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Foreign direct investment – using network analysis to understand the position of Portugal in a global FDI network[1]

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[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, IFC, BoP, ECB or the central banks and other institutions represented at the meeting.

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Filipa Lima, Flávio Pinheiro, João Falcão Silva and Pedro Matos[1]

Abstract

Understanding the role of foreign direct investment (FDI) is of utmost importance in a world economy of increasingly interdependent economies. However, the lack of an unified data source of FDI covering a long time frame has posed serious challenges to its analysis. In this article we apply methods of network analysis to build a representation of the global FDI relationships. We show how the network representation of the global FDI can be used to identify patterns, identify preferential paths for investment, establish trends and describe the relations between countries over time. We present the results by using specific visualisation tools that graphically illustrate the interlinkages between the economies, and that can be a valuable instrument for the design and deployment of regulating instruments.

Keywords: Foreign direct investment, Network analysis, Visualisation tools

JEL classification: C02, C63, F21

1. Introduction

"One picture is worth a thousand words". For producers of official statistics this translates into "*One picture is worth a thousand numbers*".

An increasingly globalized and interconnected world economy raises new challenges to the traditional macroeconomic statistics. To describe a globalized world, where national borders are less relevant, economic statistics also need to adapt and be supplemented with information on global interconnectedness. In this respect, external statistics play a crucial role in the comprehension of global phenomena.

One domain where we are likely to find ourselves immersed in a deluge of data concerns Foreign Direct Investment (FDI). FDI is a category of cross-border investment in which an investor resident in one economy establishes a lasting interest in and a significant degree of influence over an enterprise resident in another economy (immediate counterpart country). The dimensions of analysis covered in FDI include, among others, inward and outward values for stocks, flows and income, by partner country and by industry. In a world with 10 countries only, analysing the FDI links between countries based on the annual stocks would require a 100 cells matrix. Moreover, from the observation of this matrix one would not be able to say straightforward which countries are closer to which, which ones have stronger FDI links, etc.

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In order to capture the indirect foreign direct investment relationships and to have a comprehensive picture of ultimate cross-economy financial linkages and risks, FDI standard data needs to be complemented with information on ultimate counterpart economy.

This paper illustrates how the use of network analysis tools, to represent FDI country-to-country relationships, can help producers of these data to better understand and communicate them. In particular, we will illustrate how we can assess the position of a given country in a global FDI network and how it varies over time. Furthermore, a comparison between 2009 and 2018 network is addressed and the results show that the countries with more FDI interconnections usually correspond to advanced economies, financial centres, and tax benefit countries. To that end we will use data provided by the International Monetary Fund (IMF) - Coordinated Direct Investment Survey (CDIS), for all the available world countries, and focus our analysis in European economies and Portugal in particular.

The paper is organised as follows: after the introduction section, a literature review on the network analysis is presented. The methodological session describes the network approach and its fundamentals and in section 4 data variables and data sources are described. The global FDI network is represented in section 5 and section 6 concludes.

2. Network analysis and economic variables

Network analsysis has a long tradition in the study of socio-economic systems (Jackson (2010) and Schweitzer *et al.*, 2009). Network science offers a set of tools to facilitate the inference of relationships between different elements (agents, actors, individuals, etc.) of a system (Marvasi *et al.*, 2013, Giovannetti *et al.*, 2015, Newman *et al.*, 2006), while offering an opportunity to analyse the macroscopic properties that stem from the collection of relationships established between those elements. Network science constitutes a unique framework to study how information propagates through a system and failures cascade throughout its elements (Barabási *et al.,* 2016).

Ribeiro *et al.* (2018) analyzed the historical activity archives of a XVI century merchant/banker from Spain, showing a global network that exhibit properties quite similar to those of modern day banking systems, arguably raising questions on the universality of the mechanisms underlying the emergence of such structures regardless of the society technology levels. Batiston *et al.* (2016) and D'Errico and Roukny (2017) used network analysis to study the redundant capital in over-the-counter (OTC) markets and the degree to which these can be compressed in order to ease the role of the regulator. In fact, in the follow up of the 2008 financial crisis many authors have resorted to network science methods in order to disentangle the complex cascade effects observed in the banking sector.

In the context of economic development, Hidalgo *et al.* (2007) introduced the Product Space, a network that measures the knowledge proximity between products that countries can export, helping to explain both the natural laws of development of countries but also their constrains. These methods have become widely popular in economic geography by capturing the building blocks of regional technological and industrial specialization dynamics (Alstott *et al.*, 2017; Ter Wal and Boschma, 2009; and, Hidalgo *et al.* 2018). Focusing instead in the relationships between countries and not their products, the World Trade Web represents the bilateral relationships between countries obtained from the import and export flows. In the literature several works can be found that make a characterization of its complex nature (Serrano and Boguñá, 2003), but also how it has shown a rather non-intuitive stability over the years (Fagiolo *et al.* 2010).

Amighini and Gorgoni (2014) analysed the patterns of trade in auto parts and found that the rise of emerging economies as suppliers forced a change in the international market structure. On the other hand, Akerman and Seim (2014) analysed the global arms trade network and the results showed that over the years the network became more clustered and decentralised.

More recently, Amador *et al.* (2018) analysed the global value added in the trade flows to understand the structure of global value chains, using a complex network analysis to represent the value that each country added to the global value chains. According to the authors, many articles use the complex network perspective to achieve an empirical analysis of international trade interactions. In this case each country is defined as a node and the bilateral interaction between them is defined as an edge. Many studies already focus on this interaction, either on an undirected way (when the interaction is from both countries) or directed way (just from one to the other), as Kali and Reyes (2007), Fagiolo *et al.* (2010), and, Garlaschelli and Loffredo (2005). The use of network analysis can also determine the existence of a high level of clustering between two or more countries (Amador and Cabral, 2016), which may indicate common characteristics between the different countries.

The set of tools allows the identification of the full structure of interactions between many countries without any limitation on using longer time frames. According to Newman (2010) there is a set of measures to examine analytically the large-scale properties that are subject to a complex network system. This means that we can integrate the data in one single structure and analyse it according to different measures which define the properties of this structure. In addition, the network tools provide a set of visual aid for the structure representation. It uses graphs with notes that contain nodes linked by edges to support a better understanding of the relationships between each country, represented by a node. This node indicates the closeness between each country in the same group. The use of the network analysis in economics can improve the understanding of economic systems, where firms or individuals interact between each other. It also explains stylized facts and complex relationships structures, with simple models (Marvasi *et al.*, 2013).

Interestingly, there is a lack of studies exploring FDI data. Li *et al.* (2018), explores evolution on the global FDI network, from 2003-2012. The authors used network analysis tools to present and analyse the global FDI, using some metrics to define the global characteristics of the network. The authors recognized the value added from using the methodology. Furthermore, they used network analysis customization and presentation tools, such as changing the size or the colour of nodes in order to highlight the importance of each country in the network. And they also explored the potential use of two network metrics, the degree and the average path length, to better define the characteristics and the relations inside the network. Damgaard and Elkjaer (2017) focused on the role of special purpose entities (SPEs) and estimated a unique global FDI network where SPEs are removed and FDI positions are broken down by the ultimate investing economy. According to the authors total inward FDI in the new network is reduced by one-third, and financial centers are less dominant. More recently, Damgaard *et al.* (2019) estimated the global network of FDI positions while disentangling "real FDI" (the relation between an investor in one economy and an active and substantial business in another economy) and the "Phantom FDI" (investments into empty corporate shells with no link to the local real economy). Ignoring phantom investment and allocating real investment to ultimate investors increases the explanatory power of standard gravity variables by around 25 percent.

3. Methodology approach

In the following sections we will describe the key methodological aspects and main variables of interest in the context of network analysis.

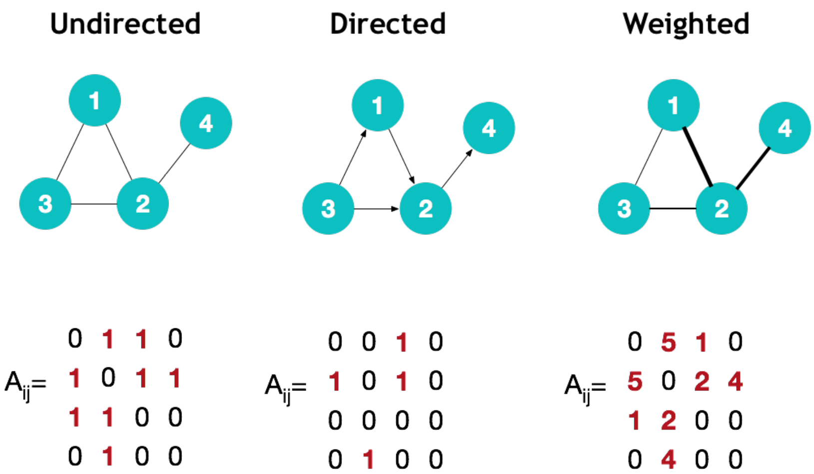
Network Analysis

Network science provides a common framework and analytical tools to extract insights from many systems and problems. In particular, and stemming from its strong complex systems roots, it is often used to link how individual/microscopic interactions lead to emergent macroscopic structures that governs the behaviour of the entire system as a whole. In that sense, and besides the analytical tools, network science has also gained some relevance for the potential to provide rich visualizations of the complex organization of such systems, allowing to highlight structures and patterns of interest. In this section, we detail the fundamentals of what makes a network and some relevant network measures. In the following sections we will detail the network inference methodology used in this work.

A network, $\mathcal{G}$, is a system composed by two sets of distinct but complementary elements: a set of N vertices/nodes ($\mathcal{V}$: $\{v_0, \ldots, v_N\}$) and a set of links/edges ($\mathcal{L}$: $\{e_{ij}, \ldots, e_{kl}\}$). Edges connect pairs of nodes, such that edge e_{ij} identifies the existence of a link between vertices v_i and v_j. Networks elements are commonly used as abstractions of entities (vertices) and existing relationships between them (edges). For instance, in a social system vertices could represent individuals with edges representing a social tie (i.e., friendship. co-work, family) between them.

Graphical representation of different types of networks (top), and the same representation in the adjacency matrix (bottom)

Figure 1



Top panel of Figure 1 shows a graphical representation of three types of networks: Undirected; Directed; and Weighted. Another common, and often algorithmic useful, representation of a network is through the adjacency matrix, see bottom panel of Figure 1 for the adjacency representation of the above networks. The adjacency matrix, A, of a network is a square matrix in which the entries a_{ij} are zero if there is no relationship between vertices v_i and v_j, and non-zero if there is a relationship. In the case of a weighted network the value of a_{ij} corresponds to the weight of the relationship, while in the case of unweighted networks it is by definition one. Moreover, in the case of undirected networks $a_{ij} = a_{ji}$. The diagonal entries of A denote self-links, that is, edges that start and end in the same node. In practice it is common to have the diagonal set to zero[2]. In the network representation each edge that connects two nodes, must have at least one arrow, indicating the direction of the investment, i.e., the investment that is made by one economy (the investor) in the other economy (the host). If an edge has two arrows, each pointing towards a different country, then both countries made an investment to each other.

It is often the case that additional information is available about the characteristics of the different elements of a network. For instance, if vertices represent individuals characteristics these may include their age, gender, or salary. Such information on vertices is typically ignored in the network construction and used only at a later stage to either validate the network, characterize its connectivity structure, or identify new relevant associations[3]. Hence, networks can be either undirected (when edges have no direction) or directed (when edges have a direction) and weighted (when edges have a magnitude or value) or unweighted (when edges weight are merely a binary value representing whether a particular relation exists or not). In general, weights can inform us on the similarity between pairs of nodes (*i.e.*, heavier links mean two nodes are more similar), or their proximity/distance (*i.e.*, how far away are two nodes, where heavier links mean two nodes are farther apart). In network analysis, It is important to clearly specify which measure is being attributed to links weight as it will impact the computation of different network metrics. The available list of characteristics and the ultimate goal of analysis will, in the end, dictate the type of networks to be generated.

Several measures can be made from networks, thus providing a characterization of its elements but also of its structure as a whole. For instance, the degree k_i of a vertex v_i represents the number of connections that vertex participates. In the case of directed networks the degree can be decomposed in two quantities: the in-degree (k_i^{in}) and out-degree (k_i^{out}). The first represents the number of links that point towards such vertex, while the second represents the number of links that point outwards of vertex v_i. It is common to characterize networks by their degree distribution, $D(k)$, that represents the fraction of vertices with degree k. From the degree distribution we can estimate the average degree $\langle k \rangle$ and degree variance $var(k)$, which is often taken as a measure of the level of the degree heterogeneity of a network. The shape of the degree distribution is one of the simplest forms to characterize the structure of a network. It can indicate the fundamental mechanics behind the process that gave origin to a network. For instance, random networks tend to have a Poisson degree distribution ($D(k) \sim \langle k \rangle e^{-\langle k \rangle}/k!$), while networks stemming from preferential attachment have scale-free degree distributions ($D(k) \sim k^{\alpha}$).

Other measures try to quantify the organization of the network. For instance, in social sciences a commonly measure of interest is the Cluster Coefficient (Newman, 2003), which can be a local measure of the nodes or a global measure of the population. It measures the number of closed triangles that are formed in the network, given the number of open triangles that exist. For instance, in social sciences this could be represented by quantifying the number of friends that have a friend in common, and thus an indicator of social cohesion. Hence high clustering is associated with more clustered networks. Often confusing is the relationship between clusters and communities in networks. Communities represent a partition of a network (in different groups) that minimize the inter-links between groups and maximizes the intra-linkages. Finding the optimal partition of a network is an optimization problem that often uses modularity as an objective function (Newman, 2006). Hence although it is expected cluster coefficient to be high inside each community or group, clustering is, in network science jargon, associated with the density of triangular motifs in the network. Networks can be thought as providing a metric that allows

2 One example to illustrate an undirected network is by thinking on a subway system map. In a subway map two stations have an undirected connection, which means that the subway can have each one either as a point of origin or as a destination. Conversely, if the subway system was directed the subway could only go from one station to the other, not doing the same way back.

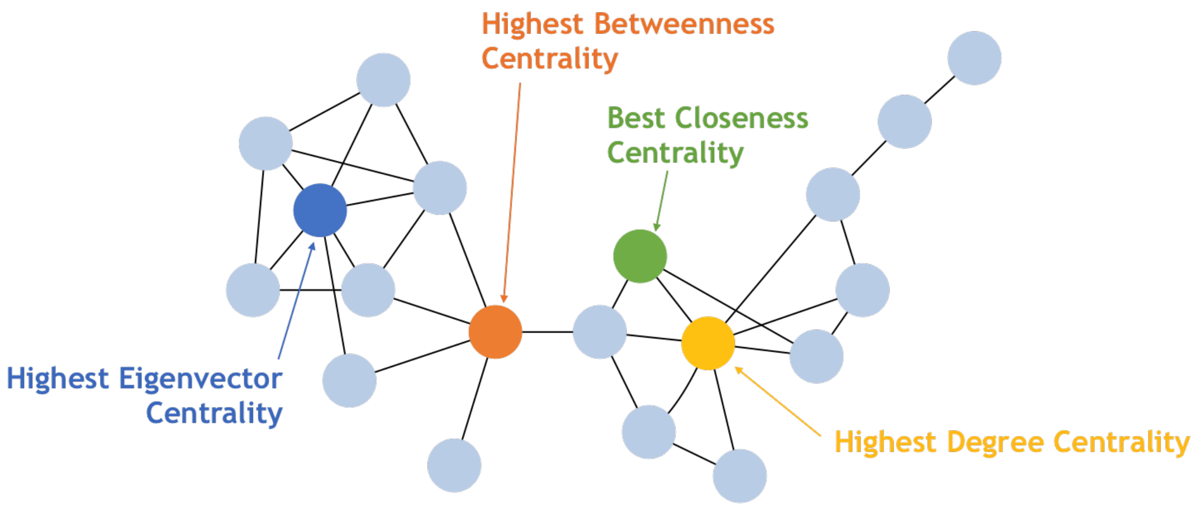
3 Likewise, information about relationships can carry important information that indicate the direction of a relationship (e.g., different people might indicate different friends) or its weight/magnitude (e.g., friendships can have different degrees of importance depending on how old they are).

to estimate the distances between elements in a system. Indeed, one can measure distances between two vertices by identifying the shortest length of the chain - edges and vertices - that would be necessary to transverse in the network to reach one element when starting from another. Naturally, this mindset needs to take into account whether the networks are weighted (in which case the chains need to incorporate the weights) or directed (in which case there are certain nodes) but arguably allows to measure distances in systems and scenarios that otherwise would be very complicated (e.g., social distance between individuals is not something that is measurable by comparing the characteristics of two individuals). In that sense, one measure of interest is the distance between two nodes, which is simply the shortest path that connects two nodes in the network. The average path length measures the average length of the shortest paths in the network, measuring thus the expected distance between any pair of nodes. Finally, the diameter of a network corresponds to the largest shortest path in the network.

Figure 2 represents a simple network with the most central nodes estimated from different metrics highlighted. As it is clear to see, although in many circumstances the same node can be the most central according to different centrality measures, it is easy to show that that is not necessarily the case.

Simple network with the most central nodes estimated from different centrality metrics highlighted

Figure 2



A common problem in many fields is to identify the most important/central elements of a particular system. In network science this is done by analysing the relative position of each element in the overall network and, in some cases, their relative importance to the functioning of the network. One classical example of the importance of network centrality measures comes from Google, whose algorithm, Page Rank, used to rank the relevance of pages to queries of users, stems from a network centrality measure (Page *et al.*, 1999)). In that sense, there are several measures of vertices centrality that are worth mentioning:

1. Degree Centrality – measures the importance of a node by their degree. Hence a node is more important the more relationships it holds;

2. Closeness Centrality – measures the importance of a node by how far away it is from the remaining nodes of the network. In that sense, the most important node is the one that stands closer to the othes;
3. Betweenness Centrality – measures importance of a node by how often it intermediates paths between other nodes. In that sense, a node is more important if it is more often the middle man in the information diffusion through the network;
4. Eigevenvector Centrality – measures the importance of a node by how likely would a random walker spend time in that specific node if the walker was left indefinetly visiting nodes of the network by transversing its edges. Pagerank is a variation of the Eigenvector.

4. Data description and sources

The direct investment comprises cross-border investment associated with a resident in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy[4]. It captures the immediate direct investment relationships, i.e., when a direct investor directly owns equity that entitles it to 10 percent or more of the voting power in the direct investment enterprise.

The direct investment is usually presented in two different perspectives – following the asset/liability principle (as introduced in the 6th edition of the Balance of Payments Manual) or directional principle (requested in previous editions). In our paper, we consider the directional principle presentation to reflect the direction of the investment. Under the directional principle, direct investment is shown as either direct investment abroad (outward investment[5]) or direct investment in the reporting economy (inward investment[6]).

The implementation of the network estimation uses statistical information on the foreign direct investment directional principle. The information was obtained from the Coordinated Direct Investment Survey provided by the International Monetary Fund. The selected data contains annual information from 2009 until 2018 on the total inward direct investment (stocks) and also inward equity direct investment (stocks). In addition, it was considered information for all the available world countries (133) with all the available counterpart countries (259) in US dollars. It reflects all the immediate direct investment relationships between resident direct investment enterprises and their non-resident direct investors (those that own 10 percent or more of the voting power in the direct investment enterprise).

5. Building a FDI global network

Here, we will consider the case where each node represents a country, while edges highlight the strength of the direct investment between two countries proxied by the Foreign Direct Investment Stock.

4 The significant degree of influence is determined to exist if the direct investor owns from 10 to 50 percent of the voting power in the direct investment enterprise. Control is determined to exist if the direct investor owns more than 50 percent of the voting power in the direct investment enterprise.

5 Investments by resident direct investors in their direct investment enterprises abroad deducted from the reverse investments by direct investment enterprises abroad in their resident direct investors.

6 Investments in resident direct investment enterprises by direct investors abroad minus Reverse investments by resident direct investment enterprises in their direct investors abroad.

Let us consider that f_{ij} represents the Inward Direct Investment Positions, US Dollars, between country i and j. By definition the FDI stock can be a positive or negative number. A negative FDI position is most likely to occur when FDI statistics are presented by partner country (i.e., directional principle) and occurs when the funding from the affiliate to its parent exceeds the investment made by the parent in the affiliate, and it can be asymmetrical, in that $f_{ij} \neq f_{ij}$. Our first step in network inference is to deal with the problem of negative f_{ij}. To that end, we shall consider the absolute values, $|f_{ij}|$. Secondly we want to analyse the proximity between countries and we need to merge both asymmetric flows into a single quantity. To that end we measure the proximity between two countries as

$$\phi_{ij} = \frac{1}{|f_{ij}| + |f_{ji}|} \tag{1}$$

where by definition ϕ_{ij} = ϕ_{ji}. Under this assumption the larger the magnitude of the FDI stock between two countries the closer, or more related, they are. In the end we obtain a proximity square matrix, Φ, that allow us to build an undirected weighted graph.

Visualizing the network spanned by Φ leads to an utterly dense structure in which is difficult to visualize any important or relevant structural properties. Hence, to visualize the network we first identify the Minimum Spanning Tree, which is the network with the minimum number of edges (and in this case total weight sum) that creates a single connected network, that is, a network in which all nodes are connected to at least another node and in which is possible to draw a path between any pair of nodes. However, since the resulting structure is very sparse and lacks any sense of structure, we add the edges with the lowest weight, which identify the closest relationships, to the network. We define a threshold on a case by case. For layout we use the Gravity Embedding from Wolfram Mathematica 12.

Note that, besides the above steps for network visualization, all other computations are done on the network spanned by the full proximity matrix (Φ).

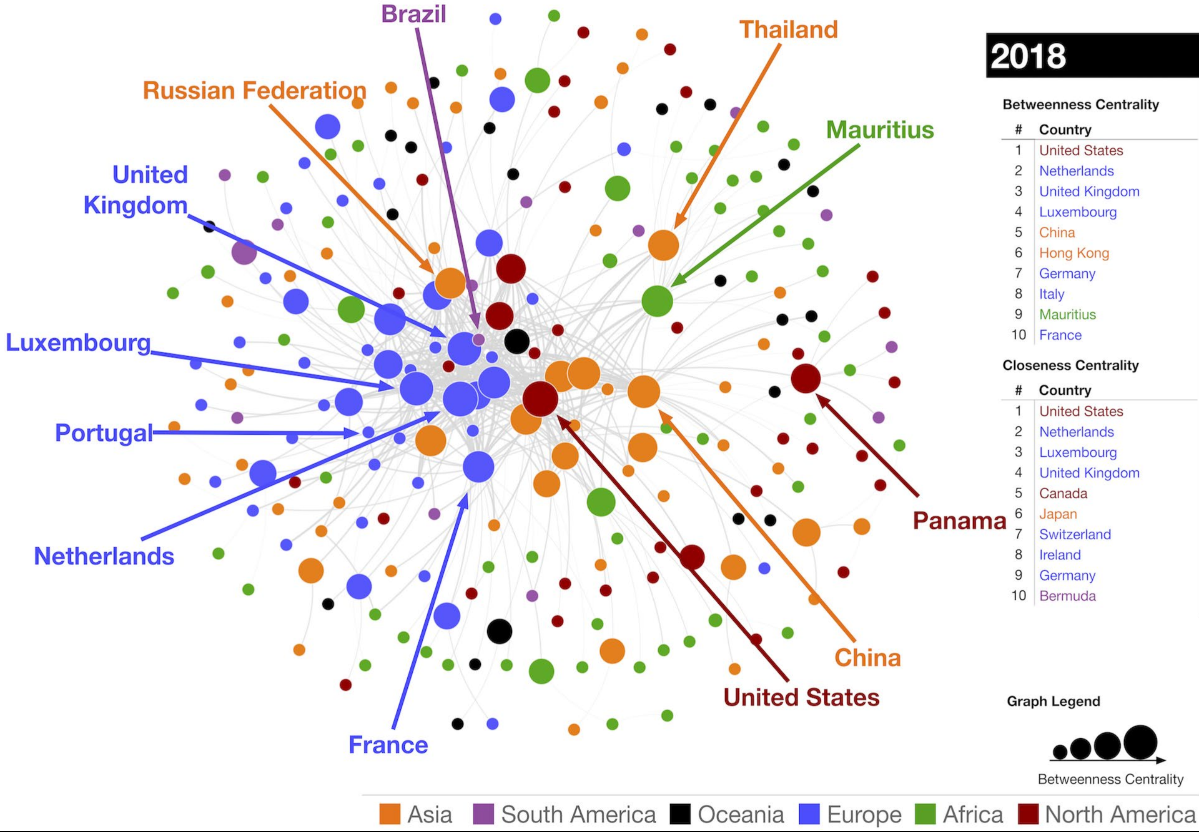
Figure 3 corresponds to the network representation of global FDI for 2018. Each node represents a country, and relationships identify the highest weight defined as above. Six geographic areas are identified by six different colours and the main players, together with Portugal, are also identified, both in terms of betweenness centrality and closeness centrality.

The most important (central) countries in terms of how often they intermediate paths (i.e., FDI relationships) between other countries (betweenness centrality) in 2018 are, by descending order: United States, Netherlands, United Kingdom, Luxembourg, China, Hong Kong, Germany, Italy, Mauritius, and France. These countries are more often the middle country in the FDI diffusion through the network. The presence in this TOP10 list is likely to be explained by the fact that the country acts as an important financial centre or as an off-shore.

The most important countries in terms of how close they are to the rest of the countries (closeness centrality) in 2018 are, by descending order: United States, Netherlands, Luxembourg, United Kingdom, Canada, Japan, Switzerland, Ireland, Germany and Bermuda. These results are consistent with the main "FDI" countries, as they usually correspond to to advanced economies, financial centres, and tax benefit countries among other country situations countries which are politically and economically stable. The results are also consistent with the World Investment Report 2019 (UNCTAD).

Network representation of global FDI (2018). In the right panel it is shown the TOP10 ranked countries by betweenness and closeness centrality.

Figure 3

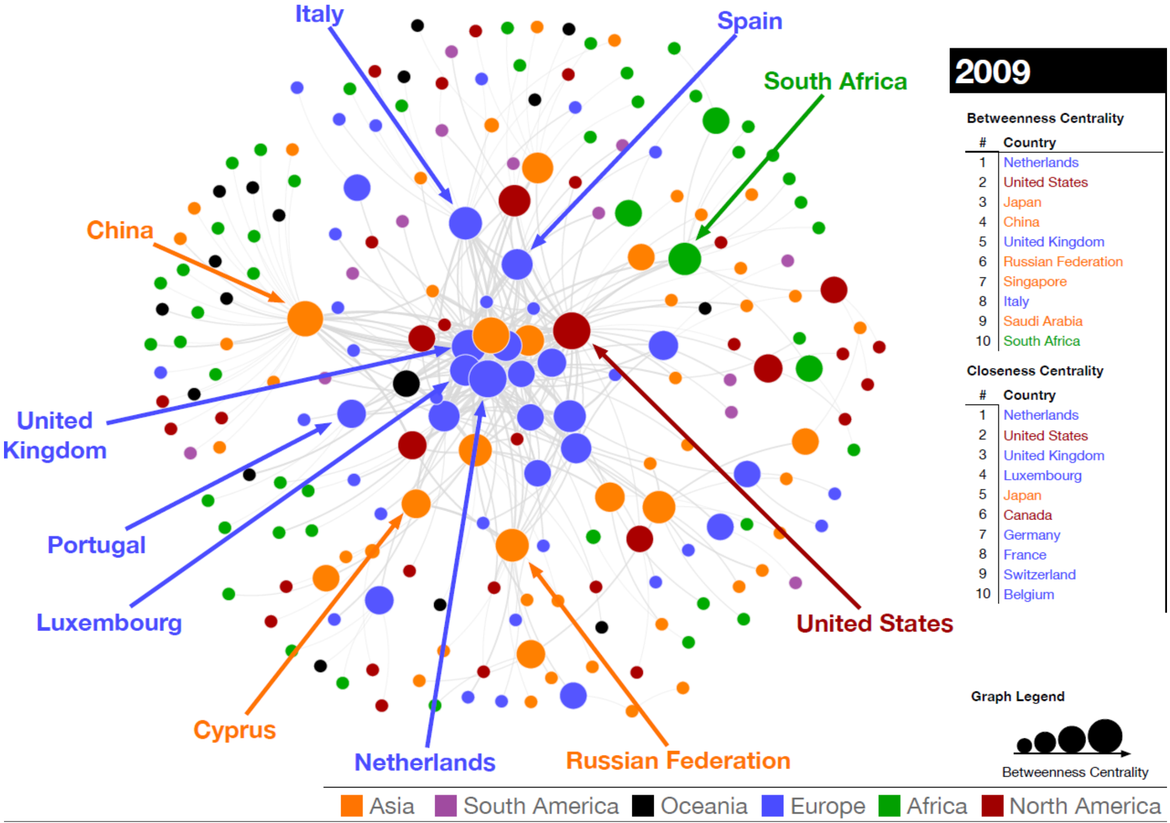


Source: IMF CDIS data and authors' calculations

Figure 4 corresponds to the network representation of global FDI for 2009. There are some differences between the 2009 and 2018 networks. One general difference relies on the closeness and centrality, which is higher in the 2009 network than in the 2018 network. Furthermore, it can be pointed that in 2009 South Africa occupied a central position in Africa, whereas in 2018 Mauritius became more important. In addition, in the 2009 network there are more European countries in the centre of the network than in 2018. Finally, it is also important to stress out that in both networks China and Russian Federation play a crucial role in Asia, while United States are crucial in North America.

Network representation of global FDI (2009). In the right panel it is shown the TOP10 ranked countries by betweenness and closeness centrality.

Figure 4

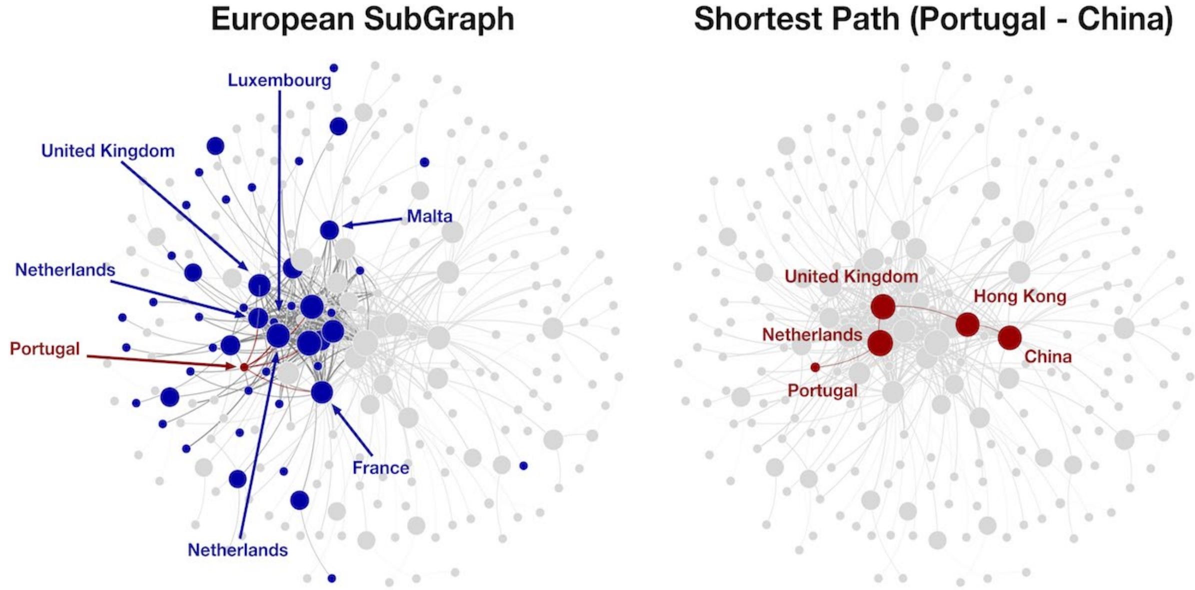


Source: IMF CDIS data and authors' calculations

In Figure 5 we zoom in this global FDI network and highlight the European FDI sub-network, i.e., the European countries highlighted in blue in the global FDI network (left panel). In addition we selected one specific case to analyse the shortest path connecting FDI between China and Portugal in 2018, where there is evidence that China is an ultimate investor in many Portuguese inward foreign direct investments, but not the immediate counterpart country in the right panel of Figure 6. According to the results obtained, the shortest path between Portugal and China passes by Hong-Kong, United Kingdom and Netherlands (immediate counterpart country). Interestingly, this is precisely the information we expect to find when considering immediate counterparts *vs.* ultimate investors. From complementary data sources we find evidence that much FDI done in Portugal by Chinese investors (ultimate counterpart) is intermediated by Dutch companies (immediate counterpart). The fact that this intermediation is captured by network science techniques using as raw data only information on the immediate counterpart illustrates the enormous potential and analytical power of these tools both for researchers and statisticians.

Network Representation of European FDI and FDI shortest path between China and Portugal (2018)

Figure 5

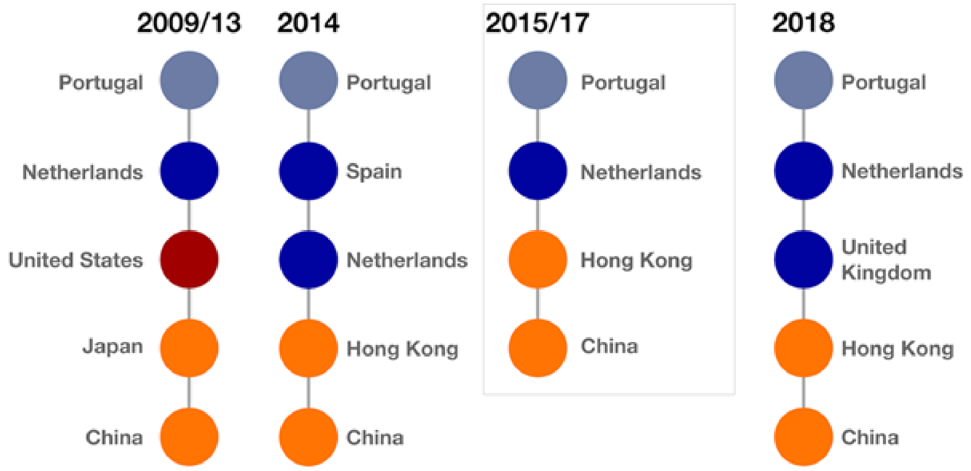


Source: IMF CDIS data and authors' calculations

The shortest path connecting FDI between China and Portugal evolved over time, as illustrated in Figure 6, between 2009 and 2018. Figure 6 shows that between 2009/2013 there were three FDI intermediate countries between Portugal and China (Netherlands, United States and Japan) whereas in 2014 these three intermediate countries were Spain, Netherlands and Hong Kong. From 2015 until 2018 only two countries (Netherlands and Hong Kong) intermediate the FDI investment of China in Portugal. In 2018 United Kingdom appears in the network close to the Netherlands and Hong-Kong.

Evolution of FDI shortest path between China and Portugal (2009-2018)

Figure 6

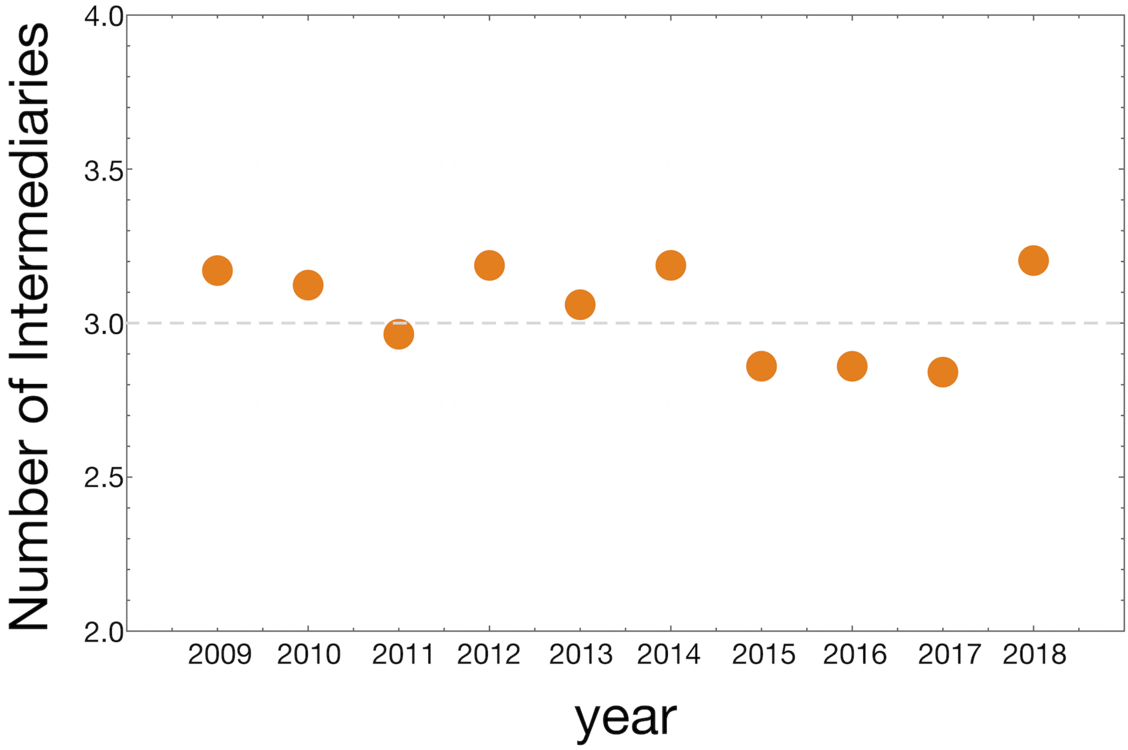


Source: IMF CDIS data and authors' calculations

On average, the number of intermediaries in the shortest paths that connect every pair of world country is around 3 and has not varied significantly over time (Figure7). Nevertheless, the composition may be different.

Average number of intermediaries in the shortest paths that connect every pair of world country (2009-2018)

Figure 7



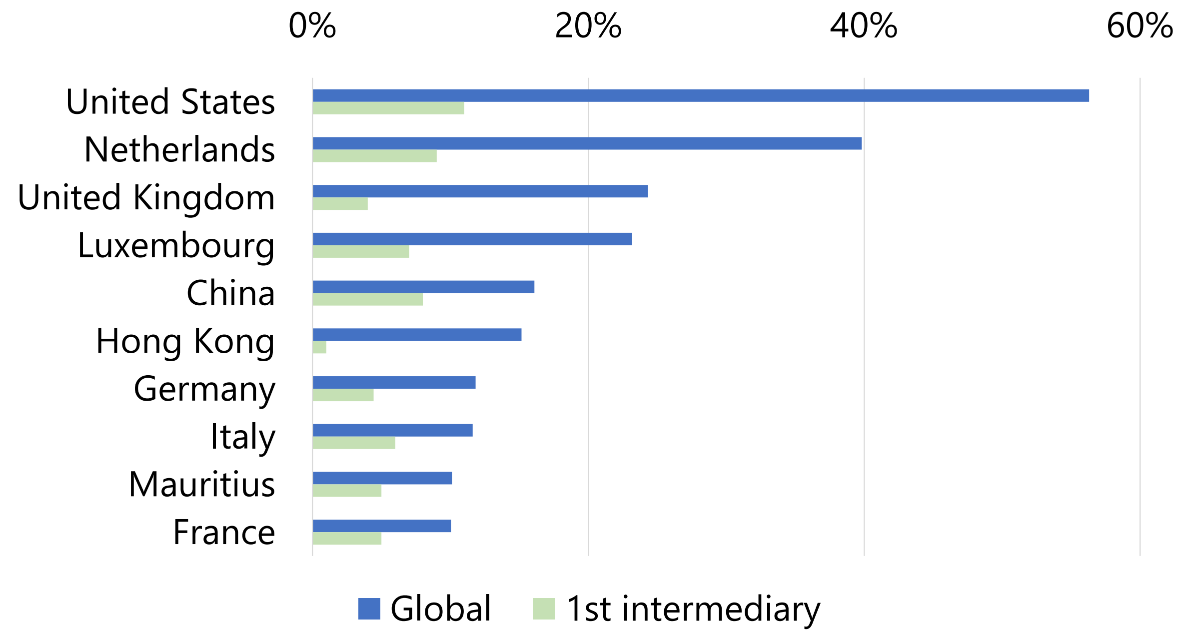
Source: IMF CDIS data and authors' calculations

Turning now to the TOP10 intermediaries in 2018, we analysed how often they intermediate any FDI relationship between any pair of countries in the world. We exclude the cases where they are the origin or the destination of the FDI itself. As we can see in Figure 8, the list is led by the United States, intermediating over 50% of all FDI paths identified; moreover, in more than 1/10 of those paths, the United States operate as first intermediary in the path. The cases of the Netherlands and the United Kingdom are also worth mentioning. Although their share as intermediaries is smaller than that of the United States for 2018, they act as first intermediaries every other path.

Finally, in Table 1, we looked at some selected countries as originators of FDI and assessed which countries were chosen as first intermediaries. The United States again dominate the table, acting as first intermediary in the most of selected countries as Germany (35%), Japan (49%) and United Kingdom (29%). Moreover, Netherlands dominates in the case of Portugal (52%) and United States (14%). Finnally, Hong Kong plays an important role in China (43%) and Cyprus in the Russian Federation (49%). It is important to refer that the results differ when different years are considered.

TOP intermediaries in a global FDI network (2018)

Figure 8



Source: IMF CDIS data and authors' calculations

Selected investors and TOP intermediaries in a global FDI network (2018)

Table 1

Investor (country)	1st intermediary (country)	1st intermediary (share, %)
China	Hong Kong	43%
Germany	United States	35%
Japan	United States	49%
Portugal	Netherlands	52%
Russian Federation	Cyprus	49%
United Kingdom	United States	29%
United States	Netherlands	14%

Source: IMF CDIS data and authors' calculations

6. Final remarks

According to the UNCTAD's count, in 2018, 55 countries and economies introduced 112 policy measures affecting foreign investment – a decrease of more than 11 per cent over the previous year's figure. Thirty-one of these measures related to new restrictions or regulations relevant to FDI, while 65 related to investment liberalization, promotion and facilitation. Accordingly, the proportion of more restrictive or more regulatory policy measures introduced soared from 21 per cent in 2017 to 34 per cent – an increase of more than 60 per cent. This ratio is the highest since 2003.

Our results are consistent with the Damgaard and Elkjaer (2017). According to these authors, The United States, Netherlands, and Luxembourg dominate the FDI network based on the CDIS. The network also reveals a very high degree of connectedness where most economies have FDI links vis-à-vis each other. Moreover, the authors conclude that some economies appear on the list of low-tax economies (Cyprus, Gibraltar, Jersey, and Mauritius) and Hungary similar to our results.

Despite the interesting results obtained so far we are aware of some limitations in this analysis and we have already identified avenues for future research and improvement. They include the following:

- Enlarging the time frame to better understand the behaviour of FDI and its main trends prior and after the global financial crisis. This will probably require combining multiple data sources.
- Creating a network analysis with only transactions data, instead of stocks.
- Conducting an in-depth analysis on the differences between direct and ultimate investors, comparing the results obtained until now with actual data on ultimate investors.
- Performing a cluster analysis for the global network of direct investment. Identifying groups of countries that have closer relations or common characteristics, will help to understand what motivates different countries to establish investment relations between them. Identifying main factors, such as proximity, language or culture.
- Analysing the impact that FDI has on the different economic sectors. Define what are the main targets of foreign investment, how have they changed over time and what is their impact for the economy.

From the above aspects, it is clear that a useful extension of this study can be conducted.

Nonetheless, from the results presented it is clear that network analysis tools present many advantages on the study of economic variables, especially when studying a large dataset with many agents. We have highlighted not only the visualisation capabilities of this methodology, but also its ability to apply metrics that provide useful information about economic relations. Therefore, in order to ensure the most efficient use of existing large data sets, without using other variables, network analysis presents itself as a tool to analyse, describe and present the results.

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Using network analysis to understand the position of Portugal in a global FDI network

Filipa Lima, Flávio Pinheiro, João Falcão Silva, Pedro Matos

Bridging measurement challenges and analytical needs of external statistics: evolution or revolution?

18 February 2020, Lisboa

BANCO DE PORTUGAL
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How can the Foreign Direct Investment benefit from the network analysis?

China Three Gorges buys EDP stake for 2.7 billion euros

Axel Bugge

5 MIN READ

LISBON (Reuters) - China Three Gorges won the competition to buy Portugal's stake in utility EDP (EDP.LS), paying 2.7 billion euros ($3.5 billion), in a privatization seen key to the indebted euro zone country's ability to sell state assets.

The deal, which also includes Chinese investment in the wider economy, is the brightest news for Portugal since it was forced to seek a 78 billion euro bailout from tl European Union and International Monetary Fund in the spring after its financing cos soared.

State holding company Parpublica said on Thursday that China Three Gorges' offer fo the 21 percent stake in EDP, Portugal's largest company, was at a 53 percent premium to its share price.

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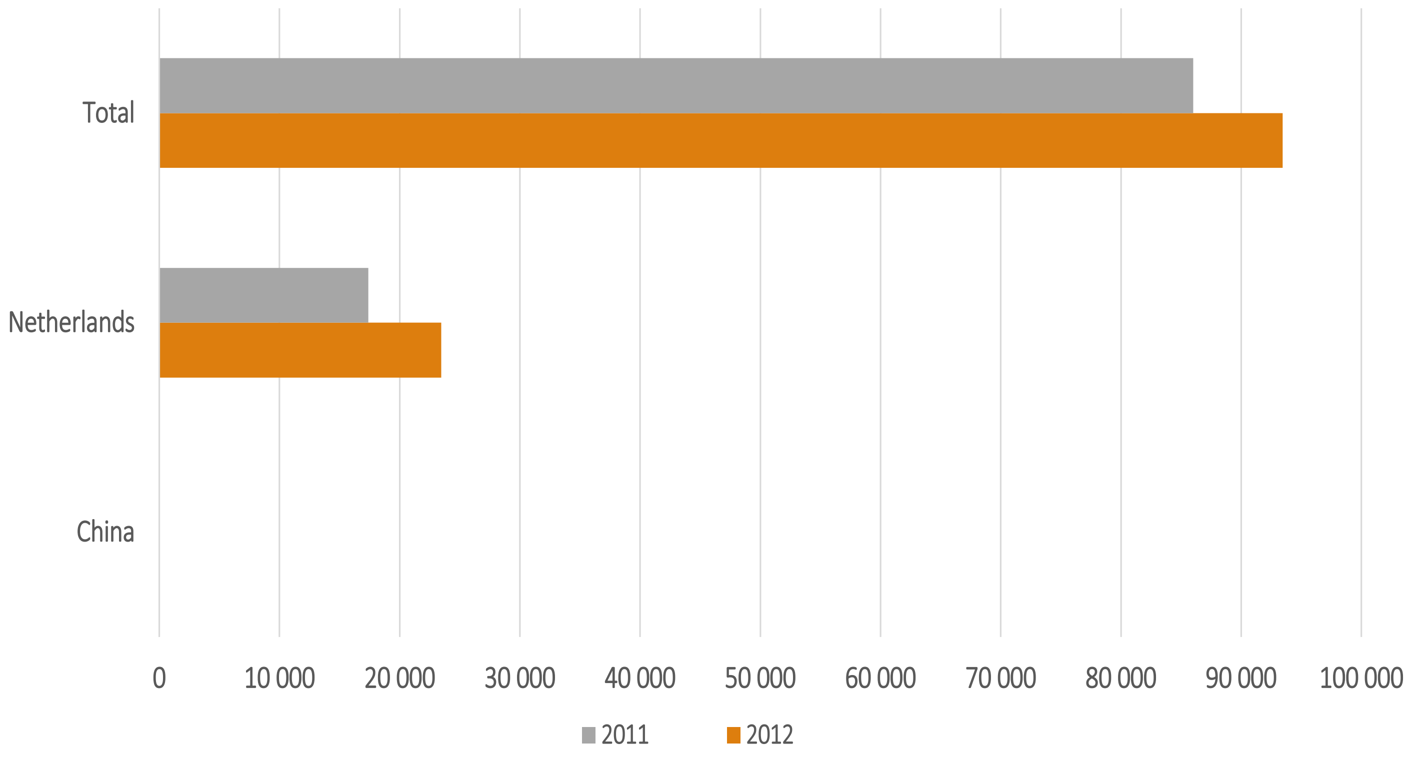
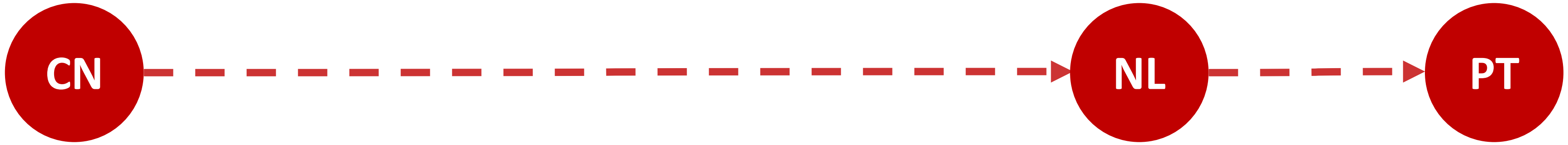
Inward Foreign direct investment – Portugal (M€)



How can the Foreign Direct Investment benefit from the network analysis?

'One picture is worth a thousand numbers'



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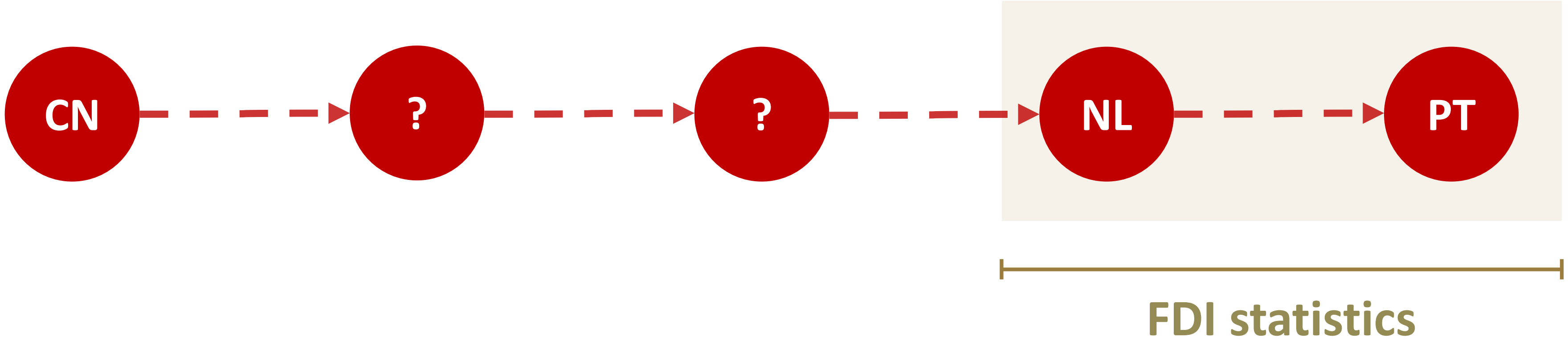

‘Immediate source of funding’

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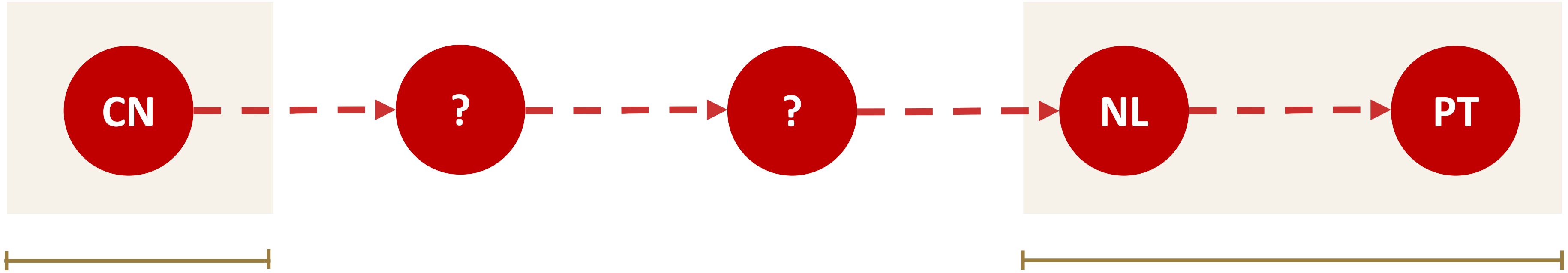


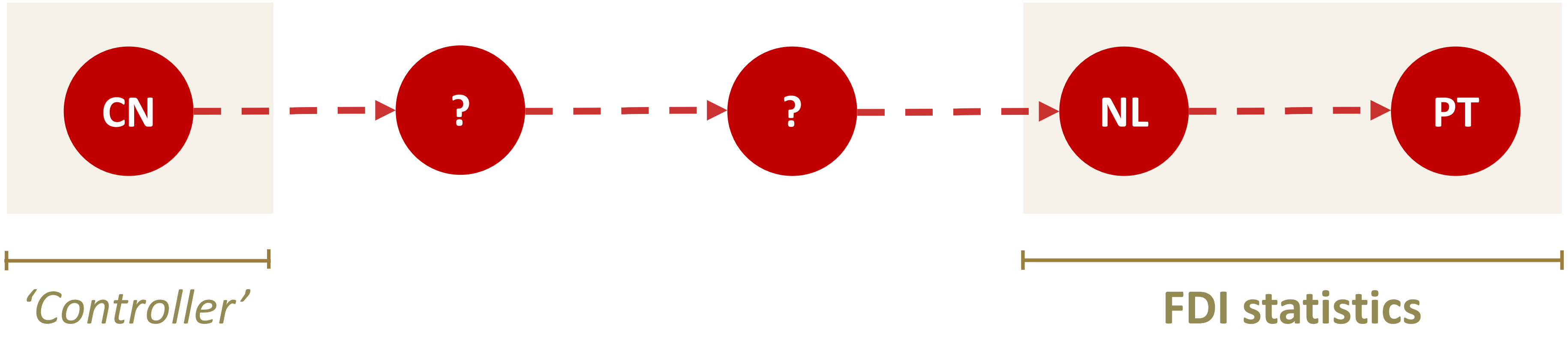
'Controller'

FDI statistics

'Immediate source of funding'

How can the Foreign Direct Investment benefit from the network analysis?

’One picture is worth a thousand numbers’



‘Immediate source of funding’

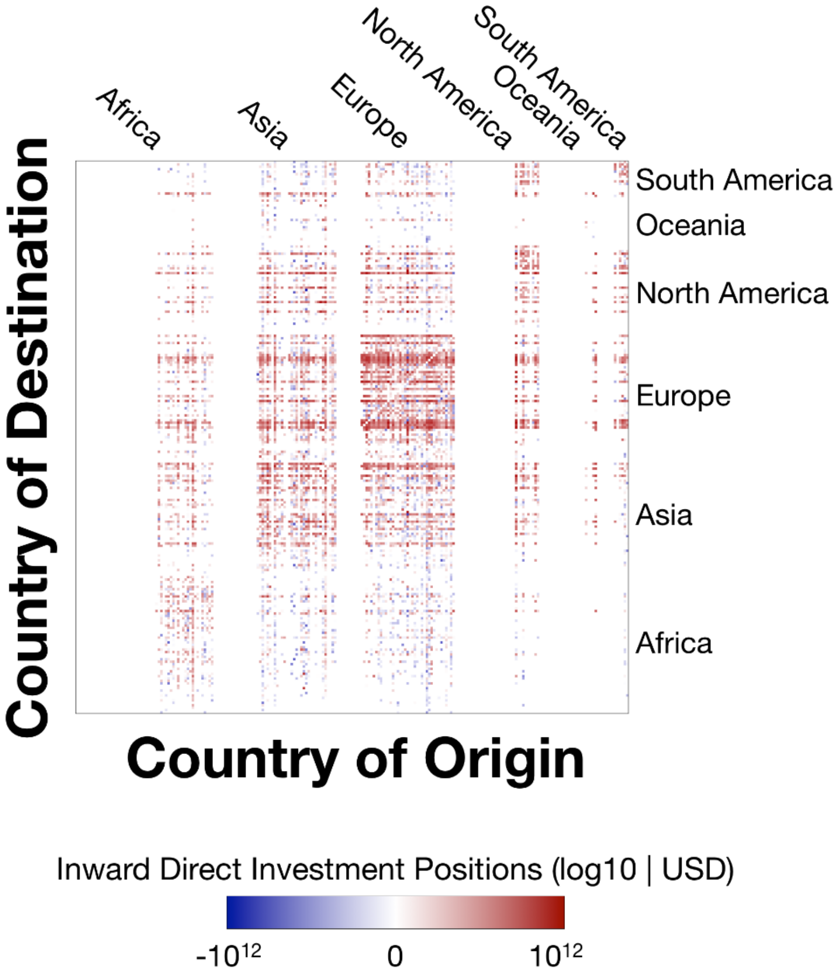
Network science offers a set of tools to facilitate the inference of relationships between different elements of a system

Aim of the paper

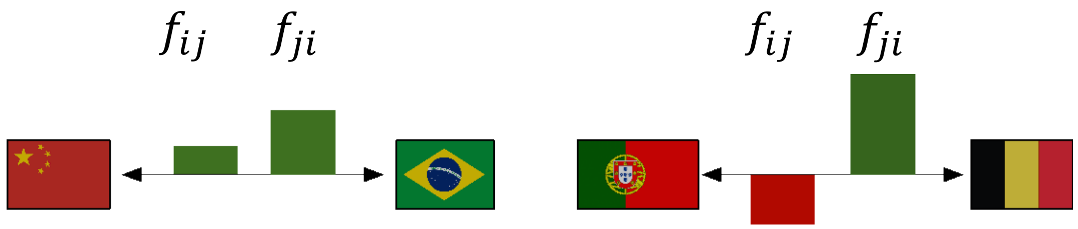
- Illustrate how the use of network analysis tools can help to understand FDI country-country relationships:
  - Inward stocks - 133 X 259 countries
  - Coordinated Direct Investment Survey
- Construct a global FDI network between 2009 and 2018
- Use the network analysis to predict the ultimate direct investor and intermediaries
- Design the shortest paths between the immediate and ultimate direct investors

Inward Direct Investment Positions (USD) [IIW_BP6_USD]

Building the FDI global network



Bilateral FDI Stocks

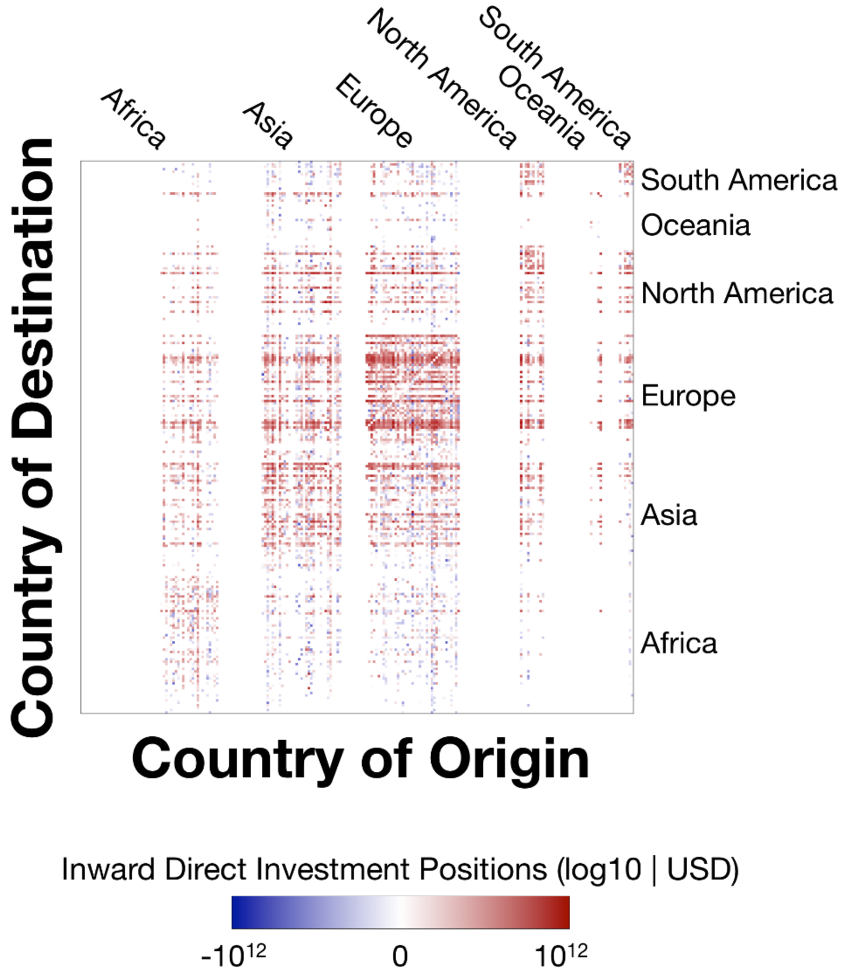


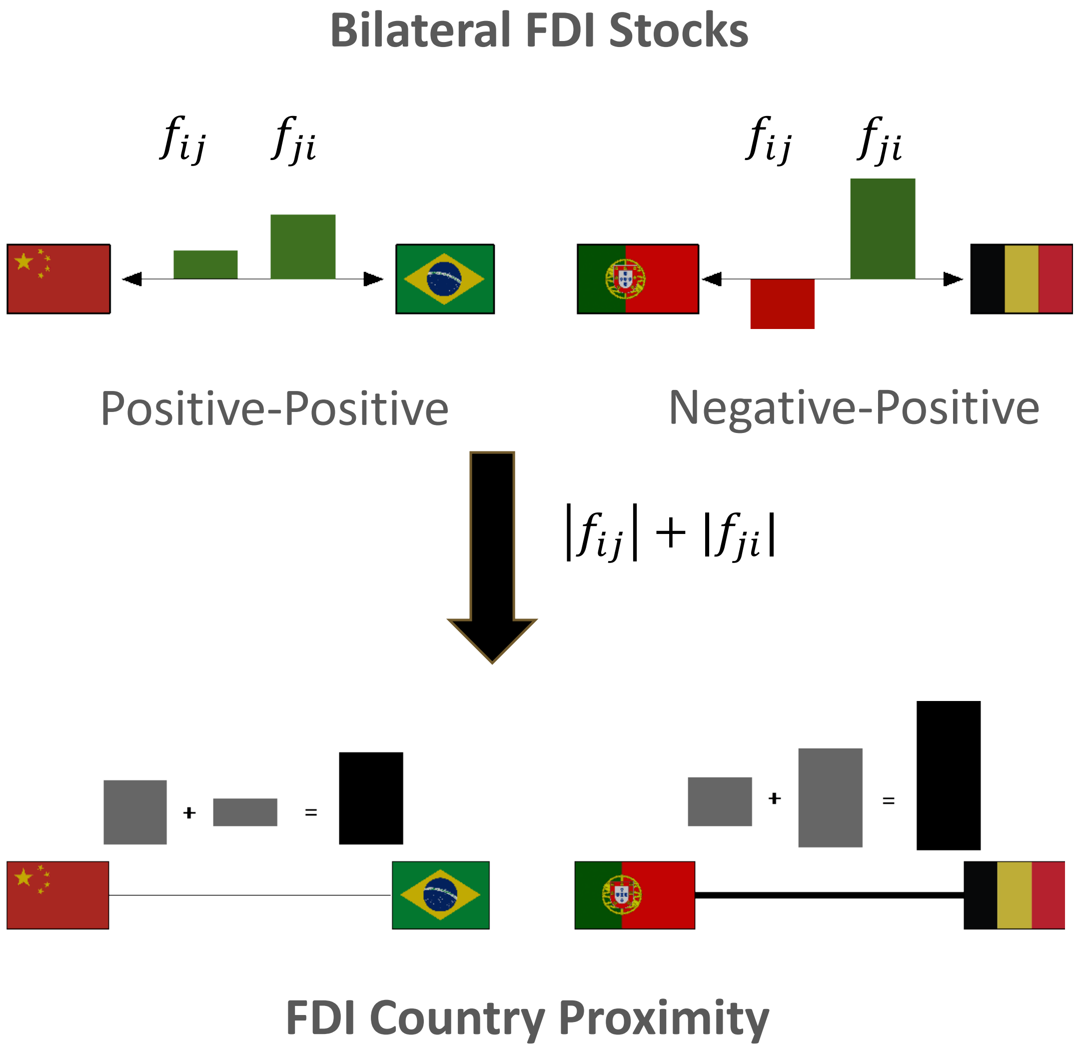
Positive-Positive

Negative-Positive

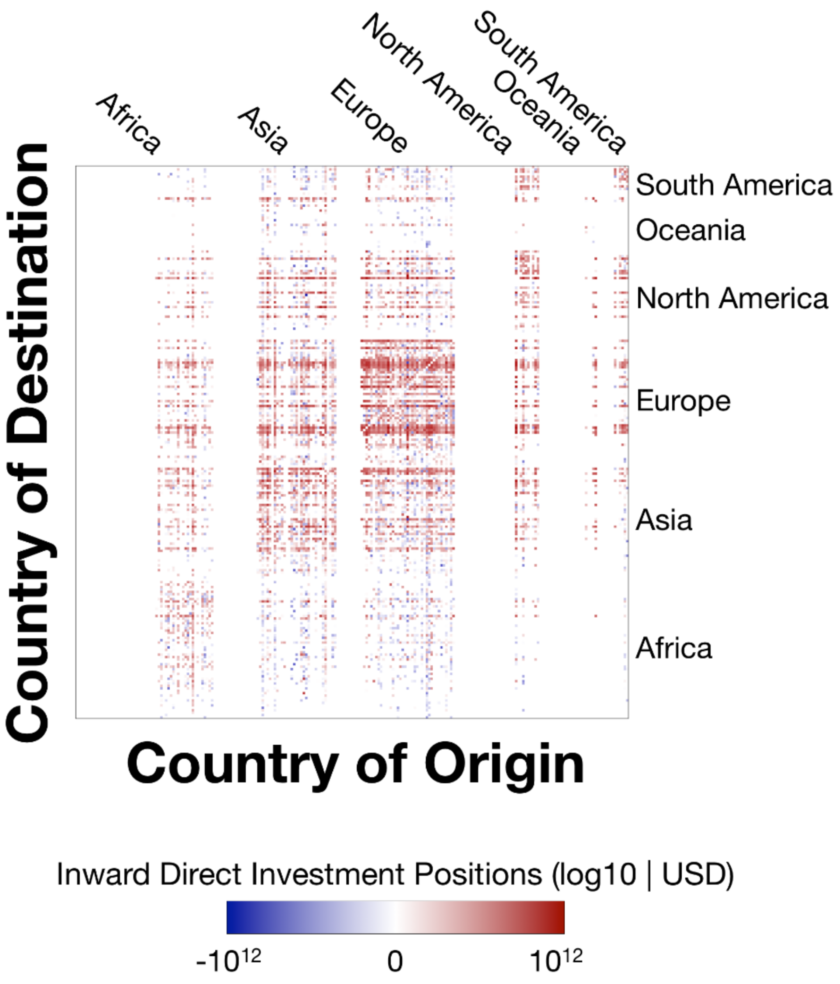
Problem: we have two directions and negative values. Can we simplify this data and still retrieve useful insights on the FDI relationships between countries?

Building the FDI global network

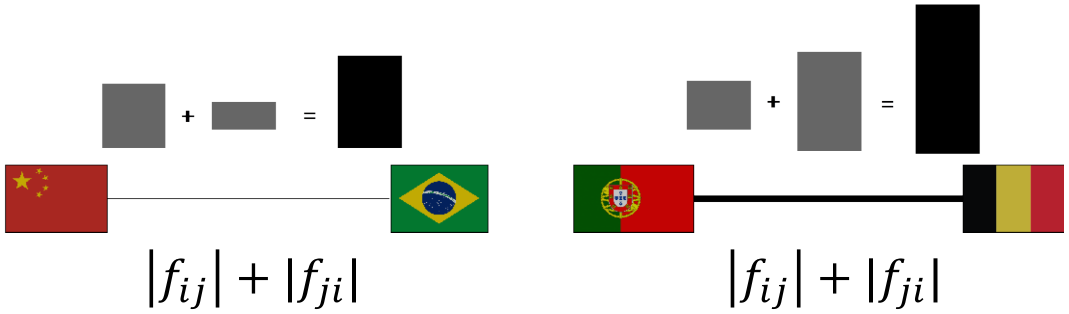




Building the FDI global network

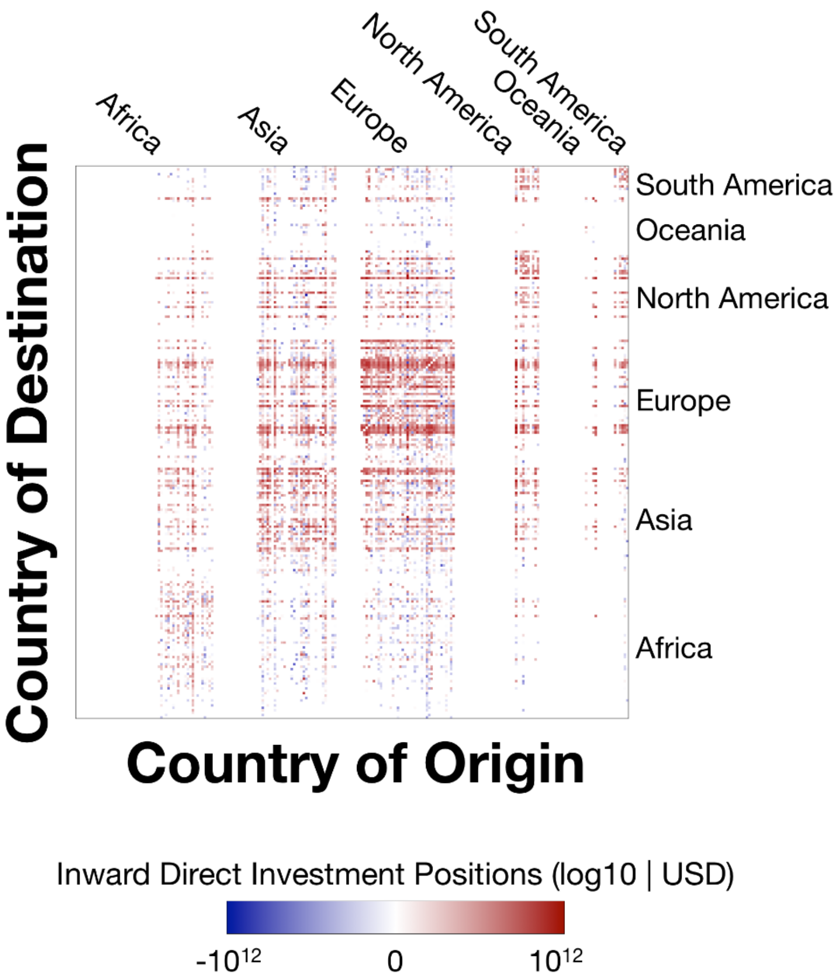


FDI Country Proximity



Countries with larger bilateral stock are closer, thus the weight of the link is heavier.

Building the FDI global network



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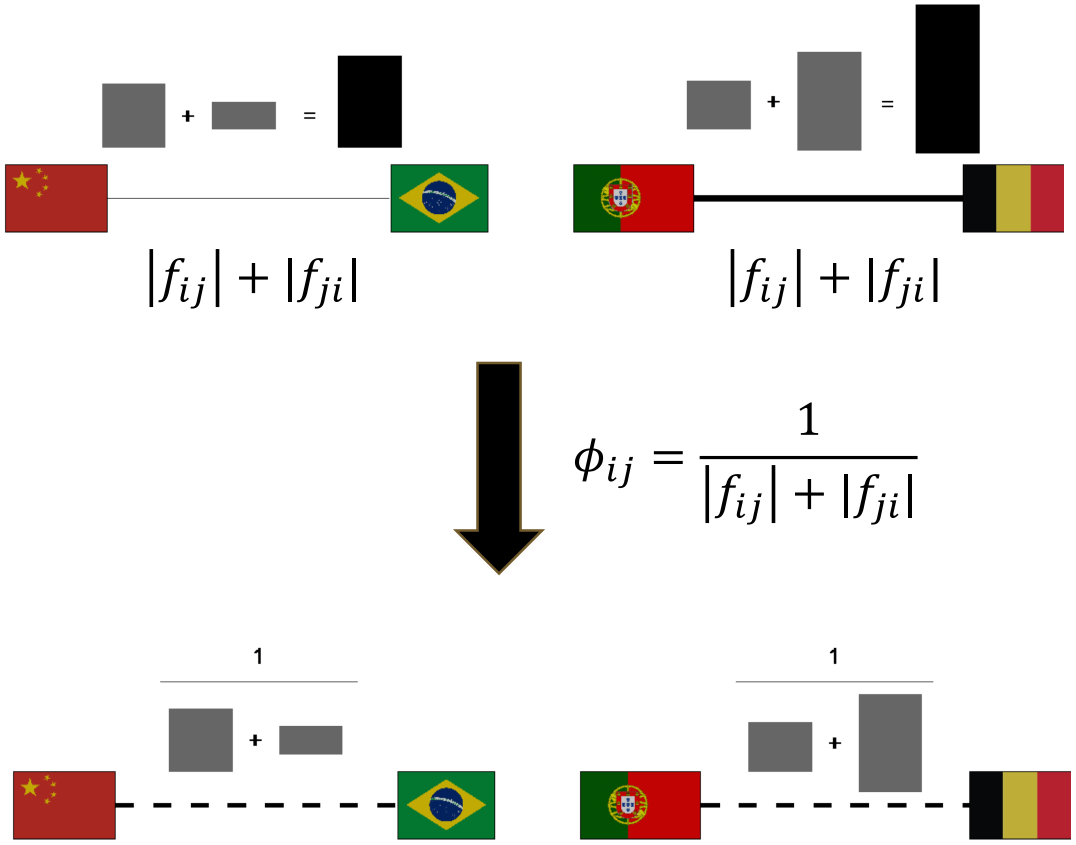
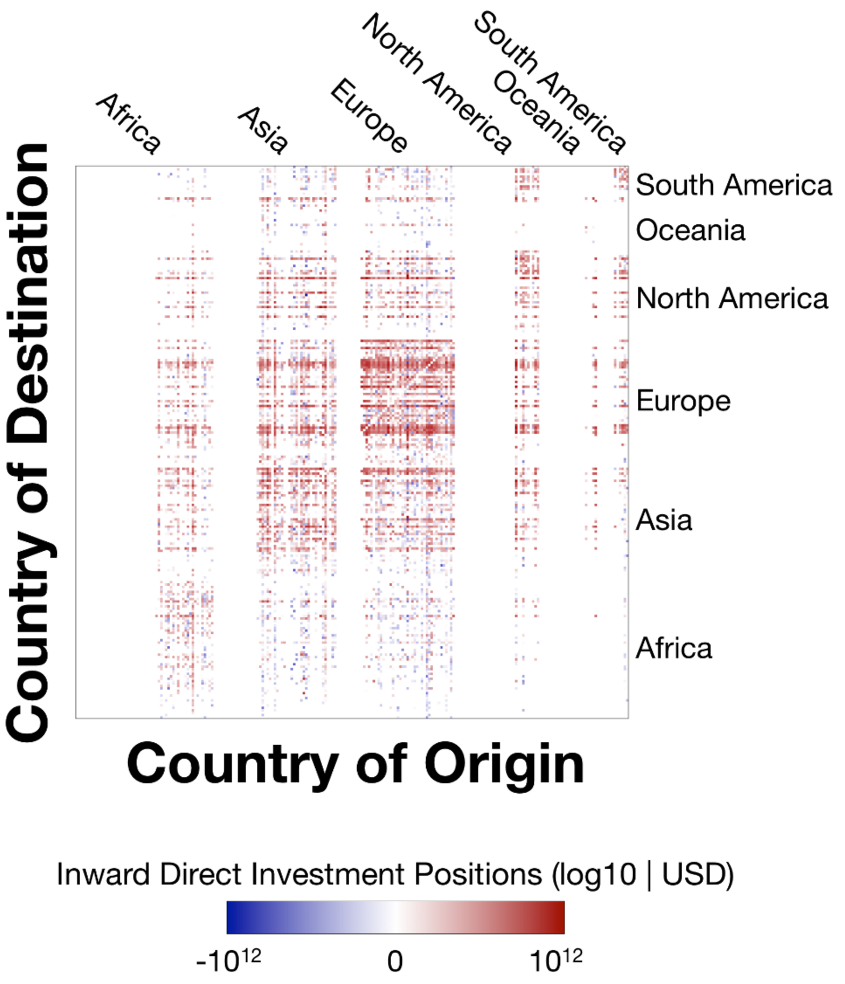
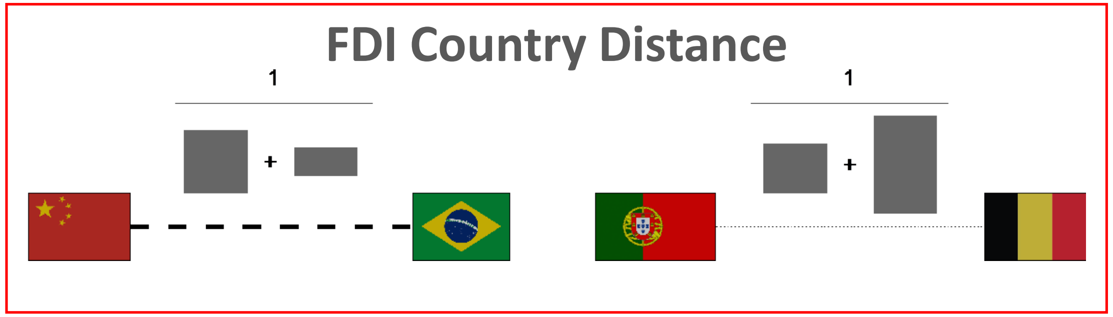


$$\phi_{ij} = \frac{1}{|f_{ij}| + |f_{ji}|}$$

FDI Country Distance





$$\phi_{ij} = \frac{1}{|f_{ij}| + |f_{ji}|}$$

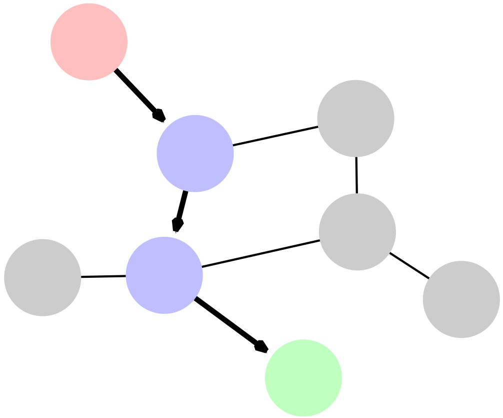
Countries with larger bilateral stock are closer, thus are at a shorter distance from each other. Meaning, the weight of the link is lighter.

Building the FDI global network

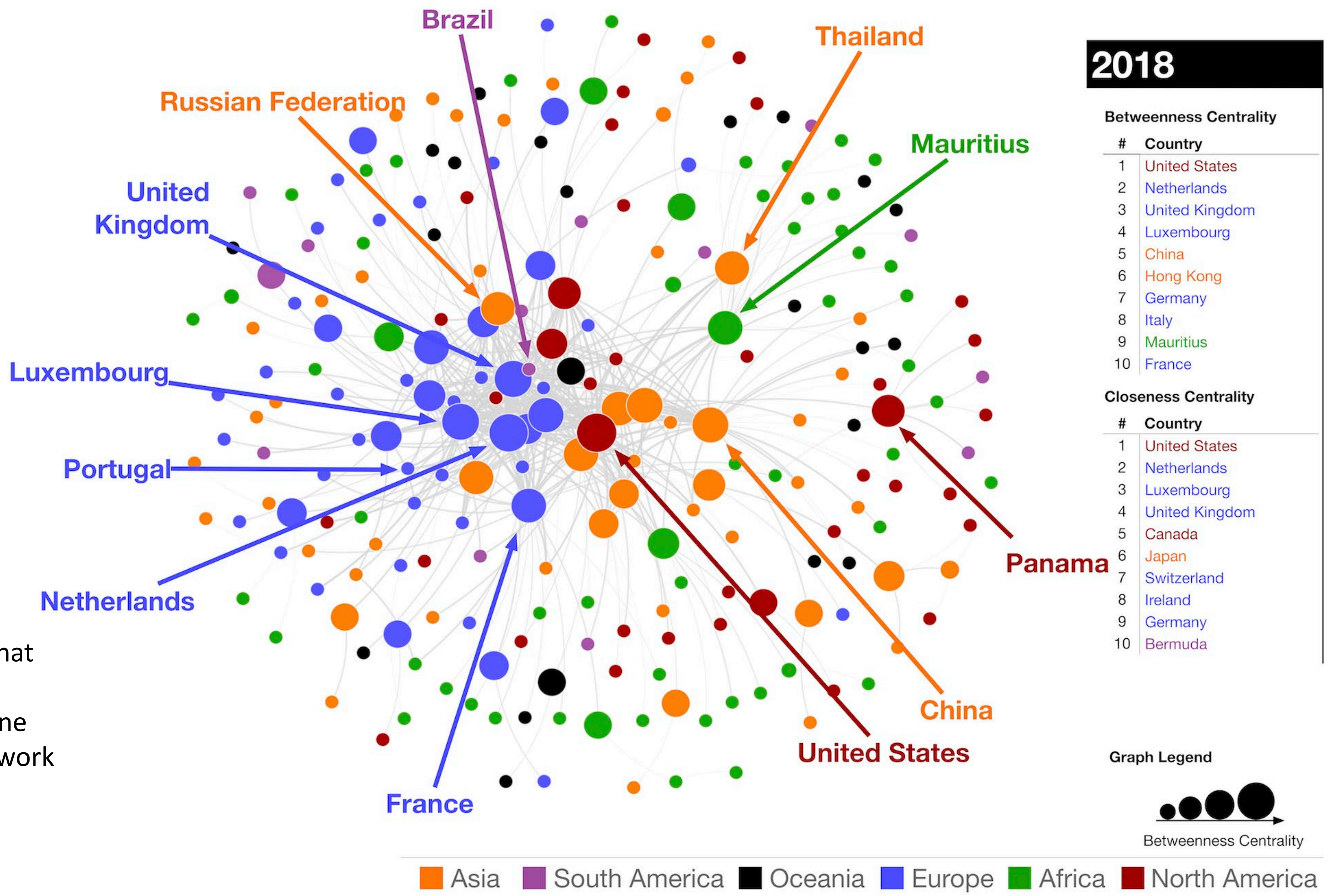
- The resulting network (G) is very dense
- For visualization we perform the following steps to generate a projection (G_p):
  - Find the Minimum Spanning Tree, the set of edges with the minimum weight (sum of distances) that connect all nodes in the network;
  - Afterwards add the edges with the lowest weights to reinforce visually which countries are closer and provide some structure to the network
- All network analysis are performed on G and visualized on G_p

FDI Network, Graphical Representation

The Network provides a “proxy” metric between elements of a system, allowing to estimate paths and distances between its elements

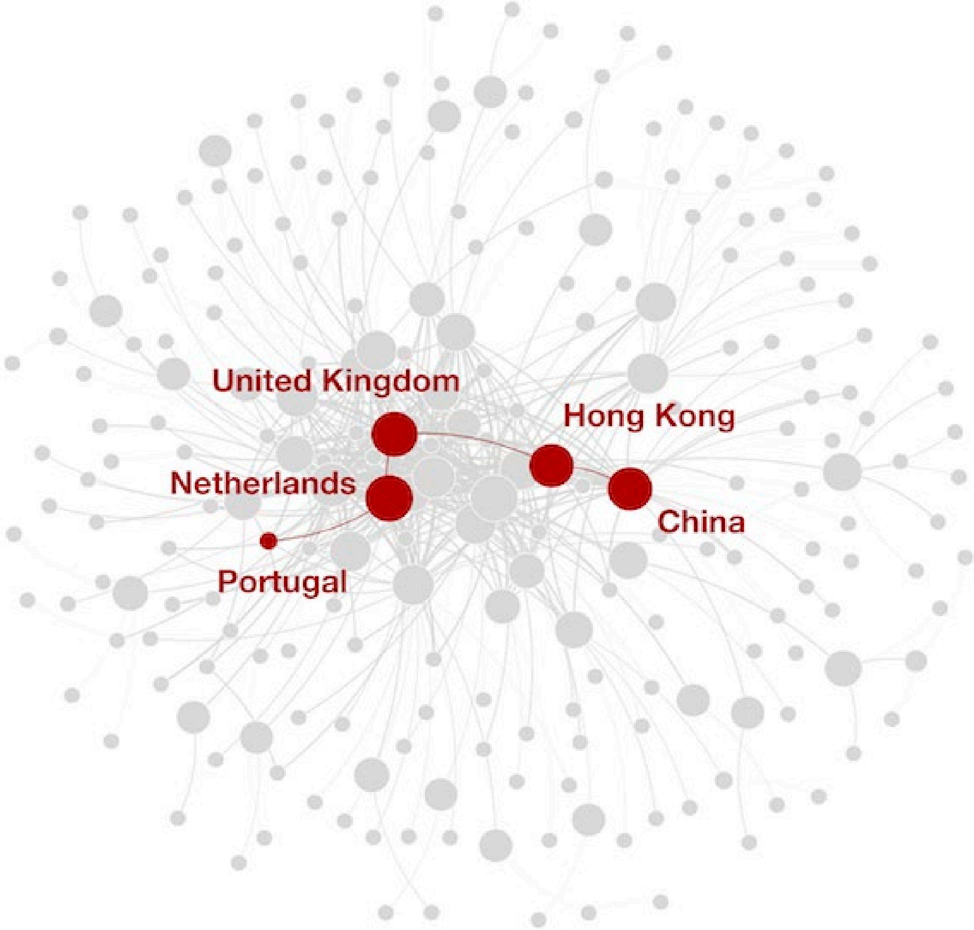


A Node with highest betweenness centrality is one that participates as an “intermediary” in many paths.
A Node with the highest closeness centrality is the one that is closer in average to all other nodes in the network

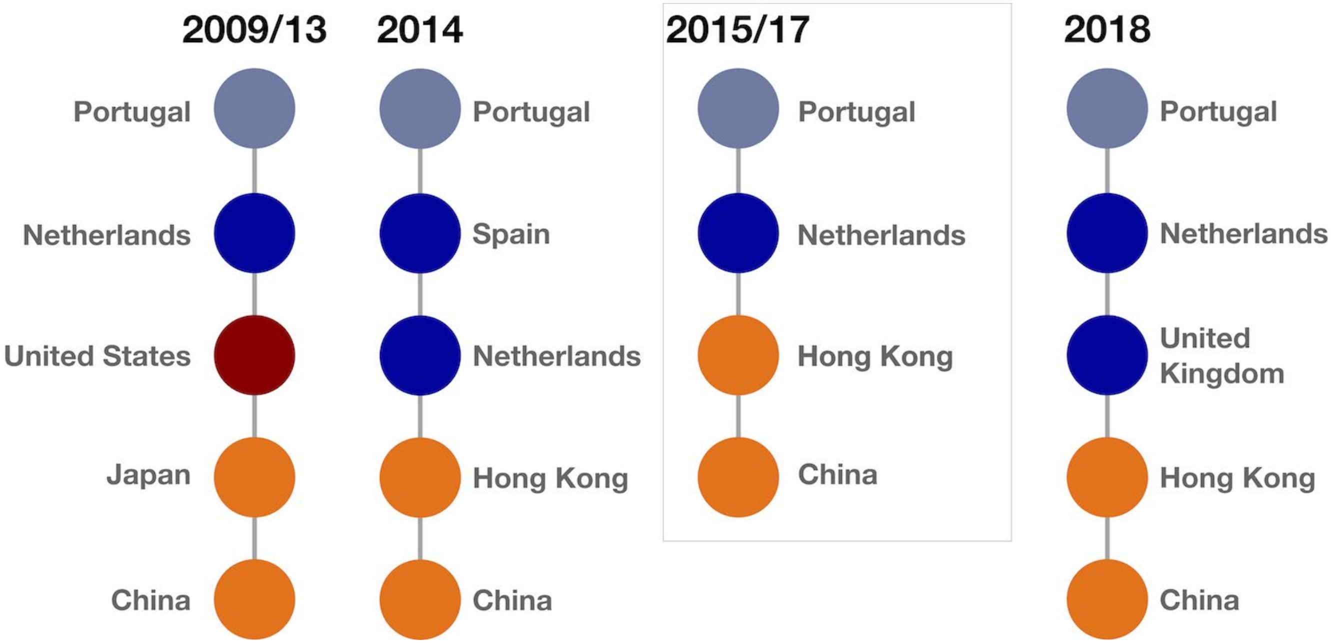


Evolution of the Portuguese – China linkages

Shortest path between China and Portugal (2018)



Evolution of the shortest path between China and Portugal (2009-2018)



How can the Foreign Direct Investment benefit from the network analysis?

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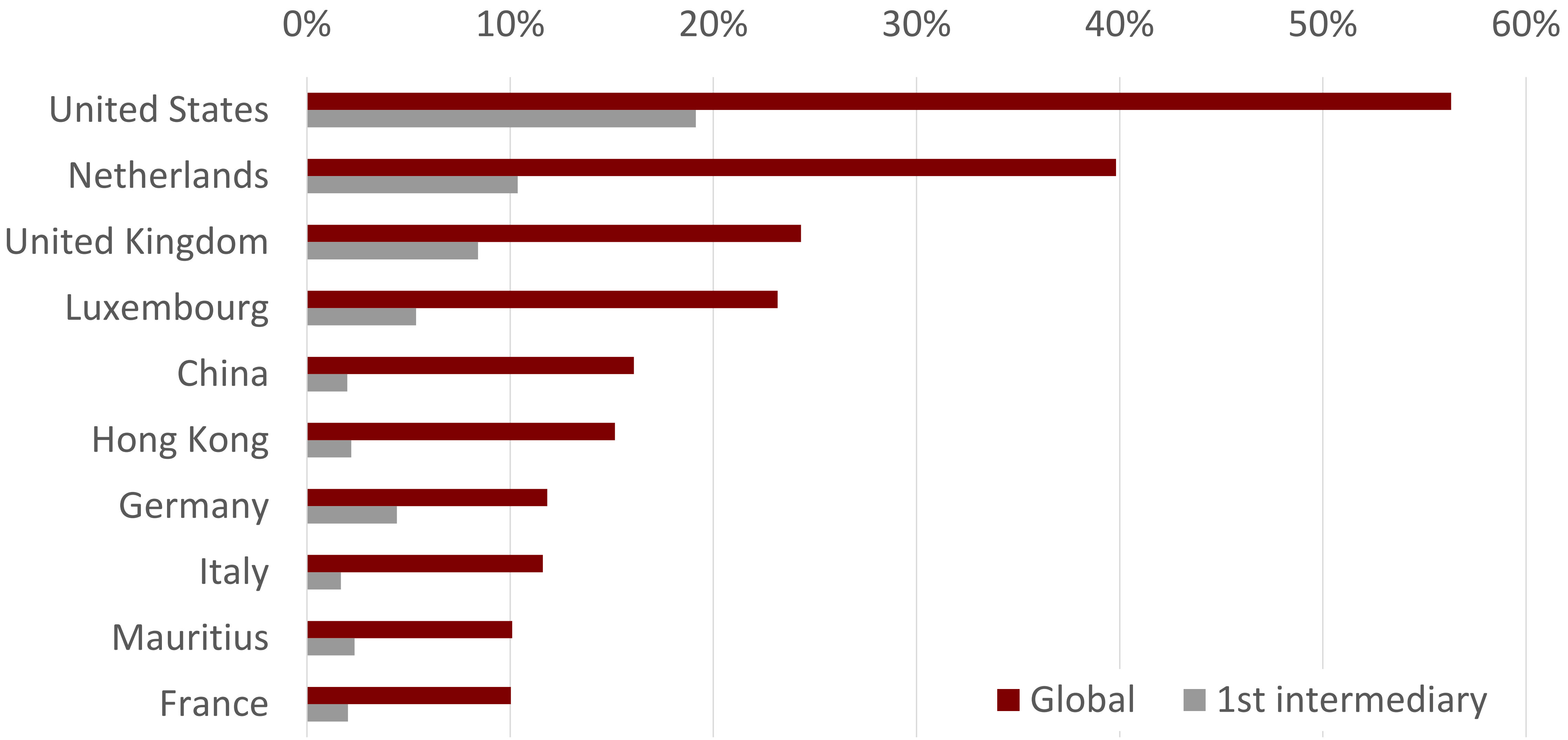
Network analysis to predict FDI linkages – TOP intermediaries in a global FDI network (2018)



Network analysis to predict FDI linkages – TOP intermediaries in a global FDI network (2018)

Investor	1st intermediary	1st intermediary (share, %)
China	Hong Kong	85%
Germany	United States	60%
Japan	United States	85%
Portugal	Netherlands	98%
Russian Federation	Cyprus	96%
United Kingdom	United States	48%
United States	Netherlands	24%

Conclusions and future work

- **Network analysis** present many advantages on the **visualization capabilities** and provide useful information about **economic relations**

- The **2009 and 2018 comparison** shows that the countries with more FDI interconnections usually correspond to advanced economies, financial centres, and tax benefit countries

- Network science illustrates the enormous **analytical power** to **predict the ultimate direct investor** and the **path** between the immediate/ultimate direct investor countries

- **In the future …** conduct an analysis on the differences between direct/ultimate investors, comparing the results (network analysis) with actual data on ultimate investors

Foreign direct investment
using network analysis to understand the position of Portugal in a global FDI network

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18 February 2020

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