The interconnected nature of financial systems: direct and common exposures

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Abstract

To capture systemic risk related to network structures, this paper introduces a measure that complements direct exposures with common exposures, as well as compares these to each other. Trying to address the interconnected nature of financial systems, researchers have recently proposed a range of approaches for assessing network structures. Much of the focus is on direct exposures or market-based estimated networks, yet little attention has been given to the multivariate nature of systemic risk, indirect exposures and overlapping portfolios. In this regard, we rely on correlation network models that tap into the multivariate network structure, as a viable means to assess common exposures and complement direct linkages. Using BIS data, we compare correlation networks with direct exposure networks based upon conventional network measures, as well as we provide an approach to aggregate these two components for a more encompassing measure of interconnectedness.
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1. Introduction

The last few years have witnessed an increasing research literature on systemic risk (for a definition see, for example, Allen and Gale (2000), Acharya (2009), Bisias et al. (2012) and Levy-

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Carciente et al. (2015)), with the aim of identifying the most contagious institutions and their transmission channels. Specific measures of systemic risk have been proposed for the banking sector; in particular, by Acharya et al. (2010), Adrian and Brunnermeier (2011), Brownlees and Engle (2012), Acharya et al. (2012), Banulescu and Dumitrescu (2015) and Hautsch et al. (2014). On the basis of market prices, these authors calculate the quantiles of the estimated loss probability distribution of a bank, conditional on the occurrence of an extreme event in the financial market.

The above approach is useful to establish policy thresholds aimed, in particular, at identifying the most systemic institutions. However, it is a bivariate approach, which allows to calculate the risk of an institution conditional on another or on a reference market but, on the other hand, it does not address the issue of how risks are transmitted between different institutions in a multivariate framework.

Trying to address the multivariate nature of systemic risk, researchers have recently proposed correlation network models that combine the rich structure of financial networks (see, e.g., Lorenz et al. (2009); Battiston et al. (2012); Levy-Carciente et al. (2015)) with a parsimonious approach based on the dependence structure among market prices. The first contributions in this framework are Billio et al. (2012) and Diebold and Yılmaz (2014), who propose measures of connectedness based on Granger-causality tests and variance decompositions. Barigozzi and Brownlees (2014) and Ahelegbey et al. (2016) extend the approach introducing stochastic graphical models.

While the literature on correlation networks has focused on the dependence structure among market prices, the focus of this paper is on correlations in network structures. Correlation network models, that tap into the multivariate network structure, seem a viable alternative to classical network models, as discussed in the recent papers by Brunetti et al. (2015). In particular, they seem to hold promise for assessing common exposures and complement direct linkages, in line with the general approach of Cai et al. (2014). However, the previous literature has neither compared the two models on the same application nor combined the two types of interconnectedness. This paper aims in particular at shedding light on these two problems, in the context of national interbank markets.

The network structure of national interbank markets has been studied, at the global level, using the Bank of International Settlements (BIS) data set: Garratt et al. (2011), McGuire and Tarashev (2006), Minoiu and Reyes (2013). In particular, Minoiu and Reyes (2013) used confidential data representing cross-border bilateral financial flows intermediated by national banking systems, and found evidence of important structural changes in financial banking networks, following the occurrence of stress events. The same authors pointed out that their results should be interpreted with some caution because of the large amount of non-reporting countries (their sample contains 184 countries, of which only 15 report bilateral positions to the BIS). Giudici and Spelta (2016) extended Minoiu and Reyes (2013), using data on the total financial exposure of each country with respect to the rest of the world: a database that, besides being publicly available, is more reliable. Applying a correlation network model to such data, one can establish indirect bilateral links between countries, that can be used to understand which countries are most central and, therefore, most contagious (or subject to contagion).

The methodological contribution of this paper is to formally compare classical networks and correlation based networks, using appropriate comparison metrics, in the modelling of interbank market flows between countries. Using the correlation as a measure of proximity in a multivariate framework, we provide measures of funding composition and portfolio similarities. From an applied viewpoint, we shed further light on the interpretation of country bilateral financial flows data, contained in the BIS statistics. We also provide an approach to aggregate the direct and indirect components of countries' exposures for a more encompassing measure of interconnectedness. Finally, we combine these measures with Credit Default Swap (CDS) spreads in order to evaluate whether and to what extent they are related to the build-up of imbalances prior to crisis events.

We find that total funding shows an increase up to the 2007 financial crisis, followed by an abrupt fall even if some countries do not follow this general trend. Moreover, we find that the proximity between the funding composition of a country with respect to the others, as well as the portfolio composition, is generally decreasing for most countries. In particular, in 2000 the funding sets were highly correlated, whereas at the end of the time sample each country exhibits a specific funding composition. This means that the funding composition of most countries has become more and more concentrated on a limited number of specific lenders. Moreover, results also suggest that the predictive power of direct linkages are clearly outperformed by the other ways of defining relationships. While linkages based upon common exposures and a combination of direct and common exposures perform equally well in forecasting crisis episodes, the predictive power obtained combining the two type of network is superior especially in periods of financial crisis.

The fact that the newly obtained predictive performance shows the overlapping exposure network increases sensibly the predictive performance of the standard exposure network highlights the importance of common exposures. From an economic point of view, this clearly shows that common exposures, or so-called funding/portfolio composition overlap, indeed are channels of contagion and should be accounted for when measuring systemic risk.

The paper is organized as follows. Section 2 introduces our methodological proposal. Section 3 describes the empirical results obtained with the application of both models to the Bank of International Settlement cross-border financial flows data. Section 4 compares our exposure measures in terms of performance in forecasting **future CDS spreads.**. Finally, Section 5 contains some concluding remarks and future research directions.

2. Measuring common exposure through correlation models

Systemic risk concerns the risks posed by balance sheet relationships and interdependencies among players in a system or market, where the failure of a single entity can cause a cascading failure, which could potentially bring down an entire system or market. These balance sheet linkages can be represented by a network that describes the mutual relationships between the different economical agents involved.

A network can be represented by means of a graph $G = (V; E)$ that consists of a set V of n vertices and a set E of m edges. A weight w_{ij}, (with $i, j = 1, ..., m$) is possibly associated to each edge $(i; j)$ and, if this is the case, a weighted (or valued) graph is defined.

In the wake of the recent crisis it has been argued that network theory can enrich the understanding of financial systems, systemic risk, and the comprehension of the factors causing failures in financial markets. Usually, researchers approached financial systems through the study of connections among financial institutions exploring banking liabilities and claims because credit inter-linkages play a crucial role in propagating, absorbing or magnifying shocks. However, despite the fact that the topology of a network is known to play a major role in robustness against shocks, the lack of bilateral data have prevented the systematical investigation of the topological properties of the international financial network. Fortunately, whenever the data are missing or confidential, correlation based networks seem a viable alternative to classical network models. While the literature has focused on dependence structures among market prices, the focus in this paper is on correlations in network structures.

In the present study the set of nodes represent countries, while the set of edges depends on the definition or the meaning of a link. In particular we define four types of networks as Figure 1 exemplifies. In this way, when we consider contagion via portfolio exposure (the out-flow case) we also have a network construction similar to a bipartite graph, in which there coexist two dynamics: one among fully reporting countries, described by direct flows and one among all countries, described by common exposures. Indeed, in the construction of common exposures we consider also countries that are outside the sample of the direct exposures.

FIGURE 1 APPROXIMATELY HERE

The aim of the paper is, in fact, to study and to compare networks of direct flows between countries' banking sectors with common exposure networks based on correlations between streams of loans (see, for instance, Mantegna and Stanley (1999) and Mantegna (1999) for an introduction to correlation networks). A link between two countries in a direct network represents a flow of funds, in millions of dollars, between a borrower and a lender. A link in a common exposure network, instead, measures the similarity between the funding composition or between the portfolio allocations of two countries, depending on whether in-flows or out-flows are used to compute the correlations. While in a direct network the links are directional, from a lender to a borrower, in common exposure networks they are undirected, and they are computed starting from the correlation between the in-flows (out-flows) of a country with respect to all other countries. Thus, in the common exposure networks, the weight attached to each link codifies the similarity between the two countries referring to that link in terms of their funding or portfolio composition (see Javarone and Armano (2013)).

To exemplify, at each point in time, we can describe each country by means of two vectors $1 \times N$ encompassing loans from and to all other countries (in- and out-flows) at that time. If we define with $In^{i,t} \in \mathbb{R}^{1\times N}$ the vector that represents the quantity each country invests in i at t, then the scalar $In_j^{i,t}$ is the quantity invested in country i by country j at time t. Analogously if we let $Out^{i,t} \in \mathbb{R}^{1\times N}$ be the vector that represents the quantity country i invests in all other countries at t, $Out_j^{i,t}$ is the scalar that describes the amount invested by country i in country j at time t.

In an in-flow common exposure network, that we called *funding composition similarity network*, the weighted link d_{ijt}^{In} between two countries is the similarity between the two vectors $In^{i,t}$ and $In^{j,t}$, that contain the amounts invested by all other countries, respectively in i and j in t. It represents the proximity between the funding composition sets of the two countries:

$$d_{ijt}^{In} = 2 - \sqrt{2\left(1 - C_{In^{i,t},In^{j,t}}\right)} \tag{1}$$

where $C_{In^{i,t},In^{j,t}}$ is the correlation between the two funding composition sets at time t. A high value of d_{ijt}^{In} means that the total funding the two countries receive from the investors has the same composition, and therefore they have similar funding risk.

Differently, in an out-flow common exposure network, the so-called *portfolio similarity network*, the weighted link d_{ijt}^{Out} between two countries is the similarity between the two vectors $Out^{i,t}$ and $Out^{j,t}$, that contain the amounts invested by countries i and j in all other countries at time t:

$$d_{ijt}^{Out} = 2 - \sqrt{2\left(1 - C_{Out^{i,t},Out^{j,t}}\right)} \tag{2}$$

where $C_{Out^{i,t},Out^{j,t}}$ represents the correlation between the two portfolio composition sets. A high value d_{ijt}^{Out} means that i and j invest similar proportions of funds in all other countries and, therefore, they have overlapped portfolios, and similar credit risk.

One of the problems that has received much attention in the study of financial networks has been determining interconnections among institutions with the aim of evaluating the impact that an institution's bilateral exposures has on other institutions within the system. In this literature, interconnectedness is related to the detection of the most central players in the network. The simplest way of measuring the centrality of a node is by counting the number of neighbours it has. Or, in the weighted case, summing the weights of the links associated to a node.

In the case of direct weighted networks, we can define two local measures of centrality, the in- and the out-strength, defined as follows. Let $\mathbf{W}_t$ be a weighted adjacency matrix such that w_{ijt} is the quantity lent from j to i at time t. The in-strength of country i in a direct (real) network R, at time t is defined as:

$$S_{i,t}^{I,R} = \textstyle\sum_j w_{ijt} \tag{3}$$

and symmetrically the out-strength is defined as:

$$S_{j,t}^{O,R} = \textstyle\sum_i w_{ijt}. \tag{4}$$

In other words, the in-strength of a country in a given period, represents the total funding that such country receives from other countries in that period. The out-strength, on the other hand, represents the total portfolio of that country invests in all others.

For the common exposure network the in-strength for country i at t can be defined as the sum of the similarities between the funding composition set of a country and those of all other countries in that period:

$$S_{i,t}^{I,C} = \textstyle\sum_j d_{ijt}^{in} \tag{5}$$

Symmetrically, the out-strength can be defined as the sum of the similarities between the portfolio allocation of that country and the portfolio allocation of all other countries:

$$S_{i,t}^{O,C} = \sum_i d_{ijt}^{out} \tag{6}$$

The higher $S_{i,t}^{I,C}$ the higher the similarity of the composition of the funding of country i with respect to all other countries. In other words, country i has a set of investors that invest amounts in all other countries in a proportional way. A low value of $S_{i,t}^{I,C}$ instead means that country i has a set of investors that is specific to that country. Similar considerations can be done looking at $S_{i,t}^{O,C}$ in terms of portfolio allocations.

Summarizing, while $S_{i,t}^{I,R}$, $S_{i,t}^{O,R}$ describe the total funding a country receives from the others or the total investment in other countries; $S_{i,t}^{I,C}$, $S_{i,t}^{O,C}$ describe the similarity of the funding composition of that country with respect to the others, or the similarity of portfolio allocations of that country with respect all others.

Having introduced, and compared, direct and correlation networks, it is quite natural to aggregate them into a measure of systemic risk that uses both the direct and the common exposure networks. To achieve this aim, for each time period we perform the following steps.

The first step normalizes the elements of each weighted adjacency matrix by subtracting their mean and dividing by their standard deviation:

$$\hat{w}_{ijt} = \frac{w_{ijt} - \langle w_{ijt} \rangle}{\sqrt{\langle w_{ijt}^2 \rangle - \langle w_{ijt} \rangle^2}} \tag{7}$$

$$\hat{d}_{ijt} = \frac{d_{ijt} - \langle d_{ijt} \rangle}{\sqrt{\langle d_{ijt}^2 \rangle - \langle d_{ijt} \rangle^2}} \tag{8}$$

In such a way the obtained elements represent two z-scores associated to each link. They indicate whether, for each pair of countries, their weighted link is above or below the mean and by how many standard deviations. Note that this step purifies the series from the trend component. For the direct network a positive z-score associated to a link means that the flows between the two countries are greater than the mean (a negative z-score less than the mean). For the common exposure network a positive z-score means that two countries funding (portfolio) compositions are more similar than the mean (a negative z-score less than the mean).

The second step deals with the creation of a *combined matrix* for each time period. At a given t, each element of this object is obtained as a linear combination of the corresponding elements of the normalized direct and common exposure networks. The weights of the linear combination are the normalized singular values of the matrix obtained by aligning the two vectorized adjacency matrices.

More formally, we create a new matrix $\mathbf{F}_t$ defined as

$$\mathbf{F}_t = \left[\begin{array}{ccc} vec\left(\hat{\mathbf{W}}_t\right) & \vdots & vec\left(\hat{\mathbf{D}}_t\right) \end{array} \right]$$

then we approximate the matrix using the singular value decomposition $\mathbf{F}_t \approx \mathbf{U}_t \mathbf{\Sigma}_t \mathbf{V}_t$, with

$$\mathbf{\Sigma}_t = \left[\begin{array}{cc} \sigma_{1,t} & 0 \\ 0 & \sigma_{2,t} \end{array} \right]$$

finally we compute the weight as $\alpha_t = \frac{\sigma_{1,t}}{\sum_{i=1}^{2} \sigma_{i,t}}$, symmetrically $(1-\alpha_t) = \frac{\sigma_{2,t}}{\sum_{i=1}^{2} \sigma_{i,t}}$.

Notice that the weights change over time but not over nodes, and represent the strength of the two effects (direct vs common exposure) in the composition of the combined effect. More formally, the generic elements i, j of the combined matrix at time t is:

$$m_{ijt} = \alpha_t \hat{w}_{ijt} + (1-\alpha_t)\, \hat{d}_{ijt} \tag{9}$$

where $\hat{w}_{ijt}$ and $\hat{d}_{ijt}$ are the normalized links between country i and country j at time t produced by the directed and by the common exposure matrix respectively. The parameter α_t governs the strength of the two components in generating the mixed links m_{ijt} at time t.

3. Empirical network analysis

This section provides the empirical analysis on both direct and common exposure networks.

3.1. Data

The Bank of International Settlements (BIS) produces statistics on international banking activities. The International Banking Statistics comprises consolidated banking statistics (CBS), which measure worldwide consolidated claims of banks headquartered in reporting countries, including claims of their own foreign affiliates but excluding interoffice positions. These statistics build on measures used by banks in their internal risk management systems, and include data on off-balance sheet exposures, such as risk transfers, guarantees and credit commitments.

We employ the consolidated banking statistics on ultimate risk basis that are based on the country where the ultimate risk or obligor resides, after taking into account risk transfers. Note that, since the statistics capture banks' worldwide consolidated positions, the CBS reporting area is not synonymous of the location of the banking offices participating in the data collection. That is, a reporting country should consolidate the positions of all banking entities owned or controlled by a parent institution located in the reporting country, thus including banking entities which are actually domiciled elsewhere.

Reporting institutions are financial institutions whose business is to receive deposits, or close substitutes for deposits, and to grant credits or invest in securities on their own account. Thus, the community of reporting institutions should include not only commercial banks but also savings banks, credit unions or cooperative credit banks, and other financial credit institutions. Unfortunately a number of countries do not report their statistics on the asset side (out-flows). In our available dataset there are only 12 fully reporting countries and more than 240 that do not report. In addition, for historical reasons among others, the time series contain varying starting dates, as well as a number of missing values. To address the above data quality issues we split the analysis of the in- and out-flows in two different databases. More precisely, for what concerns the funding side, we restrict the analysis to the 33 largest economies (for which the received loans sum up to last 100000 billion dollars for the period from 1998 to 2013). The considered time period starts from the third quarter of 1998 (Q3–1998) to the last quarter of 2013 (Q4–2013). On the other hand, for the investment side we are forced to use only 15 reporting countries, from the third quarter of 1998 (Q3–1998) to the last quarter of 2013 (Q4-2013)[5,6]. Notice that the proposed strategy is consistent with Basel III regulation that look separately at the lending and borrowing sides of banks' balance sheet to evaluate their systemic importance (Board (2013)).

FIGURE 2 APPROXIMATELY HERE

Figure 2 shows some preliminary network statistics. Both the network density reported in panel (a) and the fraction of reciprocated links in panel (b) have grown through time. The density

[5]Countries selected for in-flows analysis: AT = Austria, AU = Australia, BE = Belgium, BR = Brazil, CA = Canada, CH = Switzerland, CN = Cina, CZ = Czech Republic, DE = Germany, DK = Denmark, ES = Spain, FI = Finalnd, FR = France, GB = Great Britain, GR = Greece, HK = Hong Kong, IE = Ireland, IN = India, IT = Italy, JP = Japan, KR = South Korea, KY = Cayman Islands, LU = Luxemburg, MX = Mexico, NL = The Netherlands, NO = Norway, NZ = New Zeland, PL = Poland, PT = Portugal, RU = Russia, SE = Sweden, SG = Singapore, US = United State.

[6]Countries selected for out-flows analysis: AT = Austria, BE = Belgium, CH = Switzerland, DE = Germany, DK = Denmark, ES = Spain, FR = France, GB = Great Britain, JP = Japan, NL = The Netherlands, SE = Sweden, US = United Stat.

has increased from 35 to 55 percent, between 1999 and 2013, while the fraction of reciprocated links has reached 35 percent at the end of the sample time. The network diameter shown in panel (c), the average path length displayed in panel (d) and the average betweenness of panel (e) all suggest that the network is more concentrated during the financial crisis period. Finally, the network remains weakly dissortative through all the sample time, meaning that nodes with a high strength are linked mostly with nodes having low strength values[7]

3.2. In-strength: funding risk

This section encompasses the results from the application of the direct and of the common exposure networks to BIS data. In particular it refers to in-strength; the funding risk of the countries.

Figure 3 shows the two strength measures for each country: in blue we report the evolution of the in-strength of each country in the direct network, and in green the evolution of the strength for the funding composition similarity network [8]. Plots are on two different scales; as the left y-axis refers to the in-strength of the direct network and the right y-axis refers to the the funding composition similarity network. Each series has been normalized dividing it by the number of all possible $n-1$ peers a country has. The three colored vertical bars distinguish between the pre-crisis phase 2007–08, the first wave of the crisis 2008–09 and the second wave 2009–10. The title of each subplot represents the name of the considered country.

FIGURE 3 APPROXIMATELY HERE

From Figure 3, two general trends appear for the direct and for the funding composition similarity strengths. Regarding the former, that measures total funding, some countries show an increase of the in-strength up to the 2007 financial crisis, followed by an abrupt fall; these countries are BE, ES, FR, GR, GB, IE, IT, NL, PT in Europe, and the US. However, some countries do not follow this general trend: for instance, AU, CA, BR, DE, KR, LU, RU and the Baltic countries, whereas CN, HK, CH, JP, KY, MX, SG, IN show an ever increasing in-strength.

[7] **In 2013 the network become more sparse and, at the same time also clusterized. The distances between countries in different clusters increase resulting in a higher diameter and average path length. Also the less dissortative behavior is caused by this clusterization episode that made countries to lend to/borrow from similar countries that lies in the same cluster. This behavior on the other hand is highly temporal and does not affect the overall results of the paper.**.

[8] Remember that the similarity matrices are symmetric.

Regarding the latter, the strength, that reflects the proximity between the funding composition of a country with respect to the others, is generally decreasing for most countries, except for BR, DE, HK, IN, MX PT and SG. In 2000 the funding sets were highly correlated, whereas at the end of the time sample each country exhibits a specific funding composition. This means that the funding composition of most countries has become more and more country specific. This means that, after an extraordinary expansion phase, the crisis acted as a rebalancing force in the market. To further understand this behaviour, Figure 4 shows the change over time of the standard deviation of the funding composition of each country.

FIGURE 4 APPROXIMATELY HERE

Figure 4 shows that the overlapping of the funding composition of most countries decreases after the financial crisis, especially for countries such as US, GB and IT. Thus, reading jointly Figures 3 and 4, the funding concentration started piling up before the crisis but increased considerably afterwards. Before the crisis, we observe an increase in the total funding of countries, given by specific investments in those countries and not by a generalized increase in the overall system funding. After the crisis, we observe a decrease in total funding which does not directly correspond to a higher diversification but rather to a further concentration.

Note from figure 14 that Germany (DE) shows a remarkable positive correlation between the in-strengths calculated starting from the direct and from the common exposure networks especially before the global financial crisis. Differently from other countries, DE has attracted new investors that were previously investing in other countries; a flight to quality effect. After the crisis, instead, the investors set of DE has become more country-specific, like that of other countries.

3.3. Out-strength: exposure risk

We now consider the out-strength; the portfolio allocation risk of the countries. The out-strength calculated for the direct network measures the total out-flows of a country, which is nothing else than the sum of its investments in all other countries. On the other hand, the strength for the portfolio similarity network measures the average distance of a country's portfolio composition with respect to those of the other countries. Thus it function as a measure of credit risk.

Figure 5 shows the strength for each country. In blue we report the results for the out-strength of the direct network, while in green for the out-strength of the portfolio similarity network. Plots are on different scales (left real and right proximity), and each series has been normalized as in the case of the in-strength. The three colored vertical bars distinguish between 2007–08, 2008–09, 2009–10. The title represents the name of the country.

From Figure 5 we can see that the crisis affects the direct out-strength of many core European countries: AT, BE, CH, DE, FR, NL, GB but not that of non EU-countries such as US, JP and the one of SE and ES. This can be explained again by the rebalancing role played by the financial crisis that piled up after 2007. The trend of the out-strength of the portfolio similarity networks is decreasing for most of the countries as for the funding composition. Looking at the correlation between the two series (reported in Appendix), it is negative for most of the countries. Economically, while European countries have decreased their investment flows after their crisis, the contrary has occurred outside Europe.

FIGURE 5 APPROXIMATELY HERE

3.4. Mixed strength measure

Figure 6 shows the dynamic of the weights used to mix the two types of networks according to equation 9. In particular Figure 6(a) emphasizes the pattern of the weights adopted for building the mixed network for the in-flow case, while panel 6(b) is related to the dynamic of the weights of the out-flow network. From Figure 6(a) it clearly emerges that the direct component has the largest impact on the combined network; the gap between the two increases until the 2007 financial crisis where it stabilizes. In any case, the two weights have a very similar impact throughout. Regarding Figure 6(b), beside the fact that also in this case the behavior of the direct component plays the major role in the combined network, the patterns of the two components are less volatile with respect to the in-flow network.

FIGURE 6 APPROXIMATELY HERE

Below, in Figure 7 we report the in-strength of the combined network. The same strategy has be applied also to the out-strength and the results are shown in Figure 8. Notice that a high positive strength could mean either that the total funding (lending) of a country is high or that the funding (lending) composition has a low concentration or both: in all cases, the higher the strength the higher the risk. On the contrary, the lower the strength the lower the risk. TOGLIERE???

Looking at Figure 7 it seems that the financial crisis works as a tipping point for most countries, after which a regime switch happens. On one hand, many countries present a fall of the mixed in-strength measure during the financial crisis. Some of them, mostly European countries: AT, BE, CZ ES, GR, GB, IT, PT, PL, DK, IE NO and JP have not yet recovered. Others, such as FR, IE, BR, FI, NL, SE together with US, instead have.

On the other hand, another group of countries have not been affected at all by the crisis, and maintain the same risk profile throughout. This group includes off-shore countries (HK, LU, KY) flight to quality countries (CH, DE) and emerging countries (IN, KR, MX). Investments in all these countries seems to remain stable during distress periods. Finally, the remaining countries show a more volatile in-strength measure.

Looking at Figure 8, results are in line with the findings shown in Subsection 3.3. We can observe the strength of most of the EU countries to decrease near the crisis period. Exceptions to this trend are Spain and Sweden (ES, SE) that do not decrease their lending during the financial crisis. On the other hand, non-EU countries (US, JP) display an increasing strength over most of the sampling periods.

FIGURE 7 APPROXIMATELY HERE

FIGURE 8 APPROXIMATELY HERE

We finally remark that, to evaluate the robustness of our model, we have performed a sensitivity analysis on the weight parameter of the mixed network, α. The results, reported in Appendix indicate the stability of our findings. In the Appendix we have also reported, for each country and for three different sub-samples (1999–2007, 2007–2010 and 2010-2014), the correlation between of the strengths computed on the different types of networks.

4. Predictive performance

This section compares the use of direct exposures, common exposuresand mixed exposure in a predictive model of systemic banking crises. The aim of this subsection is to validate the proposed systemic risk measure in a predictive performance setting. Specifically, we investigate whether the inclusion of contagion networks in the computation of CDS spreads helps in predicting their next period values and thus country banking systems vulnerability. Indeed, financial distress of a banking system can be directly measured by the risk premia implied by the corresponding set of CDS spreads but, on the other hand CDS spreads are bilateral agreements and do not take contagion into account. Networks linkages in this sense are helpful for incorporating information about how risks are transmitted between different entities in a multi-dimensional framework.

In so doing, we postulate a contagion model between banking systems, based on the matrices W, D or M, so that we modify the idiosyncratic distress measure into a measure that incorporates not only CDS spreads, but also how they interact with the rest of the global financial system via multiple linkage types

In particular, we compare the predictions obtained using only the information embedded in the past CDS spreads values with the ones obtained using both past CDS spreads values and past network values, merged in a network based spreads measure. To achieve the aim we employ quarterly based CDS spreads of 23 countries[9] recorded during the period Q4-2007 to Q4-2014, therefore we restrict our original dataset to accommodate for the CDS database.

In more detail, we perform an out of sample analysis, with the aim of predicting one step ahead CDS spreds. When we rely only on past CDS values we use the average of the last n_1 values to forecast the CDS spreds in next period as:

$$\hat{c}_{it} = \sum_{x=t-n_1}^{t} \frac{c_{ix}}{n_1}.$$

with $\mathbf{C}$ being the matrix of CDS spreads at each point in time[10] and the superscript $\hat{o}$ refers to the forecasted variable.

When using also the network structures derived in the previous subsection, we embed networks topologies and CDS spreads within the strength-centrality measure. In this way, we can we obtain modified CDS spreads and, consequently, default probabilities that take into account contagion between the different countries. More formally we use a linear combination merging measures of individual risk (CDS) and interconnectedness. In principle, we adapt the strength centrality aggregating, over node values (i.e., individual risk) and over link values (i.e., intercon-

[9]Countries selected for the forecast analysis: AT = Austria, AU = Australia, BE = Belgium, CA = Canada, CH = Switzerland, DE = Germany, ES = Spain, FI = Finalnd, FR = France, GB = Great Britain, GR = Greece, HK = Hong Kong, IE = Ireland, IN = India, IT = Italy, JP = Japan, KR = South Korea, NL = The Netherlands, NO = Norway, PT = Portugal, SE = Sweden, SG = Singapore, US = United State.

[10]Since we have a vector of CDS spreads for each country along time, these vectors form a matrix if they are considered together.

nectedness). First we compute the modified in-stregth centrality as:

$$\tilde{s}_{it} = \sum_j n_{ijt} c_{it}$$

where $\mathbf{N} = \{\mathbf{W}, \mathbf{D}, \mathbf{M}\}$ depends on the network type used for the analysis. Then, the multivariate CDS spreads values are found as:

$$\widehat{c_{it}^{Mult}} = \widehat{c_{it}} + \textstyle\sum_{x=t-n_1}^{t} \frac{\tilde{s}_{ix}}{n_1}$$

In this way we modify the univariate CDS spreads into multivariate spreads taking into account contagion effects arising from changes in the spreads of other countries and changes in flow amount (W), composition (D) or both (M). The choice of different adjacency matrices implies different contagion processes and feedback effects from the banking sector even if the underlying contagion mechanism is the same. The matrix W identifies the flow of funds between lenders and borrowers. Upon its normalization, each link is associated with a weight, valued between 0 and 1, which indicates the percentage of the CDS spread that a lender country passes to the borrower in the case of the calculation of the in-strength[11]. In both cases, the larger the flows the higher this percentage is. In this way the magnitude of contagion depends on the amount of financial flows between the two country banking sectors. While computing the modified in-strength, this contagion mechanism is in accordance with the analysis of Freixas et al. (2015) who claim that contagion can occur through direct liquidity shortages (funding risk)[12]. However, financial contagion does not come only through direct exposure, but also from common exposures, that is, common funding sources or overlapping portfolios. For instance, changing perspective, if we consider liquidity problems with an asset side approach, it is important to state that, when a bank incurs in a liquidity shortage, it will be forced to sell its assets, and this will bring a contingent decrease in the price that will affect all banks, with the possibility that other institutions may be forced to do the same sale operation, selling additional assets. The idea behind using D as a source of contagion[13] is precisely to model contagion due to common exposures.

[11] Or, as the other way round, the percentage of the CDS spread that a borrower country passes to the lender in the case of the out-strength.

[12] On the other hand, the out-strength takes into account counterparty risk (credit risk)

[13] normalized as in the case of **W**.

The mixed network (M) allows us to take into account both contagion mechanisms but also the fact that it could be the case in which an increase of the CDS spread of a borrower produces a decrease in the CDS value of the lender[14]. This occurrence happens when the value of the link is negative or, in other words, when the predominant element in the composition of M has a negative Z-score (or both components have negative z-scores). This means that the two countries have a flow and/or a similarity below the average. Economically this means that the CDS spreads of the two countries can be considered as complementary goods. For instance, suppose that the spread of country i CDS increases meaning that the country in now more risky, this occurrence will drive the demand for the CDS of i to decrease. If m_{ij} is negative, this means that the demand for the CDS of j will increases (being the two CDS complementary goods) making the risk premia of the CDS of country j to decreases and so its spreads. On the other hand two countries' CDS connected by a positive link can be considered as substitute goods for which an increase in the spread of i-th country CDS will lead the demand for that CDS to decrease, this mechanism (via the positive $m_{i,j}$ link) will lead also the demand for the j-th country CDS to decrease leading a higher risk premia and consequently an higher spreads of the country j CDS.

To evaluate the predictive power of our proposed methods, we present the results from an out-of-sample predictive analysis. Specifically, at time t the objective is to predict the one-step ahead value of the spreads.

To achieve this aim we first compare i) a model based only on the average of the last n_1 observed past spread values; ii) a model based the modified network contagion effect. Then we compare iii) the real network based contagion model, iv) the common exposure based contagion model and v) the mixed network based contagion model.

For all models we compare the predictive Root Mean Squared Errors (RMSE), for different n_1 lengths: $N = 1, ..., 4$ quarters and their binarised version.

Table 1 and 2 show the RMSE obtained by forecasting future CDS values with different models and different information about past CDS spreads. In particular the first table encompasses the results disaggregated by period while the second table shows the results disaggregated by country.

In order to have an easier displayable summary information about the results we also employ

[14]Or vice versa depending on whether we are calculating the in- or the out-strength

binary heat maps. In the first exercise we set a performance indicator equal to 1 (red color) when the RMSE of i) is higher than that of ii) and 0 otherwise (blue color). For the second case we set the performance indicator equal to 1 (red color) when the RMSE of the forecast obtained with the real network (iii) is higher than that of the predictions obtained using the common exposure (iv) and the ones obtained with the mix network (v), and 0 otherwise (blue color).

From Figure 9 note that, our proposed method is clearly superior during crisis times. From Figure 10 note that the common exposure and the mixed networks outperform again the real during crisis times[15]. Finally Figure 11 shows the same indicator variables disaggregated for each country and computed during the crisis period. From the figure it is clear that the the common exposure and the mixed networks outperform the results obtained with the real network for most of the countries.

In our view, this highlights the importance of common exposures. Indeed, while the information content in the two ways of defining exposures seems to be similar enough for the common and the mixed measures to perform on par, the results still point to the fact that the use of common exposures provide an added value in signaling crises. From an economic point of view, this clearly shows that common exposures indeed is a channel of contagion and should be accounted for when measuring systemic risk.

FIGURE 9 APPROXIMATELY HERE

FIGURE 10 APPROXIMATELY HERE

FIGURE 11 APPROXIMATELY HERE

5. Conclusions

Measuring portfolio similarity is a central task when modeling systemic risk and interconnectedness in financial systems, particularly for complementing measures based upon direct exposures. In this contribution we have shown that correlation network models that aim at capturing

[15]Results obtained with the out-strength are similar to the ones exposed here and for sake of brevity are not reported.

the multivariate network structure provide suitable means for representing the indirect dimension of systemic risk through common exposures. Moreover, we have provided an approach for combining direct exposures and correlations into one measure of systemic risk.

We have applied our proposed methods to the Bank of International Settlements consolidated banking statistics, with the aim of identifying central and important countries in the context of interconnectedness of the banking sector. This is particularly relevant in the case of banking sector distress and abrupt changes in liquidity and funding.

From an economical view point our empirical findings give two main results. Before the crisis, the total funding of most of the countries had increased via specific funders' investments and not by a generalized increase. After the crisis, we observe a decrease in total funding which does not correspond to a higher diversification but, rather, to a further concentration. Moreover, the evidence from the mixed network suggests that the financial crisis worked as a tipping point for most countries. Besides that, off-shore and flight to quality countries maintain the same risk profile throughout.

We have finally combined our proposed measures with CDS spreads, in order to assess whether and to what extent they are related to the build-up of imbalances prior to crisis events. The exercise clearly shows that common exposures are an important channel of contagion and should be accounted for when measuring systemic risk.

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Appendix

Figures 12 and 13 report the sensitivity analysis of the strength related to the combined network for different values of the parameter α. First of all it has to be notice that the results obtained with the α parameter calibrated to the data (red line) are similar to the one obtained with $\alpha = .5$, despite this fact, the results are not exactly equal because this parameter, calibrated to the data, is time dependent. Secondly, for most of the countries, the higher α, the more the importance of the real network, the higher the strength of the mixed network. This path is true for most of the countries but not for all. Exceptions are GB and US for instance, but also DE, BR and MX.

FIGURE 12 APPROXIMATELY HERE

FIGURE 13 APPROXIMATELY HERE

We also have reported, for each country and for three different sub-samples (1999–2007, 2007–2010 and 2010-2014), the correlations between of the strengths computed starting from the different types of networks.

In particular Figure 14 presents the correlation for the in-strength while Figure 15 reports the result for the out-strength. From both figures it becomes evident that, during the period 1999-2007 the correlations between each type of strength have the lowest values, and most of them, in particular the correlation between the real and the distance based strength takes negative values. During the crisis period, on the other hand, this measure becomes positive for most of the countries.

FIGURE 14 APPROXIMATELY HERE

FIGURE 15 APPROXIMATELY HERE

Tables and Figures

	ORIG. L.1	ORIG. L.2	ORIG. L.3	ORIG. L.4	REAL L.1	REAL L.2	REAL L.3	REAL L.4	DIST L.1	DIST L.2	DIST L.3	DIST L.4	MIX L.1	MIX L.2	MIX L.3	MIX L.4
Q4-14	395.22	395.34	381.22	353.31	393.46	393.57	379.29	351.11	391.22	391.26	376.67	347.87	386.65	386.76	371.79	342.25
Q3-14	119.62	132.57	141.95	138.62	118.31	131.21	140.64	137.25	116.55	129.41	138.85	135.36	112.36	125.65	135.44	131.86
Q2-14	48.66	32.93	15.23	20.80	51.25	35.13	16.16	19.90	54.44	37.86	17.26	18.31	57.83	40.02	17.21	15.26
Q1-14	999.31	83.50	65.23	36.86	1013.15	86.33	67.79	38.97	1031.67	89.93	71.11	41.62	1069.67	94.22	74.51	44.30
Q4-13	1947.06	1248.81	101.96	87.00	1972.90	1265.60	105.06	89.88	2007.17	1288.45	109.20	93.87	2078.19	1335.23	114.38	98.14
Q3-13	2841.16	2377.19	1604.15	68.87	2878.60	2408.79	1625.57	72.43	2928.82	2451.16	1655.42	76.64	3032.30	2538.74	1716.27	82.75
Q2-13	3728.56	3497.14	3111.70	2340.93	3778.26	3543.76	3153.56	2372.09	3843.09	3605.30	3208.44	2414.96	3979.74	3732.87	3322.96	2503.03
Q1-13	4625.54	4625.19	4624.93	4624.89	4688.34	4687.17	4686.85	4687.39	4766.80	4766.88	4767.38	4767.29	4936.25	4935.49	4934.11	4934.26
Q4-12	601.95	90.04	62.78	24.50	548.18	112.91	90.86	68.27	484.37	172.32	158.04	145.61	341.15	326.53	318.61	310.49
Q3-12	1275.45	750.92	111.55	85.78	1230.63	699.23	131.57	108.61	1175.27	637.56	186.06	169.91	1047.85	496.29	334.83	325.67
Q2-12	2153.03	1590.19	994.45	117.84	2119.94	1548.99	944.77	137.98	2077.14	1499.10	887.41	190.58	1979.32	1381.01	750.36	338.91
Q1-12	3070.85	2686.93	2112.80	1479.54	3049.76	2660.46	2077.91	1434.83	3020.40	2625.76	2035.76	1384.36	2955.85	2547.04	1935.81	1262.66
Q4-11	3993.93	3838.08	3581.51	3167.17	3984.26	3826.53	3566.55	3146.39	3969.91	3809.49	3545.78	3120.09	3938.52	3772.82	3499.51	3058.07
Q3-11	1386.88	1302.08	1180.26	941.16	1381.29	1295.40	1172.22	930.24	1371.99	1284.88	1159.48	913.80	1353.44	1263.17	1133.70	879.10
Q2-11	1223.33	1208.13	1175.16	1138.88	1220.51	1205.10	1171.71	1135.07	1215.44	1199.88	1166.05	1128.65	1206.36	1190.30	1155.28	1116.88
Q1-11	274.55	243.32	233.97	210.75	272.41	240.91	231.48	208.00	267.78	235.78	226.40	202.81	261.78	228.82	219.15	194.78
Q4-10	127.58	103.99	71.47	57.05	125.95	102.26	69.98	55.58	121.86	97.69	65.16	50.90	118.25	93.91	62.19	47.26
Q3-10	164.06	142.50	118.83	78.70	162.64	140.87	116.99	76.60	159.61	137.33	112.90	71.71	156.59	133.90	109.07	67.77
Q2-10	126.17	115.39	95.47	74.61	125.72	114.29	94.24	73.36	123.14	111.85	91.39	70.25	120.96	109.55	88.94	68.19
Q1-10	161.67	161.34	155.20	140.10	162.22	161.22	154.43	139.17	160.14	159.46	152.93	137.35	158.36	157.72	151.07	135.04
Q4-09	60.73	55.21	45.87	35.91	66.76	60.12	48.65	35.50	63.16	56.98	45.93	34.58	61.89	55.66	44.53	33.24
Q3-09	57.56	63.10	57.76	48.32	64.09	71.39	65.15	53.39	60.12	66.59	60.65	49.14	58.98	65.35	59.32	47.80
Q2-09	50.68	64.99	84.10	81.30	58.84	73.98	94.94	92.46	54.58	69.69	89.74	86.89	54.03	69.23	89.18	86.08
Q1-09	38.62	34.73	37.34	52.48	32.40	29.06	35.21	56.32	36.77	33.95	39.34	57.74	37.57	34.97	40.50	58.67
Q4-08	101.57	92.77	83.52	65.49	98.44	89.31	79.74	61.33	99.25	90.12	80.55	62.11	99.27	90.14	80.58	62.25
Q3-08	112.84	107.30	102.10	99.97	110.69	104.88	99.50	97.35	111.52	105.76	100.37	98.17	111.54	105.77	100.36	98.15
Q2-08	44.90	42.39	39.23	36.22	44.41	42.01	39.20	36.39	44.29	41.73	38.59	35.63	44.24	41.66	38.48	35.53
Q1-08	21.35	18.94	15.07	9.37	20.23	17.83	14.12	10.02	20.64	18.15	14.16	8.61	20.67	18.16	14.14	8.39
Q4-07	29.90	29.12	27.72	25.08	28.86	28.03	26.58	23.87	29.43	28.63	27.18	24.45	29.50	28.70	27.25	24.51
Q3-07	14.59	15.39	15.22	14.82	13.24	14.13	13.92	13.47	14.15	14.99	14.81	14.39	14.28	15.11	14.94	14.52

Table 1: Average RMSE by time. Each column identifies the RMSE obtained by forecasting the next period CDS spreds values using different information and prediction methods. In particular ORIG. identifies results obtained employing only past CDS values, REAL. encompasses the results obtained with past CDS values along with the direct/real network, DIST. encompasses the results obtained with past CDS values along with the funding composition similarity network, MIX. identifies the results obtained with past CDS values together with the mixed network. Moreover L.1 means that we use only 1 lag past CDS value, L.2 stands for 2 lags, L.3 stands for 3 lags and L.4 stands for 4 lags.

	ORIG. L.1	ORIG. L.2	ORIG. L.3	ORIG. L.4	REAL L.1	REAL L.2	REAL L.3	REAL L.4	DIST L.1	DIST L.2	DIST L.3	DIST L.4	MIX L.1	MIX L.2	MIX L.3	MIX L.4
AU	42.9305	42.7629	42.6390	41.9968	42.8948	42.7601	42.6842	42.1141	42.8591	42.8241	42.8839	42.4941	42.8480	42.8577	42.9742	42.6743
AT	64.0259	63.2740	62.4964	60.8915	63.4887	62.8175	62.1918	60.9212	63.2131	62.6343	62.1529	61.1332	63.2471	62.6473	62.1415	61.0805
BE	69.5083	66.3359	64.6486	62.9434	68.1205	65.0394	63.5330	62.1891	66.6812	63.7262	62.6330	62.0089	66.2223	63.2741	62.1523	61.6277
CA	37.0739	36.3676	35.3910	35.9149	37.1754	36.5049	35.5685	36.1800	37.2910	36.6731	35.8034	36.5394	37.2554	36.6258	35.7417	36.4550
FR	48.5149	47.0200	45.3005	43.4790	47.7337	46.2705	44.6396	43.0952	46.1405	44.8097	43.4355	42.4888	46.6857	45.3239	43.8618	42.6817
FI	23.9162	23.3979	22.7829	21.7610	23.1115	22.7249	22.3459	21.7774	23.4268	22.9833	22.4966	21.7251	23.4681	23.0141	22.5143	21.7107
DE	27.1799	26.5784	26.1057	27.0406	26.3987	25.9144	25.6298	26.9786	26.2814	25.7983	25.5342	27.0076	26.4470	25.9373	25.6315	27.0190
GR	5651.2869	5429.0597	5070.8177	4486.3685	5636.8740	5411.9424	5049.0760	4456.8002	5614.6455	5386.0053	5017.7723	4417.6312	5566.6204	5330.4741	4949.2603	4328.0458
HK	40.7331	39.0580	37.8243	37.2150	40.8161	39.2433	38.2462	38.0884	40.7937	39.2082	38.1563	37.8811	40.8168	39.2188	38.1259	37.7503
IN	134.8102	132.1020	128.9308	116.0738	143.7140	141.7780	139.6127	127.3542	136.6780	134.1340	131.1778	118.3607	135.8694	133.2431	130.1615	117.2788
IE	205.3611	185.0405	161.9288	133.4877	203.8054	183.6975	160.8255	132.6205	198.1608	178.8891	157.2432	130.2539	197.6805	178.5374	157.1068	130.3688
IT	117.9790	114.6540	112.0327	110.3549	115.1560	111.9206	109.7400	109.3591	113.6978	110.6323	108.7485	108.9671	113.1213	110.1502	108.4049	108.8241
JP	31.9071	31.3001	30.0731	31.0421	30.5711	30.2228	29.2652	30.7576	30.1445	29.8888	29.0306	30.7961	30.4639	30.1435	29.2099	30.8057
KR	100.5365	97.7259	92.5870	84.3289	100.7022	97.9365	92.8519	84.6876	101.7972	99.2497	94.3968	86.5669	101.7315	99.1754	94.3090	86.4078
NL	38.1987	37.9842	37.2946	35.5317	37.4515	37.3769	36.8721	35.4397	37.4940	37.3878	36.8556	35.3978	37.4938	37.3750	36.8214	35.3463
NO	14.4996	14.6793	14.9255	15.1505	14.3647	14.6085	14.9496	15.3344	14.3259	14.5785	14.9323	15.3343	14.3363	14.5853	14.9362	15.3376
PT	296.8011	262.0699	224.6042	185.4766	291.8550	256.8098	219.3120	180.8509	282.4133	246.8381	209.4746	172.8787	283.4749	247.9918	210.6263	173.7602
SG	27.5372	27.0776	26.4446	25.9469	26.9592	26.6173	26.1608	25.9719	26.8833	26.5762	26.1739	26.0669	27.0156	26.6628	26.1873	25.9644
ES	91.3704	86.1970	79.2023	70.5918	89.4968	84.4165	77.5480	69.2265	87.3454	82.4050	75.7067	67.7103	83.4973	78.8451	72.5470	65.3582
SE	40.2672	39.1433	38.6729	37.8958	40.3250	39.2120	38.7692	38.0387	40.4307	39.3461	38.9676	38.3488	40.5444	39.4866	39.1696	38.6523
CH	48.2001	47.1586	44.5664	36.8294	48.3101	47.2917	44.7246	37.0141	48.8266	47.9189	45.4814	37.9223	49.2247	48.3911	46.0570	38.6590
GB	37.1794	36.0749	36.3548	36.0444	37.0929	36.0135	36.3617	36.1566	36.9810	35.9956	36.5302	36.5691	36.9817	35.9925	36.5082	36.5012
US	18.0045	17.7665	17.9750	17.2540	20.6013	20.9392	21.8764	21.9223	18.0968	17.9333	18.2504	17.6281	18.0162	17.7700	17.9719	17.2565

Table 2: Average RMSE by country. Each column identifies the RMSE obtained by forecasting the next period CDS spreads values using different information and prediction methods. In particular ORIG. identifies results obtained employing only past CDS values, REAL. encompasses the results obtained with past CDS values along with the direct/real network, DIST. encompasses the results obtained with past CDS values along with the funding composition similarity network, MIX. identifies the results obtained with past CDS values together with the mixed network. Moreover L.1 means that we use only 1 lag past CDS value, L.2 stands for 2 lags, L.3 stands for 3 lags and L.4 stands for 4 lags

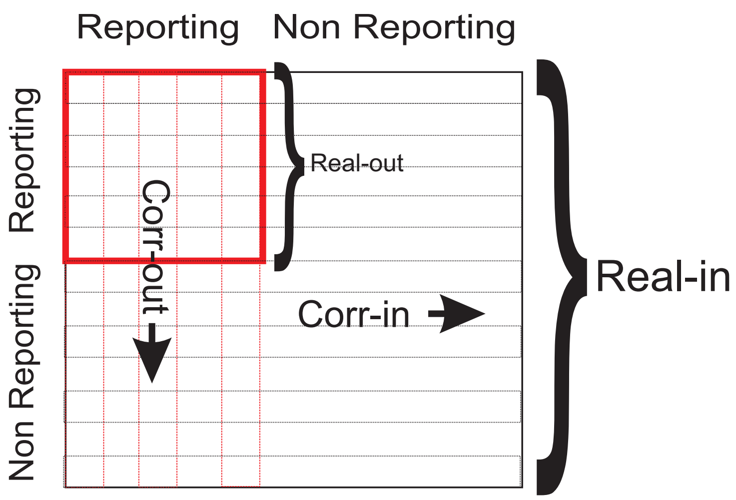


Figure 1: Exemplification of networks construction. For the in-real network we use the bilateral data of the 33 countries reported in the Data Section (both reporting and non reporting); for the funding composition similarity network we compute the distance between each pair of rows of the in-real network (emphasized with dashed black rectangles). For the out-real network we use bilateral data of the 12 countries that report along the periods we consider (red square); for the portfolio composition similarity network we compute the distance between each pair of columns involving the reporting countries (emphasized with dashed red rectangles).

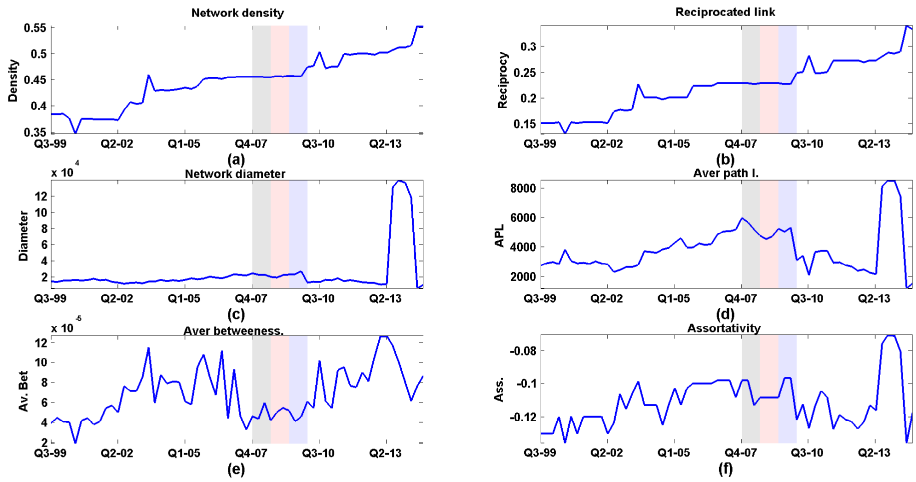


Figure 2: Preliminary network statistics along time. In particular panel (a) shows the network density, the number of the links over the maximum number of links. Panel (b) shows the fraction of reciprocated links. Panel (c) reports the network diameter, i.e. the largest of the shortest path. Panel (d) shows the average path length, i.e. the average of the shortest paths between any pair of countries. Panel (e) shows the average betweenness coefficient that is the number of shortest paths from all vertices to all others that pass through a particular node. Panel (f) shows the assortativity coefficient, that is the correlation between nodes strength and average nearest neighbour strength.

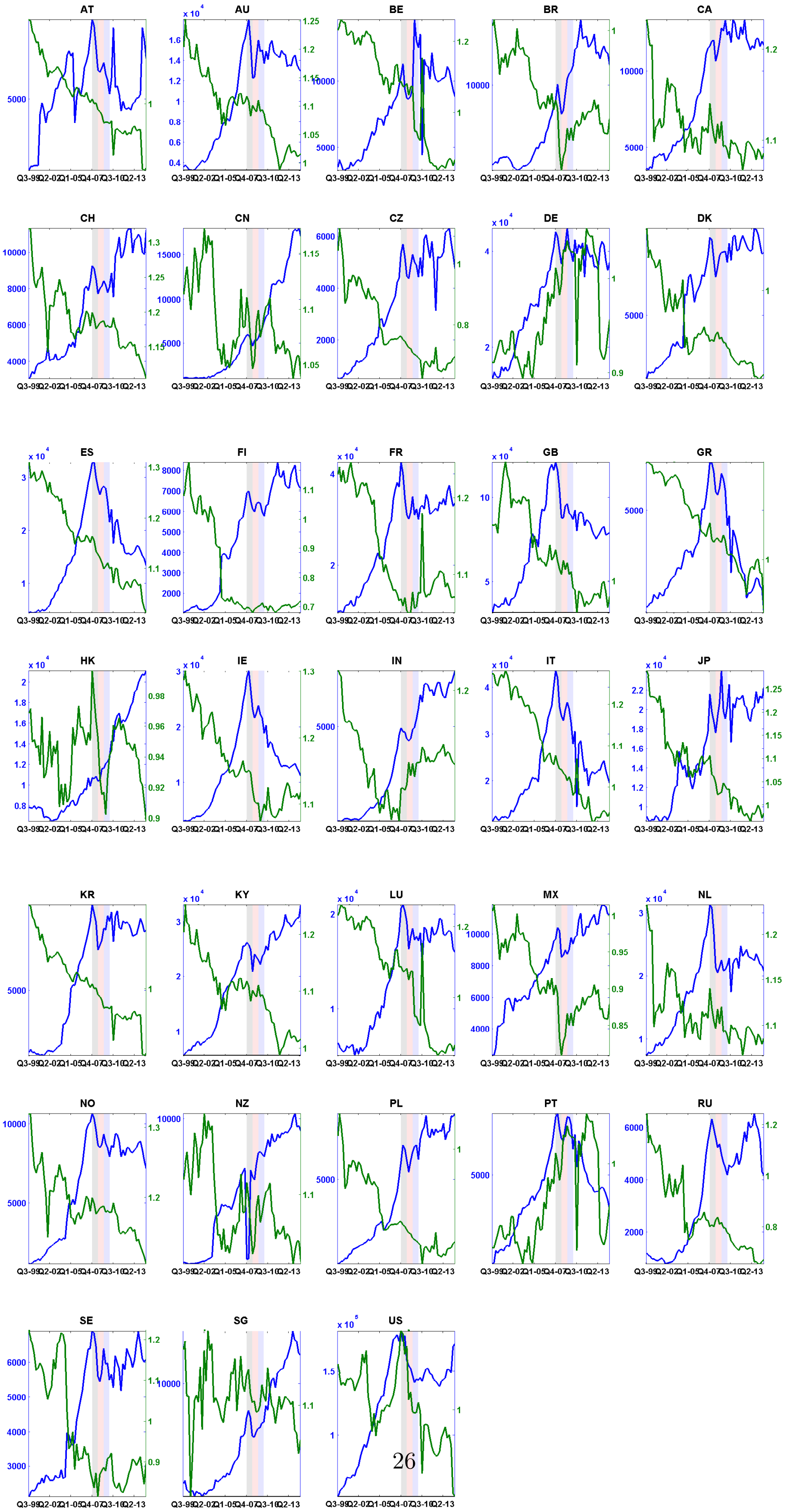


Figure 3: In-strength of each country for the direct (blue) and for the funding composition similarity (green) networks, the title of each panel represents the country for which the statistics are computed. The three vertical bars emphasize the pre-crisis and crisis periods (2007-08; 2008-09 and 2009-10).

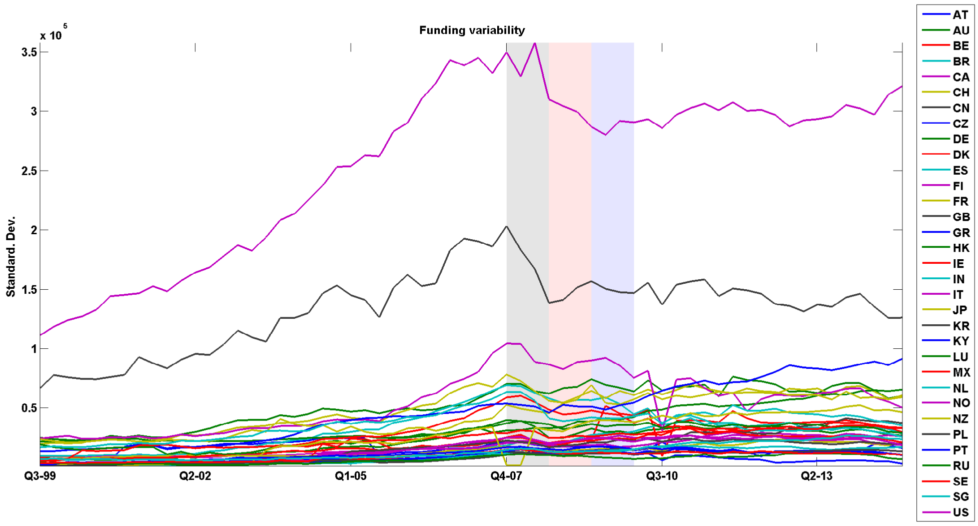


Figure 4: Change over time of the standard deviation of the funding composition of all countries. Each line is associated with a country and the legend emphasizes to which color a country correspond to.

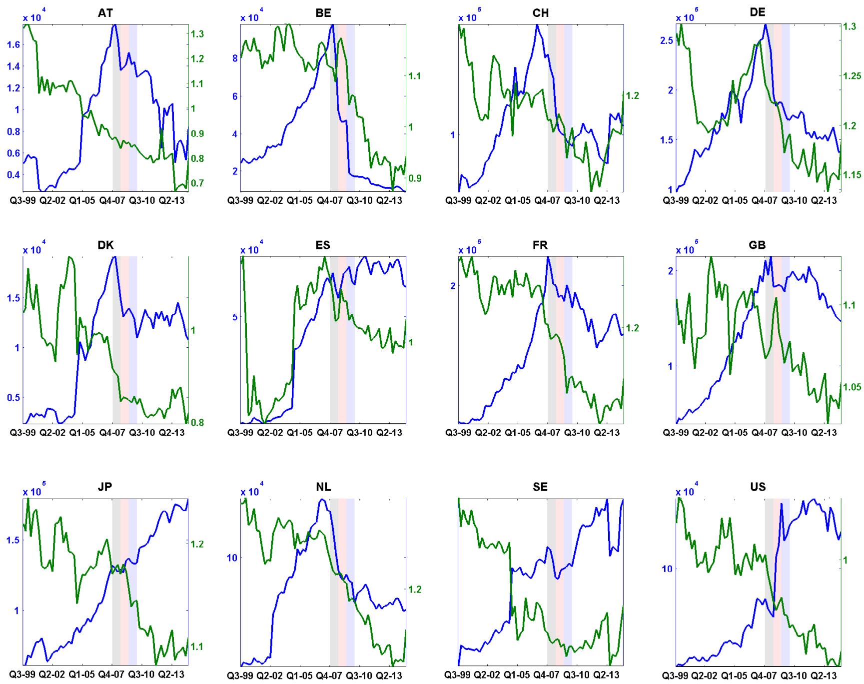
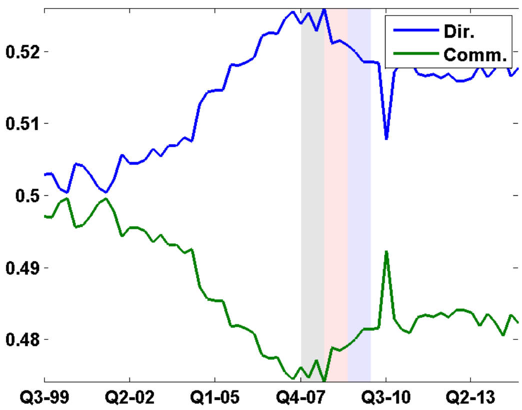
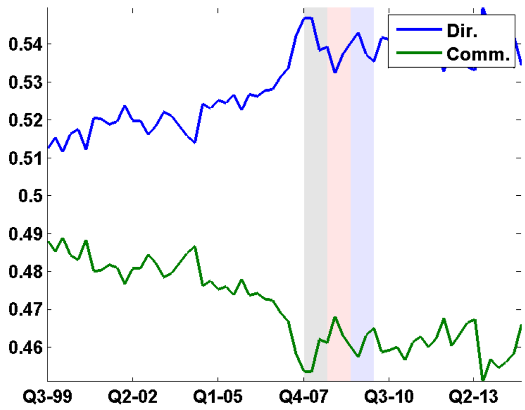


Figure 5: Out-strength of each country for the direct (blue) and for the portfolio similarity (green) networks, the title of each panel represents the country for which the statistics are computed. The three vertical bars emphasize the pre-crisis and crisis periods (2007–08; 2008–09 and 2009–10).



(a) in-flow weights



(b) out-flow weights

Figure 6: Weights associated to the direct (green) and to the funding composition similarity (blue) component of the mixed network for the in-flow network (a). Weights associated to the direct (green) and to the portfolio composition similarity (blue) component of the mixed network for the out-flow network (b).

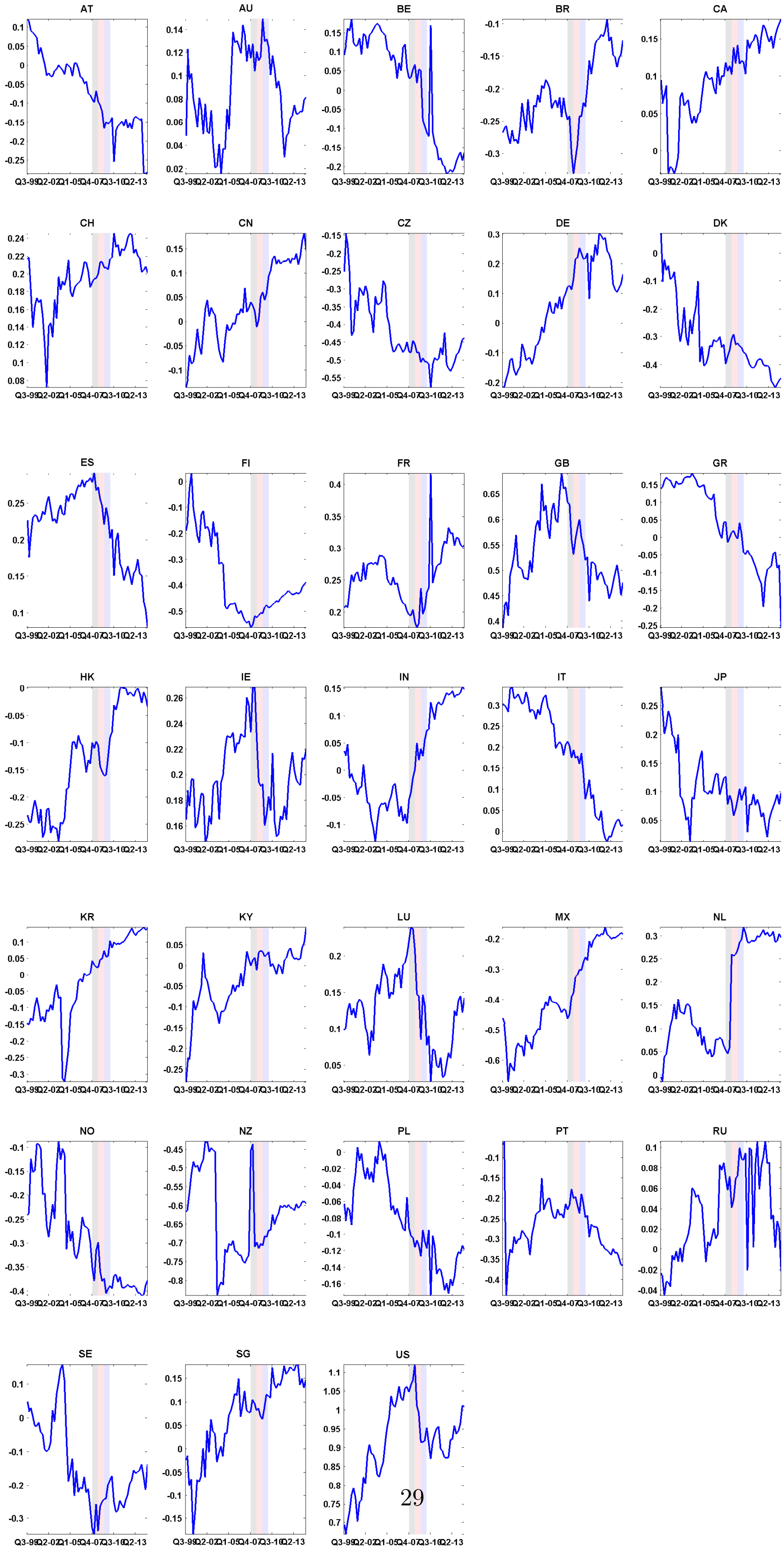


Figure 7: Strength of the combined in-flow adjacency matrix, the title of each panel represents the country for which the statistics are computed. The three vertical bars emphasize the pre-crisis and crisis periods (2007–08; 2008–09 and 2009–10).

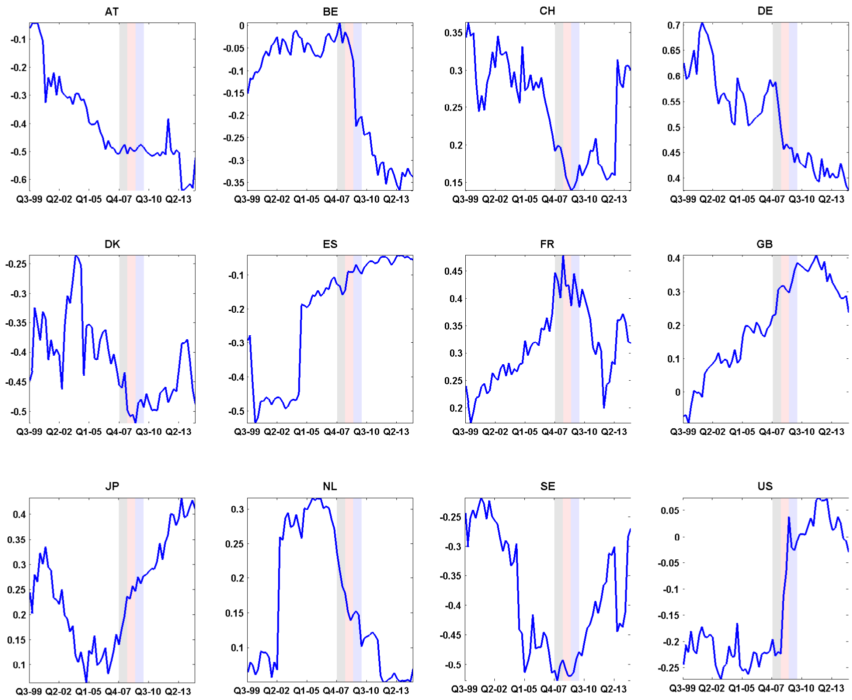


Figure 8: Strength of the combined out-flow adjacency matrix, the title of each panel represents the country for which the statistics are computed. The three vertical bars emphasize the pre-crisis crisis periods (2007–08; 2008–09 and 2009–10).

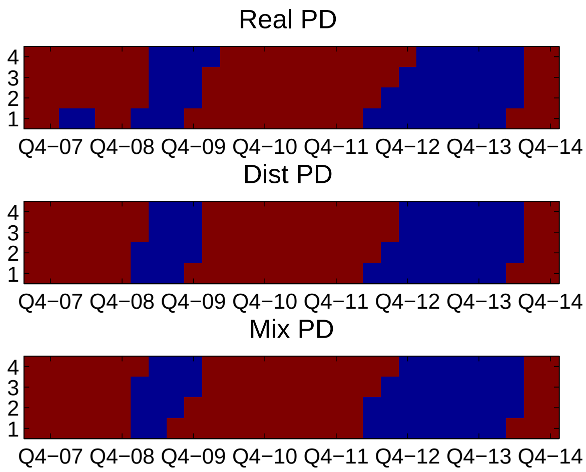


Figure 9: Predictive performance, binary representation of RMSE differences: the blue color emphasizs when the RMSE of the model based only on the average the past spread values is higher then the one obtained with a model based the modified network contagion effect. In particular in the upper panel we employ the real network, the central panel encompass the results obtained with the common exposure network and the bottom panel the mixed network

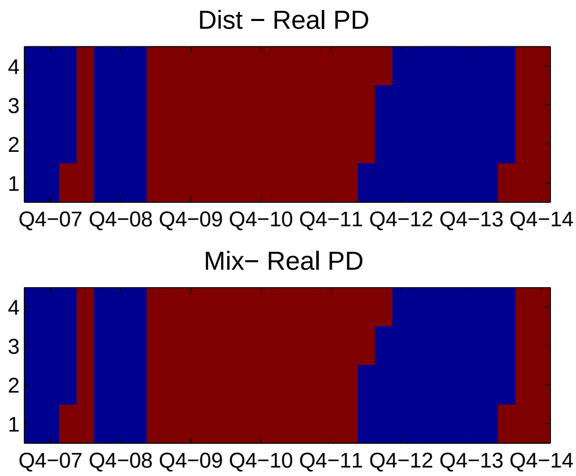


Figure 10: Predictive performance, binary representation of RMSE differences: the blue color emphasizes when the RMSE of the model based on the real network contagion effect is higher then the ones obtained employing the common exposure contagion effect (central panel) and the ones obtained employing the mixed network contagion effect.

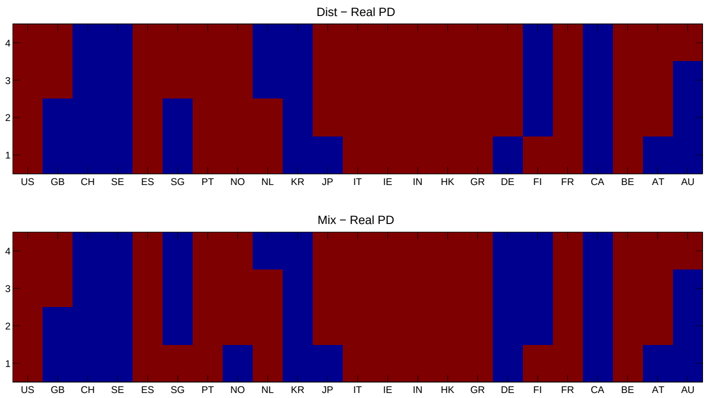


Figure 11: Predictive performance by country, binary representation of RMSE differences: the blue color emphasizes when the RMSE of the model based on the real network contagion effect is higher then the ones obtained employing the common exposure contagion effect (central panel) and the ones obtained employing the mixed network contagion effect.

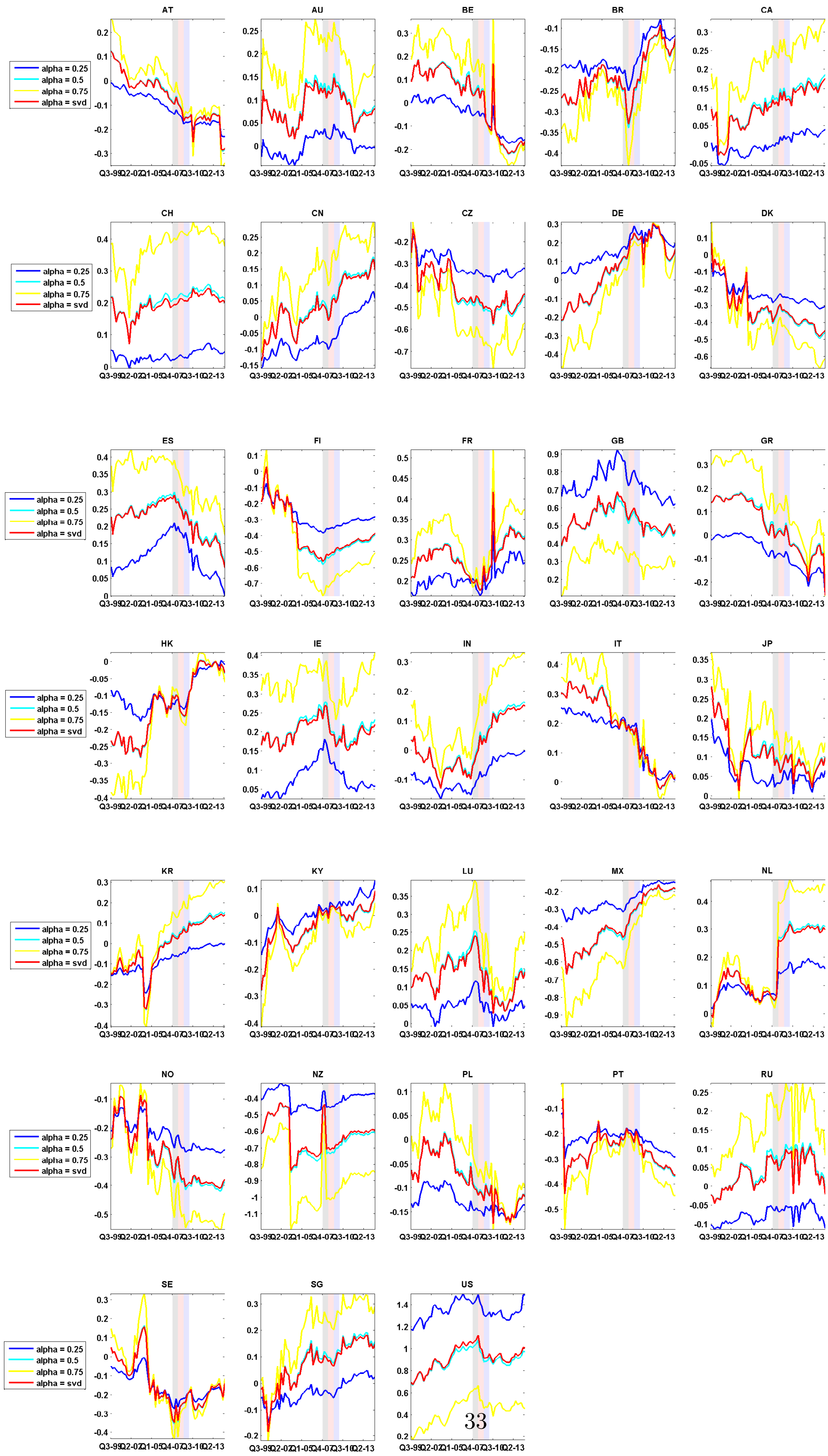


Figure 12: Sensitivity analysis of the change in the strength of the combined in-flow adjacency matrix for different values of alpha. The title of each panel represents the country for which the statistics are computed. The three vertical bars emphasize the pre-crisis and crisis periods (2007–08; 2008–09 and 2009–10).

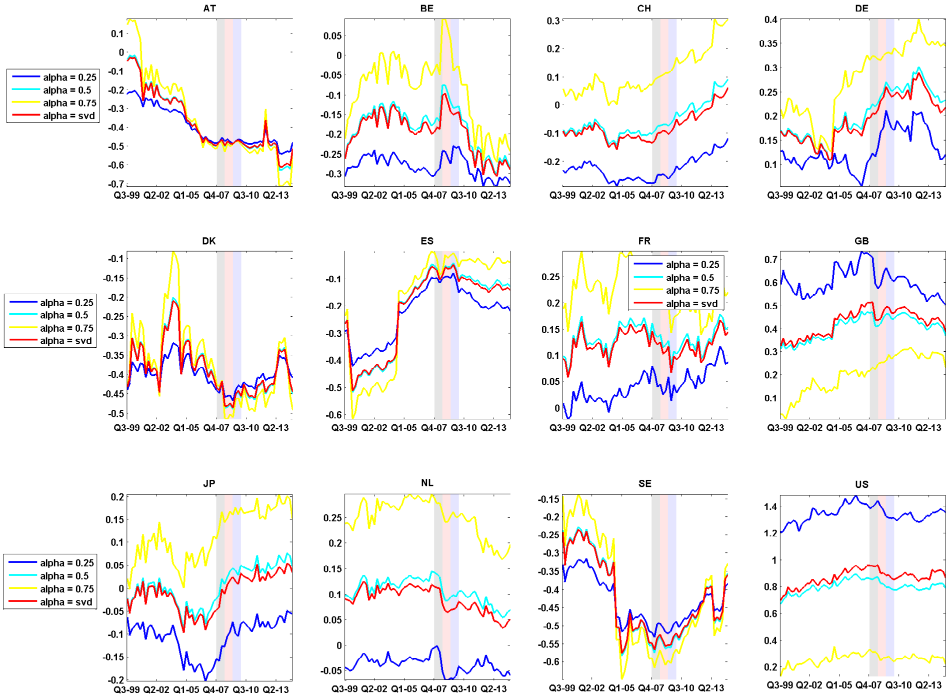


Figure 13: Sensitivity analysis of the change in the strength of the combined out-flow adjacency matrix for different values of alpha. The title of each panel represents the country for which the statistics are computed. The three vertical bars emphasize the pre-crisis and crisis periods (2007–08; 2008–09 and 2009–10).

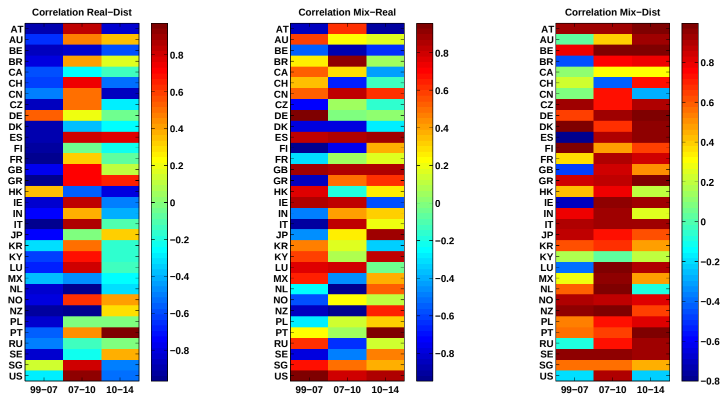


Figure 14: Correlation between in-strength direct network (a), strength of the funding composition network (b) and of the strength computed for the in-mix network (c). For each country and for three different periods (1999–07; 2007–10 and 2010–14).

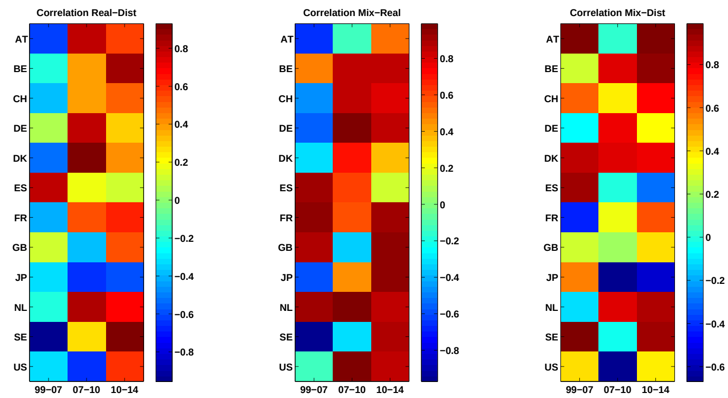


Figure 15: Correlation between out-strength direct network (a), strength of the portfolio composition network (b) and of the strength computed for the out-mix network (c). For each country and for three different periods (1999–07; 2007–10 and 2010–14).