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The Network View: applications to international trade and bank exposures

Luis Fernández Lafuerza and Gonzalo de Cadenas-Santiago

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Luis Fernández Lafuerza and Gonzalo de Cadenas- Santiago[2]

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Abstract

Systems of interconnected elements are increasingly important in economic applications. This paper elaborates on some ideas of network analysis and its application to the study of systems of economic interest. It focuses on the Identification of influential and vulnerable elements, from both a global and a local perspective. The presented ideas are applied to the analysis of the international trade network and the banking funding network.

Keywords: networks, international trade, bank exposures

JEL classification: C65

1: The authors thank the valuable comments and suggestions made by J.J. Cubero and A. Ugarte.
2: Luis Fernández Lafuerza (lflafuerza@gmail.com) is currently at CEMFI, Gonzalo de Cadenas (gcaden1@mapfre.com) is affiliated with Mapfre.

1 Introduction

The world is increasingly interconnected. Financial linkages (IMF, 2010), trade flows (WTO, 2013) and social networks (Digital Future Report, 2015) make developments in separate locations ever more interdependent. Traditionally, researchers have focused on the analysis of a particular unit (such as a single country or sector) with a more limited interest in the relations among several of these units. In recent years, a different paradigm that centers in the study of the structure of interrelations of the units composing a system has emerged (Jackson 2008; Newman, 2010). The “network view” has proven fruitful in diverse disciplines, from epidemiology (Anderson and May, 1992) and ecology (Bascompte, 2007) to engineering (Meyn, 2008) and sociology (Granovetter, 1975), and increasingly in economics (Jackson, 2014). Common to these diverse research agendas is the interest in a structure of interrelations, which is modeled as a network. This commonality has facilitated the exchange of ideas and methods originating in different disciplines and the development of a framework with diverse tools and concepts.

When analyzing a system, network modeling typically makes (sometimes strong) simplifying assumptions on the behavior of the units composing the system, in order to center on the role of the structure of interactions. When interconnections are the critical aspect determining system-wide behavior, network modeling is highly informative. It can highlight particularly influential or vulnerable elements (Kitsak et al., 2010), suggest ways to improve the functioning of the system (Meyn, 2008) and help predicting its evolution (de Lucio et al., 2015).

In this paper we will present some basic ideas of network analysis and apply them to the study of international trade and bank financing networks. In Section 2 we will present the theoretical background of network analysis and put forward the measures of influence and vulnerability. In Section 3 and 4 we analyze international trade and banking funding networks, respectively. Some additional details are left for two appendices.

2. Theoretical background: network analysis

A *network* or graph is essentially a representation of the relations between a set of elements. Mathematically, it can be described by a set $A = \{n_1, \ldots, n_N\}$ of N nodes and a real-valued NxN matrix, S. S is sometimes called the *adjacency matrix* and its elements, $S_{i,j}$, called *links*, represent relations between nodes n_i and n_j. If S is not symmetric (i.e. $S_{i,j} \neq S_{j,i}$ for some $i, j \in \{1, \cdots, N\}$) we say that the graph is *directed*. If the elements of S take values different from zero and one, we say that the graph is *weighted*; in this case the value of a given link, $S_{i,j}$, represents the intensity of the relation between nodes n_i and n_j. For example, in the case of bank exposures, the nodes, n_i, would correspond to banks and the links, $S_{i,j}$, could correspond to exposures. Sometimes links of several types are considered (Kivelä et al., 2014).

There are a large number of magnitudes characterizing the properties of networks. Of particular interest are measures of the *centrality* or "importance" of each node in the network, as well as the importance of each node with respect to a particular other node. This will be the main focus of the present analysis. Several measures have been proposed in the literature to quantify centrality (see, for example, Jackson 2008 or Newman 2010). A network can represent very different types of relations, and the most appropriate centrality measure will depend on the particular application. If, for example, the network represents the streets of a city, joined at intersections, and we are interested in traffic volume, the number of shortest paths going through an intersection can give us a good idea of the importance of the intersection (perhaps to assign more resources to keep it in good state). This corresponds to the measure *betweenness centrality* in the network literature. If we want to establish the locations from which it is easier to access other nodes in the network (perhaps to locate there an emergency service or a pizza delivery) we might be interested in the average distance from a node to all the rest, corresponding to the *closeness centrality* measure (see, Jackson 2008 or Newman 2010 for a precise definition and discussion of these and other centrality measures).

In economic applications, we are particularly interested in situations in which the network represents the possibility of shocks to be transmitted between the nodes. Examples include exposures in a bank network, exports in a trade network and frequency of communication in a social network. In these cases the elements of the adjacency matrix, S, will describe the shock-transmission process. We will define the matrix S in such a way that $S_{i,j}$ represents the fraction of a shock to node n_i that is transmitted (directly) to node n_j. The shock received by node n_j can in turn be transmitted, so that node n_k will receive a shock of magnitude $S_{i,j}S_{j,k}$ that can, in turn, be transmitted further. We note that $s_i \equiv \sum_j S_{i,j}$ is the total fraction of a received shock that node n_i transmits; $s_i < 1$ if the shock is in part absorbed or dissipated at node n_i (for example due to the presence of reserves in a banking network), and $s_i > 1$ if node n_i amplifies the shock (for example a very active individual in a social network spreading a piece of news). In this sense, matrix S contains two pieces of information, the transmission strength, s_i, of each node and the relative relations of the nodes, $S_{i,j}/s_i$.

If the largest eigenvalue of matrix S is smaller than one (which holds if $s_i < 1$ for every node) the total effect of an initial shock will be finite, while it will diverge if the largest eigenvalue is larger than or equal to one[3]. In the former case, the most relevant one in usual applications, the total effect on the system that an initial shock to a given node causes, gives a measure of the centrality of that node. In order to calculate the total effect on the system we will use the following notation. Let us define I_i as the $nx1$ (column) vector that takes the value 1 in position i and 0 in all the rest, and c^ias the $nx1$ vector which takes a value equal to the total loss of node n_j in position j when node n_i takes an initial shock of one unit. We can express in vector form the total loss (discounting the initial shock) of the nodes, c^i, iteratively as:

$$c^i = S'I_i + S'^2 I_i + S'^3 I_i + \cdots = S'\left(\mathbb{I} + S' + S'^2 + S'^3 + \cdots\right)I_i, \quad [1]$$

where S' denotes the transpose of S. This can be re-written[4] as:

$$c^i = S'(\mathbb{I} - S')^{-1} I_i.$$

The sum of the elements of c^i, the total loss of the system caused by an initial loss of one unit of node n_i, yields the measure of the centrality or influence of this node in the whole network. In a somewhat more compact notation, we see that the centrality of each node is given by the following column vector:

$$c = \mathbf{1}'S'(\mathbb{I} - S')^{-1} = (\mathbb{I} - S)^{-1} S\mathbf{1}, \quad [2]$$

with $\mathbf{1}$ the $nx1$ vector of ones. Equation [2] corresponds to the Katz-Bonacich centrality (Katz 1953, Bonacich 1987) (also known as alpha centrality), and is closely related to Google's Page Rank (Brin and Page 1998), with parameter $\alpha = 1$. This type of calculation has been used in the context of contagion in financial networks by Glasserman and Young (Glasserman and Young 2015). If the largest eigenvalue of S, λ_m, is larger than or equal to one, the outlined approach yields divergent quantities. A possibility to make the analysis applicable is to multiply S by a factor, α, smaller than the inverse of its largest eigenvalue ($\alpha = 0.85/\lambda_m$ is a common choice).

We also see that $((\mathbb{I} - S)^{-1} S)_{i,j}$ gives the total loss of node n_j after an initial loss of one unit of node n_i, that is, a measure of the influence of n_i on n_j. In this sense, the matrix $M_0 = (\mathbb{I} - S)^{-1} S$ determines the transmission of shocks through the network.

An alternative interpretation of expression [2], used originally by Katz (Katz 1953) is as follows. Let us assume that the centrality of each node is the sum of two components. The first is equal to the total proportion of a shock that it transmits, $s_i = S\mathbf{1}$. The second equals a combination of the centralities of its neighbors, weighted by the proportion of a shock that the node transmits to each neighbor. In vector notation, we have:

$$c = S\mathbf{1} + Sc \Rightarrow c = (\mathbb{I} - S)^{-1} S\mathbf{1}.$$

The equivalence is, again, valid if the largest eigenvalue of S is smaller than one. Note that in this interpretation, the centrality that node n_j "transmits" to node n_i is given by $S_{i,j}$, that is, it goes in opposite direction than the shock does. A node is more central if it transmits shocks to central nodes.

3: The diverging magnitude of the shock when the largest eigenvalue is larger than one is an artifact of the assumed linearity; in practice non-linear effects will make the shock saturate eventually. This situation corresponds to a linearly unstable system.
4: The assumption that the largest eigenvalue is smaller than one implies that $(\mathbb{I} - S')^{-1}$ exists and equals the (convergent) series in [1].

Expression [2] can be generalized in important ways. So far we have studied the total impact of a shock of absolute value 1 to a given node. It is often more relevant to consider the effect of a shock to a node *proportional* to some property of the node, measuring the probability or the size of the likely shock. For example, in a bank exposures network it would seem natural to consider shocks proportional to the assets of the nodes, the idea being that shocks with the same value relatively to the nodes assets are considered to have the same probabilities. In this case, [2] will be modified into:

$$c = D(\mathbb{I} - S)^{-1} S\mathbf{1} = DM_0\mathbf{1}, \quad [3]$$

where D is a diagonal matrix whose elements quantify the likely size of an external shock to the nodes. In the context of trade networks of critical resources, $D_{i,i}$ has been taken to be a measure of "political stability" of country i (since some important mineral resources are produced in countries subject to strong geopolitical risk, see Klimek, Obersteiner and Thurner 2015). In other cases it might be relevant to consider the *relative* effect over node j. Then the relevant expression would be:

$$c = M_0 B\mathbf{1}, \quad [4]$$

With B a diagonal matrix whose elements normalize the suffered shock at each node by some measure of the size of this node (this is a modification often considered for Katz-Bonacich centrality). Clearly, we can also combine the previous measures to obtain:

$$c = DM_0 B\mathbf{1}. \quad [5]$$

It is interesting to note that in this formulation the determinants of the influence of a node are neatly separated. The size or inherent instability of the node is captured by matrix D, while the network connectivity enters through the matrix $M_0 = (\mathbb{I} - S)^{-1}S$. If, in addition, we are interested in relative effects and some nodes are "bigger" or more resilient that others, this is captured by matrix B. The matrix $M = D(\mathbb{I} - S)^{-1}S$ (or $\widehat{M} = D(\mathbb{I} - S)^{-1}SB$ when relative effects are relevant), characterizes how shocks initiate and propagate through the network, and will be denoted the *Vulnerability-Influence matrix*. The elements of the Vulnerability-Influence matrix quantify how a shock to one node affects another, taking into account indirect as well as direct effects. In this sense, the matrix provides a simple and informative summary of the shock transmission process in the network.

Another relevant question consists on quantifying how important indirect (network) effects are, relative to the direct effects produced by immediate contacts. The *network multiplier* of the influence of node n_i on node n_j is given by the total influence of n_i on n_j divided by the direct effect, i.e. $M_{0i,j}/S_{i,j}$. When this magnitude is close to one, indirect influences are relatively unimportant, and network effects can be neglected. Conversely, if this magnitude is much larger than one, indirect influences dominate, and network effects are essential when assessing the possible influence of one node in another.

The dual question to the influence of the nodes is their vulnerability. $\sum_i M_{0_{i,j}}$, the sum of the elements of column j of matrix M_0, quantifies the expected loss of node j when a shock of 1 unit occurs on a node chosen uniformly at random. In vector form:

$(\mathbf{1}'M_0)' = M_0{}'\mathbf{1}.$ [6]

Again we might want to consider that the probability or expected size of socks differs between nodes; in that case, the relevant matrix will be $M = DM_0$:

$(\mathbf{1}'M)' = M'\mathbf{1},$ [7]

(note that D and B are diagonal matrix, so they are symmetric). If the relevant issue is the relative effect over the nodes, we should use a matrix of the form M_0B. Combining both ideas, we get:

$\left(\mathbf{1}'\widehat{M}\right)' = \widehat{M}'\mathbf{1}.$ [8]

Finally, the elements of column j of matrix M (or M') quantify how vulnerable node n_j is to shocks in the other nodes of the system, that is, a measure of centrality with respect to node n_j.

3. Application: trade networks

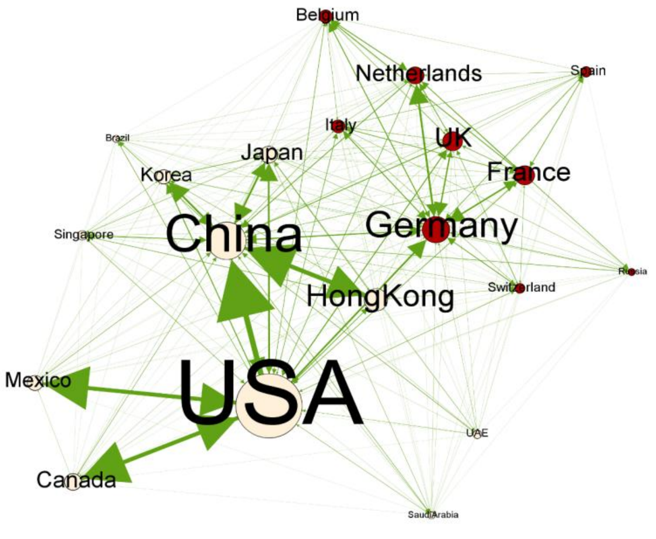
We consider now an application of network ideas to the analysis of international trade relations. If country n_i suffers an economic shock it might, as a result, reduce its imports from country n_j. This will tend to reduce the income of country n_j which might, in turn, reduce its imports from other countries. In this way, trade relations determine a network through which shocks can be transmitted. In order to define the "shock-transmission" matrix, S, we need to make some assumptions. We will assume that if country n_i suffers an economic negative shock of magnitude 1 it will reduce its imports from country n_j by an amount $I_{i,j}/G_i$, where $I_{i,j}$ are n_i's imports from n_j and G_i is n_i's GDP. We further assume that the total income of n_j will be reduced by this same amount. This corresponds to a worst-case scenario in the sense that n_j does not redirect any of the lost exports to n_i to other countries. The elements of the shock-transmission matrix, S, are then, simply given by $S_{i,j} = I_{i,j}/G_i$.

We will base our analysis on open data provided by the IMF. The Direction of Trade Statistics (DOTS) reports yearly data on merchandise exports, with a breakdown by country of origin and destination. For simplicity, we will restrict ourselves to data on exports from the 51 countries with the largest value of exports, to a total of 186 receiving countries. This captures around 90% of total world exports.

Figure 1 represents the network of international trade in 2015, limited to the 20 countries with the largest exports for better visualization. The size of the nodes is proportional to their relative importance in World imports, the links and arrows to the (gross) bi-lateral trade, with arrows pointing from importer to exporter (the direction in which shocks propagate). The two different colors of the nodes correspond to the two groups found with the community detection algorithm of Blondel et al. (2008).

Figure 1

International trade network in 2015. Nodes size is proportional to the imports of the corresponding country. Arrow size is proportional to the value of (gross) imports, pointing from importer to exporter



Source: BBVA Research

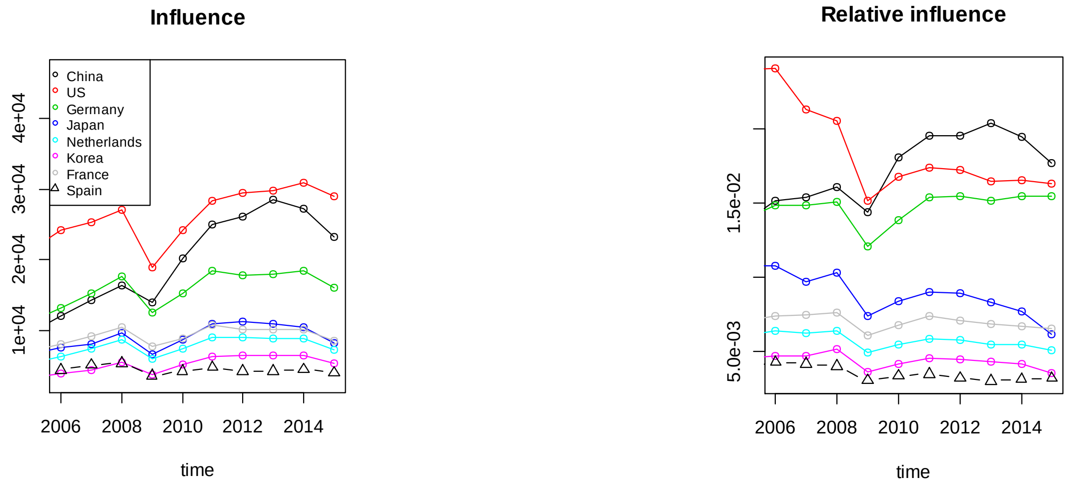
The US appears as the largest importer, with very large net imports from China, and large imports and exports to Canada and Mexico. European countries are densely connected to each other, with Germany being the largest exporter. China has strong import and export relations with Japan, Korea and, specially, Hong Kong. For reference, in Appendix 1 we include some plots representing the time evolution of basic statistics of international trade.

We will now quantify the influence and vulnerability of the different countries to trade shocks, following the analysis of the previous section. As mentioned at the beginning of this section, the shock-transmission matrix is simply given by $S_{i,j} = I_{i,j}/G_i$. We will assume that potential external shocks are proportional to the GDP of each country, so the Vulnerability-Influence matrix will be given by $M = G(\mathbb{I} - S)^{-1}S$, with G a diagonal matrix with elements equal to the GDP of each country. In some cases, we will be interested in the total effect over a node relative to the GDP of that node; the Vulnerability-Influence matrix will, then, take the form $\widehat{M} = G(\mathbb{I} - S)^{-1}SG^{-1}$. We are considering yearly data, so that the GDP and yearly imports of the countries define a different network for each year, allowing us to examine the time evolution of several properties. For some applications it might be relevant to average values for several years to obtain a single network, but this is an approach not followed here.

Figure 2 shows the influence of the different countries, in absolute terms (using M) in the left panel and in relative terms (using $\widehat{M}$) in the right panel. Data in the left panel correspond to total drop of exports, in million USD, caused by an initial 1% drop in GDP in the corresponding country. In the right panel, data corresponds to the decrease as a percentage of GDP averaged over all countries after a 1% drop of GDP in the corresponding country. In absolute terms, the US appears as the most influential country in the whole sample period, followed by China (since 2009) and Germany. In relative terms, China is the most influential country since 2010. The increase in China's influence respect to that in the US when measured in relative terms arises from the fact that China imports from smaller countries, which are potentially more vulnerable to a decrease of Chinese imports. The left panel of Fig. 2, absolute influence, is very similar to the figure of total imports (left panel of Fig. A1), suggesting that absolute influence is largely driven by the value of total imports.

Figure 2

Influence of main countries. Left: Total drop in exports (in Million current USD) caused by an initial 1% drop of the GDP of the corresponding country. Right: Decrease in exports as percentage of GDP, averaged over 51 countries, caused by an initial 1% drop of the GDP of the corresponding country

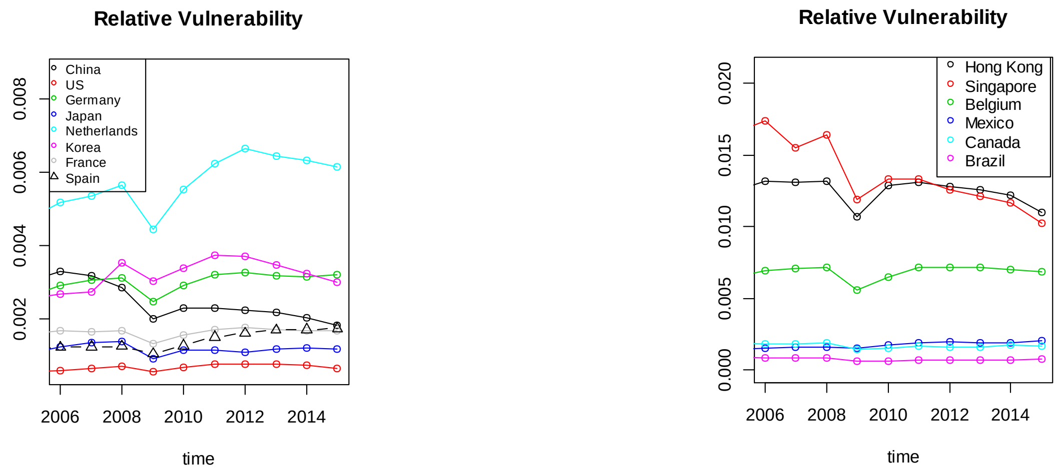


Source: BBVA Research

In Fig. 3 we show the relative vulnerability (based on $\widehat{M}$) of the main countries, as well as that of the most vulnerable countries. We have used expression [8] (with $B = D = G$), and further divided by the number of countries, so that data corresponds to the percentage drop in GDP when a country chosen uniformly at random suffers a 1% drop in GDP. Among the large countries, Netherlands appears clearly as the most vulnerable, followed by Korea and Germany. The right panel shows that Hong Kong, Singapore and to some extent Belgium, are highly vulnerable to trade shocks. Comparing the figure with that of imports/GDP (Fig. A2 in the appendix) shows that the vulnerability is largely driven by the imports to GDP ratio.

Figure 3

Relative vulnerability. Drop in exports as a percentage of GDP in the corresponding country when a country chosen at random suffers a 1% drop in GDP. Left: main exporting countries. Right: most vulnerable countries

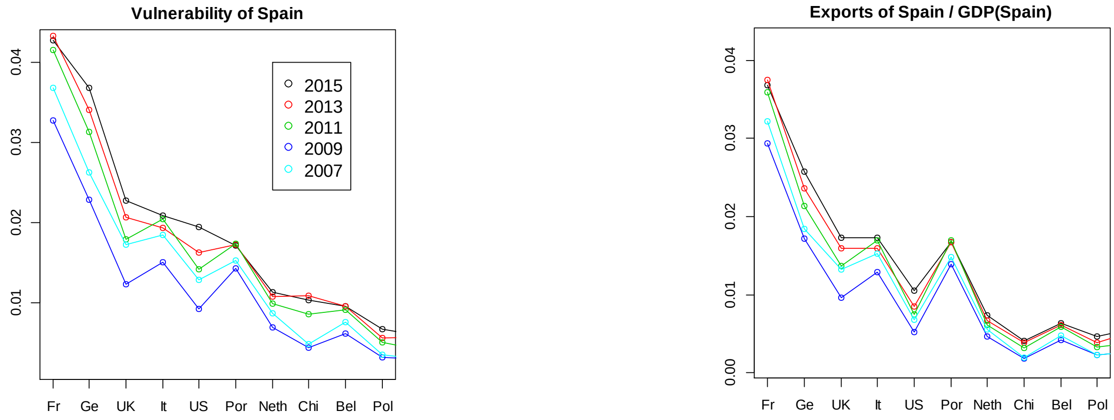


Source: BBVA Research

In Figure 4 we plot the vulnerability of Spain to the 10 countries to which it was most vulnerable in 2015. Now the X-axis indicates a country and the different curves correspond to different time periods. The data in the left panel indicate the percentage points decrease in GDP in Spain after a 1% decrease in GDP in the corresponding country. For comparison, in the right panel we plot the Spanish exports as percentage of GDP to the various countries. The figure shows that the total effect over Spain is larger than its direct exposure (due to indirect effects) and the amplification varies across countries. It also shows that the vulnerability increases with the ratio of exports to GDP. This fact is examined in Figure 5, where we display the network multiplier of Spanish vulnerability, which is the ratio of the total decrease in Spanish GDP when a given country's GDP drops by 1%, to the direct decrease of Spanish imports from that country. The network multiplier measures the ratio of the total effect to effect considering only direct interactions, and in this sense quantifies the importance of the network.

Figure 4

Left: Relative vulnerability of Spain, i.e. drop in Spanish exports as percentage of Spanish GDP when the country in the X-axis suffers a 1% drop in GDP. Right: Exports of Spain to main exports destinations over GDP of Spain

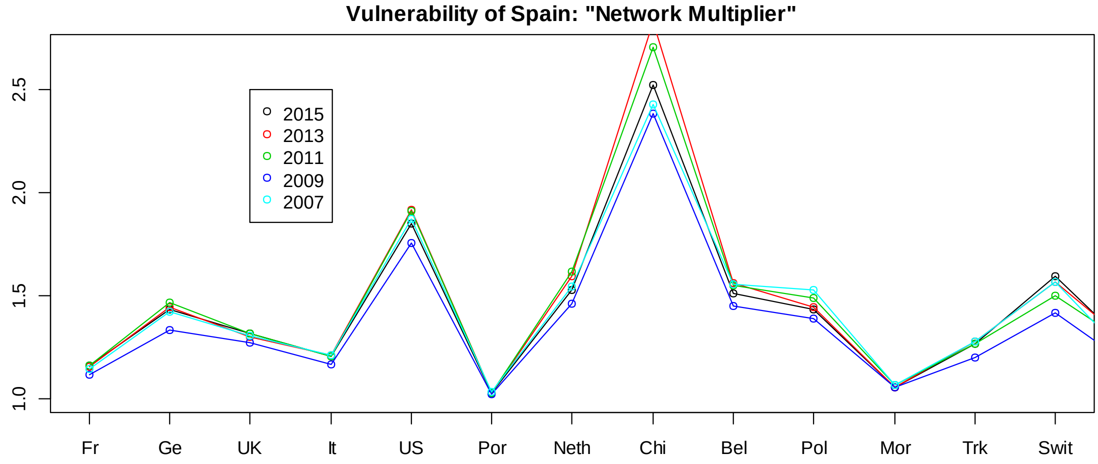


Source: BBVA Research

Figure 5 shows that for some countries such as France or Portugal the total impact is very similar to the direct impact, so that network effects can be neglected. Other countries such as China and the US have a large network multiplier indicating that a shock to these economies can have an impact in Spain through the trade channel considerably larger than that indicated by direct exposures.

Figure 5

Vulnerability of Spain's network multiplier. Drop in exports of Spain when the country in the X-axis suffers a 1% drop in GDP (total effect) divided by 1% of Spanish exports to that country (direct effect)

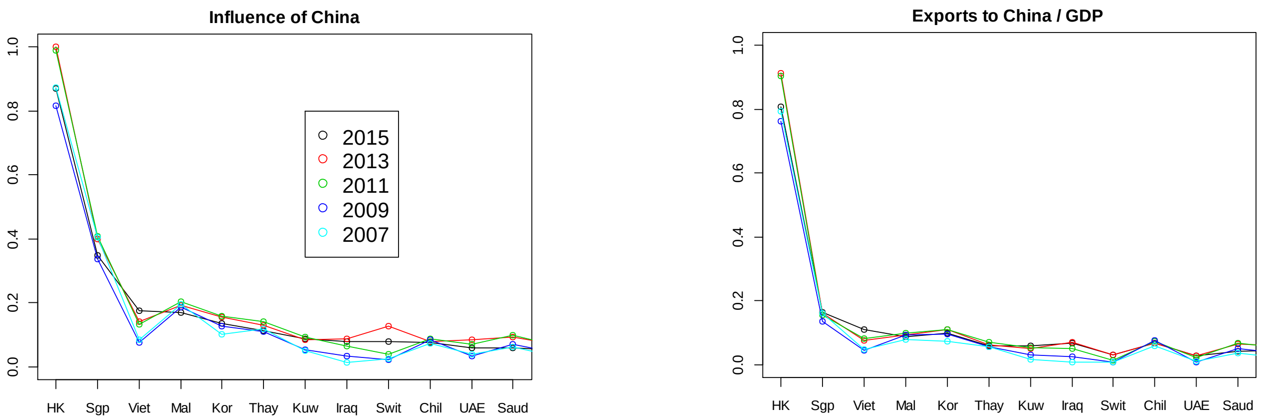


Source: BBVA Research

In Figure 6 we depict the influence of China, disaggregated by country, for the 12 countries that appear more vulnerable to China in 2015. In the left panel, data correspond to the percentage points decrease in GDP in the corresponding country when Chinese GDP drops by 1%. For comparison, the right panel depicts exports of the countries to China as a percentage of their GDP. Again the total effect over the countries is larger than that indicated by direct exposures, with an amplification varying among countries. Note that Hong Kong, officially the Hong Kong Special Administrative Region of the People's Republic of China, has a special relation with China that affects the interpretation of the results. A relevant modification of the present analysis would be to consider Hong Kong and China a single node.

Figure 6

Left: Influence of China i.e. percentage drop of exports in the country indicated in the X-axis when China suffers a 1% drop in GDP. Right: Exports to China of the X-axis country divided by the countries' GDP

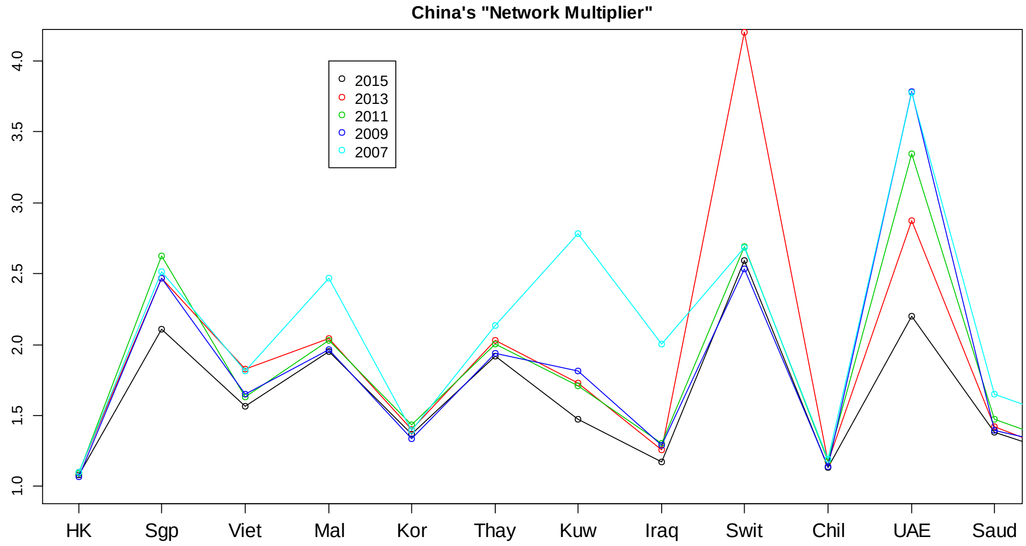


Source: BBVA Research

Figure 7 depicts China influence's network multiplier. The multiplier is typically rather high, indicating that the potential impact over these countries over the trade channel of a decrease in Chinese GDP is rather larger than that indicated by direct exposures.

Figure 7

China's influence Network Multiplier. Decrease in exports of the country indicated in the X-axis when China's GDP drops by 1% (total effect) divided by 1% of the X-axis country's exports to China (direct effect)

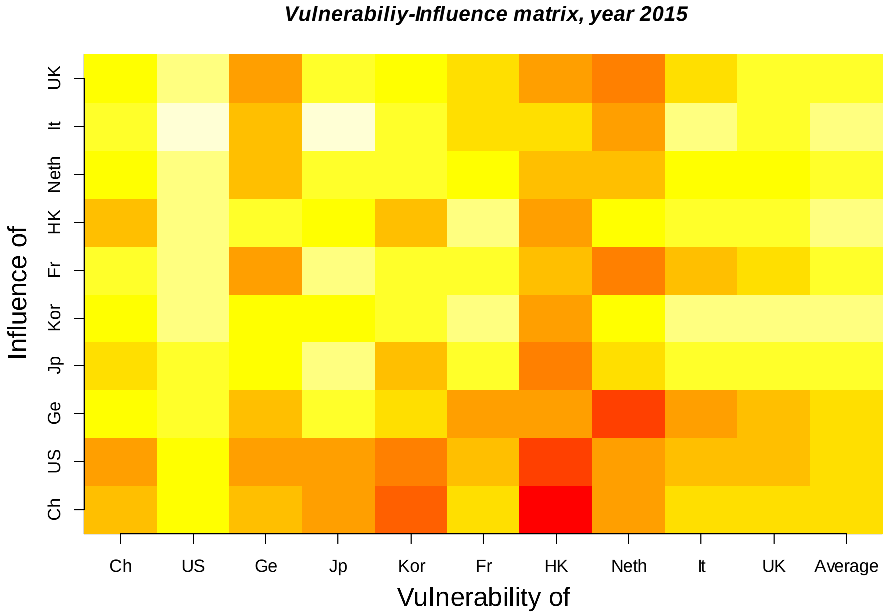


Source: BBVA Research

Finally, in Figure 8 we present the Vulnerability-Influence matrix, scaling and normalizing by GDP, $M = G(\mathbb{I} - S)^{-1}SG$, restricted to the 10 countries with largest exports. Each line depicts, in color coding (small-medium-large → white-yellow-red), the relative influence of the country indicated in the Y-axis over the countries indicated in the x-axis. In turn, each column indicates the vulnerability of the country indicated in the X-axis to the countries indicated in the Y-axis. We have added an additional column to the right of the figure indicating the average influence (arithmetic mean) of the countries in the Y-axis, which corresponds to our measure of relative influence. We can see that Hong Kong is very vulnerable to China (not too surprising since Honk Kong is a Special Administrative Region of China) and the US and fairly vulnerable to basically all other countries. The Netherlands is particularly vulnerable to Germany, the UK and France. Among the countries shown, China's influence is more concentrated in particular countries (notably Hong Kong and Korea and to a lesser extent Japan and the Netherlands), while US' influence is more evenly distributed.

Figure 8

Vulnerability-Influence matrix in 2015. Each column indicates the relative vulnerability of the X-axis country to the Y-axis country (X's decrease of exports as percentage of GDP when Y's GDP drops by 1%). The rightmost column is the arithmetic mean over the 51 considered countries relative vulnerability to the country in the Y-axis i. e. Y-axis country relative influence. Color coding: Low-medium-high → white-yellow-red



Source: BBVA Research

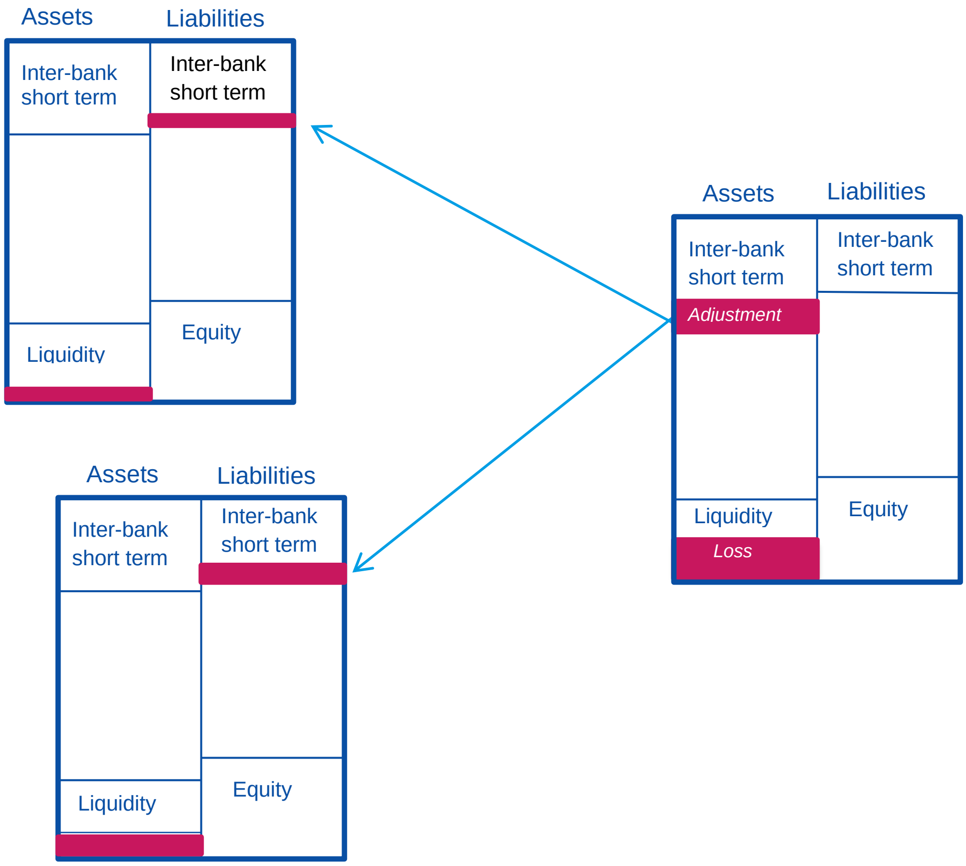
4. Application: Bank funding network

We now consider the analysis of the network of international banking funding. We are particularly interested in the transmission of liquidity shocks between countries. The nature and properties of the bank funding network as well as the data available is somewhat more complicated than that of the international trade network. Therefore, we will dedicate the following section to examine these issues in some detail.

Banks balance sheets include short-term liabilities and short term loans over other institutions as well as liquid reserves. If bank A is subject to a liquidity shock (for example due to new regulation or having to pay for unexpected legal proceedings) it might choose to withdraw or refuse to roll over short-term funding to other institutions (this is particularly likely when the market is under stress, sot that raising new funding is difficult). This would lead to the liquidity shock to be transmitted to debtors of bank A, as illustrated in figure 9.

Figure 9

Illustration of liquidity shock transmission between banks



Source: BBVA Research

We see that the set of inter-bank short-term liabilities forms a network through which liquidity shocks can be propagated. Keeping faithful to the "network view" we will strongly simplify the shock transmission process to focus on the effect of the network structure. In particular, we will assume that when a bank suffers a liquidity shock of size 1 it withdraws short-term funding from its debtor institutions for a value $(1 - l_i/a_i)$, with l_i/a_i the liquid reserves to assets ratio (in this way, the bank maintains its liquid reserves to assets ratio constant[5]). This modeling approach is similar to that used in Gai, Haldane and Kapadia (2011). In that work, however, it was assumed that banks withdraw a given proportion of their lending once their liquid assets fall from a predetermined threshold. That leads to discontinuous "contagion" effects, which depend non-linearly in the initial shock size. Glasserman and Young (2015) analyze a similar model for the transmission of defaults between financial institutions. In their main model institutions transmit a fraction of the received shock, but only once they are in default. That type of modeling leads to the same results as our analysis if it is restricted to the set of defaulted (or in our case "liquidity-stressed") nodes, see Glasserman and Young (2015).

4.1 Preliminary data analysis

Detailed data of interbank claims at the individual institution level is not available. Nevertheless, we have access to data at the country level, so the unit of our study will be the country banking system rather than the individual bank. We will base our analysis on public data from the Bank for International Settlements (BIS) international banking statistics. The data include international claims of banks[6] in a number of reporting countries, with a counterparty-country breakdown. The frequency is quarterly. The data are aggregated at the country level, so that the total value of claims of banks headquartered in country i on institutions on country j are reported. We will consider consolidated statistics[7], since we judge that they better capture country risk exposure better than locational banking statistics. We will focus on "Immediate counterparty basis", that we regard more relevant for liquidity risk. A maturity breakdown is only available for "international claims" which are those in which the claim is booked in a banking office outside counterparty country (i. e. claims of a given Banking institution in a given country over the residents in that country will not appear in the maturity breakdown), so we will consider "all maturities", which also include claims on residents. This will tend to overestimate liquidity shock transmission; an alternative approach that considers only claims with maturity smaller or equal to one year is followed in Appendix 2. A currency or counterparty sector is not available for these data. The reporting institutions of interest are "Domestic banks", that is, "Banks whose controlling parent institution is located in the reporting country, regardless of whether the controlling parent is a banking or non-banking entity." (BIS 2013). We will examine how network measures evolve over the period 2006Q1-2016Q1. The 27 countries in the following list (which we will refer to as reporting countries) provide a detailed report of the claims of their banks over all the other countries: Austria, Australia, Belgium, Brazil, Canada, Chile, Denmark, Finland, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, Panama,

5: If a banks suffers a liquidity shock of size Δ, it converts $\Delta(1 - a_i/l_i)$ loans into cash, so its liquidity to assets ratio changes as $\frac{l_i}{a_i} \to \frac{l_i - \Delta + \Delta\left(1 - \frac{l_i}{a_i}\right)}{a_i - \Delta} = \frac{l_i(1-\Delta/a_i)}{a_i - \Delta} = \frac{l_i}{a_i}$.

6: "Reporting institutions cover mainly internationally active banks. In particular, they cover institutions located in each reporting country whose business it is to receive deposits (and/or close substitutes for deposits) and to grant credits or invest in securities on their own account." "At present, no precise criteria are used to determine the set of internationally active banks. It is expected that all banking offices with substantial international business, ie cross-border positions and/or local positions in non-domestic currencies, would be included in the reporting population. In addition, all foreign-owned banking offices in a reporting country are also expected to be included in the reporting population, even if these banking offices do not have substantial international positions." (BIS 2013).

7: They measure worldwide consolidated claims of banks headquartered in reporting countries, including claims of their own foreign affiliates but excluding inter-office positions. These statistics build on measures used by banks in their internal risk management systems." (BIS 2013). In this way, for example, the Spanish banking system includes Mexican assets and liabilities from BBVA Bancomer and Turkish ones from Garanti Bank.

Portugal, South Korea, Spain, Sweden, Switzerland, Turkey, Taiwan, United Kingdom and United States. 169 additional countries, which do not report the claims of their banks over the different countries, are considered as possible counterparties of the 27 reporting countries. It is worth noting that China, which banking system is increasingly interconnected abroad, is a not reporting country, so we lack data on the claims of its banks over other countries.

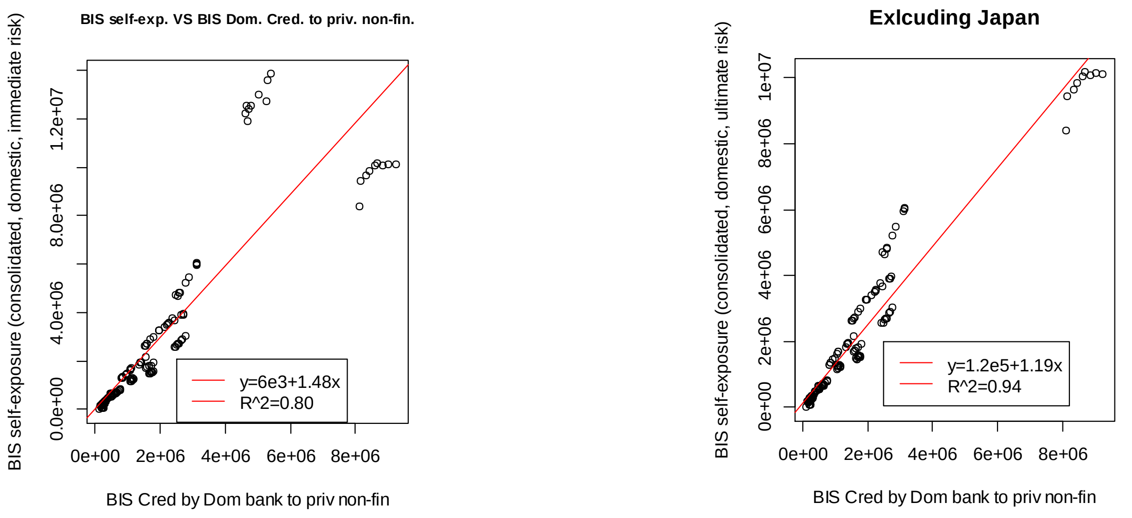
Based on these data we can build a matrix, G, whose elements, $G_{i,j}$, measure the funding exposure of country n_j to country n_i. In order to build liquidity shock-transmission matrix we need to model the propagation process. As mentioned earlier, if l_i/a_i is the liquid reserves to assets ratio of node n_i, we will assume that a fraction $(1 - l_i/a_i)$ of any liquidity shock received by n_i is transmitted, while the rest is absorbed by the liquid reserves of the node. The relevant matrix for shock propagation is, then, $S_{i,j} = (1 - l_i/a_i)G_{i,j}/\sum_k G_{i,k}$. Information of bank liquid reserves to assets ratio by country is reported by the World Bank. Unfortunately, the data from the World Bank misses most developed countries, so we complemented the data with data provided by the commercial site Trading Economics (Trading economics 2016). These data, however, only covers up to 2011. Liquidity data is provided at the yearly frequency, to obtain data at the quarterly frequency, it is interpolated, as explained below for the BIS data.

We are considering claims of banks in all sectors (banks, non-bank private and official), so that a liquidity shock will have effect over all the economy. However, we do not know how non-bank sectors will propagate the received shock. Given the data limitations, our analysis assumes that a shock to a country non-bank sector is propagated as if it was suffered by the bank sector. This could be justified if the non-bank sector compensates liquidity shortages with lending from the corresponding country bank sector, but we expect, that in general, we will tend to overestimate the propagation of shock. One could also use alternative data sources to infer exposures to non-bank sectors. In particular IMF's Coordinated Portfolio Investment Survey (CPIS 2016) seems particularly promising, since it reports holdings of portfolio investment securities of a large number of countries with a counterparty country breakdown. An important difference between analysis at the bank level and at the country level is that in the latter case, self-exposures (of banks in one country to residents in the same country) are possible (indeed they are very large, see below).

A first look at the data reveals the following. There is a large heterogeneity in funding exposures, with a median of 37, an average of 27449 and a standard deviation of 366603 (all magnitudes in million current USD and taking positive values only). This is not surprising, given the large economic heterogeneity in the set of countries considered. The values are relatively stable; if we look only at exposures larger than 250M USD, the average quarterly relative change is 14% with a standard deviation of 46%. Yearly, the average relative change is 31% with standard deviation 72%. Self-exposures (of banks based in one country to institutions in the same country) are (when reported) very large, averaging 68% of total exposures of a country, but are only reported from 2013Q4 onwards for some (reporting) countries and from 2014Q4 onwards for others. Many data points (24%) are missing. Missing data points could be set to zero, but given the high persistence found, this could lead to large errors. It seems to us that a more appropriate procedure is to use data from other quarters to complete missing data points. The procedure used is the following. For a given missing data point we look for the closest available data points in previous and posterior quarters. The imputed value is then the weighted average of these two values, weighted by the (complementary of the) distance to the missing data points. If only a value from posterior quarters is available, this value is copied (similarly if only a value from some previous quarter is available). Using this procedure we can complete all missing values which are reported in at least one quarter. Australia, Brazil, India, Mexico, Panama and Portugal never report self-exposures, so we cannot use data from other years to input a value. To overcome this problem, we use data of credit by domestic banks to the private non-financial sector, from the BIS “total credit” series. These data exclude credit to financial corporations and to the official sector, so it is not equivalent to self-exposures from the International Banking Statistics series. To ascertain the level of comparability of these two data bases, Figure 10 plots both values for all the years and countries in which both series are available.

Figure 10

Regression of BIS exposures of a country to institutions in the same country (see main text for details) on Credit by Domestic Banks to Private non-financial institutions. Left: all countries with data. Right: excluding Japan



Source: BBVA Research

We see that, except for Japan[8], BIS International Banking Statistics self-exposures and total credit from domestic banks to the private, non-financial sector are highly correlated, with a linear regression explaining 94% of the variance in the data. We, therefore, use the regression results and the total credit series to complete missing self-exposure values (for countries other than Japan), and do this before using data coming from different quarters. Missing data is reduced to 34% (from 60%) after this procedure and these values are set to zero. Given the imputation of data performed, the results before 2014Q4 -particularly before 2013Q4- should be interpreted very tentatively.

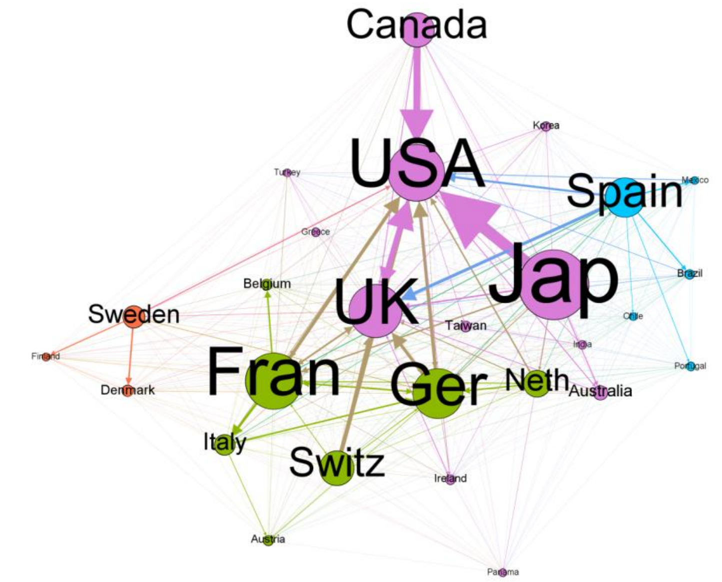
8: This is probably due to the exceptionally large level of public debt of Japan.

4.2 Network analysis

Figure 11 shows a representation of the network of international banking funding in 2016Q1 for the 27 BIS reporting countries. The size of the nodes is proportional to the total amount of claims of the corresponding country (including claims inside the country, that, for better visualization are not represented as links), while the size of the arrows is proportional to the claims of banks in one country in another, pointing from creditor to debtor. The colors correspond to the four groups found with the community-detection algorithm of Blondel et al. (2008).

Figure 11

International Bank financing network in 2016Q1. Node sizes: total claims of that country's banks. Arrow size: claims of banks in one country to institutions in another, from creditor to debtor



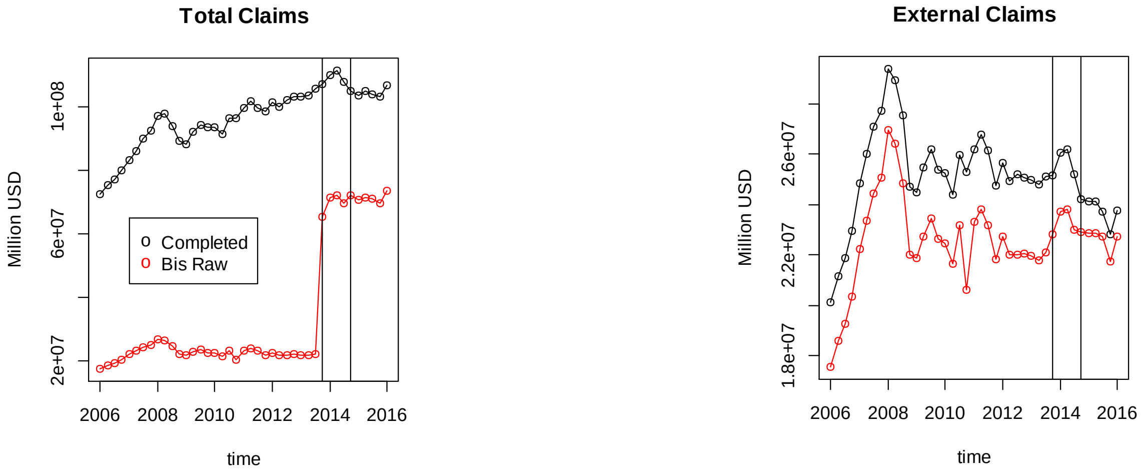
Source: BBVA Research

Japan and the US appear as the largest lenders, with the US receiving large amounts of lending from many different countries. The European countries are highly interconnected between them, with the Nordic countries and Spain with the Latin American countries forming separate groups. It is also noteworthy that relations are highly asymmetric (arrows in one direction larger than in the opposite), with, for example, institutions in the US receiving much more funding from foreign banks than US banks provide to foreign institutions. An important missing element is China; as mentioned above, not being a BIS reporting country, we lack data on the claims of its banks over other countries.

In Figure 12 we show the time evolution of the total claims reported by the list of the 27 reporting countries. Before 2013Q4 the values reported directly by the BIS (BIS Raw in the figure) are much smaller since they do not include self-exposures. The vertical lines indicate the time periods when BIS starts to report self-exposures. The difference between "Raw" and "Completed" data is due to values missing in the raw data that are interpolated in the completed data. We see that the total data accounts for around $100 trillion (values are in current USD, which should be taken into account when making inter-temporal comparisons). We also see that external claims sharply peaked in 2008Q1, being around 80% of peak value on 2016Q1.

Figure 12

Left: Total claims of banks in BIS reporting countries. Before 2014Q4 many countries did not report claims over domestic institutions. Raw data in red, interpolated as detailed in the main text in black. Right: Foreign claims

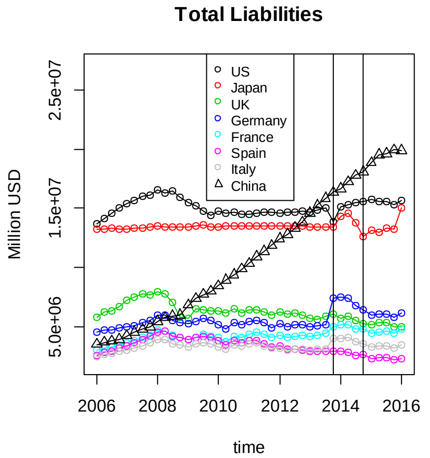


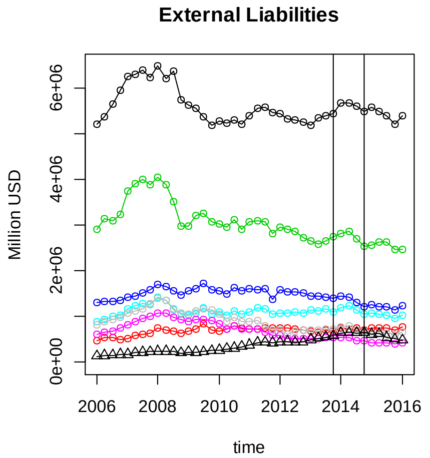
Source: BBVA Research

Figure 13 plots the liabilities of the larger countries. The US, Japan and China stand out in total liabilities, with China going through a very large increase during the sample period. Japan and China, however, have rather small quantities of external liabilities. The UK appears second in value of external liabilities, with around half as much as the US. Figure 14 displays the claims of the main countries (we do not have data on external claims of China, since it is not a BIS reporting country). The amount of external claims of German, French and British banks peaked in 2008. External British claims rebounded and grew until around 2012, when they started declining. The amount of external claims of Japanese banks markedly increases, becoming the largest by the end of the time period. As can be seen in figure 15, the US is (inside our set of countries) a large net borrower, while Japan and France (also increasingly Spain) are net lenders. It is also noteworthy that in 2009 the external claims of US banks more or less double (this is not an artifact of the data reconstruction procedure, it is apparent in the BIS original data).

Figure 13

Total (left) and external (right) liabilities of institutions in the country indicated by the color coding owned by BIS reporting banks. In this and the following figures, branches and subsidiaries have been consolidated and assigned to the parent institution's country, and the interpolated data is used

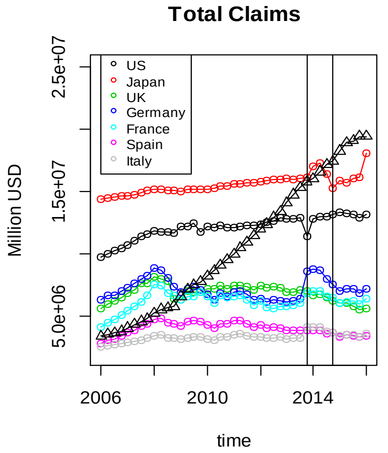


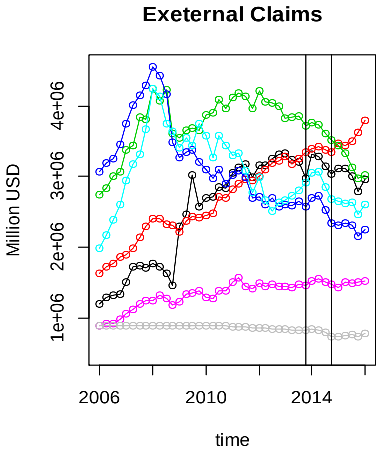


Source: BBVA Research

Figure 14

Total (left) and external (right) claims of banks in the country indicated by the color coding

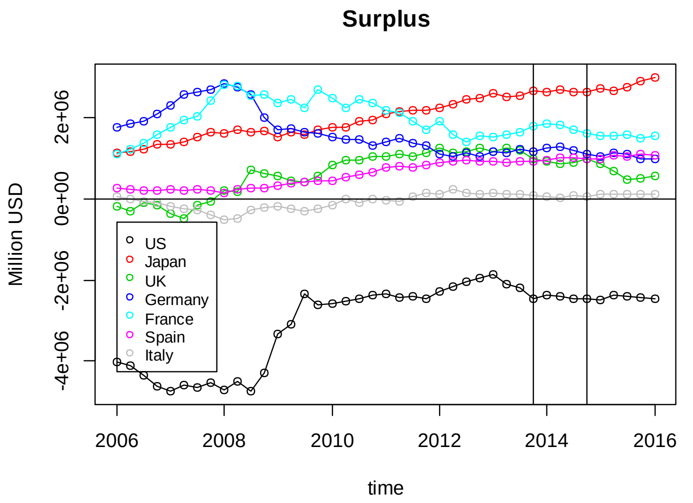




Source: BBVA Research

Figure 15

External claims of banks residing in the country indicated by the color code minus claims of foreign banks over institutions in that country



Source: BBVA Research

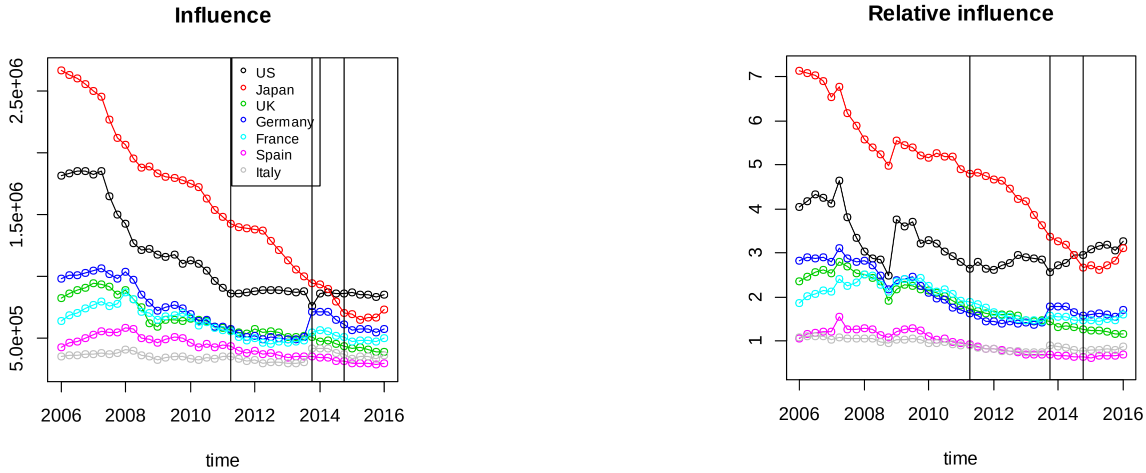
4.3 Network analysis results

We move now to quantify the importance and the vulnerability of the different BIS reporting countries, given the data caveats stressed in previous section.

Figure 16 shows the influence of the most important countries. The measure in the left panel is based on expression [3], with initial shock scaling (diagonal matrix D) proportional to the total claims of the countries. Each time series quantifies the potential total loss to the system (in million dollars) of a one percent loss of (liquid) assets of the corresponding country. We see that Japan and the US have the largest influence, but it markedly decreases through the period. This decrease is largely driven by the increase of the liquidity buffers. The influence of main European countries tends to peak around 2008. In the right panel we use expression [5], where the losses caused on each county are normalized dividing by the GDP of the country, to better quantify relative effects of a shock to one country over the others. We further divide by the number countries, so that the measure corresponds to the average loss in percentage points of GDP, when the corresponding country loses 1% (liquid) assets. The picture is relatively similar for the two measures. The vertical line in 2011Q2 (yearly data was assigned to the second quarter of each year) marks the limit of the available data on banks liquid reserves to assets. Data after 2011Q2 should, therefore, be interpreted with care. Using a more complete data set on banks liquid reserves to assets ratio would be important to verify the robustness of the results that we reported.

Figure 16

Influence of main countries. Left: Total drop in worldwide banks' assets (in Million current USD) caused by an initial loss in the indicated country of banks' assets of a value of 1% of the GDP of the country. Right: Drop in banks' assets as percentage of GDP, averaged over all countries, caused by an initial loss in the indicated country of banks' assets of a value of 1% of the GDP of the country

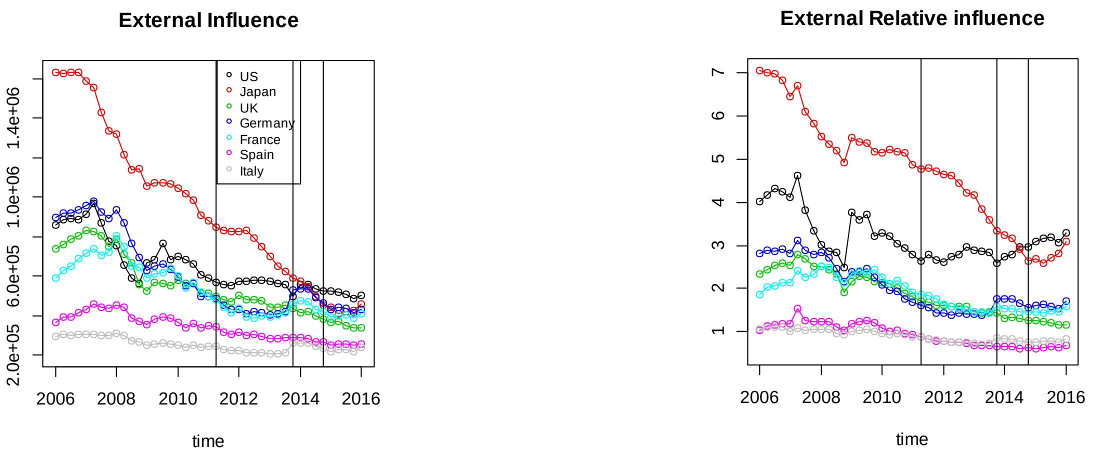


Source: BBVA Research

Figure 17 plots the same results as Fig. 16 but subtracting the effect on the country that receives the shock itself. We obtain a similar picture, except that now the US has an external absolute influence similar to that of Germany the UK and France.

Figure 17

Same as Fig. 16 but excluding the drop in banks' assets in banks located in the country receiving the initial shock

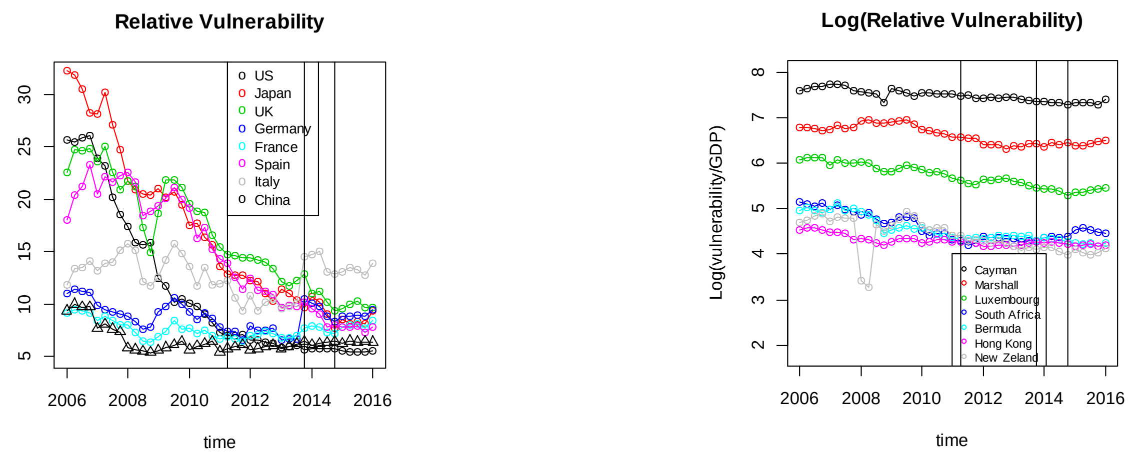


Source: BBVA Research

Figure 18 shows several countries vulnerability, using expression [8]. The left panel shows results for the main countries. Japan, US, UK and Spain stand out as the most vulnerable to funding shocks at the beginning of the sample period, with the vulnerability quickly decreasing. By the end of the period, Italy appears as the most vulnerable country. In the right panel we plot results for the 7 most vulnerable countries on 2016Q1. They are mainly offshore financial centers, but somewhat surprisingly South Africa and New Zealand are also highly vulnerable.

Figure 18

Relative vulnerability. Drop in bank assets value as a percentage of GDP in the corresponding country when a country chosen uniformly at random suffers a 1% drop in its banks assets. Right: main countries. Left: most vulnerable countries (in log scale)

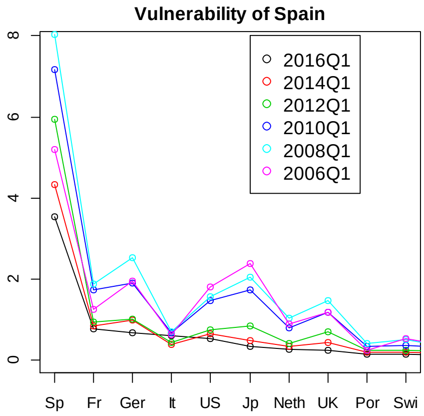


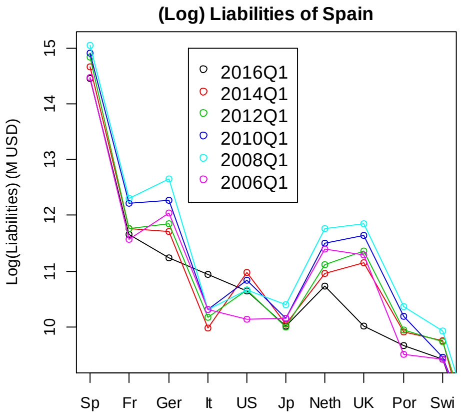
Source: BBVA Research

In figure 19 we show the vulnerability of Spain to particular countries. Now the X-axis denotes a country (as indicated in the figure), while different curves correspond to different years. Countries are order by their effect over Spain in 2016Q1. In the left panel, the Y-axis corresponds to the loss (in percentage points of GDP) in Spain when the banks in the corresponding country suffer a shock of 1% to their (liquid) assets. In the right panel we plot the direct claims of Spain in the different countries. We see that, despite having a small direct exposure to Japan, the effect of a shock to Japan can be severe to Spain due to indirect exposure and small liquidity buffers of Japanese banks. Conversely, despite having a relatively large direct exposure to the Netherlands, its effect over Spain is smaller, due to limited indirect effects. This idea is analyzed further in figure 20, where the ratio of the total effect to the direct effect (first term of the right-hand side of [1]) is plotted. When this ratio is close to 1 indirect influence is small and network effects can be neglected. Countries for which this ratio is large have a potential total influence much larger than the suggested by the direct exposures.

Figure 19

Left: Left: Relative vulnerability of Spain, i.e. drop in Spanish banks' assets as percentage of Spanish GDP when the country in the X-axis suffers a 1% drop in banks' assets. Right: Liabilities of Spanish banks to the X-axis countries over GDP of Spain

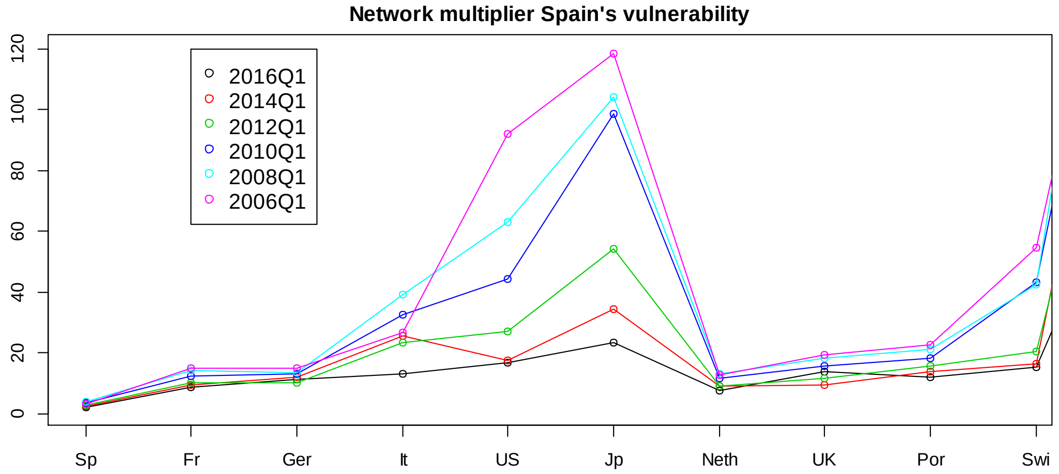




Source: BBVA Research

Figure 20

Spanish Vulnerability Network multiplier: Ratio of total drop in Spanish banks' assets when the banks in the country in the X-axis suffer a shock (including indirect effects) to the drop due to direct exposure

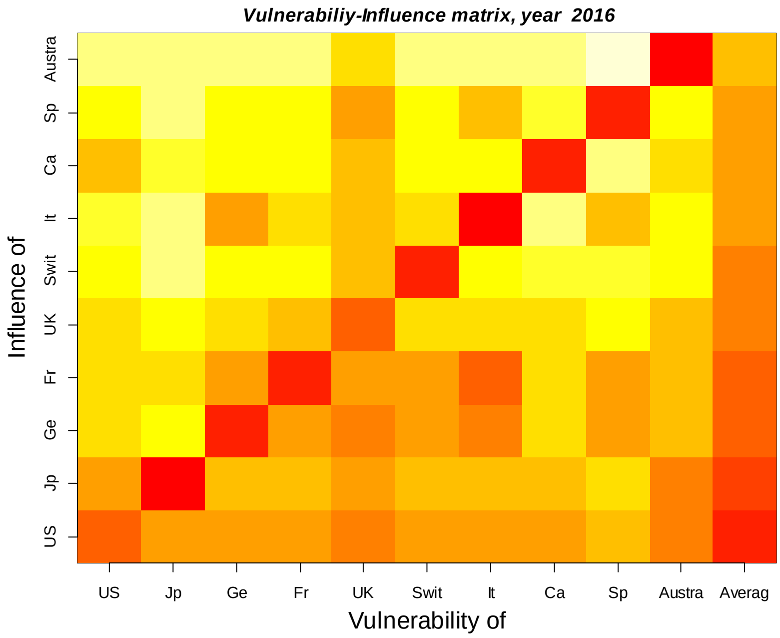


Source: BBVA Research

Finally, in figure 21 we represent the vulnerability-influence matrix, DMB in section 2, restricted to the 10 countries with highest relative influence in 2016. Here every row represents, in color coding, the relative influence (scaled by the assets of the influencing country and normalized by the GDP of the influenced country) of the country indicated in the y-axis over the countries indicated in the x-axis. In turn, every column represents the relative vulnerability of the country indicated in the x-axis to the countries in the y-axes. We have added an additional column to the right of the figure depicting the average relative influence of each country in the y-axis. We see that banks in a given country are particularly vulnerable to liquidity shocks originated in the same country. The UK and The US are somewhat less vulnerable to themselves and more to third countries, probably due to the high level of internationalization of their banking systems.

Figure 21

Vulnerability-Influence matrix in 2016Q1. Each column indicates the relative vulnerability of the X-axis country to the Y-axis country (X's drop in banks' assets as percentage of GDP when Y's banks suffer a 1% drop in assets). The rightmost column is the arithmetic mean over all the countries relative vulnerability to the country in the Y-axis i. e. Y-axis country relative influence. Color coding: Low-medium-high → white-yellow-red

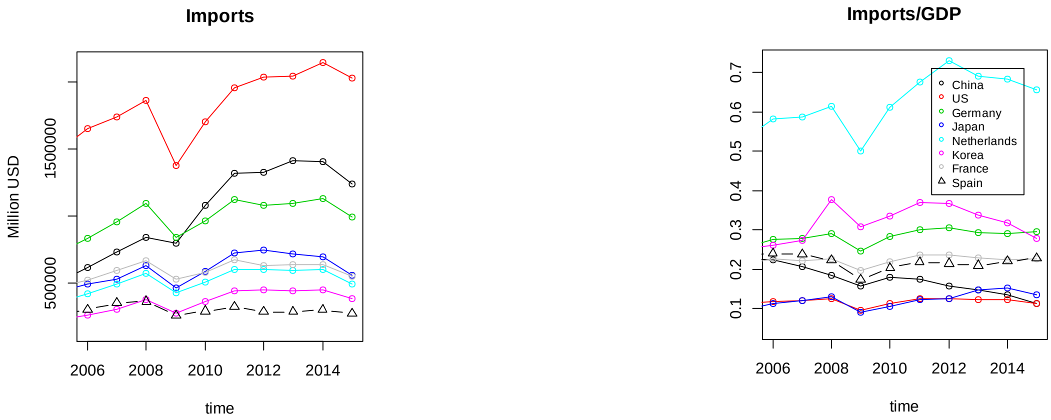


Source: BBVA Research

Appendix 1: Basic trade data

Figure A.1.1

Imports of main countries



Source: BBVA Research

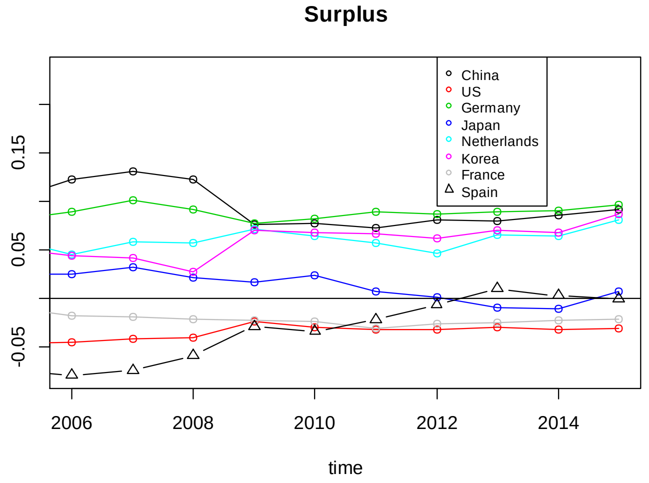
Figure A.1.2

Exports of main countries

Source: BBVA Research

Figure A.1.3

Surplus of main countries



Source: BBVA Research

Appendix 2: Results on bank funding networks using instruments with maturity $\leq$ 1 year only

We now repeat the analysis of the bank funding network but using data of claims with maturity smaller or equal to one year only, which probably capture liquidity risk better. As mentioned in the beginning of section 4, the problem with this data is that is reported only for international claims, so that claims with maturity smaller or equal to one year of banks over institutions in their same country are not reported. To solve this difficulty, we will assume that the ratio short-term (with maturity smaller or equal to 1 year) claims over country A that banks in country A hold to the total claims over country A held by banks is independent of the maturity of the claims. We will use the data discussed in section 4 to compute the ratio of bank claims over a country held by domestic banks. This will then be used to input the short-term claims over institutions in a given country held by banks in the same country.

The results are summarized in the following set of plots.

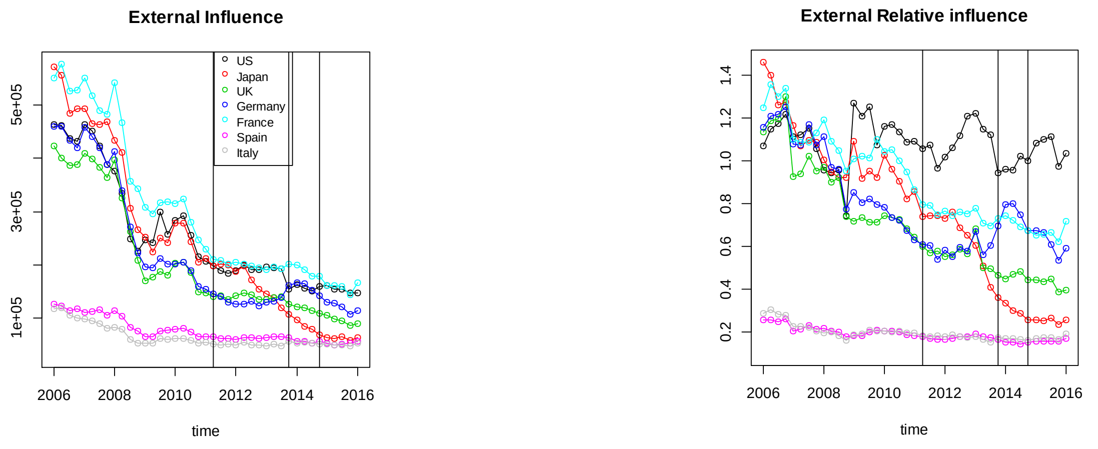
Figure A.2.1

Influence of main countries

Source: BBVA Research

Figure A.2.2

Influence of main countries

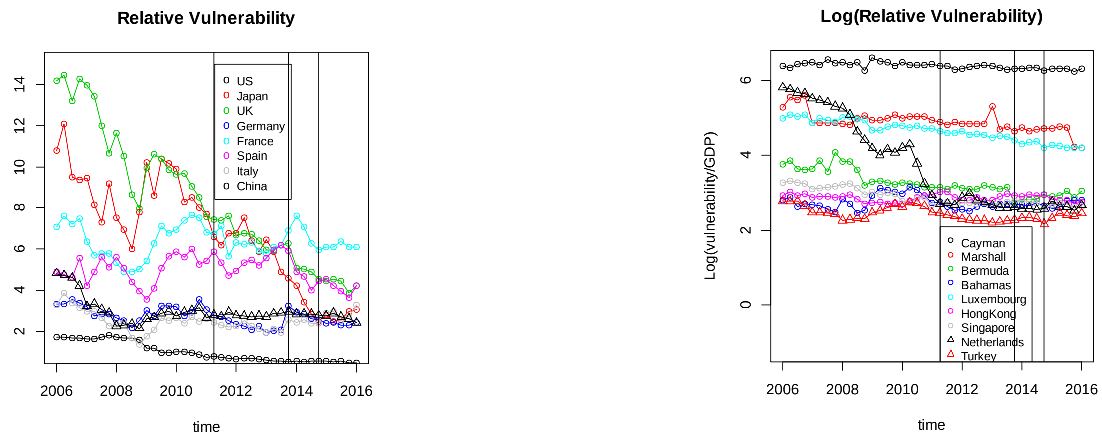


Source: BBVA Research

Now, relative to the other countries, the influence of France increases substantially, while that of Japan and the US decreases.

Figure A.2.3

Relative vulnerability of main countries (left) and most vulnerable countries (right)

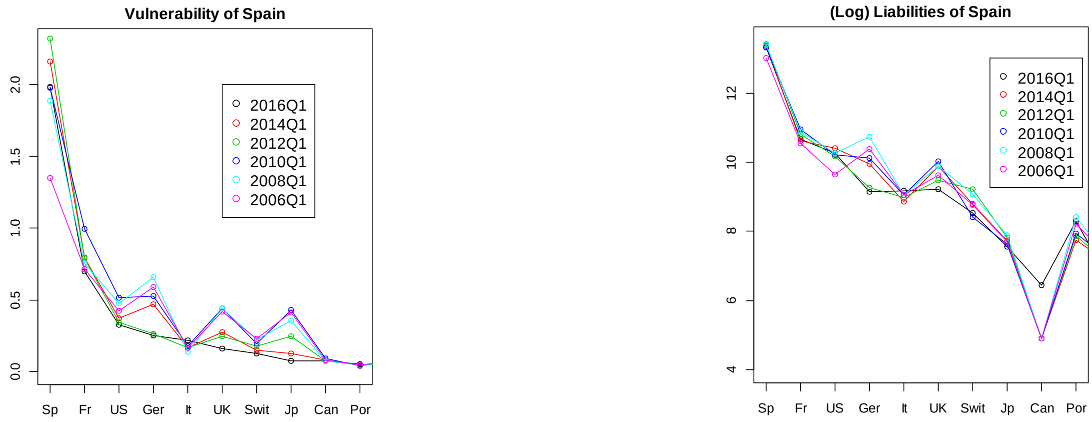


Source: BBVA Research

The vulnerability of the UK and France increase, with France becoming the most vulnerable country (as opposed to Italy when considering all maturities) in 2013Q3 and remaining so until the end of the sample period. The vulnerability of the US is reduced even further. The Netherlands appears now extremely vulnerable in the 2006-2010 period, and Turkey and Singapore also appear rather vulnerable.

Figure A.2.4

Vulnerability of Spain and Spanish banks' short-term liabilities

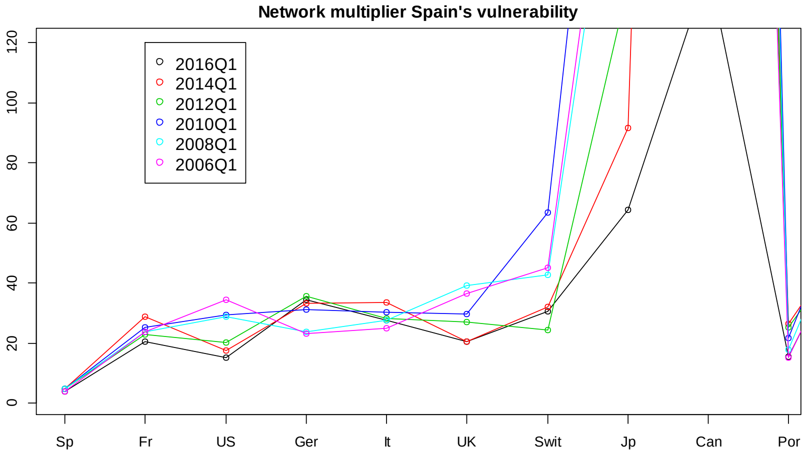


Source: BBVA Research

The countries with respect to which Spain appears most vulnerable remain relatively unchanged, but the US and Switzerland appear now more influential with respect to Spain.

Figure A.2.5

Network multiplier of Spanish vulnerability

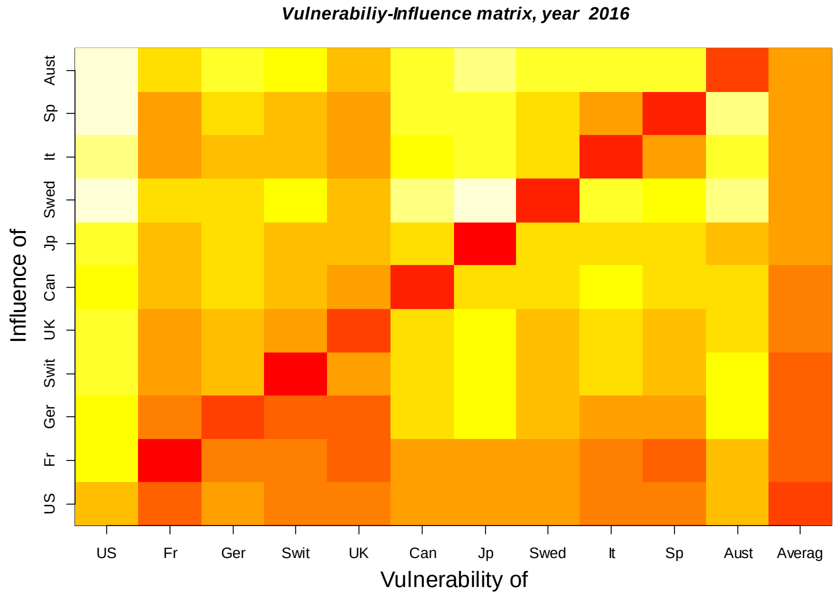


Source: BBVA Research

Spain's network multiplier is now generally larger (except for the US in some quarters), with Japan and Canada reaching very large values, signaling that now network effects are more important.

Figure A.2.6

Vulnerability-Influence Matrix of Banks short-term lending in 2016



Source: BBVA Research

The Influence-Vulnerability matrix is affected to some extent. For example, Switzerland now appears influential to France, the UK and Spain, while it only seems relevant for the UK before. Switzerland now appears more vulnerable to Germany and the UK.

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Contact details:
BBVA Research
Azul Street, 4
La Vela Building - 4 and 5 floor
28050 Madrid (Spain)
Tel.: +34 91 374 60 00 and +34 91 537 70 00
Fax: +34 91 374 30 25
bbvaresearch@bbva.com
www.bbvaresearch.com