Signed spillover effects in sovereign and corporate credit markets

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Abstract

Obtaining spillover effects from variance decompositions has found widespread use in the literature. However, spillovers arising out of interconnectedness, for example, between financial assets can be further decomposed into both sources of shocks and whether they amplify or dampen volatility conditions in the target market. We show how to use historical decompositions to rearrange the information from a VAR to include the sources, direction and signs of spillover effects. We apply the methodology to a panel of CDS spreads of sovereigns and financial institutions for the period 2003-2013 and show how they contribute to changes in credit risk. Significantly, we are able to discriminate between positive and negative shocks in a manner not done previously and, therefore, provide new insights into the evolution of CDS interconnectedness across various dimensions.

Keywords
Networks, Credit Risk, Historical Decomposition, Spillovers

JEL Classification Numbers
C32, C51, C52, G10

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1 Introduction

Identifying the ultimate sources of shocks in a complex system of interacting entities is a much sought after objective. If source(s) can be promptly identified, then policy can be effectively aimed at nudging or alleviating desired or non-desired outcomes. The agenda to understand complex interactions in the economy is part of the expanding literature dealing with economic and financial networks; see for example, Acemoglu et al. (2012), Acemoglu et al. (2015), Pesaran and Yang (2016), Diebold and Yılmaz (2016), and Glasserman (2016).

The concept of interconnectedness plays a key role in understanding financial networks, but is elusive and has been defined in a number of ways. To estimate network spillovers empirically the method of Diebold and Yılmaz (2009), henceforth DY, for measuring the relative contribution of shocks from alternative sources spilling over to affect others is frequently used in the literature. In their method interconnectedness of the network is defined from a forecast error variance decomposition based on a standard vector auto-regression framework between endogenous variables (see Diebold and Yilmaz, 2014). This approach has gained popularity, with the advantages of being easy to implement and interpret, with seemingly nice forecasting properties, simple extensions to varying time horizons, as well as being applicable across many different types of applications; see for example Yilmaz (2010), Alter and Beyer (2014) and the range of applications presented in Diebold and Yılmaz (2015) and Demirer et al. (2018).

An alternative approach to measuring interconnectedness is based on pairwise Granger causality test statistics (Billio, Getmansky, Lo and Pelizzon, 2012). In the empirical application to a sample of banks, hedge funds and insurance companies Billio et al. (2012) demonstrate that the network changes over time and becomes more interconnected prior to systemic shocks. Billio et al. (2012) assume that a network is directed but unweighted which may obscure information about the relative magnitude of spillovers and its signs. Moreover, Billio et al. (2012) rely on a rolling sample analysis to capture changes in network topology over time, which means that the size of a rolling window is an additional parameter for obtaining the spillover index.

This paper proposes that further insights into the nature of spillovers or interconnectedness can be obtained by signing the contribution of the sources of volatility into those which augment observed volatility and those which dampen it. We do this by rearranging the information in the standard vector auto-regression to take advantage of the so-called historical decomposition statistics. This decomposition follows from the VARMA form of the residuals in the VAR to attribute the estimated value of an observation to its component shocks. Historical decompositions (HD) have been used previously in the macroeconomic VAR literature since Burbidge and Harrison (1985), and by Dungey and Pagan (2000), Sims (1992) but to our knowledge have not been applied in the way proposed in this paper. Indeed, HDs have fallen somewhat out of favor. However, HD are particularly useful for network analysis because they allow asking how networks would be affected by some counterfactual such as by turning off one or a combination of shocks. This approach to decomposing the sources of shocks and measuring interconnectedness does not require normalization assumptions nor (necessarily) a choice of window length to obtain a time-varying spillover index as in DY or Granger causality methods - although this can be accommodated if desired. The historical decomposition elements have additive properties and we can obtain not only the total historical decomposition spillover index from a particular source to a given entity, but also contributions of subsets of historical decompositions, and confidence bands for both.

We provide further insights into the role of shocks not evident from unsigned decompositions. To illustrate the conrtribution of this paper, we examine a set of 107 credit default swap (CDS) spreads for as selection of financial institutions and sovereigns issuing 5 year debt denominated in US dollars over the period 2003-2013. The results track the time-varying contribution of subsectors of the data to overall spreads. For example, we show that the insurance sector generally acts as a recipient of shocks exacerbating ones hitting the global CDS market during the period of the global financial crisis. Financial institutions are also the major recipients of "bad" shocks during the GFC and the European debt crisis. North America acts as a super-spreader by emitting both positive and negative shocks. Emerging and frontier markets are strongly interconnected, while the transmission from these markets to developed markets is relatively small. Both global systemically important banks and other banks are the most influential entities using other entities as a critical link in the combined network. We also show that higher order moments of the spillovers contain differing information about the evolution of the spillover index over time. More importantly, we are able to show how positive or negative shocks can amplify or dampen risk. Hence, our results can be seen as providing additional insights into the nature of risk transmission than is currently available in the existing literature.

The remainder of the article is organized as follows. Section 2 provides a theoretical motivation for a proposed spillover measure between sovereigns and financial institutions. Section 3 introduces a novel interconnectedness measure which takes into account the shocks and whether these shocks amplify or dampen volatility in the target market and discusses how to implement this measure. Section 4 introduces the data-set consisting of daily CDS spreads for sovereign nations and financial institutions and other control variables. Section 5 discusses the empirical results. Section 6 concludes.

2 Channels of interaction between sovereigns and financial institutions

Sovereigns and financial institutions are interrelated in elaborate ways. On the one hand, financial institutions may form a network in which a single bank may induce a cascade of defaults in the system (Acemoglu et al. 2015) determining risk spillovers between these institutions. On the other hand, the Eurozone sovereign debt crisis revealed how the market value of banks' holdings of domestic sovereign debt fell affecting the solvency and lending activity of these banks and leading to spillovers from sovereigns to banks. These feedback or diabolic loops (see Brunnermeier et al. 2016) between sovereign and financial institutions represent mechanisms through which systemic risk across the globe can spread. When a diabolic loop is established, and financial sector crises and sovereign debt crises coincide, the outcomes for economies are disproportionately worse than when faced with only one source of crisis. Indeed, as Gross and Siklos (2020) demonstrate, risks also spread to the non-financial corporate sector.

Economic activity of financial institutions may be affected by the fiscal condition of the government. In particular, an increase in sovereign risk may motivate governments to raise tax rates (or cut public expenditures), which reduces growth and corporate profitability (Augustin et al. 2018). This causes changes in the credit risk of a financial institution. In this case, some banks may experience an increase in sovereign risk leading to expropriation while for other banks sovereign risk may be reduced via indirect linkages with their counterparties. Classification of banks into these two categories is particularly informative in a period of stress. During this period a number of sovereigns involved in emerging systemic risk is expected to be high comparing to a calm period.

Global financial institutions invest substantially in government debt. Moreover, governments offer guarantees to ensure financial stability. Financial institutions will be negatively effected by a decline in the value of the sovereign debt assets, triggering balance sheet effects and encouraging them to change their private credit provision (Podstawski and Velinov, 2018). Hence, the concern of policy makers about a portfolio channel arising from the holding of government debt. In addition to these balance sheet effects, stress in the sovereign debt sector may also lead to concerns about the ability of the government sector to withstand and fund calls for support from the financial sector, effectively decreasing the insurance value they provide.

An inability of governments to support failing banks may be associated with a sovereign rating downgrade (Correa et al., 2014). Governments normally support systemically important banks or 'too big to fail' institutions to prevent negative consequences of cascading defaults. These defaults are costly and, according to Kaminsky and Reinhart (1999), governments may bail out troubled banks to support stability of the banking network. The instability of the banking network can even spread through banks' entire supply-chain network cthereby amplifying the original shock.

A separate channel from the sovereign to the financial sector exists via macroeconomic policy decisions. Unsustainable macroeconomic policy actions will be reflected in changes of the sovereign risk that will be transferred to the financial sector. Jordà et al. (2016) find no evidence of crisis rooted in fiscal policy for developed markets and confirm that poor public debt scenarios prior to crisis events result in longer recessions than otherwise. This result does not hold for emerging markets that have often been the source of financial crises.[1] Spillovers from sovereign to corporate risk, as previously noted, may also be channeled through the financial sector which can force a government to discontinue its financial backing of domestic corporations.

[1]The detailed review is presented in Reinhart and Rogoff (2009).

Debt re-nationalization in open economies may be a source of systemic risk in a banking network. This channel emerges when domestic sovereign risks are overestimated. As a result, domestic banks expect higher returns on domestic sovereign bonds than foreign banks. This mechanism gives rise to the doom loop, two-way link between sovereign and financial balance sheets (Farhi and Tirole, 2018). In the doom loop risk shifting is more likely for risky domestic sovereign debt than in risky foreign sovereign debt, which is consistent with the logic of Gennaioli et al. (2014).

Potential risk spillovers from the banking sector to the sovereign debt sector may originate from an increasing proportion of safe assets via the portfolio channel. The safety net channel indicates whether financial institutions receive guarantees from sovereigns. In times of stress financial institutions establish a link with sovereign bond markets via the option on government support priced into the equity value, and hence balance sheet, of the financial companies. This will lead to contraction of credit in the economy and reduce government revenues.

Financial institutions may also experience a negative shock from investments that under-perform even when sovereign debt markets perform normally. Bond holdings and payments from counterparties need to exceed outside obligations owed, the financial institution's own counterparty requirements, and the loss due to a poor investment outcome. The so-called investment channel is expected to be switched on during the global financial crisis. There is likely to be less heterogeneity in sovereign debt market investment opportunities available to the financial sector institutions than in private sector investments (Dungey et al. 2019). That is, although the failure of a relatively small private investment opportunity may cascade and cause financial stress (Acemoglu et al. 2015) there are in practice fewer sovereign bond investment opportunities. Thus, a shock in the sovereign debt market is likely to cause a simultaneous common shock to a number of entities, providing a further means of amplifying a crisis via the network.

Our empirical framework links these channels of risk transmission with network theory by differentiating 'good' from 'bad' spillovers, i.e. spillovers that are associated with negative and positive contributions to systemic risk. This will help to illustrate how combinations of events in financial and sovereign debt markets place additional stress on existing banking networks through the channels of risk transmission noted above.

3 Methodology

In this section we show how to measure connectedness from shares of historical decompositions for various entities due to external shocks. Our approach to decomposing interconnectedness has the advantage of allowing the separate identification of shocks that raise, or reduce, network connectedness. That is, by relying on historical decompositions, we separate two types of connections: amplifying or dampening. A positive weight represents an amplifying connection whereas a negative weight represents an dampening connection.[2] Taking into account that CDS

[2] Jorion and Zhang (2007) emphasize the importance of positive and negative transfer effect in the CDS market - they assign positive correlations across CDS spreads as contagion effects, and negative correlations as competition

spreads reflect a perceived risk of default, favorable news decreases the value of the CDS spread, while unfavorable news increases the value; thus positive weights identify entities that increase systemic probability of default, while entities associated with the negative values reduce the risk of default in the network. The importance of differentiating between positive and negative weights is explained by a complex interaction of the channels causing systemic risk spillovers, as discussed in Section 2.

3.1 The multivariate historical decomposition

The SVAR model of the set of variables X_t is

$$B(L)X_t = v_t + \epsilon_t, \tag{1}$$

where B(L) is a p^{th} order matrix polynomial in the lag operator L, $B(L) = B_0 - B_1L - B_2L^2 - ... - B_pL^p$; B_0 summarizes the contemporaneous relationships between the variables and is nonsingular and normalized to have ones on the diagonal, and v_t contains an intercept and exogenous variables. The $n \times 1$ vector ϵ_t contains structural shocks, where $E(\epsilon_t\epsilon_t') = D$ and $E(\epsilon_t\epsilon_{t+s}') = 0$, for all $s \neq 0$. The variances of the structural disturbances are contained in the diagonal matrix D. The reduced form representation of the model is

$$A(L)X_t = \kappa_t + u_t, \tag{2}$$

where $A(L) = B_0^{-1}B(L) = I - A_1L - A_2L^2 - ... - A_pL^p$, and κ_t contains an intercept and exogenous variables. The reduced form errors are related to the structural errors as $u_t = B_0\epsilon_t$ and $E(u_tu_t') = \Sigma$, and $E(u_tu_{t+s}') = 0$ for all $s \neq 0$. The contemporaneous identification[3] of the model is represented by a lower triangular matrix B_0.

An alternative means of organizing the estimated parameter matrices when the shocks are orthogonal is via a historical decomposition. The historical decomposition (HD) is obtained from the VAR model presented in equation (2). More specifically, equation (2) can be represented in companion form as

$$HD_t = K_t + \mathbb{A} \cdot HD_{t-1} + U_t, \tag{3}$$

where

$$HD_t = \begin{bmatrix} X_t \\ \vdots \\ X_{t-p+1} \end{bmatrix}, \mathbb{A} = \begin{bmatrix} A_1 & \dots & A_p \\ I_n & \dots & 0 \\ \dots & \dots & \dots \end{bmatrix}, U_t = \begin{bmatrix} u_t \\ 0 \\ \dots \end{bmatrix}, K_t = \begin{bmatrix} \kappa_t \\ 0 \\ \dots \end{bmatrix},$$

and I_n is assigned as an n-variate unit matrix.

effects. Billio et al. (2019) argue that neglecting the signs of the weights can lead to wrong conclusions on the connectivity structure and produce a relevant loss of information about the contagion dynamics.

[3]Other identification strategies can be also applied if necessary.

Recursively substituting in equation (3) and abstracting from initial values gives

$$HD_t = \Big(\sum_{j=0}^{t-p-1} \widetilde{\mathbb{A}}^j \Big) K_t + \sum_{j=0}^{t-p-1} \widetilde{\mathbb{A}}^j \widetilde{U}_{t-j}, \tag{4}$$

where $\widetilde{\mathbb{A}}^j = \mathbb{A}^j \widetilde{P}$, $\widetilde{U}_t = \widetilde{P}^{-1} U_t$, $\widetilde{P}\widetilde{P}' = \Sigma_U$. The historical decomposition HD_t, defined in equation (4), is a standard tool for decomposing an observed variable at any point in time into the model projection and the deviation from the projection because of shocks (see, for example, Dungey and Pagan, 2000). The historical decomposition HD_t contains two terms. The first term in equation (4) is the baseline projection. The second term in equation (4) shows the effects of shocks before period t. This term is the deviation between a time series and its projection calculated as the sum of the weighted contributions of the shocks to the series. The weights are from the impulse response functions.[4] The impact of the initial values of the data on the estimate of HD_t will vanish as time progresses if the data are stationary. This means that the analysis should focus on the latter sample period so that the initial effects cannot dominate.

The historical decomposition HD_t can also be expressed as a multivariate decomposition. The multivariate decomposition aggregates the elements of the model into a single measure similar to the network interconnectedness measure proposed by Diebold and Yılmaz (2009, 2014). Their network interconnectedness measure summarises the off-diagonal elements of a forecast error variance decomposition matrix for specifications where the elements of HD_t are of the same unit, for example, international stock returns. We interpret HD_t as a measure of the macroeconomy considered as a network. The multivariate historical decomposition is the aggregation of the elements of the variable-specific decompositions. The multivariate representation of (4) is defined as

$$MHD_t \equiv \sum_{j=0}^{t-p-1} IRF_j \circ \Upsilon'_{t-j}, \tag{5}$$

where MHD_t is an $n \times n$ historical decomposition matrix that sums up to X_t at time t, IRF_j are impulse response matrices, $\circ$ is a Hadamard product, and $\Upsilon_t = [\epsilon_t, ..., \epsilon_t]$ is the $n \times n$ matrix containing structural errors in the columns. The indices constructed from the MHD_t matrices use the information of the signs of the shocks (positive or negative), whereas the spillover indices constructed from the forecast error variance decompositions of Diebold and Yılmaz (2009) are positive by construction.

Elements of the historical decomposition matrix $MHD_{t,ij}$ lay a foundation for the connectedness measures from j to i denoted by $c^t_{i \leftarrow j} = c^t_{ij}$. It is convenient to analyze a connectedness matrix $C^t = [MHD_{t,ij}]$ where off-diagonal entries measures pairwise directed connectedness. In general $c^t_{i \leftarrow j} \neq c^t_{j \leftarrow i}$ as in- and out-degrees are not restricted to be identical. Taking into account that the sum of off-diagonal elements of the j-th row of C^t gives the signed share of the historical

[4] The impulse response functions represent the effects of a one standard deviation shock to the SVAR system occurring only at $t = 0$, which must be positive. The historical decompositions map the evolution of the variables over time by the contribution of all of the shocks in the model at all points in time. They also take into account the signs of the shocks.

decomposition coming from shocks related to other variables, total directional connectedness from others to i is defined as

$$c^t_{i \leftarrow others} = \sum_{j=1, j \neq i}^{n} MHD_{t,ij}, \tag{6}$$

and total directional connectedness from j to others as

$$c^t_{others \leftarrow j} = \sum_{i=1, j \neq i}^{n} MHD_{t,ij}. \tag{7}$$

To summarize pairwise directional connectedness for the sample T, we define

$$c_{ij} = \frac{1}{T}\sum_{t=1}^{T} MHD_{t,ij} \quad \forall i \neq j, \tag{8}$$

which can be interpreted as a static measure of connectedness between entities i and j. The total of the off-diagonal entries in C^t defines the aggregate spillover index measuring total completeness at time t as

$$HDS^t = \frac{1}{n}(e'C^t e - \mathrm{trace}(C^t)). \tag{9}$$

where e is the selection vector of ones. Static spillover measures can be obtained as simple averages of the dynamic indices for the sample T.

We use the HDS^t measure to show how the macroeconomy deviates from a multivariate projection due to shocks. In Section 5, we examine how credit risk shocks lead the economy to deviate from the multivariate projection to give us a sense of how the systemic risk rises or falls through the global market over time.

3.2 Estimating the model

A spillover measure HDS^t presented in the previous section is based on a VAR model (2) that should be estimated. Taking into consideration the potential impact of exogenous global factors, a VAR specified in equation (2) needs to be estimated in high dimension, $n = 107$. We follow Demirer et al. (2018) in using LASSO techniques that blend shrinkage and selection and prove particularly appealing for large VARs. Specifically, the LASSO-type estimator of $A_0 = [A_1, ..., A_p]$ is defined as

$$\hat{A}_0 \quad = \quad \underset{A_0}{\mathrm{argmin}} \left\{ \sum_{t=1}^{T} \|X_t - \kappa_t - \sum_{j=1}^{k} A_j X_{t-j}\|^2 + T\lambda \sum_{j=1}^{k} \|A_j\| \right\}, \tag{10}$$

where λ is a tuning parameter that directly control the penalization, $\|\cdot\|$ denotes the Euclidean norm. Given the tuning parameter λ the shrinkage estimator A_0 delivers a one step estimator of (2). Parameter λ is chosen using 10-fold cross validation with a lambda-min criterion. The parameters of model (2) are used to obtain MHD_t and to establish a structure of the network.

4 Data

Modelling the network structure between financial institutions is restrained by data availability. There are two main approaches to assessing systemic risk empirically (Benoit et al., 2017). In the first one different sources of systemic risk can be identified in isolation using confidential data, which are difficult to obtain; an example is the UK banking network examined in Giraitis et al. (2016). The second approach relies on market-based data as proxies to assess the structure on networks which could support a more efficient regulation. van de Leur et al. (2017), for example, show that the characteristics of financial networks based on market data provide valuable information that is not offered by alternative approaches. Following this strand of literature we draw on the market-based data tradition.

To measure the joint default probability of financial companies CDS spreads are normally used (Duca and Peltonene, 2013, Pan and Singleton, 2008). Five-year CDS contracts are the most traded asset in this class and are the most liquid (Bouri et al., 2017). We use these contracts, sourced from Markit, over the period from January 1, 2003 to November 21, 2013. The combined dataset contains 40 individual sovereigns and 67 institutions, for a total of 107 nodes used in the analysis[5], as listed in Tables 1 and 2.

Table 1: Sovereigns included in CDS sample data. D-Developed, E-Emerging, F-Frontier markets according to the IMF classification.

Europe	Asia	Latin America
Bulgaria (F)	Australia (D)	Argentina (F)
Czech Republic (E)	China (E)	Brazil (E)
Denmark (D)	Indonesia (E)	Chile (E)
Norway (D)	Japan (D)	Colombia (E)
Poland (E)	Malaysia (E)	Mexico (E)
Sweden (D)	Philippines (E)	Panama (F)
Russia (E)	South Korea (E)	Peru (E)
Turkey (E)	Thailand (E)	Venezuela (F)
Ukraine (F)	Vietnam (F)	
Africa	**Euro Zone**	**North America**
Israel (D)	Belgium (D)	USA (D)
Morocco (F)	Finland (D)	
South Africa (E)	France (D)	
Qatar (F)	Germany (D)	
	Ireland (D)	
	Italy (D)	
	Netherlands (D)	
	Portugal (D)	
	Spain (D)	

[5]CDS contracts are not standardized contracts and differ in the categories (see e.g. Bostanci and Yilmaz (2020)). The composition of each category changed after 2014. The CDS data before and after this date are not comparable, which justifies our sample selection before 2014.

Table 2: Financial institutions grouped by broad type. * is assigned to Global Systemically Important Banks.

Banks	Financials	Insurance
Aust & New Zld Bkg (ANZ)	ACOM CO LTD (ACO)	ACE Ltd (ACE)
Amern Express Co (AXP)	John Deere Cap Corp (DE)	Aegon N.V. (AEG)
Barclays Bk plc (BAC)*	MBIA Inc. (MBI)	American Intl Gp Inc (AIG)
BNP Paribas (BNP)*	Natl Rural Utils Coop (NRU)	Allstate Corp (ALL)
Cap One Finl Corp (COF)	Aiful Corp (AIF)	Aon Corp (AOC)
Citigroup Inc (C)*	ORIX Corp (ORI)	Assicurazioni Generali (ASS)
Ctrywde Home Lns (CCR)	Gen Elec Cap Corp (GE)	CHUBB CORP (CB)
Kookmin Bk (CIT)	Goldman Sachs Gp Inc (GS)	CNA Finl Corp (CNA)
Commerzbank AG (CMZ)*	Morgan Stanley (MWD)	Legal & Gen Gp PLC (LGE)
Deutsche Bk AG (DB)*	SEARS ROEBUCK (SHC)	MBIA Ins Corp (MBC)
Hana Bank (HAN)	Toyota Mtr Cr Corp (TOY)	MetLife Inc (MET)
HSBC Bk plc (HSB)*	Swire Pac Ltd (SWI)	Munich Re (MUN)
ING Bk N V (INT)*		Old Mut plc (OLD)
Korea Dev Bk (KDB)		Safeco Corp (SAF)
Merrill Lynch & Co (MER)		Mitsui Sumitomo Ins (TAI)
Mizuho Corporate Bk (MIZ)*		Sompo Japan Ins Inc (YAS)
Macquarie Bk Ltd (MQB)		HARTFORD FIN INC (HIG)
Natl Aust Bk Ltd (NAB)		Loews Corp (LTR)
Oversea Chinese Bkg (OCB)		
Rabobank Nederland (RAB)		
Royal Bk of Scotland (RBO)*		
Resona Bk Ltd (RES)		
Societe Generale (SOC)*		
Std Chartered Bk (STA)*		
Sumitomo Mitsui Bkg (SUM)*		
UBS AG (UBS)*		
Wells Fargo & Co (WFC)*		
Westpac Bkg Corp (WST)		

Investment	Real Estate
Daiwa Secs Gp (DAI)	EOP Oper Ltd Pship (EOP)
Bombardier (BOM)	Hammerson PLC (HAM)
Nomura Secs (NOM)	Hongkong Ld Co (HKL)
	Mitsubishi Estate Co (MIT)
	Simon Ppty Gp L P (SPL)
	Simon Ppty Gp Inc (SPG)

The sample contains three different phases[6]; Phase 1 represents the non-crisis period from January 1, 2003, to September 14, 2008. This is typical of dating conventions used in the literature to separate the pre-crisis and crisis periods; see the review of dates extant in the literature in Dungey et al. (2015). Phase 2 represents the period from September 15, 2008, to March 31,

[6]Our methodology does not require choosing these phases endogenously as spillover measures are obtained directly from a VAR. We highlight these phases for a clearer presentation of the empirical results.

2010, consistent with the period of the global financial crisis (GFC). The end of March 2010 represents the period beginning prior to the Greek debt crisis that became critical in April 2010. Phase 3 then, from April 1, 2010, to November 21, 2013, represents the period of the Greek and European sovereign debt crises.

Table 3: Summary statistics are reported for all sovereign CDS spread data used in this paper. The selected phases are respectively consistent with the pre-GFC, the GFC and the European debt crisis.

	Obs.	Mean	Std dev	Skewness	Kurtosis
Phase 1	01/01/2003 - 14/09/2008				
Banks	1488	0.4253	0.6634	6.2252	73.1315
Financials	1488	0.7426	1.4386	9.2843	131.738
Insurance	1488	0.5413	1.1174	10.551	146.240
Investment	1488	1.0126	1.6023	3.5076	19.9933
Real Estate	1488	0.5737	0.5135	2.5807	11.3350
Latin America	1488	3.3274	5.0302	4.3823	24.8403
Asia	1488	1.0935	1.3470	1.4863	4.1704
Euro Zone	1488	0.0698	0.0759	2.8669	11.6775
Europe	1488	0.9062	1.5211	2.8717	13.9841
Africa	1488	0.8038	0.7205	2.5980	11.9358
North America	1488	0.0262	0.0311	2.9249	11.0294
Phase 2	15/09/2008 - 31/03/2010				
Banks	403	1.6490	1.2574	2.1977	8.4938
Financials	403	12.719	32.619	6.6554	58.383
Insurance	403	3.6890	5.1029	2.4613	9.2081
Investment	403	1.9650	1.1711	1.0721	2.8133
Real Estate	403	2.6080	2.4492	1.4525	4.1223
Latin America	403	6.3541	8.8135	2.2891	7.7371
Asia	403	2.0159	1.5864	1.7696	7.0876
Euro Zone	403	0.8250	0.5597	1.5966	6.8034
Europe	403	3.4588	6.4693	3.8884	20.298
Africa	403	1.9245	0.9750	1.3394	4.5551
North America	404	0.4169	0.1834	1.1935	3.9374
Phase 3	01/04/2010 - 21/10/2013				
Banks	951	1.3971	0.6334	1.6584	6.8687
Financials	951	6.3933	10.211	2.0464	5.9045
Insurance	951	1.8314	2.1538	3.7857	20.033
Investment	951	1.4738	1.0772	0.5886	2.2274
Real Estate	951	1.1053	0.4586	0.6091	2.8172
Latin America	951	3.7769	5.6733	3.1106	14.840
Asia	951	1.3284	0.7275	1.6687	6.1909
Euro Zone	951	2.5872	2.5487	1.9267	7.1373
Europe	951	1.6592	1.9220	2.2460	7.9880
Africa	951	1.4990	0.5059	0.5376	2.5000
North America	951	0.3067	0.0801	-0.2616	2.3762

Summary statistics, reported in Table 3, show an increase in mean spreads for most groups of institutions and sovereigns, reflecting the perceived increase in risk during this turbulent period in international debt markets. Skewness in Phases 2 and 3 are both lower than in phase 1, except in Asia and Europe (phase 2), which implies asymmetry across regions, notably in the case of the Euro Zone. Moreover, kurtosis is much higher before the GFC for most of the entities. Some of these results might reflect actions taken by the authorities that were more aggressive in the US than in Europe (see Borio and Zabai, 2016).

To control for exogenous common factors we use a combination of the following global indicators: the West Texas Intermediate US dollar based international index for crude oil prices, the VIX index, regarded as a standard measure of investors' risk aversion, and the MSCI world index capturing performance of the global stock market.

5 Empirical results

This section begins with a discussion of static spillover indices obtained from historical decompositions (see Section 3). Next, we present dynamic spillover indices and discuss how different groups of entities contribute to the emergence of systemic risk whose sign changes over time.

5.1 Static connectedness

Figure 1 shows a heatmap of the average historical decomposition of the shocks contributing to observed CDS spreads for each of the sovereigns in the sample. The vertical axis identifies the spreading country, and the horizontal axis gives the recipient of shocks measured as the average of those shocks across the sample. Lighter colours indicate a positive transmission - that is the shock increases the CDS spread in the recipient market. Darker colours indicate a negative transmission - the shock decreases the CDS spread in the recipient market. Shading is shown on the right hand side bar of Figure 1. Overall, the table is primarily shaded approximately at average of zero recipient/transmission shocks, that is, on average the effects are largely cancelled out over the sample.

It is critical to differentiate negative in-shocks from positive out-shocks in Figure 1 - across the rows the sources and signs of in-shocks to the target listed in a particular row are given; down the columns gives the effect of out-shocks sourced from the country listed for that particular column to each of the potential recipients listed in a row. This analysis allows us to develop the concept of super-spreaders - nodes where shocks are propagated with strong effects to other nodes - and super-absorbers, nodes which receive a diverse range of shocks and turn them into relatively average transmissions. Reading across rows there are a few countries which show some variety in their sources of shocks. Consider, the row labelled Argentina which exhibits both amplifying and dampening shocks sourced from its partners, namely it receives 'good' shocks from Brazil that can be classified as a super-spreader because CDS spreads are narrowed. Shocks from Turkey are mainly positive, increasing the CDS spreads for Argentina. In a network framework each of these represents an in-shocks from the contributing markets but they are signed as to whether they amplify or dampen the effects of those shocks on Argentina. All of these countries are, of course, prominent among the group of emerging market economies. Other interesting examples of markets which display skew in their sources of shocks (across the rows) are Ireland, Portugal, Ukraine and Venezuela. These countries include the members of the GIIPS (Greece, Ireland, Italy, Portugal, Spain) group in the Eurozone or countries that experienced civil unrest.

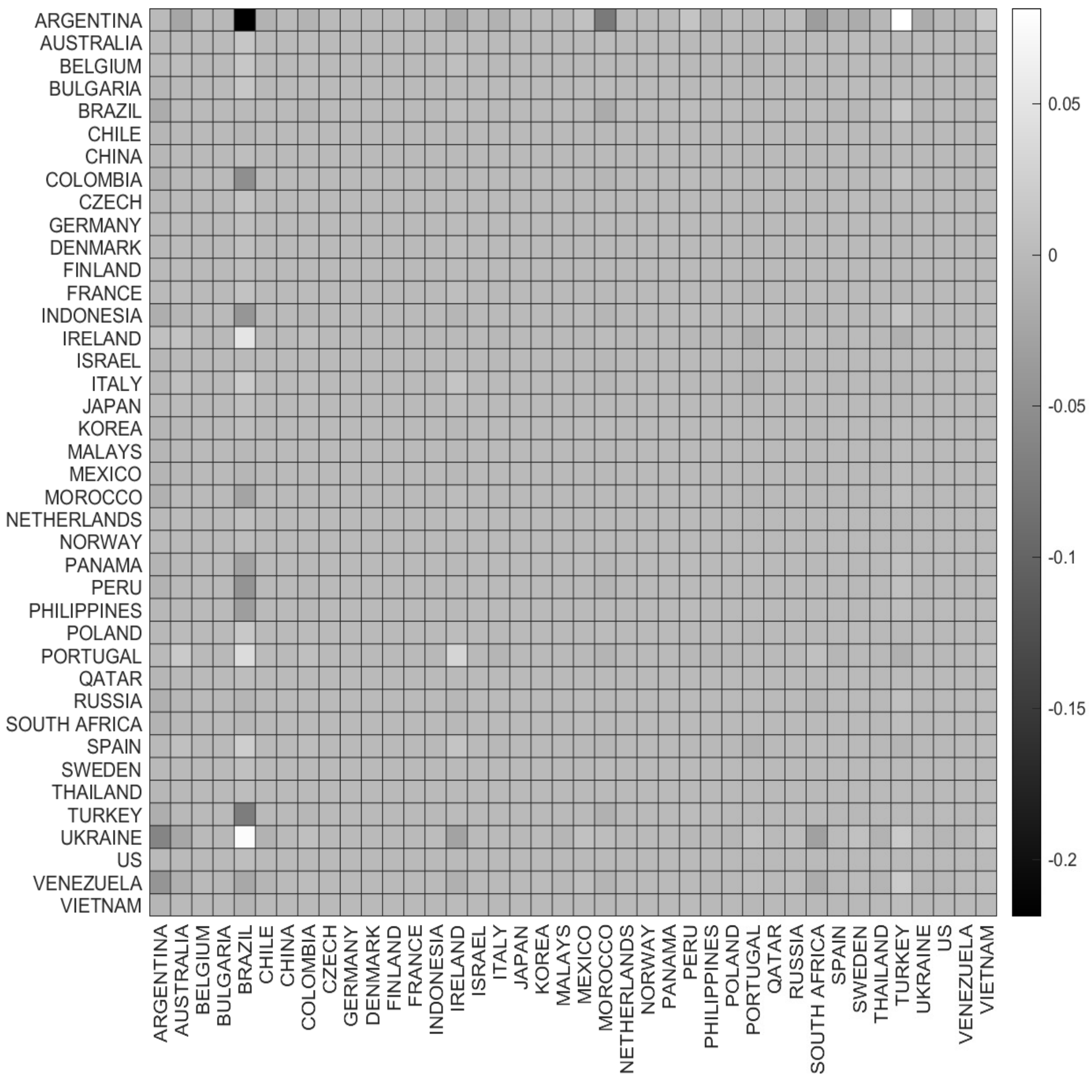

Figure 1: Heat map for sovereigns. Effects from columns to rows represent averages of historical decompositions over the whole sample. Dark colors show negative contributions to CDS spreads, bright colors are associated with positive contributions.

Figure 2 shows the same heat map this time for the network of financial institutions. Reading across the rows it is apparent that AIF, AIG, MBI, MBC and, to some extent, SHC receive a diverse set of shocks.[7] Looking at the columns for the sources of shocks, we can see that AIG, MBI and MBC are not distinctly different to other companies. These institutions are subject to diverse of positive and negative shocks. Thus insurers are performing the role of absorbers, smoothing shocks coming from other institutions and emitting shocks with little signed effects on other financial institutions. For example, AIF can be classified as a super-absorber. From this point of view these insurers are acting to stabilise the financial system, rather than potentially disrupt it. This result supports arguments that the role of insurers in they system is distinct to that of credit creating institutions (see Biggs and Richardson, 2014).

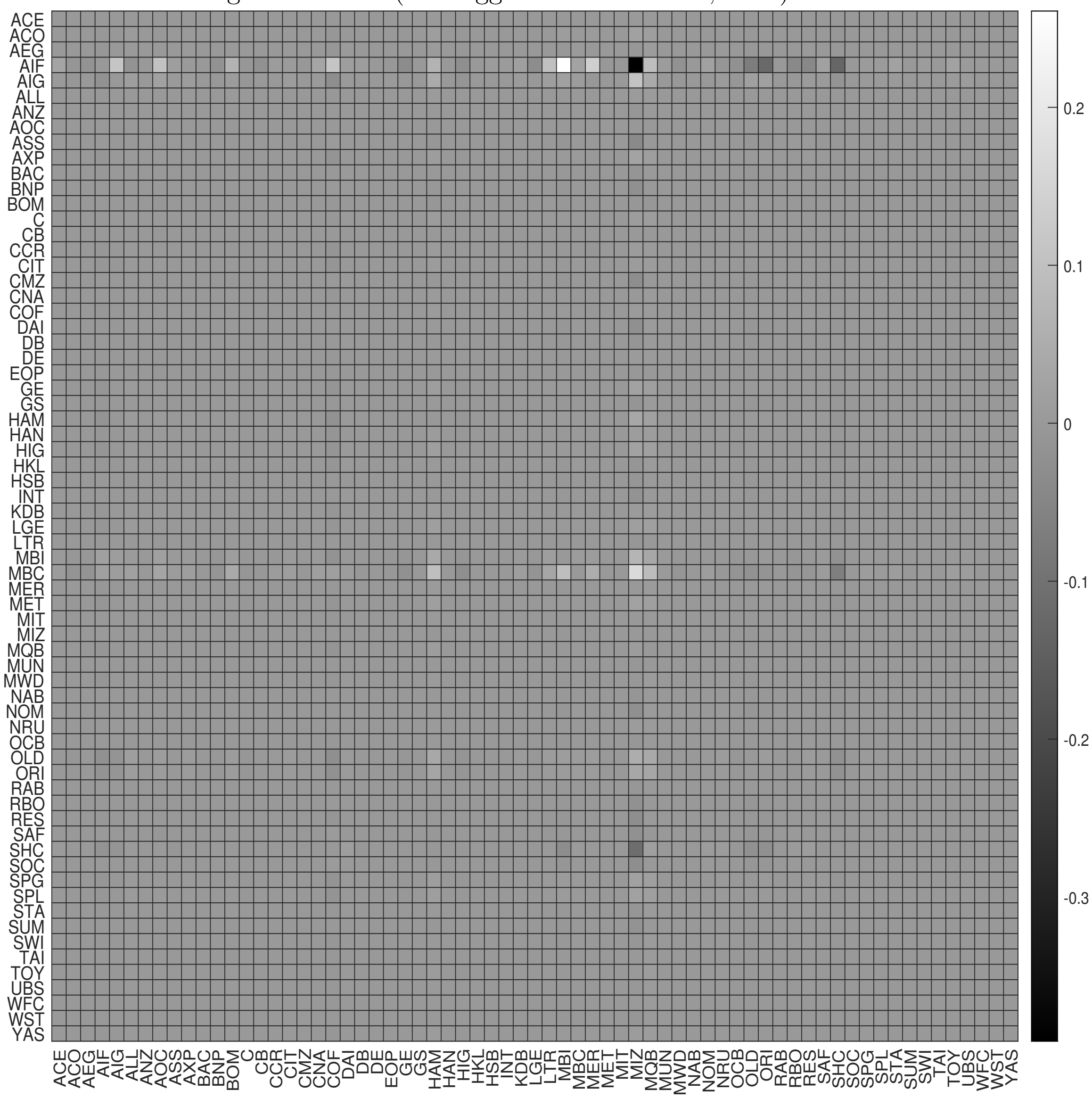

Figure 2: Heat map for financial companies. Effects from columns to rows represent averages of historical decompositions over the whole sample. Darker colors show negative contributions to CDS spreads, brighter colors - positive contributions.

[7]MBI and MBC are the insurance and financial arms of the same company (MBIA), and represent the largest bond insurer in the market. The Aiful Corporation (AIF) is a Japanese financial services provider.

There are also two distinctly different vertical lines in Figure 2; from MIT (Mitsubishi Estate Co) and MIZ, a Japan based financial conglomerate. Both of these firms are heavily invested in the transport and asset financing sector. The result that transport and finance are important in spreading shocks is interestingly paralleled by the recent finding of Pesaran and Yang (2016) that the transport and warehousing sectors of the US economy are routinely considered to be among the most important sectors of the US economic network.

A similar heat-map, showing spillovers from the financial companies to the sovereign nations, is provided in Figure 3. Mizuho (MIZ) plays a role of super-spreader emitting significant shocks stabilizing systemic risk in Argentina, Brazil, Ireland, Italy, Portugal, Spain, Turkey and Venezuela. Four of the five GIIPS economies are now implicated. Ukraine receives mainly positive shocks, while Argentina absorbs spillovers minimizing its CDS spread.

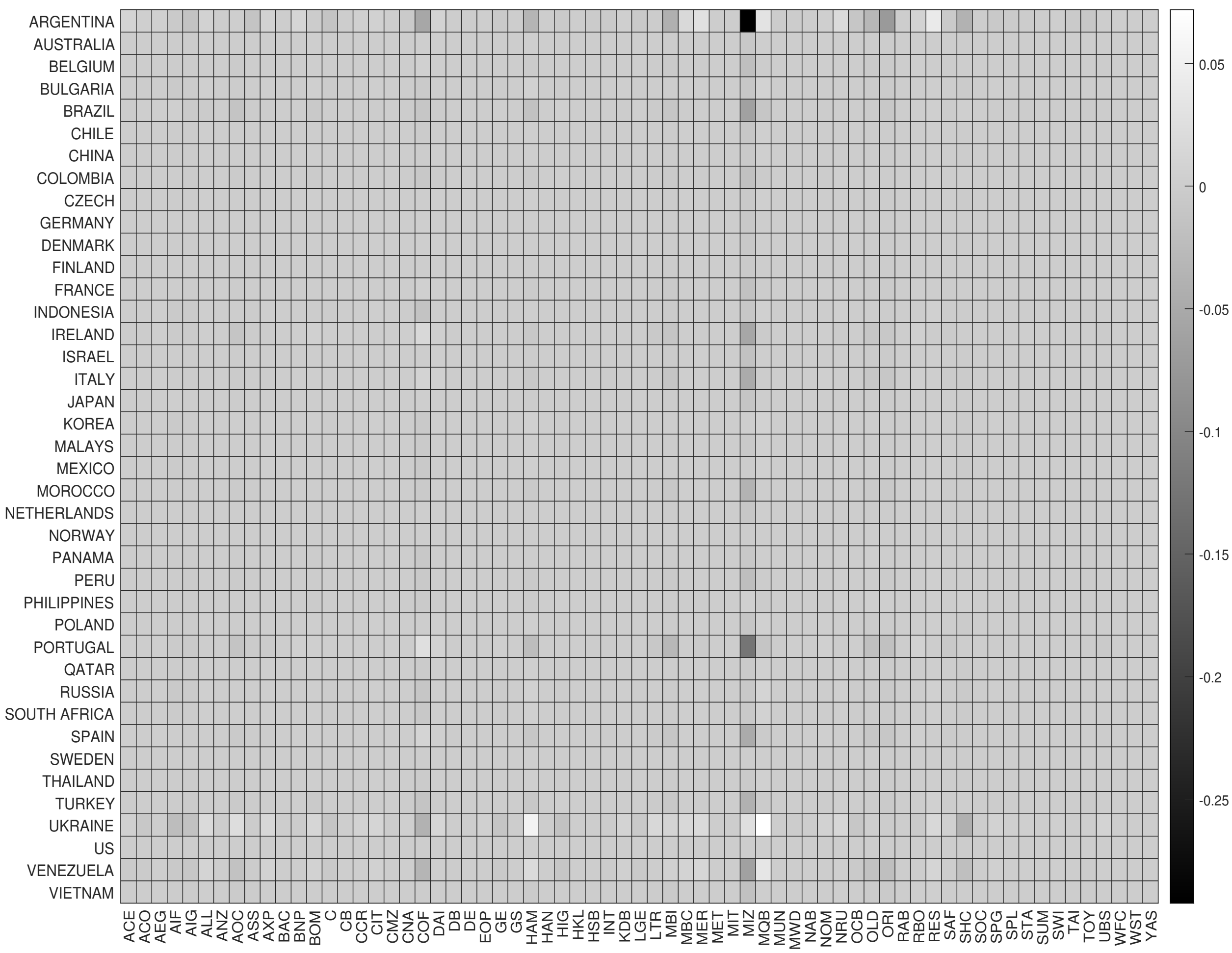

Figure 3: Heat map of spillovers from financial institutions to sovereigns. Effects from columns to rows represent averages of historical decompositions over the whole sample. Dark colors show negative contributions to CDS spreads, bright colors - positive contributions.

One may wish to examine the heatmaps showing spillovers from the sovereign nations to the financial institutions. A similar diagram is not shown to preserve space but is available on request. The most notable feature of this diagram is that most of the shocks from the sovereigns are positive with an exception of Brazil which generates large positive spillovers to MBD and AIF.

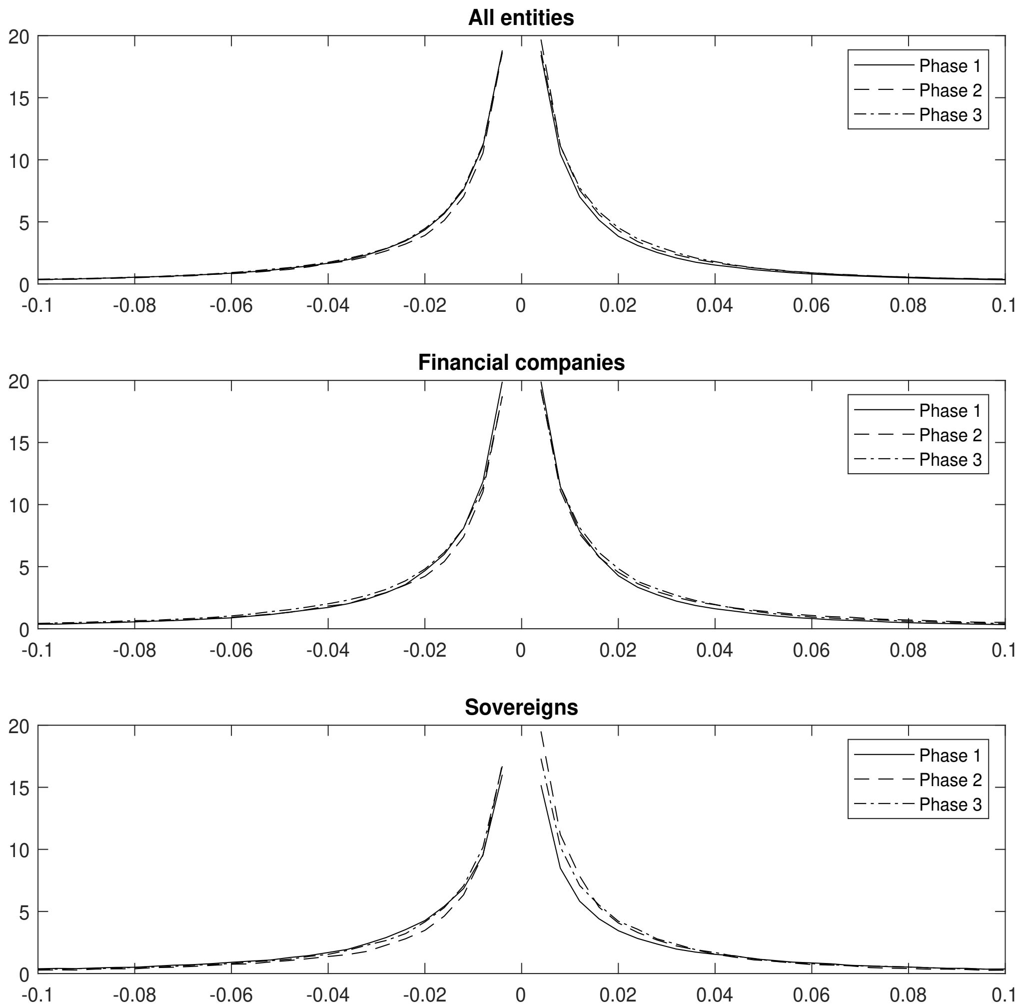

Figure 4: Densities of shocks in 3 phases (pre-GFC, GFC and European debt crisis). Dates of these phases are presented in Table 3. Values around zero are not ploted for a visualization purpose.

To illustrate how the distribution of shock effects changes over the sample period, Figure 4 presents the distributions of the sizes of the shocks in each of the three phases of the sample: pre-GFC (Phase 1), GFC (Phase 2) and European debt crisis (Phase 3). The top panel shows the distribution of the shocks in the whole network and the lower panels provide the distribution for the financial companies and sovereigns. In the pre-crisis period, the distributions are relatively symmetric and tails are thin for all panels. During the GFC we see that the shock distribution of the whole network moves to the right - that is there are more positive (amplifying) shocks present compared to the pre-crisis period. This pattern is particularly pronounced in the sovereign network where the distribution is more leptokurtic, implying a greater proportion of larger signed shocks. In phase 3 there is also some evidence of a shift to the right in the distribution of the spreads. This differs from Phase 2, where the entire financial sector was exhibiting stress whereas the focus is now on the banking and financial institutions sector. By contrast, Phase 3 sees a greater emphasis on the sample including the European sovereign debt crisis. These changing higher-order moments of our shocks are consistent with the findings in Fry et al. (2010) that contagion and crises are evident in higher-order moments of returns and volatilities (see the discussion in Section 5.6 below).

5.2 Dynamic connectedness

As well as the average effects discussed in the previous subsection we also compile spillover indices based on the DY methodology (using a 10 day ahead forecast period and the rolling window size of 510 days) and the proposed historical decomposition method (Figure 5). The nature of the construction of these indices means that the scales are quite different - the HD method has a direct interpretation as the average size of the spillovers to CDS spreads from all sources in the system, and it can be seen that this is typically quite small, and often insignificant in the early part of the analysis based on the 99% error confidence bands. The DY index has larger (always positive) values due to normalization between 0 and 1 discussed by Diebold and Yılmaz (2015). The DY spillover index increases dramatically in late 2007, probably associated with the events of Bear-Stearns and hedge funds in the middle of that year. The HD model picks up at that point, but picks up much more substantially at a date closer to the stress associated with Lehman Bros collapse and the subsequent problems in the remainder of the system. Interestingly, the DY spillover index does not fall dramatically with the introduction of TARP or the NBER dating of the ending of the US recession as often used elsewhere in the literature (see Dungey et al. (2017) for a comparison of systemic risk indices at the end of this period) but remains elevated. The HDS index, however shows some reduction in the effect of the spillovers on CDS spreads post-GFC, but a resurgence of positive effects around the period of uncertainty surrounding the future of Greece in late 2009 - early 2010 and the re-emergence of negative effects around European debt markets in 2011.

Figure 6 presents the HDS indices for the financial institutions and the sovereigns separately extracted from the combined network. It is immediately apparent that the spillover effects from the two sources have dramatically different time paths. Prior to the GFC in 2007 and 2008, financial institutions were in fact behaving in a way which reduced the average CDS spread. Only when the GFC became well-established did the contribution of financial institutions peak, and even then, the greatest contributions were observed in 2009, rather than around the time of the collapse of Lehman Bros.

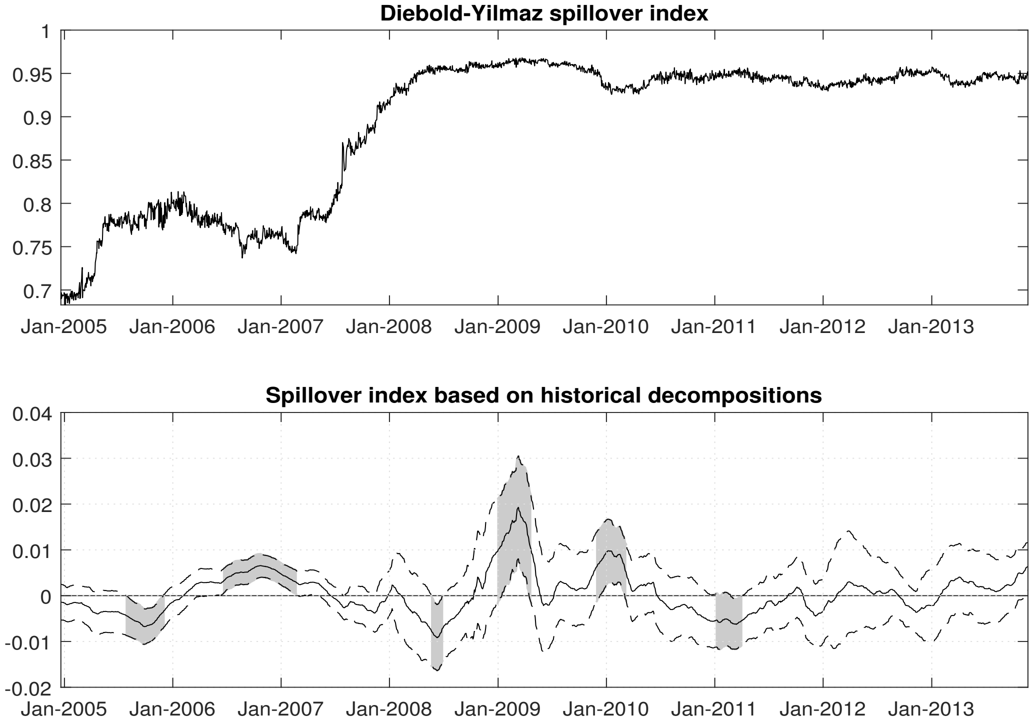

Figure 5: DY and HDS indices estimated from equation (9) for 107 CDS spreads. The DY index is obtained using a 10 day ahead forecast period and the rolling window size of 510 days. Shaded areas represent 99% confidence intervals obtained via wild bootstrapping.

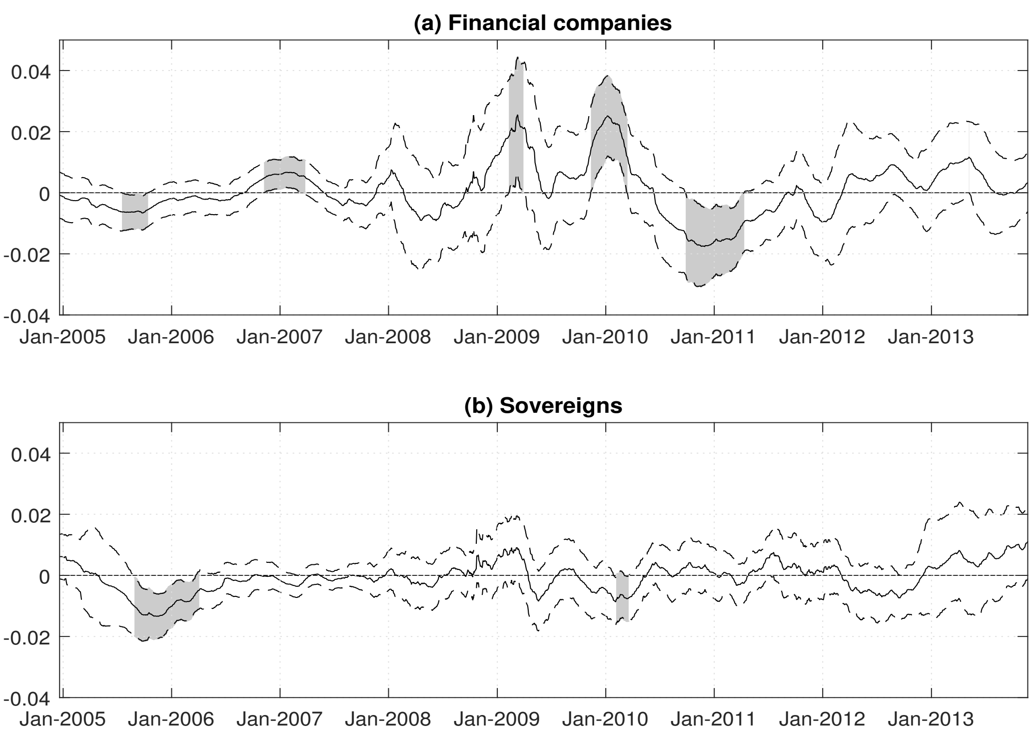

Figure 6: HDS indices for financial institutions and sovereigns. Shaded areas represent 99% confidence intervals obtained via wild bootstrapping.

In early 2010 when the Greek crisis, subsequent IMF programs, and European debt problems unfolded, both sovereigns and financial companies shows significant spillovers (Figure 6). During this period financial companies pushed CDS spreads up while sovereigns reduced them. This scenario is consistent with the theoretical model of Farhi and Tirole (2018) where both banks and government interact establishing so-called diabolic loops which increases the risk of insolvency. During the period from 2013 the contribution to spillovers in the CDS markets from sovereigns and financial companies has been positive but insignificant, and on average similar to levels attained before the GFC. This pattern is consistent with Bostanci and Yilmaz (2015) who found that connectedness of the global sovereign market by the end of 2013 returned back to the same level reached before the GFC.

5.3 Contribution by type of entity

As the contributions of each of the sources of shock are additive in our approach we can compile sub-series to illustrate the contribution of particular types of institutions to CDS spreads. For each of the types of financial institutions Figure 7 shows their difference between in- and outgoing HDS spillover indices calculated from positive and negative shocks separately. This allows us to identify when a specific group of entities played the role of a recipient or spreader of a positive or negative shocks. Positive values in Figure 7 show an absorbing regime of negative (continuous curve) and positive (dashed curve) shocks, while negative values highlight when a group of entities was a spreader.[8]

The main result from Figure 7 is that the largest spreaders of shocks is North America, as seen in the bottom left hand panel (k). Other spreaders have a substantially smaller impact on the rest of the system. As a recipient, however, North America does not receive a great deal of impact from others. Interestingly there is a clear cycle of 'bad' spillovers followed by 'good', or negative, shock transmission in North America. Hence, in early 2008, North America generated spillovers reducing CDS spreads, but this state is replaced by a spike in 'bad' spillovers around the GFC. A similar pattern is observed in 2010, 2011 and 2012.

The contributions of financial institutions (Figure 7b) are substantially greater than, for example, those for banks for example. Financial institutions mainly absorb shocks over the sample. This is also consistent with Gross and Siklos' (2020) findings for the Eurozone. The general pattern of timing of the contributions from this sector show how, in general, each of the financial sector shocks were acting to hold spreads down in early 2008 as 'good' spillovers were stronger during this period. Evidence of a change is apparent in this sector which, in late 2008, goes through a period where it serves to raise spreads. A brief period of dampening aligns with the approval of the TARP refinancing programs and the severing of the financial sector from the real economy which became more pronounced in early 2009. When the Greek debt crisis erupts in April 2010 to maximum effect with the subsequent implementation of the IMF programs from April 2010,

[8] The scales for each sub-figure differ, sometimes substantially. Using the same scales is analytically intractable.

the impact of financial spreads again amplifies average CDS spreads and this effect was almost as high during the European sovereign debt crisis as during late 2009 - representing the exposure of the European crisis to the financial markets.

Banks spread both positive and negative spillovers between 2005 and 2013 while, at the same time, insurance companies were mainly responsible for absorbing interconnectedness. More specifically, Figure 7c shows that the 'bad' shocks received by insurance companies amplified volatility during the 2008-2009 crisis. However, in the spreading of shocks during the crisis of 2008-2009 and through to 2010 it is very apparent that banks had a different role. Banks were contributing to dampening and amplifying shocks in the system prior to the GFC and have largely remained that way since. However, insurers had a dampening effect during 2010-2011, the period prior to the largest disruptions in European markets. That is, the insurers were at this time receiving amplifying shocks and distributing dampening ones. The other particularly interesting spreader category is real industry (panel e) where dampening shocks were dominant prior to the GFC. During the build up to the GFC and its initial stages industry shocks were still dampening, but this was reversed during late 2008, consistent with the breaking of linkages between the real economy and financial sector noted in Dungey et al. (2017) due to the introduction of TARP and the rescue of AIG.

The contribution of sovereign spread shocks by region (except North America) is rather more complex than for financial institutions, despite their high degree of interconnectedness as evidenced in Dungey et al. (2019). Before the GFC the largest contributions come from Latin American and Asia. In each of these the pre-GFC indices were mainly negative - the Latin American sovereigns were contributing to increase spreads, reflecting their historically relatively bad performance during this period. The Asian sovereigns were also generally worsening. Europe was hit hard by the credit crunch conditions which resulted from the GFC, and their reduced prospects due to an inability access to credit are reflected in the pronounced positive contribution to CDS spreads during the GFC period. Post-GFC, however, this region contributed dramatically to CDS spreads with a mix of positive and negative effects. In the last part of the sample while non-Euro Europe is not really contributing much to either amplifying or dampening spreads, Africa does add to spreading 'good' (i.e., negative) shocks.

5.4 Developed vs emerging markets

We segment the results on spillovers by stage of market development using the IMF classification of developed, emerging and frontier markets (see Table 1). The contribution of shocks sourced from markets at different stages of development to the recipient markets are illustrated in Figure 8. The transmissions to developed markets from emerging markets (Figure 8a) are relatively large before the GFC. This is an interesting result since it is often assumed that transmission operates in the opposite direction. Emerging markets were a net source of amplification for developed markets prior to the GFC, and have remained a source of increased premia between 2009 and 2012. The effects from frontier markets on developed markets are consistently small with wide confidence intervals providing evidence of large uncertainty around the frontier markets.

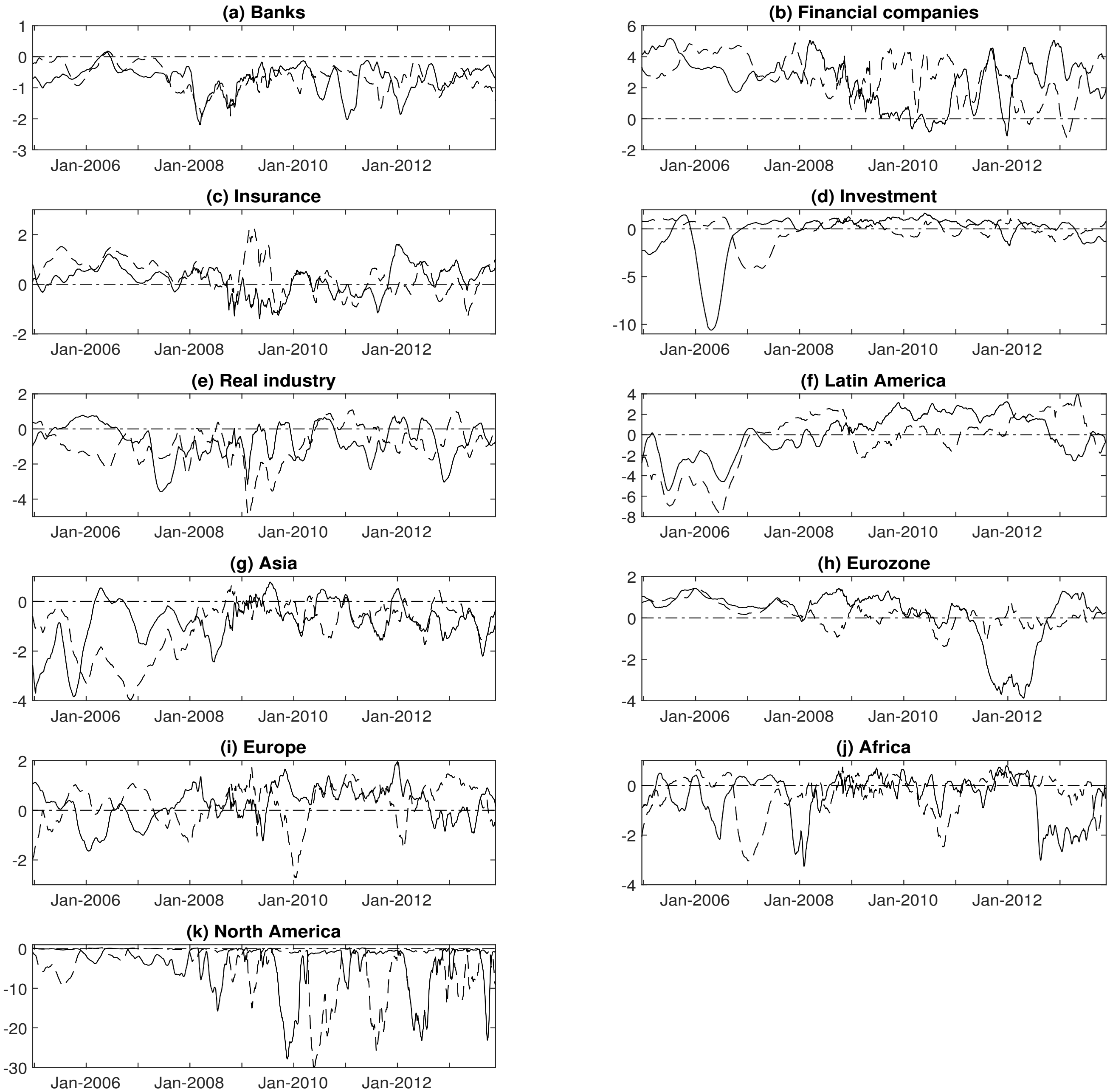

Figure 7: Interconnectedness between different groups of financial institutions and sovereigns. Dashed curves represent indices obtained from shocks with positive signs, continuous curves are estimated from shocks with negative signs. Each index is calculated as a difference between in- and out-coming spillovers as explained in Section 3.

Emerging markets experienced little increase in CDS premia as a result of shocks from developed markets[9], while shocks in frontier markets reduced CDS premia in emerging markets prior to 2009; between 2010 and 2012 a similar pattern is also pronounced (Figure 8). In the other direction, however, frontier markets received substantial premium amplification from developed markets after 2009, and particularly post the 2012 problems in European sovereign debt markets. Frontier markets received more volatile effects from emerging markets - prior to 2007, emerging market shocks were dampening frontier market spreads, possibly attracting investors to these markets - but the risks were rapidly reassessed in 2008 and 2009, and frontier markets suffered a dramatic amplification of shocks until early 2010.

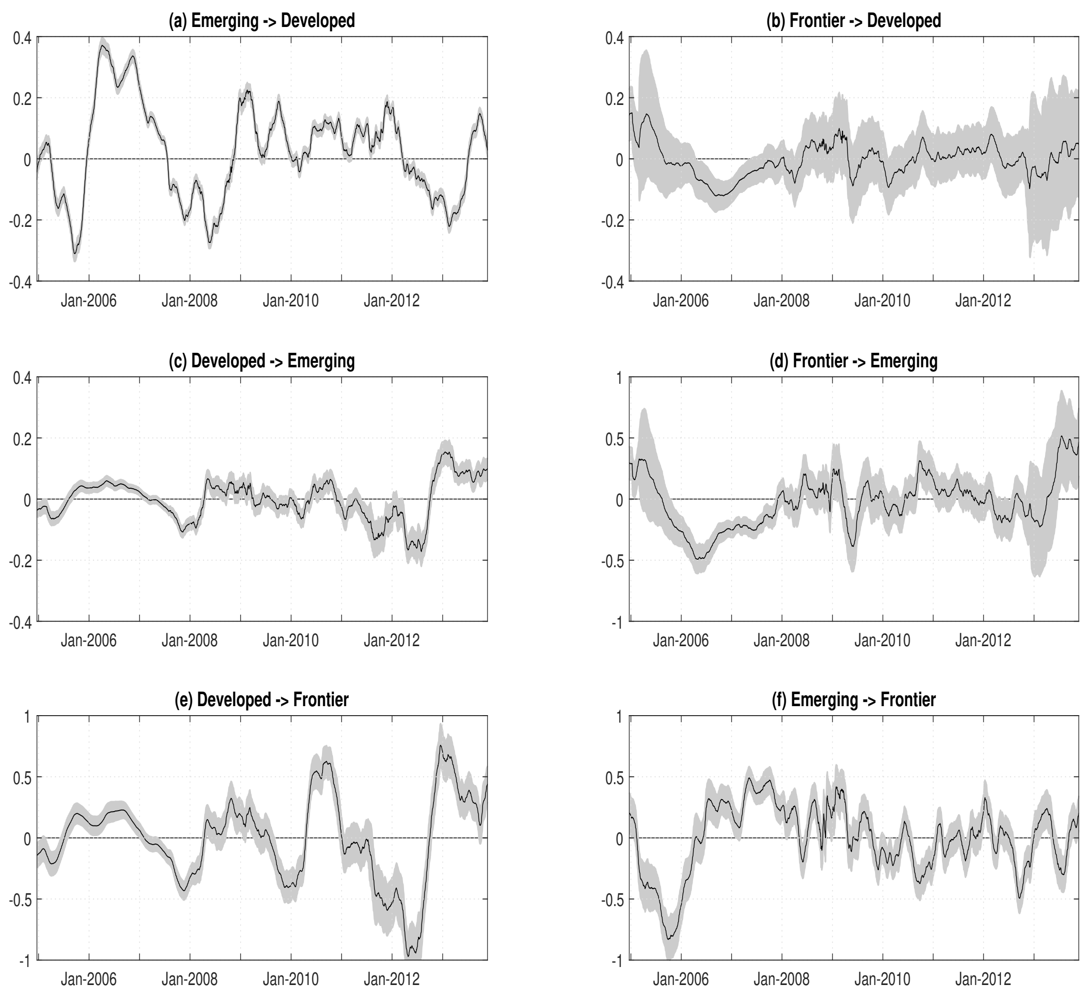

Figure 8: Spillovers between different groups of financial institutions estimated from equations (6) and (7). 99% confidence intervals are obtained via wild bootstrapping.

[9]This finding is consistent with Chen et al. (2016) who found that emerging markets became economically more resilient after the GFC. This is also in contrast to the centre and periphery arguments of Kaminsky and Reinhart (2003).

5.5 Global systemically important banks

Figure 9 provides spillover indices between banks which have been designated as globally systemically important (SIBs), other banks and other types of financial institutions. It is immediately clear that the largest effects are apparent in shocks spreading from SIBs and Banks to other types of institutions (panels e and f). The SIBs are clearly an import source of shock amplification especially before 2010, consistent with the literature which supports regulating banks for systemic risk reasons. However, the influence of shock amplification from SIBS to other banks (panel c) is not more significant than amplification from other entities to the banking part of the network (panel d). That is, while SIBs are important, it is not clear that to non-banks there is a huge distinction between SIBs and non-SIB institutions. While SIBs were generally a source of amplifying shocks before 2009, the non-bank sector transmissions were dampening the transmissions to SIBs (panel b). This may be an indication of the successful application of policy aimed to prevent credit restrictions from reducing economic activity in the GFC period. However, without a clear counterfactual it is difficult to be conclusive. The clearest message from the SIB and non-SIB distinction is that both SIBs and other banks are interrelated during the GFC, creating a certain amplifying effect between them. Interestingly other entities do not differentiate between SIBs and other banks, as the spillover patterns are similar between 2005 and 2013 as evident in panels b and d.

5.6 Index distribution and moments

While the mean bilateral spillover, defined in (9), provides a summary of network activity, it may obscure a great deal of relevant information, particularly if the underlying distribution of the data is asymmetric and has significant kurtosis. This information is particularly valuable during the crisis when banks with greater upper tail dependence have higher CDS spreads (see e.g. Meine, Supper, and Weiss, 2016). A more complete summary of spillover activity must take account not only of the location but also of the shape of the spillover density. For a given moment t, one may approximate the empirical distribution of pairwise spillover effects via kernel density estimation (see e.g. Greenwood-Nimmo, Nguyen, and Shin, 2017).

Consider an $h \times 1$ vector of grids $z = (z_1, ..., z_h)'$, which covers the range of pairwise spillovers in matrix C^t. The density of pairwise spillovers is estimated from

$$\hat{g}_t(z_k) = \frac{1}{b_t}\Big(\frac{1}{n(n-1)}\Big) \sum_{i,j=1;i\neq j}^{n} K\Big(\frac{z_k - c_{ij}^t}{b_t}\Big), \quad k = 1, ..., h, \tag{11}$$

where K is a kernel and b_t is a bandwidth at time t. To ensure that $\hat{g}_t(z_k)$ integrates to unity over the selected range of grid points, the following standard normalization is employed as

$$\hat{f}_t(z_k) = \frac{\hat{g}_t(z_k)}{RIE\Big(\hat{\mathbf{g}}_t\Big)}, \tag{12}$$

where $RIE\left(\hat{\mathbf{g}}_t\right)$ denotes a numerical Riemann sum of $\hat{\mathbf{g}}_t = (\hat{g}_t(z_1), ..., \hat{g}_t(z_h))'$. Following Silverman (1986), a Gaussian kernel with the rule-of-thumb bandwidth $b_t = 1.06\hat{\tau}_t(n(n-1))^{-0.2}$, is considered as a benchmark, where τ_t is the cross-sectional standard deviation of c_{ij}^t. However, given that the spillover density exhibits departure from normality when working with CDS data, right and left skew might be pronounced.[10]

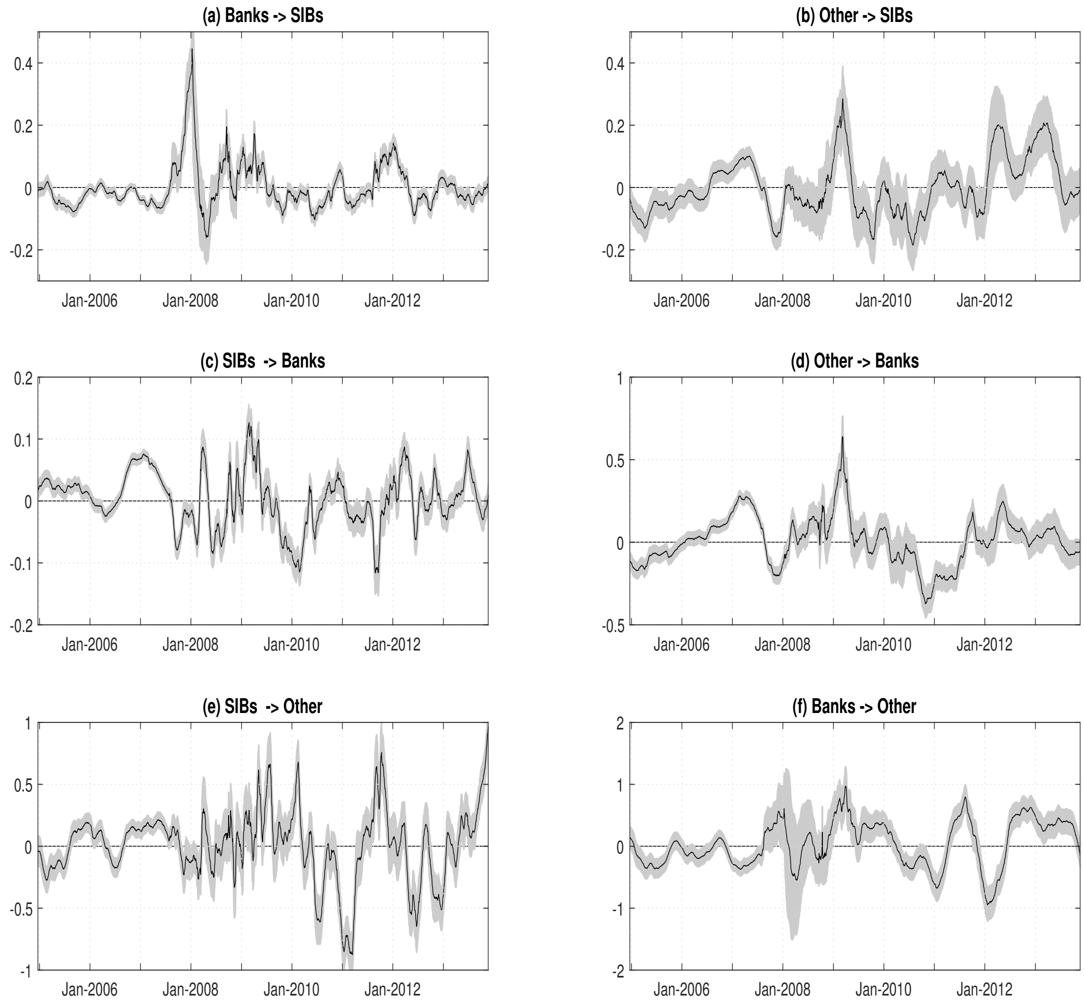

Figure 9: Interconnectedness indices between different groups of global systemically important banks and other financial institutions estimated from equations (6) and (7). 99% confidence intervals are obtained via wild bootstrapping.

[10]An original DY spillover index often has a right skew and is bi-modal in some cases - requiring a careful robustness check including alternative kernels and bandwidths.

The first four moments of the HD spillover index estimates for all 107 nodes are shown in Figure 10, with the moments for the financial companies and sovereigns indices given separately as the dashed and dotted lines respectively. Three things are immediately apparent. First, both skewness and kurtosis of the combined and financial institution networks are positive and co-move between late 2009 and early 2010, which implies significant default risk premia in the financial industry. An interesting pattern in the skewness of these networks is observed on the first day of the GFC (15th of September 2008) when the third moment jumped up by more than 5 basis points. This finding is consistent with Fry et al. (2010) who argue that higher moments are informative in predicting contagion. Second, the spillover variance for the combined and financial networks increases across the sample. Moreover, there is a distinctly observable shift from pre-2008 to post-2008 in the level and volatility of each of the indices. For example, a substantial increase in volatility in mid-2011 coincides with the decision of EU to postpone the bailout plan. Third, while before and during the GFC volatility of the combined network is mainly driven by financial institutions, after the European debt crisis of 2010, the variance of the combined network emanates from both financial institutions and sovereigns. Overall, the sovereigns can be distinguished from the financial institutions in that the increase in variance, skewness and kurtosis comes later in the sample, closer to the problems associated with the Greek and subsequent European sovereign debt crisis.

To summarize the evolution of the whole degree distribution for each day t we construct a sequence of $t = 1, ..., T$ spillover densities. The pre-crisis period is considered as a benchmark characterized by a density f_{nc}, which is compared with f_{cr}, a density during a crisis. Using the following common divergence criteria, an evolution of the spillover density from a non-crisis to a crisis phase can be assessed as

$$DH(\hat{f}_{cr}, f_{nc}) = sup_z|\hat{f}_{cr} - f_{nc}|/sup_z f_{nc}(z), \tag{13}$$

$$DM(\hat{f}_{cr}, f_{nc}) = \int |\hat{f}_{cr}(z)dz - f_{nc}(z)|dz, \tag{14}$$

where $\hat{f}_{cr}$ is the estimated density during the crisis, DH is the Hilbert norm and DM is the distribution mass difference. Each of these quantities is non-negative and takes the value zero if $\hat{f}_{cr} = f_{nc}$. Moreover, $DM \in [0, 4]$, with $DM = 4$ when $\hat{f}_{cr}$ and f_{nc} do not overlap at all over the selected range of grid points.

Using the same spillover densities for the combined network as in Figure 10, we estimate DH and DM quantities for each day t. A non-crisis density f_{nc} is obtained from the historical decomposition spillovers in December 2004. As follows from Figure 11 both DH and DM measures show similar patterns, namely between 2006 and 2008 the dissimilarity between the crisis and non-crisis spillover distributions increases and achieves its peak in February 2012. This peak concurs with the beginning of the second economic adjustment program when Euro area leaders agreed to extend Greek (as well as Irish and Portuguese) loan repayment periods from 7 years to a minimum of 15 years and to cut interest rates to 3.5%. After February 2012 the divergence stays at the relatively high level a sign of a deep crisis in the financial and sovereign CDS markets, confirming the results of Oh and Patton (2016) that the joint probability of distress (a measure of systemic risk) is substantially higher after 2011 than in the pre-crisis period. This finding is also consistent with the pattern of increasing variance from Figure 10, which allows to consider volatility in the CDS market as one of the main sources of systemic risk. Overall, the analysis of the spillover density across a range of moments permits a deeper understanding of the changing interconnectedness of the global CDS market.

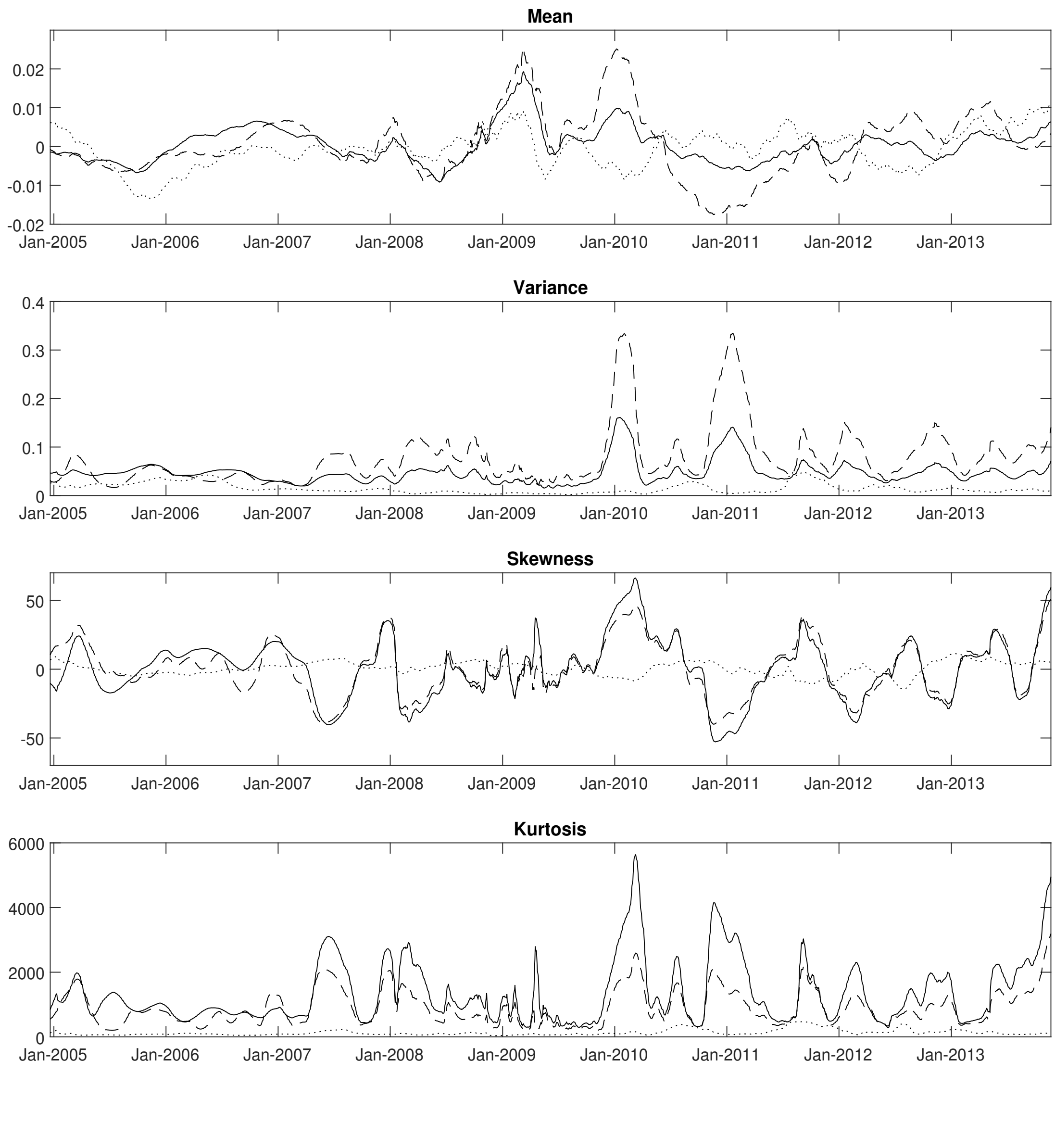

Figure 10: Moments of the spillover density obtained from equations (11) and (12). Continuous line shows the moments of the network density for all 107 entities, dashed line - the financial institution network, dotted line - the sovereign network.

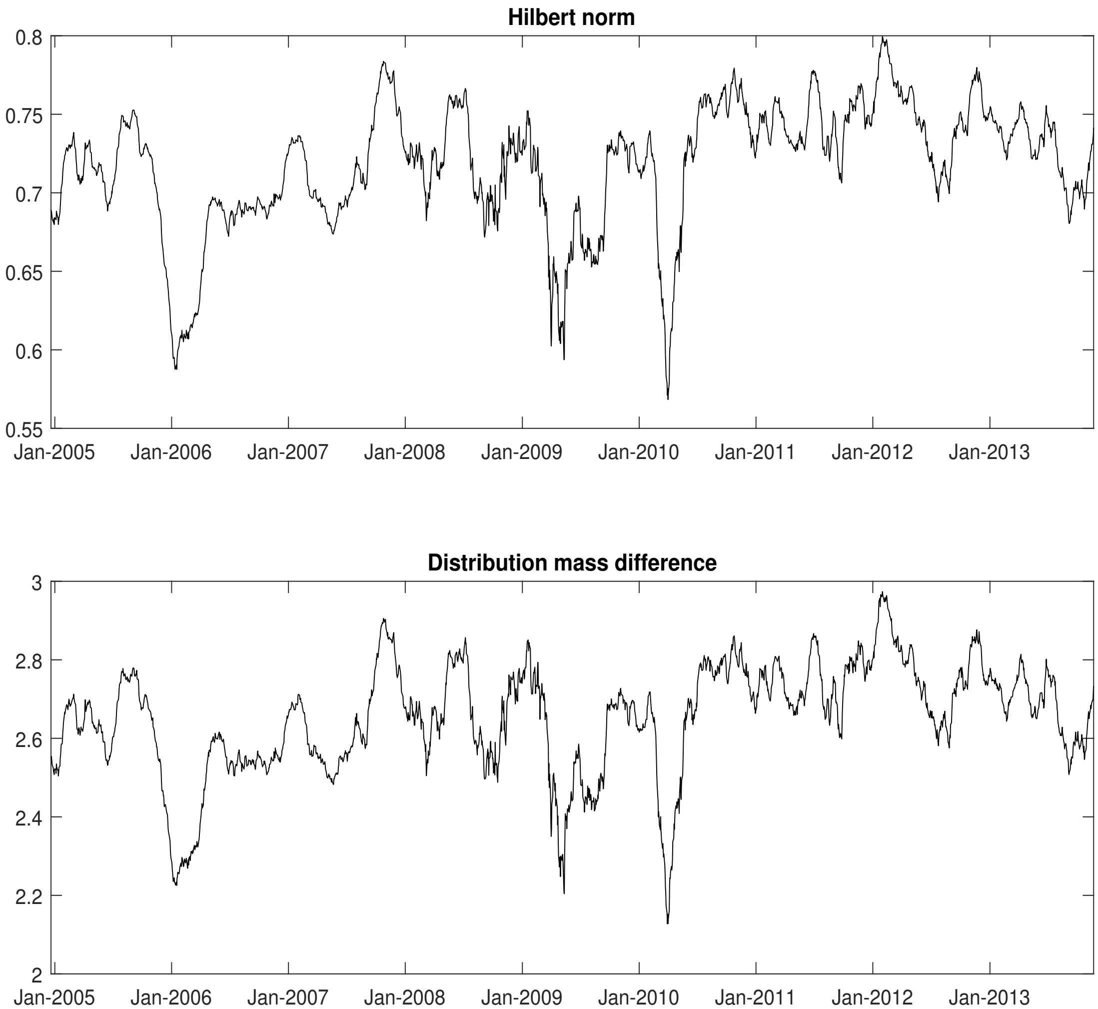

Figure 11: Hilbert norm and Distribution mass difference estimated from equations (13) and (14) respectively for all 107 entities.

6 Conclusion

This paper has shown how an alternative decomposition of the information available in a VAR representation of the strength of network linkages between markets provides information on sources, direction and whether links amplify or dampen the transmission of shocks across a network. We show how the work relates to the popular (unsigned) Diebold and Yilmaz spillover index, and the extra information which can be obtained by knowing not only the source, direction and relative size of shocks, but also the sign (amplifying or dampening) of their impact. We emphasise that this is a different finding from direction. The direction of a shock indicates the flow of a causal event in one node to the other node. The contribution of signing indicates whether that transmission has a positive or negative impact on the volatility of the target node. This is important for policymakers as not all transmissions necessarily increase volatility, and it may be advantageous during periods of stress to be able to identify and target channels which exacerbate conditions whilst allowing those which calm them to remain. An example of where these mechanisms are debated in the literature concerns the role of short-sales restrictions (see for example Dungey, McKenzie and Yalama, 2013).

The proposed interconnectedness measure based on historical decompositions is easy to implement since it does not require a rolling window estimation or any normalization scheme (although these can be imposed if desired). The historical decomposition elements have additive properties and we can obtain not only the total historical decomposition spillover index from a particular source to a given entity, but also contributions of subsets of historical decompositions, and confidence bands for both.

Our empirical findings confirm that both sovereigns and financial institutions significantly contribute to systemic risks of the global CDS market. During the GFC both sovereigns and financial institutions induced high connectedness associated with positive variations in CDS spreads, while after the European debt crisis high spreads were also present for sovereign issuers. Banks and North America are found to be the largest spreaders of shocks, while financial institutions mainly receive systemic risk from others. Developed and emerging countries spread a significant amount of risk which was absorbed by frontier markets. Systemically important global banks and other banks used connections with other institutions as a critical link in the combined network. An examination of the time-varying higher order moments of the spillover density permits a deeper understanding of the changing interconnectedness of the global CDS market.

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