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Abstract

Financial contagion among countries can arise from different channels, the most important of which are financial markets and bank lending. The paper aims to build an econometric network approach to understand the extent to which contagion spillovers (from one country to another) arise from financial markets, from bank lending, or from both. To achieve this aim we consider a model specification strategy which combines Vector Autoregressive models with network models. The paper contributes to the contagion literature with a model that can consider bank exposures and financial market prices, jointly and not only separately. From an empirical viewpoint, our results show that both bilateral exposures and market prices act as contagion channels in the transmission of shocks arising from a country to international financial markets. While the impact of the former is more stable in time, the latter is more volatile and reacts to a wider variety of events.

Keywords:
Financial Contagion, Network Models, VAR, Bank Lending, Financial Markets.

1. Introduction

Financial systems of different countries are interdependent. With globalization, the interactions between countries, through financial institutions and markets, has become more complex and it has increased the exposure of countries to contagion, as clearly demonstrated by the the global financial crisis, and the following European sovereign debt crisis. The aftermath of those crisis has stimulated a vast research activity, which can be classified in two main streams. The first stream focuses on the "physical" interconnectedness that emerges from bank lending transactions, collected from balance sheet information, and modelled with financial network models (see Avdjiev et al., 2019; Bluhm and Krahnen, 2014; Cont et al., 2013; Georg, 2013; Halaj and Kok, 2015; Minoiu and Reyes, 2013). The second explores the "statistical" interdependence that emerge from the co-movement of financial market prices, using vector autoregressive (VAR) models (see Acharya et al., 2017; Adrian and Brunnermeier, 2016; Ahelegbey et al., 2016a; Barigozzi and Hallin, 2017; Basu et al., 2016; Billio et al., 2012; Diebold and Yilmaz, 2014; Hautsch et al., 2015).

Financial network models are able to represent and summarise the bilateral relationships between institutions, such as lending transactions, by means of graphical representations and centrality measures. This allows to understand which institutions are more connected to

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others, and which are most central. While financial network models can reveal how contagion is transmitted within a financial system, they cannot assess how external shocks impact the system. Therefore, concentrating only on bank exposures while ignoring the impact of common "systematic" factors can lead to inaccurate assessment of the system's vulnerability.

On the other hand, under the assumption that all relevant information is incorporated in market prices, a VAR model is able to disentangle the "systematic" risk, due to common market factors, from the "idiosyncratic" one, resulting from direct interconnections between institutions. Nevertheless, the global financial crisis has revealed that many institutions tend to withhold vital information from the public presenting "window dressed" reports to reassure market players (such as rating agencies, investors, and clients). Therefore, estimating financial contagion using only market-based prices may yield results that are influenced more by speculative behaviors and the inability of the public to process institutional signals, rather than being influenced by the effect of firm-level information on risk exposures. In addition, it is known that financial prices that signal the performance and standing of institutions reflect firm-level information as well market and speculative behaviour (Roll, 1988).

To summarise, the use of bilateral exposures allows to describe only one side of inter-country relationships, while the market-based co-movements tell another side of the story. Indeed Langfield and Soramäki (2016) argued that financial systems are characterized by a multiplicity of different types of links due to the complex types of transactions that may arise. This implies that several networks should be constructed from different financial perspectives, and that no single network is always superior to others (Roukny et al., 2013).

In this work, we aim to understand contagion between financial systems, and explore country level interdependence from a dual point of view, that of bilateral lending exposures and that of market price co-movements. To achieve our aim we propose a network based VAR model. The model combines the market-based linkages estimated via VAR models, estimated using country stock market indexes (obtained from the Bloomberg database), with the bilateral linkages estimated from the direct financial flows between countries banking systems (obtained from the Bank for International Settlements consolidated banking statistics).

From a methodological viewpoint, the approach discussed in this paper contributes to the two previously mentioned streams of research, and considering bilateral exposures and financial prices in a complementary fashion. From an empirical viewpoint, the paper shows that both bilateral exposures and market prices act as contagion channels in the transmission of shocks arising from one country's system to another. The impact of the bilateral exposure is more stable in time, and acts as an amplifier during financial crisis.

The paper is organized as follows: Section 2 presents the econometric methodology; Section 3 describes the data; Section 4 reports the empirical results; and Section 5 contains concluding remarks.

2. Econometric Methodology

We present the network-based VAR model for analyzing financial interconnectedness using equity market indexes and bank lending data, aggregated at the country level.

2.1. Network VAR Model Formulation

Let Y_t denote an n-dimensional vector that captures country market performances, by means of the equity market index returns of n countries at time period t, and L_t denote an n-dimensional vector that captures country lending performances, by means of the total bank lending flows of n countries at time period t. We assume without loss of generality that the realization of (Y_t, L_t) follow a VAR(p) process described by

$$Y_t = \sum_{s=1}^{p} A(s)Y_{t-s} + \sum_{s=1}^{p} B(s)L_{t-s} + U_t \tag{1}$$

$$L_t = \sum_{s=1}^{p} C(s)Y_{t-s} + \sum_{s=1}^{p} D(s)L_{t-s} + V_t \tag{2}$$

where $A(s)$, $B(s)$, ($C(s)$ and $D(s)$ are coefficient matrices that measure the effect of Y_{t-s} and L_{t-s} on Y_t and L_t, respectively, and U_t and V_t are n-dimensional error terms independent of Y_{t-s} and L_{t-s}, for all lags $s = 1, \ldots, p$. Following the financial network literature, we can employ $A(s)$, $B(s)$, ($C(s)$ and $D(s)$) to build adjacency matrices that can define network structures that can describe contagion mechanisms. More precisely, denote with G_A and G_B the weighted adjacency matrices of the equity-to-equity ($Y_{t-s} \to Y_t$) and lending-to-equity ($L_{t-s} \to Y_t$) relations. They can be calculated as follows:

$$G_A(i,j) = \begin{cases} \sum_{s=1}^{p} A_{ij}(s), & \text{if} Y_j \to Y_i \\ 0, & \text{otherwise} \end{cases}, \quad G_B(i,k) = \begin{cases} \sum_{s=1}^{p} B_{ik}(s), & \text{if} L_k \to Y_i \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $A_{ij}(s)$ measures the effect of $Y_{j,t-s}$ on $Y_{i,t}$ and $B_{ik}(s)$ is the effect of $L_{k,t-s}$ on $Y_{i,t}$. Following a similar reasoning, we denote with G_C and G_D the weighted adjacency matrices of the equity-to-lending ($Y_{t-s} \to L_t$) and lending-to-lending ($L_{t-s} \to L_t$) relations. That is:

$$G_C(i,j) = \begin{cases} \sum_{s=1}^{p} C_{ij}(s), & \text{if} L_j \to L_i \\ 0, & \text{otherwise} \end{cases}, \quad G_D(i,k) = \begin{cases} \sum_{s=1}^{p} D_{ik}(s), & \text{if} Y_k \to L_i \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $C_{ij}(s)$ measures the effect of $L_{j,t-s}$ on $L_{i,t}$ and $D_{ik}(s)$ is the effect of $Y_{k,t-s}$ on $L_{i,t}$.

We are assuming that the links in G_A, G_B, G_C and G_D are all directed, indicating temporal relationships, whose weights are the sum of the corresponding VAR lag coefficients.

2.1.1. VAR Network Estimation

While the literature on financial networks is split between "deterministic" approaches to compute adjacency matrices, based on lending flows; and "stochastic" approaches, based on the correlations between market prices, we propose to unify the estimation of the different adjacency matrices under the same VAR modelling framework. The estimation of the four-layered networks can be viewed as a VAR model selection problem. Commonly discussed techniques in the literature to solve this problem include Granger-causality (Ding et al., 2006; Granger, 1969), Bayesian graphical VAR (Ahelegbey et al., 2016a,b), and shrinkage-based methods (George et al., 2008; Tibshirani, 1996; Zou and Feng, 2009). Here we consider the conditional Granger-causality of (Ding et al., 2006) which builds on the bivariate Granger-causality of Granger (1969). We apply the multivariate least squares estimator for the VAR coefficient matrices and check if the following hypothesis holds true:

$$H_0(\theta): \ \theta_{ij}(1) = \ldots = \theta_{ij}(p) = 0 \quad \Longrightarrow \quad G_\theta(i,j) = 0$$

$$H_1(\theta): \ \forall s = 1, \ldots, p, \ \exists \ \theta_{ij}(s) \neq 0 \quad \Longrightarrow \quad G_\theta(i,j) = \sum_{s=1}^{p} \theta_{ij}(s)$$

where $\theta = \{A, B, C, D\}$. The hypothesis can be tested with an F-test.

2.2. Network Centrality Estimation

Once the four adjacency matrices are calculated, it is important, especially for interpretational purposes, to "condense" the information contained in the network representation into summary centrality measures, that indicate, in our context, the importance of each country in the each of the four contagion mechanisms: equity-to-equity, lending-to-equity, equity-to-lending and lending-to-lending.

Let G be an n-node weighted network graph where $G(ij)$ measures the presence or absence of a link from node-j to node-i, with a weight value. The in-degree of node-i, denoted by $\overleftarrow{D}_i$, and the out-degree of node-j, by $\overrightarrow{D}_j$, can be defined by

$$\overleftarrow{D}_i = \sum_j \mathbf{1}(|G(ij)| > 0), \qquad \overrightarrow{D}_j = \sum_i \mathbf{1}(|G(ij)| > 0) \tag{5}$$

where $\mathbf{1}(|G(ij)| > 0)$ is the indicator function, i.e., unity if the absolute value $|G(ij)| > 0$ and zero otherwise. Thus, $\overleftarrow{D}_i$ counts the number of links directed towards node-i, while $\overrightarrow{D}_j$ is the number of links going out of node-j.

We can also calculate centrality measures that take into account the importance of neighborhood of a node in a network graph. For example, the hub and authority centrality assign a score to nodes in the network in a way that is proportional to the importance of its neighbours. For a given weighted network graph, this involves solving the following problem

$$(G'G)\ h_v = \lambda_h h_v, \qquad (GG')\ a_v = \lambda_a a_v, \tag{6}$$

where h_v and a_v are the hub score and authority score eigenvectors, corresponding to λ_h and λ_a, the largest eigenvalues of $G'G$ and GG' respectively.

A limitation of the previous two centrality measures is the inability to distinguish the sign associated with the centrality of a node. For instance, a node may be highly connected to many others but with negative weights. Though such a node may be central in terms of out-degree and hub centrality, it may not pose any threat to the rest of nodes in the network. The negative weight may indicate flight to quality, in the case of financial prices; or portfolio diversification, in the case of bank lending. Thus, drawing conclusions on the centrality of a node without taking into consideration the signs associated with the weights can lead to drawing wrong conclusions about the importance of a node, especially in the spread of risk.

Thus, we propose the use of a weighted version of the in- and out-degree network measure, which we refer to as in- and out-exposure, calculated as follows:

$$\overleftarrow{E}_i = \sum_{i \neq j = 1}^{n} G(i, j), \qquad \overrightarrow{E}_i = \sum_{i \neq j = 1}^{n} G(j, i) \tag{7}$$

where $\overleftarrow{E}_i$ and $\overrightarrow{E}_i$ are the weighted in- and out-exposures of node i obtained by the row and column sums of G respectively. Note that the exposure metric defined here is different from the strength metric, sometimes used in the financial networks literature, which considers only the absolute values of the weights. Our proposed exposure metrics imposes no restrictions, and uses the weights with their associated signs.

3. Data Description

The data used in this study is obtained, on the bank lending side, from the quarterly inter country banks' foreign claims of national banking systems obtained from the Consolidated Banking Statistics (CBS), maintained by the Bank for International Settlements (BIS); and, on the financial market side, by daily national equity market index returns obtained from the Bloomberg database. We consider the same ten countries considered by Avdjiev et al. (2019): France-FR, Germany-GE, Greece-GR, Ireland-IR, Italy-IT, Japan-JP, Portugal-PT, Spain-SP, United Kingdom-UK, and the United States-US. With the exception of Greece, Ireland and Portugal (GIP), the rest are members of the group of the largest industrially advanced countries, whose central banks co-operate to supervise international finance. We decided to include the GIP countries because they have played significant roles, especially during the European sovereign debt crisis.

The CBS database records the worldwide consolidated claims of internationally active banks, headquartered in countries whose central banks report to the BIS, to other borrowing countries. The data includes the claims of banks' foreign affiliates, but exclude intra group positions, in accordance with the consolidation approach followed by banking supervisors. Foreign claims are defined as the sum of cross-border claims and local claims, booked by banks' affiliates located in the borrowing country.

The national equity market indexes captures the aggregate performance of the corresponding stock markets, and are considered proxy that reflect investors' expectations on the economic situation of the country. For the ten considered countries we consider the equity indexes shown in Table 2.

We first consider a summary description of the bank lending dataset. Figure 1 reports the evolution of bank lending and borrowing, overall and across the considered countries, based on the considered CBS database. Figure 1 shows an initial steady rise in aggregate interbank lending, with a peak in the first quarter of 2008, from which it goes downhill after the financial crisis, with a lower limit in 2010 Q3, and an upper limit in 2010 Q4, following public interventions. The following period is characterised by a continuous drop in aggregate interbank lending, with a recovery in more recent times.

Comparing the different countries, Figure 1 shows that between 2006 –and 2008 France and the UK dominate the lending side of the interbank market while the US, the UK and Germany dominate the borrowing side. The US becomes a strong lender from 2009 and Germany from 2014. From 2009, France replaces Germany as a strong borrower. Japan maintains a relative stable position, with a slight increase over time. The other countries have lending flows of lower magnitudes.

Overall, while the total amounts of lending and borrowing match, as expected by the nature of the data, their relative distribution changes, with lending shares that appear more variable than borrowing shares. For this reason, and also for interpretability, we will consider the amount of lending and not of borrowing as a performance measure of a country.

For a more complete understanding of the flows, it is worth considering the dynamic of net flows, defined as the difference between the amount lent and borrowed by each country. The bottom plot Figure 1, shows that the net positions decrease substantially from the aftermath of the financial crisis onwards. Before and during the financial crisis, France and the UK maintain a positive balance, while Germany and the US have a negative one. The situation of the US become positive after 2009 and that of Germany after 2014. Conversely, the balance of the UK becomes negative after 2014. Japan maintains a balanced position. Other European

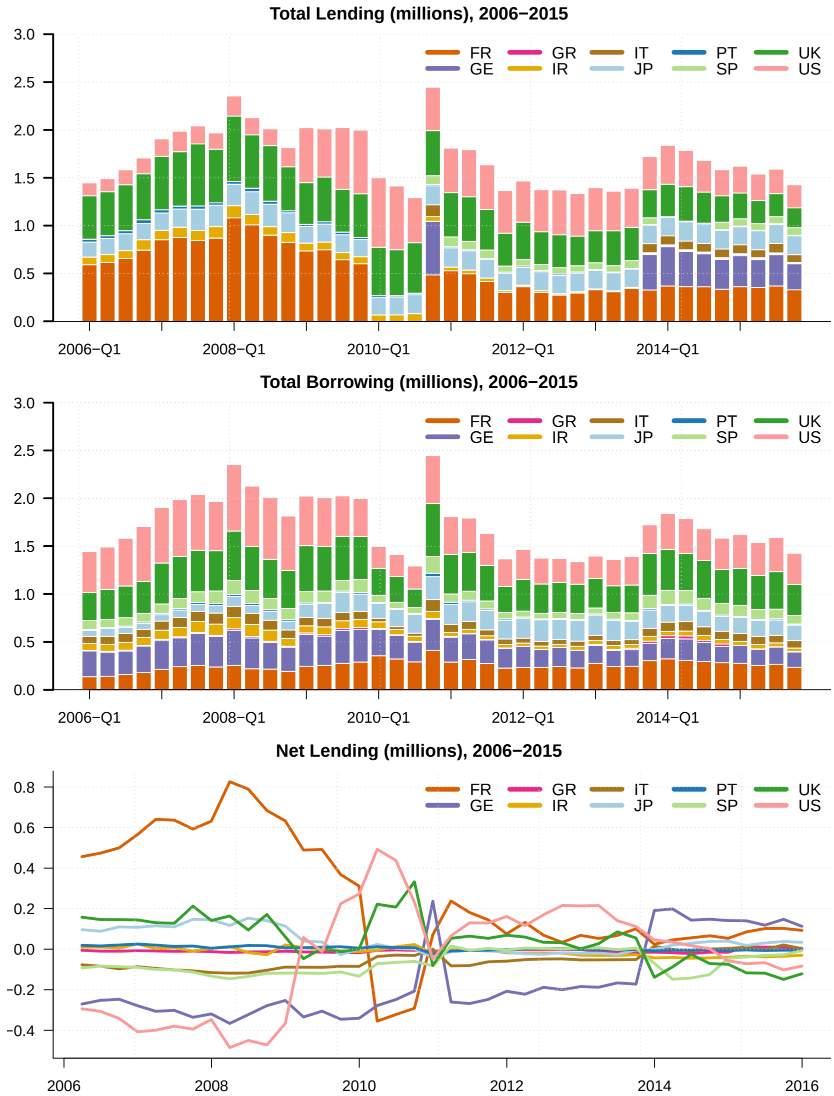


Figure 1: Financial flows between country banking systems in terms of Lending, Borrowing and Net-Lending.

countries, and particularly Spain, Italy and Ireland, show important deficit positions.

All previous findings can be reinforced from a complementary perspective, reported in Table 1. The table shows the yearly top three lenders, borrowers and net-lending countries, with their respective relative shares.

We now consider a summary description of the daily national market index returns. Figure 2 reports the log prices and the daily index returns (calculated as variations in the log prices), for the ten considered countries. Because of differences in the price values, plotting the original log prices would make some of the indexes appear flat, without significant dynamics compared to the others. To avoid this, we standardize each series to a zero mean and unit variance, and add the absolute minimum value of each series. This keeps the price representation positive, with the different series having the same scale of measurement.

Figure 2 shows a convergent decline in index prices for all countries, during the 2008–2009 crisis period. After 2009, they show a divergent behaviour between countries. The UK, US,

Years	Top Lenders		Top Borrowers		Top Surplus		Top Deficit	
	Country	Share	Country	Share	Country	Share	Country	Share
2006	FR	41.91	US	31.21	FR	32.04	US	-21.66
	UK	30.03	UK	20.5	UK	9.53	GE	-16.83
	JP	10.77	GE	16.83	JP	6.47	SP	-5.65
2007	FR	43.61	US	28.8	FR	31.64	US	-19.23
	UK	29.56	UK	21.81	UK	7.75	GE	-15.98
	JP	10.31	GE	15.98	JP	6.55	SP	-5.65
2008	FR	45.91	US	30.58	FR	35.28	US	-21.34
	UK	27.44	UK	21.54	JP	6.31	GE	-14.68
	JP	10.83	GE	14.68	UK	5.9	SP	-6.22
2009	FR	33.87	UK	23.1	FR	20.6	GE	-16.46
	US	29.64	US	22.91	US	6.73	SP	-5.99
	UK	22.41	GE	16.46	JP	0.6	IT	-4.32
2010	US	34.81	FR	20.77	US	16.73	FR	-13.49
	UK	29.79	UK	19.56	UK	10.23	GE	-7.46
	JP	11.49	US	18.08	IR	0.13	SP	-4.18
2011	US	28.29	UK	22.06	FR	9.67	GE	-14.88
	FR	26.43	US	20.93	US	7.36	IT	-4.3
	UK	25.7	FR	16.76	UK	3.64	JP	-0.62
2012	US	32.18	UK	22.64	US	12.89	GE	-14.3
	UK	24.92	US	19.29	FR	5.45	IT	-3.61
	FR	22.29	FR	16.84	UK	2.28	IR	-1.56
2013	US	27.61	UK	22.28	US	8.75	GE	-5.71
	UK	22.79	US	18.86	FR	4.18	IT	-2.41
	FR	22.36	FR	18.18	UK	0.51	IR	-2.26
2014	GE	20.85	UK	22.63	GE	9.15	SP	-6.68
	FR	20.73	US	20.2	FR	3.22	UK	-3.75
	US	20.15	FR	17.51	JP	1.84	IR	-2.44
2015	FR	22.91	UK	23.67	GE	8.4	UK	-8.18
	GE	19.7	US	22.29	FR	6.18	US	-5.23
	US	17.06	FR	16.73	JP	1.95	IR	-2.22

Table 1: Yearly Top Lenders, Borrowers and Net-Lending via financial flows between banking systems.

Germany and Japan show a swift recovery in prices, especially after 2012, which raise above the initial levels. France, Spain and, later, Ireland recover their initial levels. Italy, Portugal and Greece, on the other hand, show none or little recovery.

The returns plots, in the bottom part of the Figure, confirm that the volatility of all countries peaked during the 2008 crisis, and also during the European crisis, particularly for the European countries. Table 2 reports more numeric details on the market indexes returns, over the whole period. From the table we notice, in particular, the negative skewness for all indexes, indicating a distribution of returns asymmetric to the right; and a high value of the kurtosis for Japan and Ireland.

We can further explore the changes in daily equity returns by examining an "overall" measure of financial turbulence that summarizes all series. We follow Kritzman and Li (2010) and study the historical turbulence index (TI) calculated from the daily changes in equity returns of the 10 reporting countries over the sample period, as shown in Figure 3. The index is computed via the Mahalanobis distance measure given by:

$$TI_t = \frac{1}{n}(Y_t - \mu_e)'\Sigma^{-1}(Y_t - \mu_e) \quad (8)$$

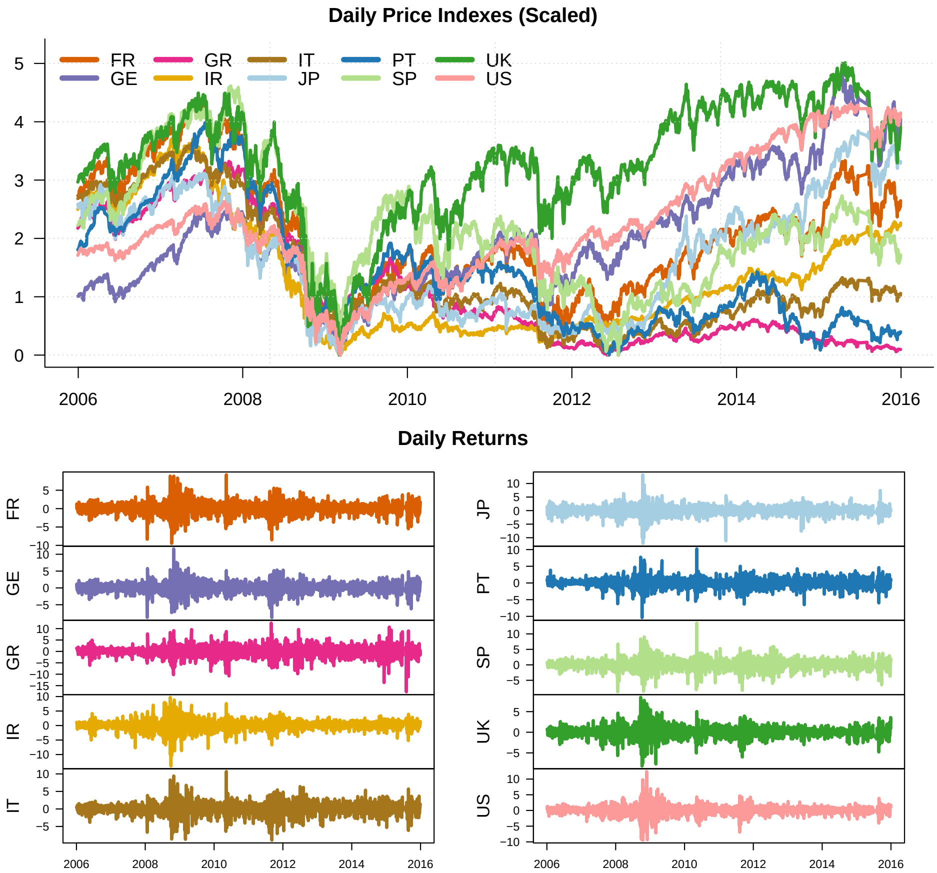


Figure 2: Time series of scaled daily log prices and their corresponding variations for the national equity indexes of France-FR, Germany-GE, Greece-GR, Ireland-IR, Italy-IT, Japan-JP, Portugal-PT, Spain-SP, United Kingdom-UK, and the United States-US.

Country	Index	Mean	Sdev	Min	Max	Skew.	Kurt.
France	CAC 40	-0.001	1.560	-9.472	9.221	-0.171	4.585
Germany	DAX	0.031	1.517	-8.833	11.588	-0.179	4.937
Greece	ASE	-0.080	2.294	-17.713	12.404	-0.322	4.571
Ireland	ISEQ	-0.003	1.695	-13.964	9.733	-0.539	6.945
Italy	FTSEMIB	-0.023	1.733	-8.917	10.684	-0.235	3.613
Japan	NKY	0.007	1.669	-12.111	13.235	-0.446	7.140
Portugal	PSI 20	-0.021	1.400	-10.379	10.196	-0.212	4.784
Spain	IBEX	-0.005	1.652	-8.716	13.484	-0.060	5.076
UK	FTSE 100	0.005	1.300	-8.178	8.469	-0.230	5.463
USA	SPX	0.023	1.398	-9.470	12.404	-0.235	10.059

Table 2: Descriptive Statistics for Equity Market Index returns.

where TI_t is the turbulence index at time t, Y_t is an n vector of daily equity returns, μ_e is the sample average historical equity return vector, and Σ is the sample covariance matrix of the historical returns over the sample period. In a nutshell, the turbulence index captures the average degree of unusual changes in daily returns and their interactions. Figure 3 shows that the turbulence index peaks during the financial crisis, the sovereign crisis and the Chinese stock market fall. A closer look at the plot shows that the peak of unusual return values in

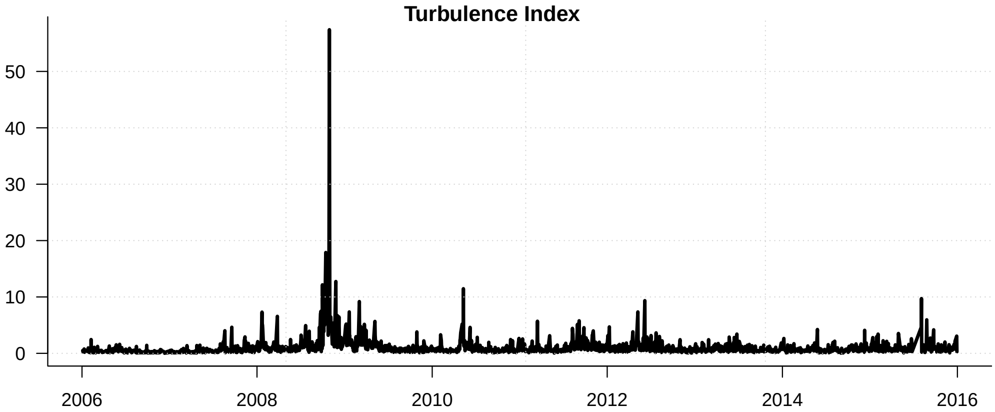


Figure 3: Historical turbulence index from daily returns of the 10 reporting countries.

the system occurred during the global financial crisis, and particularly around 29-10-2008. In addition, peaks are observed in correspondence to the sovereign and Greek crisis, around 11-5-2009 and with the Chinese stock market fall around 4-8-2015.

Overall, the descriptive analysis shows that, while quarterly bank flows are rather stable over time, albeit with some variations in lending compositions between the different countries, daily market returns are more volatile and more sensible to exogeneous shocks.

4. Empirical Findings

We now proceed with the application of our proposed models to the available country data, on equity market indexes and on lending flows. To bring both datasets at the same frequency level, we interpolate lending data from quarter to daily periods. For scaling purposes we express both variables on a common logarithmic scale. More formally, we let:

$$Y_t = log(P_t) - log(P_{t-1})$$
$$L_t = log(F_t)$$

where P_t indicate the value of a national market index at time t (price), and F_t indicate the total amount of lending from a country to all the ten countries in our sample, at time t. In this way, both Y_t and L_t express time variations: in the market index price and in the outstanding lending amount, respectively, for each country.

We focus our analysis on the interconnectivity among the ten considered countries, for the period between 2006-Q1 to 2015-Q4, which we interpret in terms of contagion and vulnerability of the countries involved. We consider, without loss of generality, four non-overlapping sub-periods, that cover the Pre-crisis, the Global Financial Crisis, the Sovereign Debt Crisis, and the Post-crisis periods. Accordingly, in the following we will show the obtained four network representations and, specifically, the Lending-to-Lending, Lending-to-Equity, Equity-to-Equity and Equity-to Lending adjacency graph, for each sub-period of analysis. We also interpret the graphs using four of the network centrality measures previously described: in- and out-degree, in-and out-exposure, for the same periods.

We present the network models in Figures 4, 5, 6 and 7, which cover four non-overlapping periods representing the Pre-crisis (2006-2007), the Global Financial crisis (2008-2009), the

European Sovereign Debt Crisis (2010-2012) and the Post-crisis period (2013-2015), respectively. Within each Figure, we provide four networks, starting from the Lending-to-Lending, then the Lending-to-Equity, followed by the Equity-to-Equity and last the Equity-to-Lending networks. In each network, nodes represent the ten countries, while links resemble the direction and strength of the relationships between countries. The links are colored based on the sign of the associated interdependence: a positive relationship between two countries is plotted in green and a negative one is plotted in red.

We also analyze and compare the estimated networks (lending-to-lending, lending-to-equity, equity-to-equity and Hybrid) using the centrality measures over the four non-overlapping study sub-periods. The used centrality measures include out-degree and out-exposure, which are provided in Tables 3 and 4, in addition to in-degree, and in-exposure, that are provided in Tables 5 and 6. Within each centrality table (I) denotes the Pre-Crisis (2006–2007) sub-period, (II) is for the Global Financial Crisis (2008–2009), (III) refers to the European Sovereign Debt Crisis (2010–2012) and (IV) represents the Post-Crisis (2013–2015) sub-period.

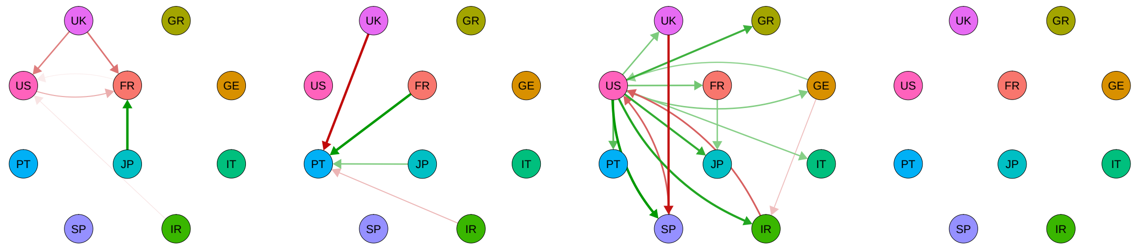
	Lending-to-Lending				Lending-to-Equity				Equity-to-Equity				Equity-to-Lending			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
FR	3	2	2	6	1	0	1	0	1	3	6	0	1	1	0	1
GE	0	0	2	7	0	0	0	0	2	3	5	1	0	3	1	1
GR	0	0	0	6	0	0	0	0	0	3	1	1	0	0	0	0
IR	2	3	3	5	1	0	3	0	1	0	0	0	0	0	1	0
IT	0	0	2	7	0	0	0	0	0	0	0	3	0	0	0	0
JP	2	3	3	4	1	0	0	5	0	0	0	0	0	0	1	0
PT	2	3	3	4	0	0	3	0	0	1	0	0	0	2	0	0
SP	0	0	4	3	0	0	4	0	1	3	4	0	1	0	2	0
UK	4	4	2	4	1	0	0	0	1	0	0	2	0	0	2	0
US	2	4	6	5	0	0	2	0	9	9	9	9	0	1	0	0
Ave	1.5	1.9	2.7	5.1	.4	0	1.3	.5	1.5	2.2	2.5	1.6	.2	.7	.7	.2

Table 3: **Out-Degree (Unweighted Network)**. (I) Pre-Crisis (2006–2007), (II) Global Financial Crisis (2008–2009), (III) European Sovereign Debt Crisis (2010–2012), (IV) Post-Crisis (2013–2015).

	Lending-to-Lending				Lending-to-Equity				Equity-to-Equity				Equity-to-Lending			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
FR	.02	0	.01	-.03	-.09	0	.08	0	.78	-2.3	-1.7	0	0	0	0	.01
GE	0	0	-2.7	-3.6	0	0	0	0	1.03	1.13	-1.4	-.38	0	0	0	0
GR	0	0	0	.83	0	0	0	0	0	.62	-.03	.17	0	0	0	0
IR	-.01	.01	-.03	.08	-.03	0	-1.3	0	0	0	0	0	0	0	0	0
IT	0	0	2.8	3.2	0	0	0	0	0	0	0	.42	0	0	0	0
JP	0	-.01	0	0	.18	0	0	-.51	0	0	0	0	0	0	-.01	0
PT	0	0	.01	-.07	0	0	-.39	0	0	.16	0	0	0	0	0	0
SP	0	0	-.1	-.01	0	0	-2.4	0	-.35	-.87	.88	0	0	0	0	0
UK	-.02	.01	.02	-.04	-.03	0	0	0	-.23	0	0	-.4	0	0	0	0
US	0	0	-.16	.1	0	0	-.68	0	5.46	5.09	3.89	3.3	0	0	0	0
Ave	0	0	-.01	.05	0	0	-.48	-.05	.67	.38	.16	.31	0	0	0	0

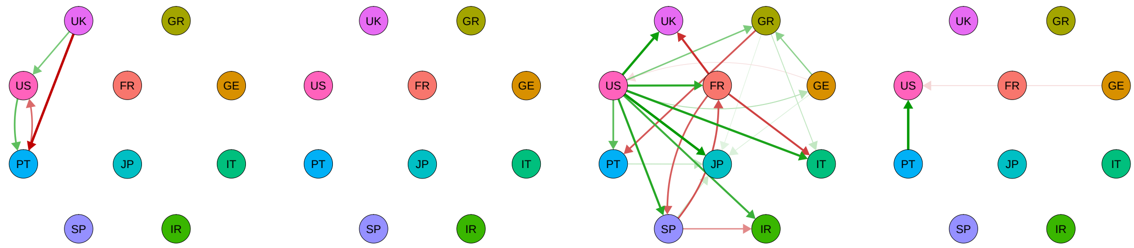
Table 4: **Out-Exposure (Weighted Network)**. (I) Pre-Crisis (2006–2007), (II) Global Financial Crisis (2008–2009), (III) European Sovereign Debt Crisis (2010–2012), (IV) Post-Crisis (2013–2015).

The empirical findings from Figures 4, 5, 6 and 7 and the corresponding centrality measures can be organised according to the different network types, which correspond to different potential contagion transmission channels. For the sake of brevity, we will focus the explanation on the most important findings.



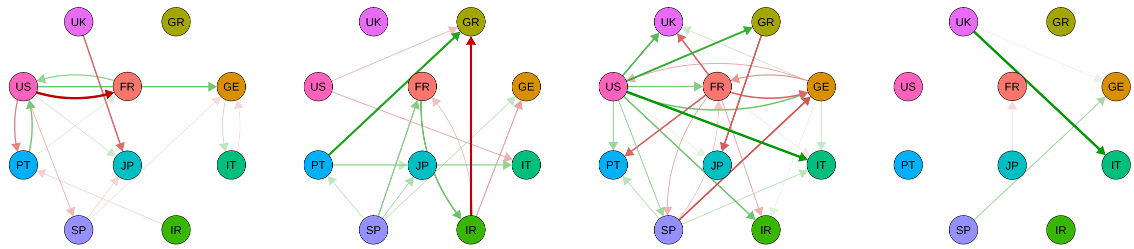
(a) Lending-to-Lending (b) Lending-to-Equity (c) Equity-to-Equity (d) Equity-to-Lending

Figure 4: Pre-crisis period (2006-2007).



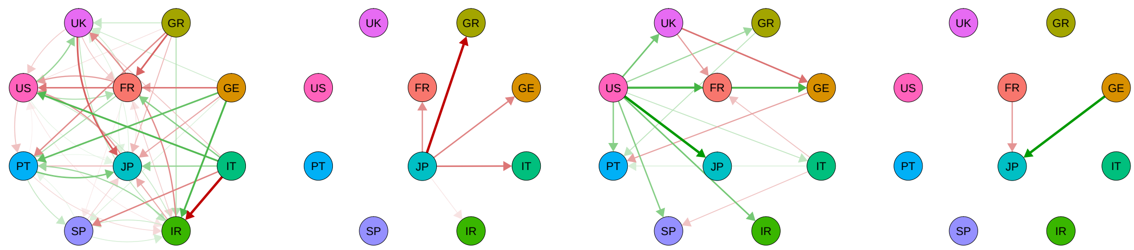
(a) Lending-to-Lending (b) Lending-to-Equity (c) Equity-to-Equity (d) Equity-to-Lending

Figure 5: Global Financial crisis period (2008-2009).



(a) Lending-to-Lending (b) Lending-to-Equity (c) Equity-to-Equity (d) Equity-to-Lending

Figure 6: Sovereign crisis period (2010-2012).



(a) Lending-to-Lending (b) Lending-to-Equity (c) Equity-to-Equity (d) Equity-to-Lending

Figure 7: Post-crisis period (2013-2015).

4.1. Lending-to-lending

The lending-to-lending network in Figure 4 shows that, during the Pre-Crisis sub-period, the banking system of France positively affected that of the US, that is, an increase in the lending volumes of the former led to an increase in the lending volumes of the latter. This relationship may be explained by lending-borrowing dependence between the banking sys-

	Lending-to-Lending				Lending-to-Equity				Equity-to-Equity				Equity-to-Lending			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
FR	3	0	2	6	0	0	2	1	1	2	3	3	0	0	1	0
GE	0	0	3	0	0	0	2	1	1	1	3	2	0	0	2	0
GR	0	0	0	0	0	0	3	1	1	2	1	1	0	0	0	0
IR	0	5	4	8	0	0	1	1	2	2	3	1	0	1	0	0
IT	0	0	3	0	0	0	2	1	1	3	4	1	0	0	2	0
JP	5	4	4	9	0	0	2	0	2	5	2	1	2	1	0	2
PT	1	3	3	8	4	0	1	0	1	2	3	4	0	0	0	0
SP	0	0	1	5	0	0	0	0	2	2	2	2	0	0	0	0
UK	3	4	5	7	0	0	0	0	1	2	3	1	0	2	1	0
US	3	3	2	8	0	0	0	0	3	1	1	0	0	3	1	0
Ave	1.5	1.9	2.7	5.1	.4	0	1.3	.5	1.5	2.2	2.5	1.6	.2	.7	.7	.2

Table 5: **In-Degree (Unweighted Network)**. (I) Pre-Crisis (2006–2007), (II) Global Financial Crisis (2008–2009), (III) European Sovereign Debt Crisis (2010–2012), (IV) Post-Crisis (2013–2015).

	Lending-to-Lending				Lending-to-Equity				Equity-to-Equity				Equity-to-Lending			
	I	II	III	IV	I	II	III	IV	I	II	III	IV	I	II	III	IV
FR	-.01	0	-.06	.03	0	0	-1.15	-.14	.72	.24	.39	.28	0	0	-.01	0
GE	0	0	2.7	0	0	0	-1.24	-.13	.59	.49	.36	.18	0	0	0	0
GR	0	0	0	0	0	0	-.49	.04	.64	.81	.28	.22	0	0	0	0
IR	0	-.01	0	0	0	0	.08	-.16	1.05	.03	.21	.4	0	0	0	0
IT	0	0	-2.8	0	0	0	-.43	-.12	.66	.03	.11	.29	0	0	0	0
JP	0	.01	-.02	.02	0	0	-.9	0	1.2	1.21	.38	.42	0	0	0	0
PT	-.01	.02	0	.02	.03	0	-.63	0	.52	.97	.29	.39	0	0	0	0
SP	0	0	-.02	.4	0	0	0	0	.43	-.37	-.14	.42	0	0	0	0
UK	0	-.01	-.02	.01	0	0	0	0	.68	.04	-.03	.54	0	.01	0	0
US	.01	0	.01	0	0	0	0	0	.23	.39	-.23	0	0	0	0	0
Ave	0	0	-.01	.05	0	0	-.48	-.05	.67	.38	.16	.31	0	0	0	0

Table 6: **In-Exposure (Weighted Network)**. (I) Pre-Crisis (2006–2007), (II) Global Financial Crisis (2008–2009), (III) European Sovereign Debt Crisis (2010–2012), (IV) Post-Crisis (2013–2015).

tems of two countries. Precisely, an increase of French bank lending is also accompanied by borrowing from US banks. Conversely, the banking systems of the US negatively affect that of France, and can be explained by a "substitution" effect: when US banks increase their lending, US corporates, banks and countries borrow less from other banking systems and, in particular, from France. A third relevant finding is that the German banking system appears isolated and, therefore, neither contagious nor vulnerable to contagion.

Moving to the financial crisis period, the lending-to-lending network in Figure 5, in comparison with Figure 4, individuates more potential contagion channels. The strongest ones involve country banking systems that decrease lending, following the financial crisis, thus generating contagion among each other. This is the case for the relationship from the US to Portugal, from Ireland to Portugal, and from Ireland to Japan. Note that Germany is still isolated.

The lending-to-lending network in Figure 6 shows that, during the European Sovereign Debt Crisis, the most important channel of contagion is from Italy to Germany. The reduction of lending in the balance sheets of Italian banks reduces borrowing from German banks. Conversely, the link from Germany to Italy is negative, indicating a substitution effect: German banks increase their lending within the country, considered safer, and correspondingly they borrow less from other banking systems and, in particular, from Italy.

Figure 7 shows that the Post-crisis sub-period lending-to-lending network is similar to that of the Figure 6, with Italy positively affecting Spain (contagion effect) and Germany negatively affecting Spain (substitution effect).

The centrality measures in Tables 3 and 4 show that, while the average out-degree and in-degree (number of connections) has increased along time, indicating a growing number of interconnected countries, the average out-exposure and in-exposure have remained stable. However, the distribution of weights has changed. Before and during the financial crisis, the most contagious countries are France and Ireland, with weights equal to .02 and .01. After the crisis, the most contagious country is Italy, with a much higher weight of 2.8 (during the sovereign crisis) and of 3.2 in the post crisis period. On the other hand, Tables 5 and 6 shows that the most vulnerable countries (with the highest weighted degree) appear to be the US, Japan and Portugal (before the sovereign crisis, with weights between .01 and .02; Germany and Spain, during and after the sovereign crisis (with a much higher weights, respectively of 2.7 and .40).

4.2. Equity-to-equity

The equity-to-equity network in Figure 4, for the pre-crisis period, is highly connected, and shows the dominance of the US financial market: its SPX index positively affects all other equity indexes, indicating a possible contagion effect of a financial market downturn in the US to the other markets. Other sources of financial contagion, to a lesser extent, are the financial markets of France and Germany, with the latter the only market that can backfeed contagion on the US.

The equity-to-equity network for the financial crisis period, in Figure 5 has more interconnections with respect to Figure 4 with the US equity index strongly again affecting the indexes of all other markets. There are also negative links, from the French index to some other countries: Italy, Spain, United Kingdom, possibly indicating diversification behaviors in a "flight-to-quality" effect.

The equity-to-equity network for the Sovereign crisis Figure 6 confirms the US equity index dominance over other country indexes and, in addition, France increases its role of "flight-to-quality" for peripheral countries, along with Germany. In the post-crisis period, the equity-to-equity market slightly lowers its interconnectedness, and becomes very similar to the network in the pre crisis period.

In terms of centrality measures, Tables 3 and 4 show that the equity-to-equity network is quite stable in average number of connections, but decreases in terms of average weights, indicating a lower relative importance with respect to the lending-to-lending network. The tables clearly indicate the US as the most contagious financial market, with the highest out-degree and out-exposure. Table 4 shows that some European countries have also an important contagion impact in some periods: France and Germany in the pre-crisis period; Germany and Greece in the financial crisis period; Spain in the sovereign crisis period; Italy in the post-crisis period.

Tables 5 and 6 show that the most vulnerable financial markets appear to be: Japan and Ireland (in the pre-crisis period); Japan, Portugal and Greece (during the financial crisis); Japan, France and Germany (during the sovereign crisis); Japan, Spain and the UK (in the post-crisis period).

4.3. Lending-to-equity

In the pre-crisis period, only a few lending flows are found to affect equity markets, in Figure 4. The strongest one is positive, from Japan to Portugal, and may indicate that the increased lending of the Japanese banking system is directed also to Portugal, increasing its financial market prices.

The lending-to-equity network in Figure 5 becomes completely disconnected, implying that the lending flows are unable to significantly affect the equity index of any other country. This maybe interpreted with the monetary policy interventions that occurred during this period, which increased total lending of the banking systems, but were not immediately transmitted to the real economy and, therefore, were not captured by financial markets.

The lending-to-equity network in Figure 6 shows several negative interdependences. These possibly indicate the effect of a rebalancing strategy: Spain and Ireland reduce their total lending, but increase lending towards less risky European economies, thus increasing their market returns. The only positive dependence is found from France to Ireland, and can be interpreted with the decreased lending of the former negatively affecting market prices of the latter.

During the post-crisis period the network shows a strong negative relationship of Japan bank lending with large European country market returns. This may indicate again a rebalancing strategy, with Japan its total lending, but reducing that to European countries. The network also indicate a positive influence of Japan on Greece: again lending shrinkage determining a fall in market prices.

In terms of centrality measures, Tables 3 and 4 show a low value of the average centrality measures, consistently with the sparse network structures found for this transmission channel. The only countries whose lending activity is significantly contagious on financial markets are: Japan (pre-crisis) and France (during the sovereign crisis). Tables 5 and 6 indicate that the financial markets most vulnerable to the lending activity are Portugal, Ireland and Greece: all are relatively small markets.

4.4. Equity-to-lending

The equity-to-lending network during the pre-crisis (Figure 4) is very sparse, with few and weak connections. That of the financial crisis in Figure 5 is instead more connected and indicates, in particular, the positive effect of the German financial markets index on the lending of the UK (and of Japan). Decreasing returns in the German market cause a reduction in total lending which reduce, in particular, lending of the UK and of Japan. The negative relationship with France can instead be explained by a substitution effect between the two economies: when the German market is weaker so are the German banks and, therefore, borrowing from French banks may increase. The equity to lending network in the sovereign crisis (Figure 6) indicates again a rather sparse structure.

Finally, the equity to lending network in the post-crisis period shows a strong contagion effect of France on Japan: increasing prices in the CAC market imply increase of Japanese lending, particularly to European economies.

In terms of centrality measures, Tables 3 and 4 show a very low value of the average centrality measures for the equity to lending transmission channel. The only significant contagious country found is France (in the post-crisis period), and the only vulnerable one is the UK (during the financial crisis), consistently with the previous findings.

5. Summary and Policy Implications

In the paper, we have shown a new way to analyze BIS statistics, which combines bilateral-based and market-based financial network analyses. Our findings show that both bilateral exposures and financial markets act as contagion channels in the transmission of shocks arising from a country in the overall system. While the impact of the former is more stable in time, and amplifies during the sovereign crisis, the latter is more volatile and reacts to a wider variety of events.

The empirical findings obtained for the examined countries show that, while equity-to-equity contagion is strong before and during the financial crisis, lending-to-lending contagion becomes more relevant during and after the European sovereign crisis, and indicates, in particular, Italy as the most contagious country and Germany as the most vulnerable one. Contagion through financial markets mainly emanates from the US, with most other markets being vulnerable to it, including Japan and the UK. Contagion across markets, namely lending-to-equity and equity-to-lending is less relevant, as expected, but significant. The lending-to-equity network shows, in particular, the potential contagion effects of a decreased lending from France and Japan on the smallest financial markets. The equity-to-lending network shows the potential contagion effect of a fall in the European market prices on the lending of the internationally active banks, from Japan and the UK.

From the viewpoint of a policy maker, our proposal could be of help in evaluating in advance the impact of a crisis in a specific country on the global system, through the found interconnectedness. While crisis can have a different nature (real, financial, or simply sentiment) its impact is transmitted to the system by means of effects that can be measured in advance either from the exposure channel or from the market channel.

More research involves extending the methodology to other countries, an particularly of those among the G-20 group. This may involve extending the methodology as for some of those countries, the BIS statistics considered here are not available.

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