Networks of the politically connected across the globe: Mappings, dimensions and composition

Simon Commander   Stavros Poupakis

This version: July 2018

Abstract

Political connections are pervasive yet rarely binary. This paper examines the network properties of such connections using a new and unique dataset that covers over 165 countries. We map networks comprising persons and entities for all the countries and sort by income, region and political system concentrating on the principal component – or Big Island – of these networks. We find substantial variation across the main network measures that we apply. Income levels and political systems are associated with substantial differences in the size of the network, the extent of integration as also in the composition. Further, the location of components of the network, notably the extent of centrality as measured by betweenness, varies significantly conditional on income and political arrangements. The paper also implements a variety of measures of centrality.

Many thanks to Maurizio Bussolo and Raluca Pahontu for numerous discussions about the issues covered in the paper. Author contact details: Simon Commander, Altura Partners and IE Business School - scommander@alturapartners.org and Stavros Poupakis, University College London - s.poupakis@ucl.ac.uk.

1 Introduction

The connections that run between politicians, political entities and economic and financial institutions, both public and private, have been widely discussed, albeit mostly imperfectly measured, in a wide range of economies. Copious examples exist of the application of political influence to achieve results that are financially or electorally beneficial to the person or entity exerting influence. Understandably, focus has tended to be on consequential applications of political influence. Yet, the reality is that connections are often pervasive – and often more insidious – than a focus on large-order instances of influence peddling would reveal. That is because the value of political connections can be substantial, while also having adverse – and often highly persistent – consequences for market structure, competition and welfare.[1]

Most documented instances of political connections are based on matching individuals and entities. But, connections are rarely binary in nature. For example, following Russia's annexation of Crimea, the sanctions that have subsequently been imposed have had the specific intention of targeting the President's close connections. As the sanctions list suggests, such connections have multiple dimensions and strands. Connections comprise not only family and friends – suggesting, in this instance, the importance of a common location – but also individuals and entities from both public and private sector business. A further feature of these connections include common work experience; in this instance, in the military-intelligence complex. In China, the prevalence of connections is even summarised by the term, *guanxi*. There is also plentiful evidence of the crucial role that political connections play in business decisions and behaviour (Pei, 2016). In short, what these - and numerous other examples - illustrate very well is the network nature of connections and their complexity.

Recent research also emphasises the way in which networks are organised, and the place in a network that specific agents occupy, as having a material impact on the consequences of connections. For example, Cruz et al. (2017) show that having a central position in a network can facilitate electoral success. Centrality provides organisational benefits and facilitates clientalist transactions. Bussolo et al. (2018) also show that the position in a network is important when looking at the relationship between political connections and firms.

Despite the apparent ubiquity of political connections, it has proven a struggle to identify politically exposed or connected persons (henceforth PEPs) and their connections in an accurate manner. Researchers have mostly assembled datasets at the level of individual countries.[2] Even where multi-country coverage has been created, the number of observa-

[1] See, for example, Cingano and Pinotti (2013).

[2] Examples include, Johnson and Mitton (2003); Diwan et al. (2015); Bunkanwanicha and Wiwattanakantang (2008); Rijkers et al. (2015); Akcigit et al. (2017).

tions has been relatively limited.[3] By contrast, commercial providers of market intelligence compile frequently updated listings of Politically Exposed Persons (PEPs) that cover a large number of countries. This information has mostly been used as part of due diligence for investors weighing up exposure to individual companies or business groups in a specific country. Consequently, there has, as yet, been no attempt, using a common set of metrics, to document the scale, type and distribution of politically exposed persons and connections across a very large number of countries. In this paper, it is precisely this gap that we address using a very large, multi-country (n>180) dataset that provides a thorough documentation of PEPs and their connections in each country. The data have been compiled using a common method across countries. This allows, inter alia, insight into the properties of networks across large numbers of countries distinguished by their differences in income, location and political systems.

Our objectives in this paper are fourfold. The first is to use this unique dataset to identify the size and format of connections – the network space – in many countries. The second is to look at how network characteristics are associated with country-level economic and political characteristics. The third is to explore whether shifts in political institutions over time are associated with shifts in network features. The fourth is to explore in more detail the matter of strategic location or centrality in networks while taking account of political systems.

The paper is organized as follows. *Section 2* provides a brief description of the data. *Section 3* lays out the ways in which we map and document networks using our dataset. *Section 4* discusses the importance of political systems and institutions as well as their measurement. *Section 5* then provides a preliminary categorization of network types and presents a number of country-level examples indicating the sorts of variation that exist across different types of political systems. *Section 6* then provides a detailed set of descriptive statistics for networks breaking down by income level, region and political system. With regard to the latter, we also look at countries that have experienced a regime switch – mostly away from autocracy – to see whether there is any material difference in network descriptives across switchers relative to those that experienced no change. *Section 7* examines the issue of centrality – or strategic importance – in networks, including its measurement. We use three examples, characterized by differences in political system, to identify centrality and its locus in network space. We show that the different measures can yield somewhat different results. Finally, we take the example of Russia where sanctions have been imposed since 2015 on a small group of targeted persons and entities. We detail the network properties of those that have been sanctioned when compared to others in the network, as well as mapping

[3] Faccio (2006), for example, assembled a dataset covering 47 countries and >20,000 firms, identifying around 540 or 2.7% as having political connections of some sort.

their distance to the Russian President. *Section 8* concludes.

2 Data description

We use a new and unique dataset – *PEPData* – that applies a common methodology to list Politically Exposed Persons (PEPs) in 185 countries or jurisdictions providing, in effect, global coverage. For our analysis, we discard information from a number of very small countries, leaving a total of 168 countries. The dataset contains very detailed, disaggregated information on country-level networks it allows linking identified PEPs to other PEPs, as well as to political parties, politicians, other individuals and companies. In all, we have about 3,100,000 observations for the countries in our analysis. The data relate to 2017, although there are historical indications of the timing when specific PEPs held political positions. The information has been compiled from a wide variety of sources, including from sanctions, regulatory and legal lists, as well as from national and international media sources.

More specifically, the data are organised for each country in five main categories. These are:

1. Political Individuals – persons currently holding or having held a political position, including in a political party or having been elected.
2. Political Party – any registered and active political party,
3. Other Individuals – any person appointed to a PEP position or appointed to a government position, as well as immediate relatives or close associates of primary PEPs,
4. State-Owned or Invested Enterprises and,
5. Private companies or financial institutions.

3 Networks - some definitions

In measuring networks, the main descriptive elements are nodes - denoting individuals or entities - and edges or links between those nodes.[4] Networks are also 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). A network consequently represents relationships between agents, while also providing some form of structure for those relationships. Figure 1 gives a simple illustration of a hypothetical network with a set of nodes and edges. That structure may, in turn, be informative about the sort of

[4] A good review of the wider literature on networks is Ward et al. (2011), see also, inter alia, Do et al. (2013); Goyal et al. (2006).

opportunities that exist. In what follows, we apply measures that are able to summarize network structure for each country. We also focus on the place of specific nodes – whether individuals or otherwise – in those networks.

In the latter respect, the notion of centrality – or how important particular nodes are in a network – is of particular interest. Centrality can be captured by a variety of measures. One approach is simply to identify the extent to which a node lies between other nodes, known as betweenness. If a node has high betweenness, it is likely that other nodes will, in effect, be dependent on it for access to rents or information or both. For example, in Figure 1 the three larger nodes at the centre have high betweenness. An additional method is to assign higher weights to links that connect a node to other central nodes. This is known as eigenvector centrality and is concerned not just with the number of links but also whether those links are themselves connected.[5] Important nodes in a network could be expected to have connections with other important nodes. The substantial network literature indicates that there tends to be significant variation in how centrality is configured. For example, in a small-world network, nodes are located in locally dense clusters that can reach other nodes through a small number of bridging connections.

While our dataset aims to encompass all PEPs and their connections in a given country, the resulting network will likely vary in terms of the extent of integration. A network could be composed of many fractions that may, at best, be weakly connected. Alternatively, most nodes may be linked in some way. This distinction has implications for how to sort components of the network. To see why this matters, Figure 2 provides a mapping of the network for one country – Bulgaria. Note that in this mapping – as in all presented in the paper - scaling is always by degree or number of edges. It is evident that there is significant fragmentation and weak connections. From a network perspective, many of these individuals or entities carry little information. Therefore, using the rule that if there is any path or link between nodes then they are grouped in the same component, we can sort the data by the largest component or big island (as well as by other components, if required). Figure 3 plots just the largest component or big island for Bulgaria that gives a very different picture from that presented in Figure 2. In general, a large share of nodes that fall in the big island indicates a high degree of integration through the network. A small big island suggests a weakly connected network with fractional parts. In the analysis that follows, we consequently pay specific attention to the big island.

[5] Given the adjacency matrix A of a network of V nodes, the eigenvector centrality of node v_i is $E(v_i) = 1/\lambda \sum_{v_i \in V} A_{v_i v_j} E(v_j)$ where λ is the corresponding eigenvalue, and the eigenvector E constructed by stacking the eigenvector centralities for all V , of the adjacency A, i.e. $\lambda E = AE$.

4 Political systems

We conjecture that the scale, structure and composition of specific networks will be influenced by factors including income level, resource endowments, region and political and other institutions. There is also evidence that economies characterized by large public ownership of companies – SOEs – tend to have a greater number of links to politicians and/or political parties.[6] For the moment, we concentrate on the role of political systems.

Regarding political institutions, we might expect that the network structure prevailing in an autocratic regime would look different from that in a democracy, not least due to variation in the incidence and format for political parties and politicians, but also because of the way in which rents are allocated in non-democratic settings. However, it is obvious that there is a wide range of autocratic systems reflecting variation in the way in which power is organized and the extent to which some form of electoral process is tolerated.[7] For example, the Polity IV dataset classifies autocracies on a scale of -1 to -10. The latter comprise repressive regimes where power is held without reference to any form of elections and where opposition is banned. Examples include Saudi Arabia and North Korea. Other regimes may effectively be one-party states with violations of political and other rights but with some semblance of elections. Examples include Egypt, Iran and Kazakhstan. Additionally, there is a group of more competitive autocracies which allow regular elections, the results of which are distorted by the exercise of executive and other power that favour the incumbent individual and/or party. Examples include Singapore and Uganda. Finally, the length of time that an autocracy has existed could also be expected to influence the way in which power and connections are organized. An autocracy that is persistent might be expected to concentrate the structure or density of the network so that the network's big island would likely have strong small world properties.

In similar vein, democracies can be differentiated by their degree of political competition and turnover, as well as by the extent to which democratic norms extend to political, civic and human rights. Examples of the latter - liberal democracy - include Western European countries while other countries, such as Bangladesh or Ukraine, could best be classed as electoral democracies. We might also expect that differences in the way democracies are organised – as for example presidential versus parliamentary systems – could carry implications for network structure.

In the analysis pursued below, we use Polity IV to characterize the political systems of individual countries. As mentioned above, the scale ranges from -10 (highly autocratic) to 10 (liberal democracy). While the network data cover only the current period, it is relevant

[6]As argued, for example, in Shleifer and Vishny (1994).

[7]A useful typology of political systems is contained in Howard and Roessler (2006).

to note that over a 30 years period (1981-85 to 2011-15) around 35% of countries remained stable political systems, whether autocratic or democratic. That is to say, in nearly two thirds of countries, some sort of switch in political system occurred within this period. Later, we exploit these dynamics to look at whether the networks of those that have switched political regimes differ materially at the end of the period from those that have remained stable.

5 Networks across political systems

We start with mappings of some country-level networks, distinguishing primarily by political system and contrasting weak and strong democracies and autocracies. We focus on the largest component or big island with scaling by degree or number of edges.[8]

As an example of a strong and durable democracy (graded 10 by Polity IV), Figure 4 maps networks in the UK. This is an example of an advanced economy with a competitive parliamentary democracy where nearly 60% of nodes fall in the big island. The figure shows a multiplicity of political parties linked, predictably, to politicians as well as to some other individuals. There are a relatively limited number of private firms and SOEs and they are largely unconnected to politicians or political parties.

Figure 5 applies the same procedure to Bangladesh that is classed as weak democracy (graded 3 by Polity IV) at a low-income level. The big island here accounts for a far smaller share of around 30%. The mapping shows a couple of political parties around which are clustered numerous politicians and other individuals. There are a significant number of edges running from them to state-owned enterprises, in particular.

Figure 6 maps the network structure for Saudi Arabia - a very strong version of a durable autocracy (graded -10 by Polity IV) where power is concentrated in the hands of an extended family with minimal mechanisms of consultation. The country is also, of course, highly dependent on natural resource rents which account for nearly 30% of GDP. Here, the big island accounts for 43% of the total network, the extent of integration through the network being strongly affected by the role and position of extended families. As such, the network map is clearly dominated by individuals with links to some political figures along with a mix of state-owned and private companies. Other natural resource economies that are family/clan based (such as Kuwait) exhibit similar features with SOEs and ruling family members having prominence. Indeed, some natural resource-rich autocracies, such as Azerbaijan, have even more concentrated nodes, reflecting the predominance of a very restricted number of influential families, as well as extreme concentration of political power.

[8] A full set of country network maps is available on request.

Figure 7 maps Rwanda, a weaker form of autocracy (graded -3 by Polity IV) in a low-income economy lacking natural resources. The main political party and linked politicians dominate with ties to mainly state-owned enterprises. The big island contains around 41% of the total network but the latter is itself relatively small with the total number of nodes <1200.

Finally, Figure 8 is for China, a particular type of autocracy with a socialist, one-party shape (graded at -7 by Polity IV) with per capita income at around 15% that of the UK. In this case, the main feature of the network map is its star format given the scale and place of the singular party (the Chinese Communist Party) that is surrounded by concentric dense clusters of political figures and SOEs, as well as some private firms. In contrast to most autocracies, however, there is a very high level of integration through the network as nearly 75% of nodes fall in the big island. This level of integration through the network is also a feature of other, one party dominated, countries, such as Vietnam.

These examples already suggest significant cross-country variation in network size and composition while indicating some association between political system, income level and resource endowments, and network size and structure. The next section explores such variation in greater detail.

6 Descriptive Statistics

We now draw on the full set of country network observations. To facilitate analysis, we group countries by certain characteristics, namely, (1) level of income, distinguishing between high, upper and lower middle and low income categories, (2) regions, grouped into seven, and (3) political system using three categories - autocracies, democracies and mixed.

The first two panels of Table 1 provide for each of the four income categories, information on the size of the network – viz., the number of nodes (either for individuals or entities) and edges (the links between nodes) - along with both expressed in per capita terms. In addition, the share in the big island is given along with the average degree (the number of links sent to the nodes), average distance or path length, and the cluster coefficient for the big island.

Although the number of nodes increases strongly in income, this is not linear. The number of nodes and edges peaks for upper middle- income countries, although the average level for high-income countries is clearly higher than for lower middle-income and low-income countries. What this, of course, masks is the very large variation in the number of nodes and edges or links across countries.[9]

[9]Brazil and the USA have over 100,000 nodes with between 250,000-300,000 edges, China and Mexico >85,000 nodes and 150-200,000 edges. India and Peru have roughly the same number of nodes (>45,000)

Normalizing by population, the number of nodes and edges increases linearly with income: high income countries have over ten times the number of nodes per capita compared to a low-income country. The size ranking also changes significantly so that both China and India have a relatively small number of nodes and edges per head of population compared, say, to either North America or Western Europe.

Concerning the extent of integration through the network, as measured by the presence and size of a big island in Panel 2, there is an unambiguous and monotonic increase in the share accounted by the BI, going from 0.34 on average in low income countries to 0.55 in high income ones. (Note that other components do not individually have significant shares). There is also some upward drift in degree and distance but this is not the case when considering only the big island. As to whether there are dense clusters of nodes (measured by the cluster coefficient), there is evidence of greater clustering in high income countries.

Turning to the composition of the network and to that of the big island in particular, Panel 3 breaks down the big island into its components. Several features stand out. Individuals comprise a larger share of the big island in richer countries, while the inverse is true for politicians. Private companies and SOEs, as well as foreign entities, have a higher share in high-income countries. Panel 4 extends by computing the centrality of these different components. This shows substantial differences across income levels. For instance, political parties and politicians have the highest shares of betweenness in low-income countries and in the case of political parties, the share is higher than in other income categories. Private firms also have high, average betweenness in low-income settings. Intriguingly, SOEs' betweenness is most pronounced in upper middle and high-income contexts.

Table 2 reports the same averages but this time breaks down across seven regions. In terms of nodes and edges normalised by population, the main outlier is North America which has a very significantly larger number than anywhere else. Although the Middle East (MENA) has the lowest share in the Big Island, the clustering coefficient is clearly larger than anywhere else. In terms of composition, although there are some differences – notably with respect to the share of politicians and foreigners – in general, the variation is not that pronounced. That is not the case for the measures of betweenness. SOE betweenness is particularly notable on average in MENA and East Asia, while that is also the case for private firms' betweenness in MENA and South Asia. Perhaps not surprisingly, given the dominance of autocracies, political parties' and politicians' betweenness MENA is clearly different from other regions.

Controlling for the political system, Table 3 shows large differences in the mean number

but the number of edges varies very significantly. The major Western European economies have between 16-30,000 nodes. Low-income countries – for example, Cambodia, Ethiopia, Ghana or Laos – have between 900-2400 nodes and 1200-5000 edges.

of nodes and edges per capita between current autocracies and democracies, in particular. The latter have far higher levels. Similarly, democracies have a significantly larger share in the Big Island than either mixed or autocratic regimes, indicating far higher integration through the network in the former. Both degree and clustering in the big island have higher average values in autocracies than elsewhere. For composition, the share for SOEs and private firms is clearly higher in autocracies than in either mixed or democracies, while the share of politicians is lower. For components' betweenness, SOE average betweenness is 45% as against 19-23% for mixed and democracies respectively. Political party and politician betweenness is far lower in autocracies, while individuals' betweenness is higher.

6.1 Political regime switching

Although our cross-sectional data do not permit any robust analysis of dynamics, we can explore the variation in network structure controlling for political system. To that end, we are interested in contrasting the network attributes of countries that have switched or not switched political systems in the period since 1980. The aim is to see whether having made a transition in political system appears to be associated with any significant difference in network characteristics.

To explore this dimension, Table 4 provides a simple transition matrix taking 1980/85 and 2010/15 as the two points in time. It can be seen that by the 2010s of the 89 countries that were classified as autocracies in the 1980s, just under a quarter had stayed as autocracies; 40% had become mixed systems and 36% had become democracies.[10] Nearly 90% of democracies in 1980 stayed that way; the remainder switched to being mixed. Of those that were mixed in 1980, over 70% became democracies and the rest stayed the same. Figure 9 identifies the spatial dimensions and shows that most shifts from autocracy to mixed systems have been in the Former Soviet Union, as also in Sub Saharan Africa. For autocracies switching to democracies, the main action has been in the former socialist economies of Eastern Europe, as well as in Sub Saharan Africa.

Table 5 now summarizes the network features of persistent autocracies compared with those that shifted to a mixed system or became democracies over the period stretching from 1980/85 - 2010/15. It can be seem that for both nodes and edges normalised by population, switchers to democracy have higher values. Similarly, the big island in countries that switched to democracy accounted for a significantly higher share. Clustering in the big island – as more generally – remains higher in persistent autocracies, as do the shares of SOEs and firms. SOE betweenness is also particularly strong in these countries.

[10]If a country did not exist in 1980 and was part of another country – for example, parts of the Former Soviet Union – the Polity value of the country it belonged to is used.

7 Identifying centrality

Earlier, we mentioned the matter of where a node or nodes sit in a network and the likely importance of centrality. It is of obvious interest to know how central and important particular nodes are in a network, not least because this might offer some possible insight of a policy nature. For example, if it is possible to identify one or more central nodes and, if for the sake of argument, those nodes represent rent-seeking entities or individuals, any policy intervention that is aimed at disrupting those central nodes may be able to exert a disproportionately large effect on the network structure and its resilience.

The descriptive tables have shown that across groups of countries, there are significant differences in betweenness across types of entities or individuals as well as across groups. However, the centrality issue is not best treated across a large group of countries, as many of the features are best understood in the context of country-level networks. The question then turns on the light that specific measures throw on the matter of centrality.

To see the effect of the choice of measure, Figures 10-12 plot the big island for three countries – Greece, Jordan and Belarus – distinguished, inter alia, by their differences in political and government systems. Two measures – degree and eigenvector centrality – are deployed for each country. Figure 10 shows that for Greece that when using degree, three main clusters are visible as organised around the principal political parties. However, when using eigenvector centrality, there is a clear change, notably in indicating the larger and more central cluster of nodes and edges accounted for by one of the current opposition parties – New Democracy – and to a lesser extent, a former governing party – Pasok – but one now in serious decline. Notably, the centrality of the current governing party – Syriza – is significantly attenuated. This obviously indicates that it is not necessarily being in power that confers greater centrality in the network as that may revolve on longer-lasting political entities. The figure also shows a rather different distribution of centrality for individuals (coloured black) with a much smaller number of individuals having centrality in the case of the eigenvector measure. The difference is even more starkly represented in the instance of Jordan (Figure 11). Both measures underline the importance of the King, family and court but, in the case of eigenvector centrality, this group effectively mops up all centrality, as against the degree measure where sets of other individuals are still relevant. A somewhat similar outcome occurs for Belarus (Figure 12), where the dominant – effectively unique – party and its associated individuals and politicians stand out dramatically when applying the eigenvector measure. As in Jordan, the degree measure gives a more diverse composition of players, notably a mix of SOEs and individuals.

7.1 Sanctioning the politically connected

Since 2015 and the invasion of Crimea, sanctions have been imposed on a mix of Russian individuals, politicians and companies. This offers an opportunity to look at the location and centrality of those persons and entities in the wider network space of Russia. To that end, we use the list of sanctioned individuals and institutions that has been put in place by a variety of governments, including the European Union, Japan and USA.[11] The avowed aim of the sanctions has been to target individuals considered to be cronies of the Russian President, as well as strategically important companies controlled by the state and/or cronies, including those specifically associated with Crimea.

To give a sense of the scope of sanctions, 66 individuals and 33 politicians have been targeted, along with 161 firms and 228 SOEs. These obviously comprise very small shares of the total number of persons or entities in the network's big island (n>58600). Table 6 compares sanctioned persons or entities relative to others in the big island. Average betweenness of the former is clearly larger, although the share that has betweenness is far lower for sanctioned persons. The eigenvector measure is also higher for sanctioned firms and SOEs but this is not the case for persons. Focussing explicitly on the nature of the connection to the president, the histograms in Figure 13 report the distance to the president and show that the sanctioned have a slightly higher probability of being closer (distance=1 or 2) than the rest, especially for persons. The average distance is somewhat smaller for both persons and entities. Extending this analysis a bit further, Figure 14 plots distance to the president, imposing the restriction that it does not exceed 2. As a node, the president lies at the centre of this figure (in the grey background). The figure picks out in red the sanctioned, whether persons or entities. Strikingly, there are two particularly prominent nodes. That to the right of the figure denotes a major, state-owned development bank while that to the left denotes one of the Russian President's closest known cronies. However, the main feature is that the links of the sanctioned are quite diverse and do not simply run through the president. This is a very different network structure from a centralised autocracy – such as Azerbaijan – where the autocrat operates as the hub of the network. In Russia, by contrast, those who are sanctioned are also clearly connected to each other with more complex ties.

8 Conclusion

Our paper has taken a unique dataset assembled with a common methodology and with global coverage of politically connected networks and mapped the varying structures and

[11] The sanctions list that has been used is that up to 2017, so does not include those names and institutions that have been added in 2018.

composition of networks across a very large group of countries. At this stage, the approach is primarily descriptive as we aim to document individual country networks while starting to explore how these networks' shape and composition varies controlling for factors such as income, location and political system.

We find very significant cross-country variation in network size and composition indicating some association between political system, income level and resource endowments and network size and structure. These differences start with basics, such as the size of the network, and the level of integration of the network, as measured by the share contained in the largest component or big island. Richer democracies clearly have more integration. Network composition appears to be materially affected by political system and resource base and this extends to the extent of centrality of particular groups, whether persons or entities. This is further linked to some striking regional variations. For example, MENA has properties that are different from other regions.

Existing research has emphasised the importance of location in network space. Having centrality in a network can, for example, enable or realise specific benefits. We have looked at centrality in three illustrative cases, differentiated by political system, and show that identification is also sensitive to how centrality is measured. Although we do not explore this dimension, it is also possible that centrality may provide a clue as to how to address networks in the event that policy-makers wish to disrupt or limit the effectiveness of a particular network of individuals and/or firms. Targeting central nodes, for example, might be expected to impose particularly disruptive effects.

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Tables and Figures

Table 1: Mean Network Measures by income

	Low Income	Lower Middle Income	Upper Middle Income	High Income
Nodes	1,611	4,843	14,186	6,856
Edges	2,943	9,080	26,903	14,310
Nodes per 1,000 people	0.11	0.24	0.68	1.24
Edges per 1,000 people	0.21	0.53	1.23	2.70
Big Island	0.34	0.41	0.46	0.55
Degree	1.87	1.94	1.88	2.11
Degree in BI	2.91	3.09	2.62	2.86
distance in BI	4.67	5.36	5.40	5.68
cluster coef in BI	0.07	0.07	0.03	0.10
SOEs	2%	3%	4%	4%
Firms	4%	4%	6%	9%
Individuals	43%	48%	52%	56%
Politicians	48%	43%	37%	30%
Non-PEPs	4%	5%	6%	6%
Foreign	4%	4%	5%	10%
SOE between	10%	23%	29%	30%
Firm between	09%	04%	04%	03%
Party between	41%	30%	26%	24%
Polit between	29%	30%	27%	28%
Indiv between	11%	14%	14%	16%
Obs	29	42	45	52

Table 2: Mean Network Measures by region

	East Asia & Pacific	Europe & Central Asia	Latin America Caribbean	Middle East & N Africa	North America	South Asia	Sub-Saharan Africa
Nodes	10,071	7,285	15,515	3,108	20,647	9,240	1,959
Edges	21,696	14,811	27,439	6,300	40,764	17,555	3,836
Nodes per 1,000 people	0.36	0.79	0.91	0.45	3.89	0.08	0.38
Edges per 1,000 people	0.76	1.71	1.65	0.95	8.23	0.13	0.83
Big Island	0.45	0.49	0.51	0.39	0.48	0.40	0.42
Degree	1.94	1.95	1.87	2.01	2.00	1.75	2.07
Degree in BI	2.95	2.62	2.53	3.18	2.60	2.76	3.20
distance in BI	5.36	5.70	5.11	6.00	5.58	5.54	4.79
cluster coef in BI	0.06	0.04	0.02	0.21	0.05	0.03	0.08
SOEs	4%	4%	3%	5%	5%	2%	3%
Firms	5%	7%	4%	11%	10%	3%	5%
Individuals	54%	52%	51%	50%	57%	58%	47%
Politicians	36%	37%	41%	34%	28%	36%	43%
Non-PEPs	4%	7%	4%	6%	7%	6%	4%
Foreign	5%	7%	4%	10%	18%	3%	5%
SOE between	31%	27%	21%	36%	17%	17%	17%
Firm between	3%	4%	3%	9%	1%	14%	5%
Party between	25%	27%	35%	12%	36%	25%	36%
Polit between	25%	31%	32%	18%	35%	27%	28%
Indiv between	16%	11%	10%	25%	10%	17%	13%
Obs	19	49	28	19	3	6	44

Table 3: Mean Network Measures by Regime 2010-2015

	Autocracy	Mixed	Democracy
Nodes	7,115	4,227	10,081
Edges	15,803	7,409	19,561
Nodes per 1,000 people	0.38	0.23	0.62
Edges per 1,000 people	0.95	0.40	1.20
Big Island	0.38	0.37	0.52
Degree	2.34	1.67	2.01
Degree in BI	3.94	2.59	2.73
Distance in BI	5.11	5.12	5.54
Cluster coef in BI	0.19	0.06	0.03
SOEs	6%	3%	3%
Firms	10%	5%	5%
Individuals	50%	45%	53%
Politicians	33%	45%	38%
Non-PEPs	5%	4%	6%
Foreign	9%	5%	5%
SOE between	45%	19%	23%
Firm between	7%	6%	3%
Party between	13%	33%	30%
Polit between	17%	28%	30%
Indiv between	19%	13%	13%
Obs	21	50	87

Table 4: Regime Switchers (rows: 1980s. cols:2010s)

		2010s		
		Autocracy	Mixed	Democracy
1980s	Autocracy	21	36	32
	Mixed	0	9	22
	Democracy	0	4	33

Table 5: Mean Network Measures by Switchers

Group.1	Auto-Auto	Auto-Mix	Auto-Dem
Nodes	7,115	4,140	4,778
Edges	15,803	7,025	9,945
Nodes per 1,000	0.38	0.17	0.51
Edges per 1,000	0.95	0.26	1.03
Big Island	0.38	0.34	0.48
Degree	2.34	1.56	2.12
Degree in BI	3.94	2.45	3.02
Distance in BI	5.11	4.94	5.52
Cluster coef in BI	0.19	0.05	0.05
SOEs	6%	3%	3%
Firms	10%	4%	5%
Individuals	50%	42%	54%
Politicians	33%	49%	37%
Non-PEPs	5%	3%	7%
Foreign	9%	4%	4%
SOE between	45%	17%	21%
Firm between	7%	6%	3%
Party between	13%	36%	31%
Polit between	17%	29%	32%
Indiv between	19%	11%	13%
Obs	21	36	32

Table 6: Network Measures comparison: sanctioned and the rest

	Indiv. & Politicians		Firm & SOEs		*Note*
	Sanctioned	Rest	Sanctioned	Rest	
Av Betweenness	483,879	42,001	1,475,979	86,187	Bigger, more connected
Share Between (out of 100%)	1.4%	29.7%	23.8%	32.2%	Bigger, more connected
Av Eigenvector	0.222	0.415	0.012	0.005	Bigger, more connected
Av Distance to All	5.2	5.2	4.7	4.9	The smaller the closer
Av Distance to President	3.0	3.5	3.0	3.3	The smaller the closer

Figure 1: An example of network structure

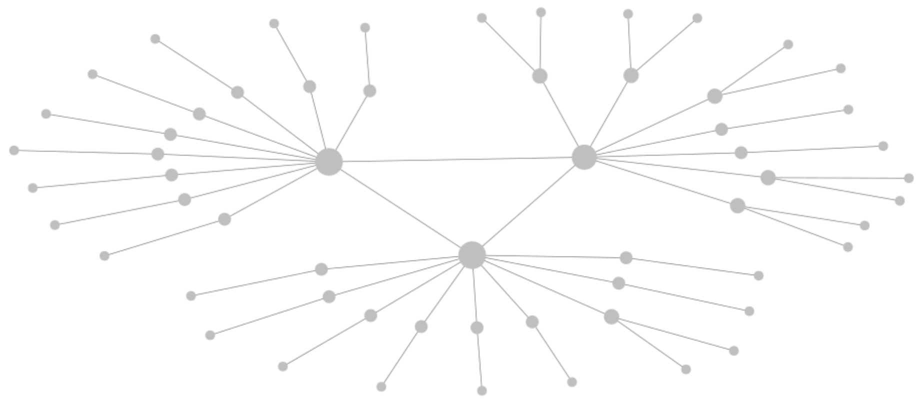


Figure 2: PEP Network in Bulgaria

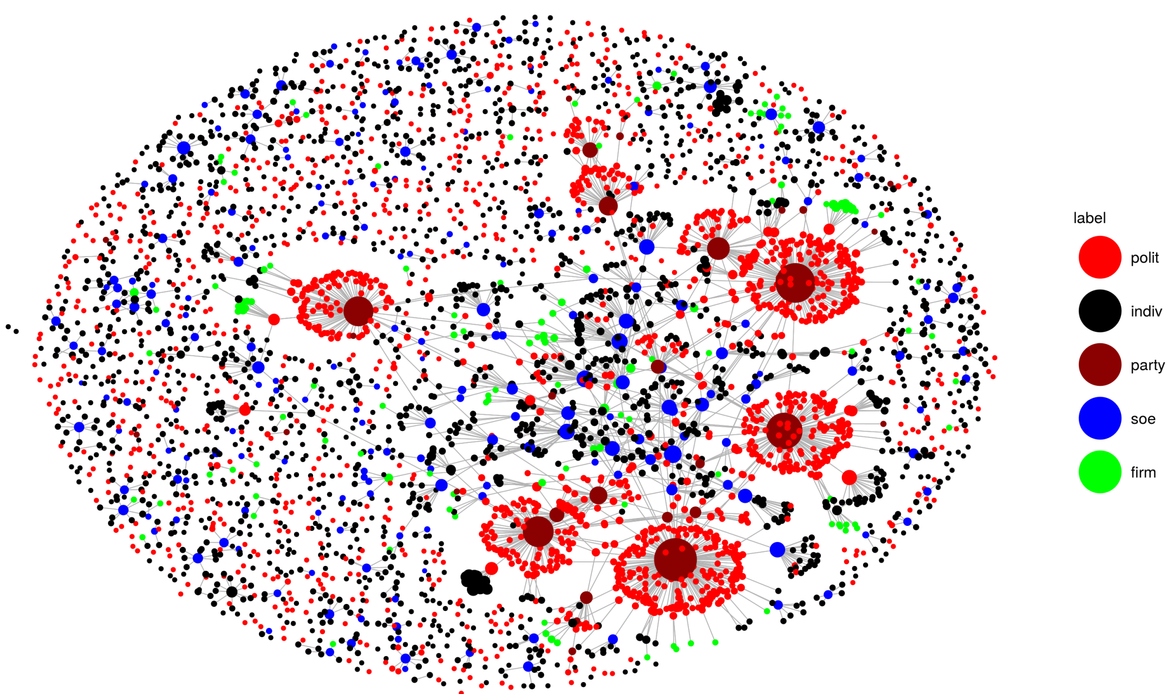


Figure 3: Big Island of PEP network in Bulgaria

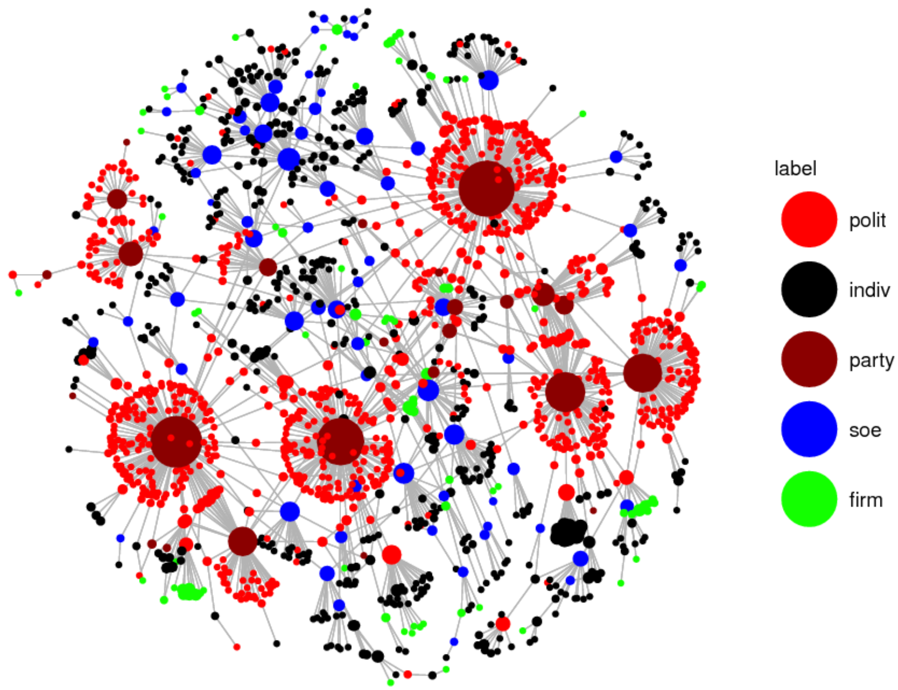


Figure 4: Big Island of PEP network in the United Kingdom

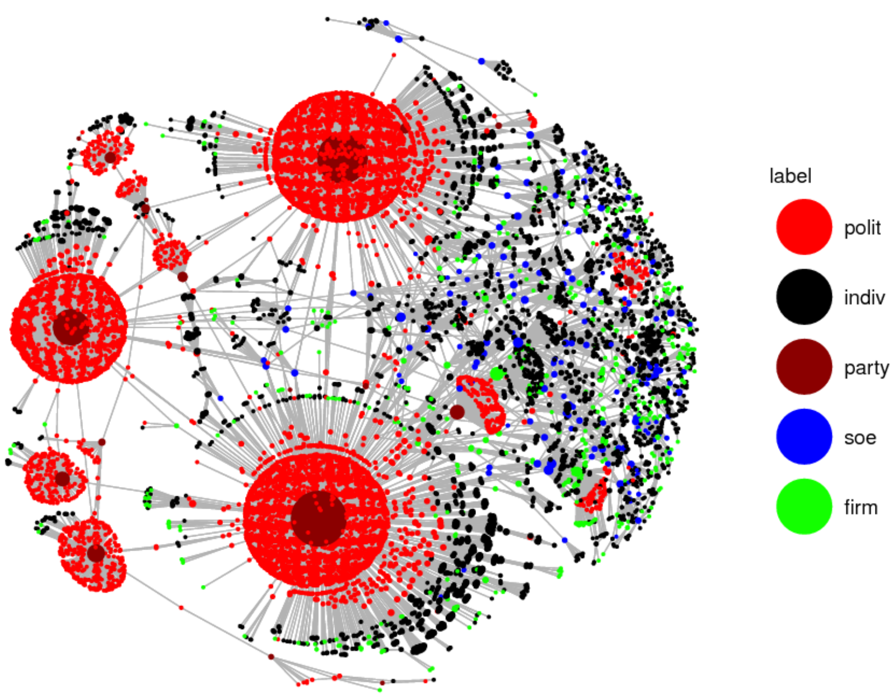


Figure 5: Big Island of PEP network in Bangladesh

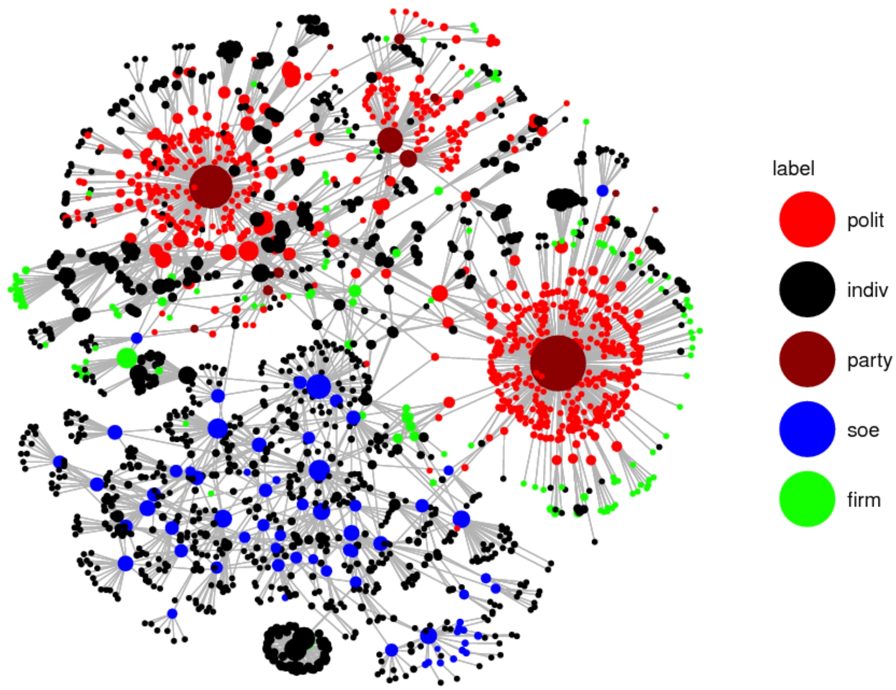


Figure 6: Big Island of PEP network in Saudi Arabia

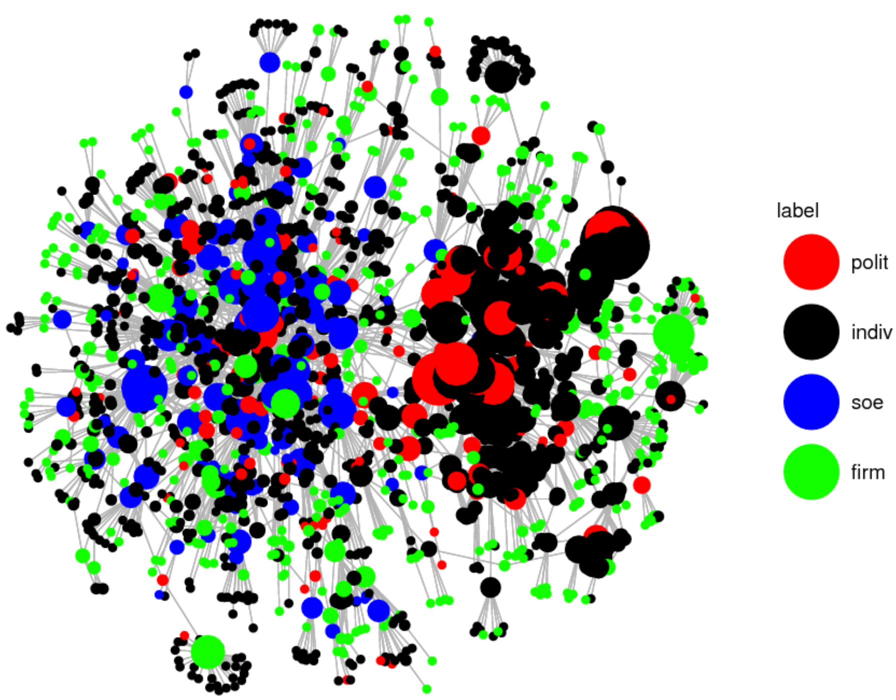


Figure 7: Big Island of PEP network in Rwanda

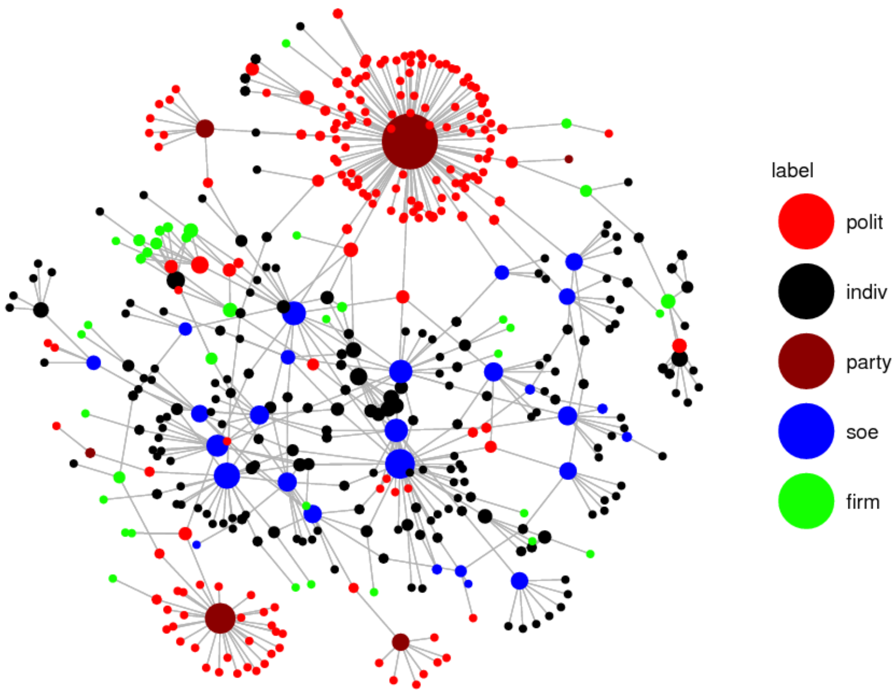


Figure 8: Big Island of PEP network in China

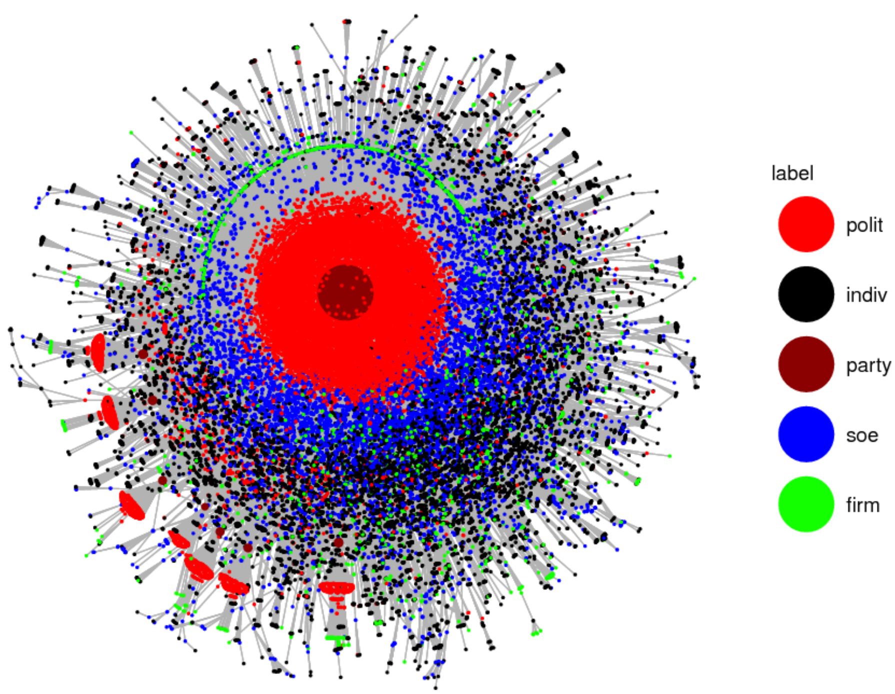


Figure 9: World switches

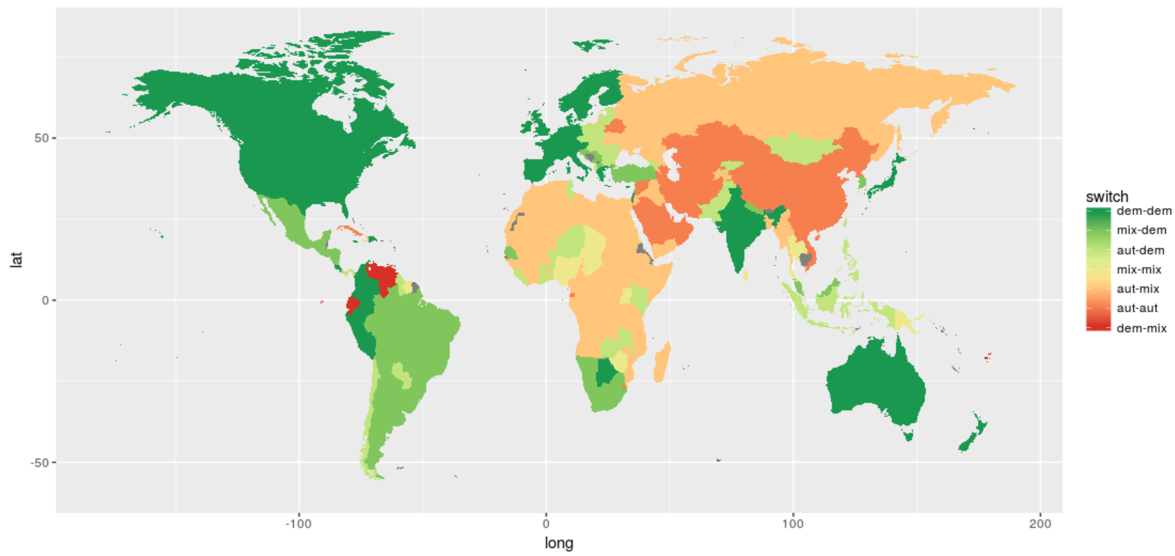
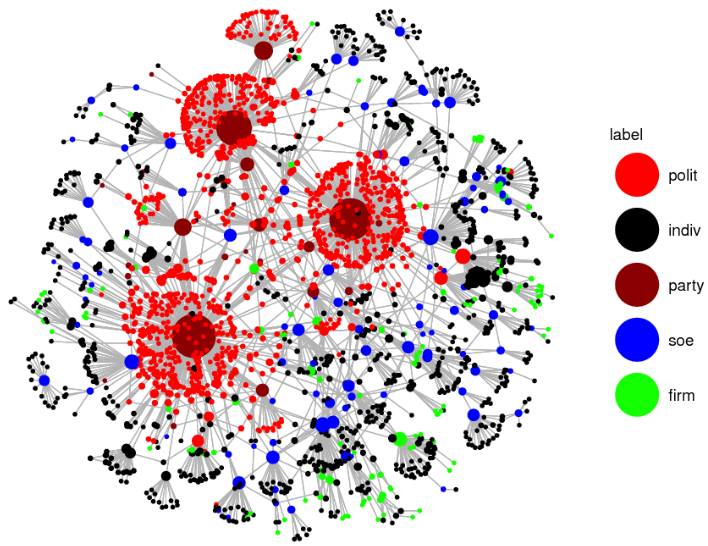


Figure 10: An example of Eigenvector importance: case of Greece

(a) Node size using Degree



(b) Node size using Eigenvector centrality

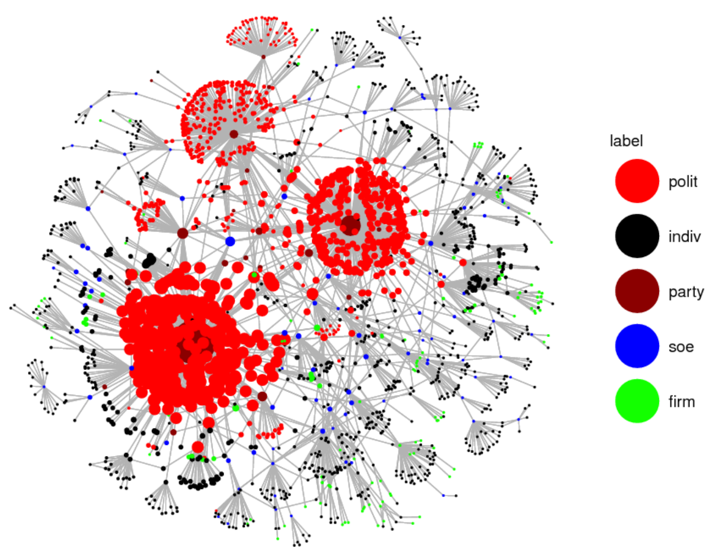
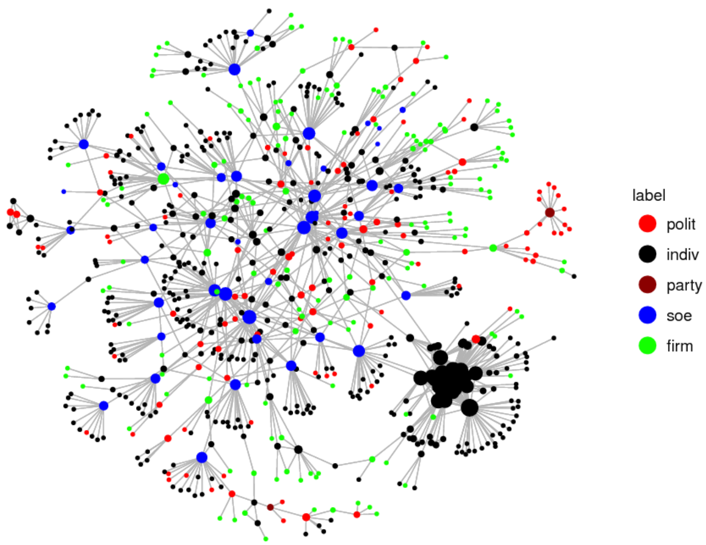


Figure 11: An example of Eigenvector importance: case of Jordan

(a) Node size using Degree



(b) Node size using Eigenvector centrality

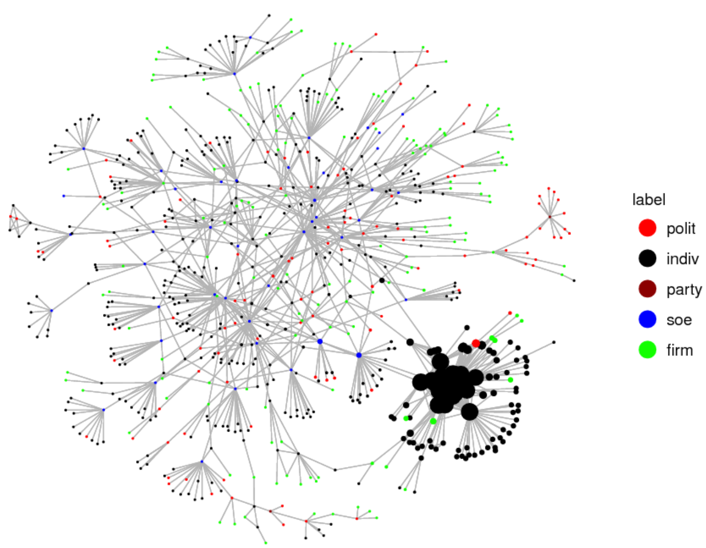
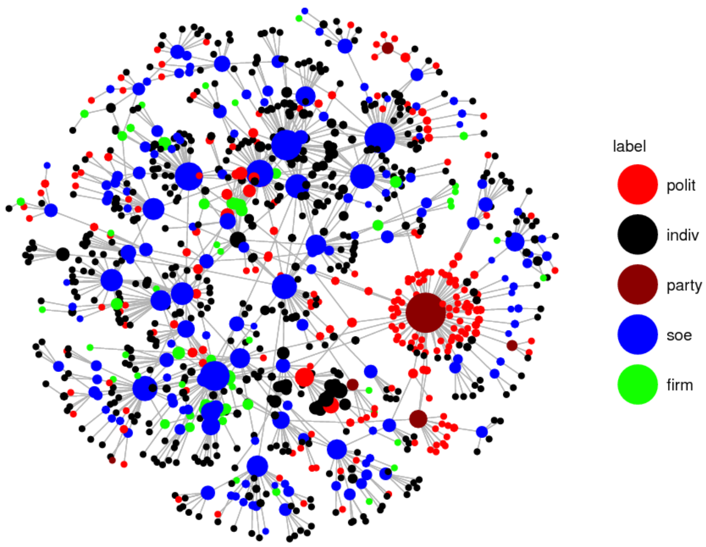


Figure 12: An example of Eigenvector importance: case of Belarus

(a) Node size using Degree



(b) Node size using Eigenvector centrality

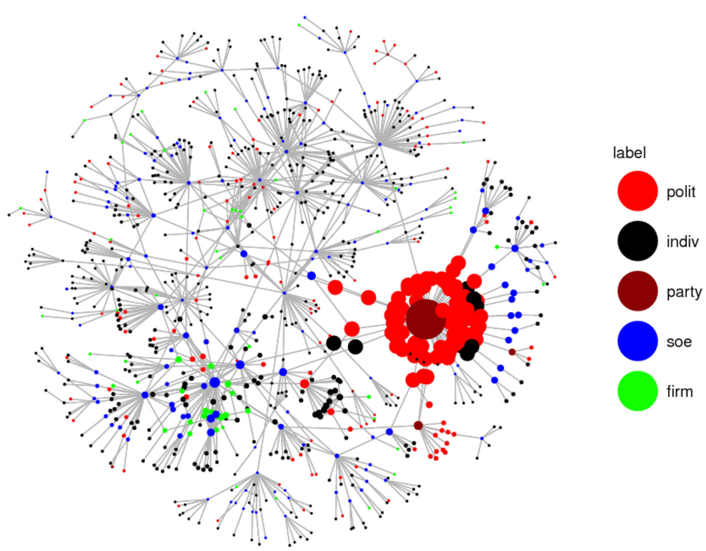


Figure 13: Distance to the President: case of Russia

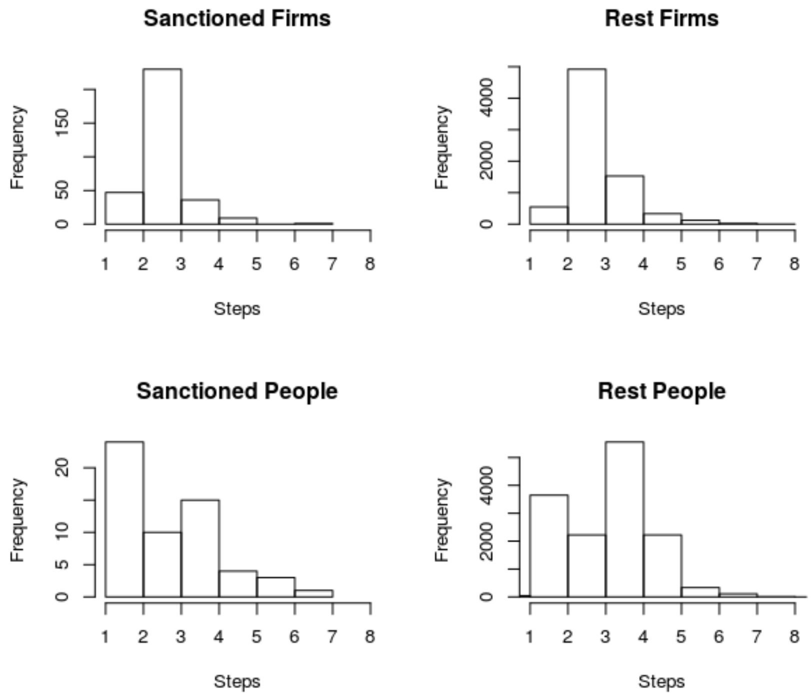


Figure 14: Neighbourhood (up to 2nd degree) of the President: case of Russia