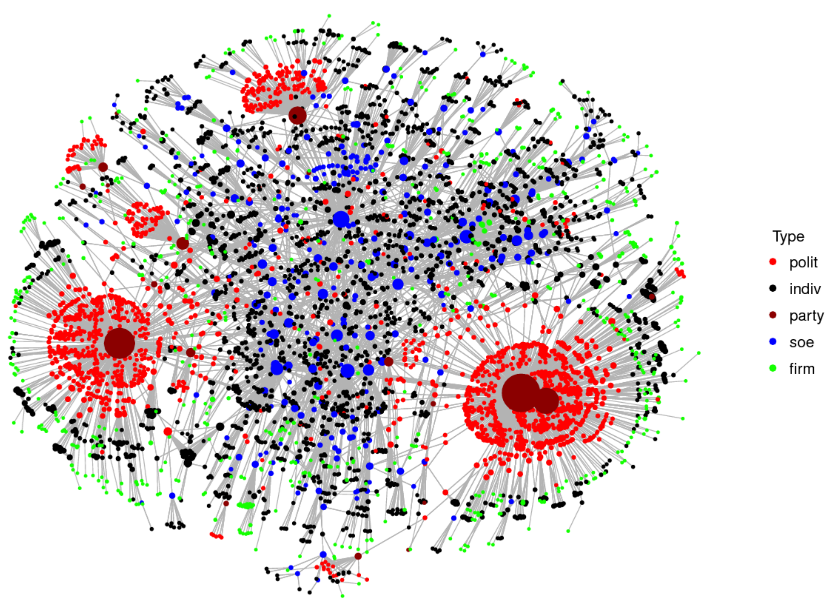

Figure C5: Romania Big Island

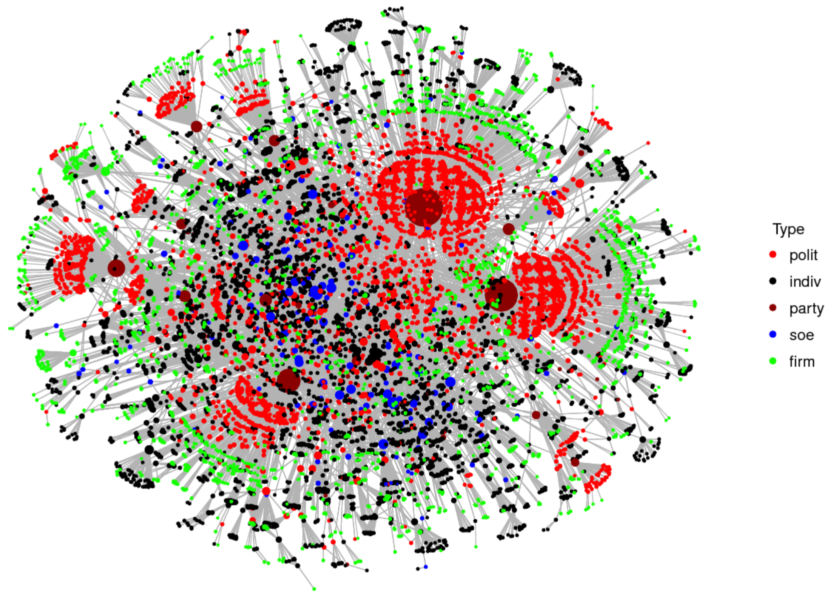

Figure C6: Russia Big Island

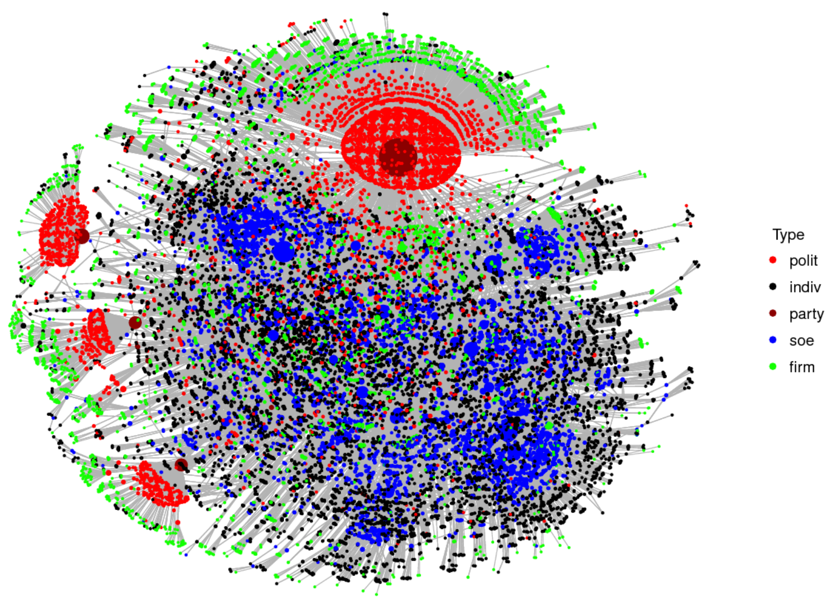

Figure C7: Spain Big Island