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Coupling direction of the European banking and insurance sectors using inter-system recurrence networks

Peter Martey Addo

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*Preliminary and Incomplete. Please do not QUOTE. *

Peter Martey ADDO[a,b,*]

[a] *Centre National de la Recherche Scientifique (CNRS), France*
[b] *Centre d'Économie de la Sorbonne (CES) - CNRS : UMR8174 - Université Paris I - Panthéon Sorbonne, France*

Abstract

Modern financial systems exhibit a high degree of interdependence making it difficult in predicting. This has raise concerns on the correct identification of coupling direction in financial sectors of the economy. This study explores a "two–way" risk connection between the European banking and insurance sector based on geometrical closeness of observations. Specifically, the study looks at the inter-system recurrence networks in tracing dynamical transitions and detecting coupling direction between these sectors. The overall results shows that the banking sector is central in risk transmission compared to the insurance sector. A comprehensive discussion of the feasibility and relevance of the approach in studying systemic risk is provided.
Keywords: Financial institutions, Recurrence networks, Systemic risk, Recurrence plots

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Email address: `peter.addo@univ-paris1.fr` (Peter Martey ADDO)

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1. Introduction

The threat of systemic risk to the financial system has drawn attention to research on uncovering dependencies among financial sectors, institutions, and economic regions/cross-borders (Hartmann et al. (2005); Cummins and Weiss (2014)). Large bank failures and insurer distress due to the recent global financial crisis have raise concerns on the proper identification of coupling direction between the banking and insurance sectors. Identifying systemic linkages through the financial sectors of the economy is relevant in understanding risk transmissions to enhance policymaking. The convergence of financial activities in the banking and insurance sectors has raised macroprudential concerns on the interconnectedness and systemic dependencies between these sectors to enhance proper monitoring. In other words, the identification of sources of systemic risk is of crucial importance to regulators for proper control.

Recent works documented in literature on systemic dependencies include Billio et al. (2012); Slijkerman et al. (2013); Cummins and Weiss (2014), among others. Most of the approaches are focused on quantification of temporal interrelationships of observations such as correlation methods, conditional mutual information methods (Addo et al. (2015)), and autoregressive models. The question that arises is whether structural characterisation based on geometrical closeness of observations provide insights to uncovering transitions and causal interdependencies. In this work, we consider the inter-system recurrence networks based on geometrical considerations to analyse systemic dependence in the financial sector.

The study examines systemic dependence between bank and insurance sectors of the financial sector to uncover the sector that poses a higher systemic threat to financial stability. We investigate these risk transmission considering the period prior to the global financial crisis, during the crisis, and post-crisis period. In particular, we study how these risk transmissions change over time and under different economic conditions. Uncovering coupling direction between these sectors is very relevant for the introduction of some regulatory measures to enhance financial stability. We claim that the identification of such coupling direction is crucial in identifying sources of instabilities or potential risks in the financial system. Overall, our findings points that risk transmissions have mainly been from the banking sector to the insurance sector and not the vice versa. To the best of our knowledge, this work marks the first application of inter-system recurrence networks in economics and finance.

The structure of the remainder of this paper is as follows. Section 2.1 presents a description of the considered datasets used in studying the coupling direction. Section 2.2 presents an overview of inter-system recurrence networks and it's associated complex network measures useful in studying nonlinear dynamics of underlying time series data. Section 2.3 provides information on available programming packages for the implementation of the method. The empirical application of the method to studying the dynamics and coupling direction prior and during the global financial crisis and the European Sovereign debt crisis is then provided. Finally, in Section 3, we discuss the results and provide concluding remarks on the advantages of this approach in the area of economics and finance.

2. Data & Method

2.1. Data description

The data used in our empirical analysis consist of daily EMU (European Economic and Monetary Union) MSCI Bank sector equity total return index and Insurance sector equity total return index over the period (29/12/2000–23/04/2015). The start date of the sample is chosen in order to study coupling direction dynamics prior and during the global financial crisis and the European Sovereign debt crisis. Our daily data are sourced from *Macrobond* database.

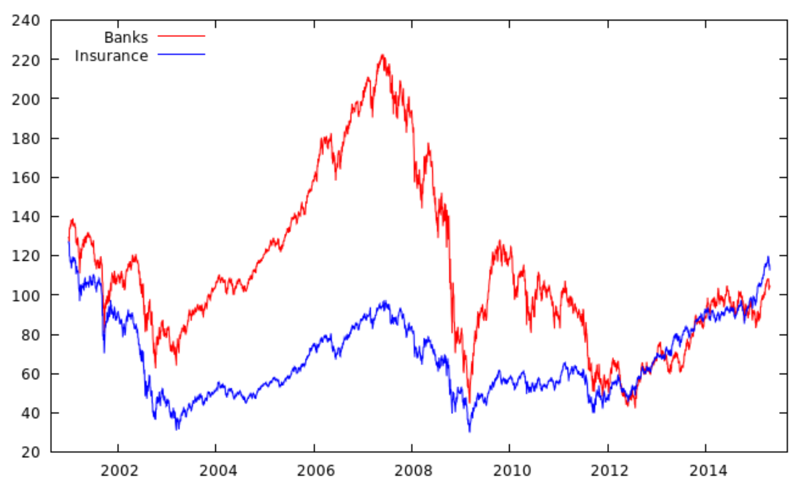


Figure 1: Daily EMU (European Economic and Monetary Union) MSCI Bank sector equity total return index and Insurance sector equity total return index over the period (29/12/2000–23/04/2015).

2.2. *Inter-System Recurrence Network & Measures for Coupling direction*

Recurrence network analysis has been successfully used in tracing dynamical transition in non-stationary time series based on mutual proximity of state vectors (observations) in phase space (Marwan et al. (2009); Donner et al. (2010b, 2011b)). Recurrence networks make use of the geometrical closeness in phase space via recurrence structure of the underlying time series by representating these structures as a connectivity pattern of an associated complex network (Donner et al. (2011a); Donges et al. (2012)). Let $\{b_i\}_{i=1}^{N_b}$ and $\{s_j\}_{j=1}^{N_s}$ represent realisations of banking sector B and insurance sector S recorded at times t_i $(i = 1, 2, \cdots, N_b)$ and t_j $(j = 1, 2, \cdots, N_s)$, respectively. Here $b_i = B(t_i)$ and $s_i = S(t_j)$. The recurrence matrix associated with the banking sector (similarly the insurance sector) is given by

$$\mathcal{R}_{ij}^{B}(\varepsilon_b) = \Theta(\varepsilon_b - \|b_i - b_j\|), \tag{1}$$

and the cross-recurrence matrix for both sectors defined by

$$\mathcal{CR}_{ij}^{BS}(\varepsilon_{bs}) = \Theta(\varepsilon_{bs} - \|b_i - s_j\|), \tag{2}$$

where $\|\cdot\|$ denotes a suitable distance norm (i.e. say the supremum norm), and $\Theta(\cdot)$ is the Heaviside function. The threshold $\varepsilon_{\cdot}$ for the recurrence analysis is chosen to be equal to $\sigma\sqrt{m}/10$, where σ is the fluctuation level in signal, m is the embedding dimension of the signal (Letellier (2006)). This choice of $\varepsilon_{\cdot}$ is such that the value corresponds to 10% of the maximum phase space diameter or such that the recurrence rate is 10% (Schinkel et al. (2008); Thiel et al. (2002); Marwan et al. (2007)). Measures based on the emergence of line structures of the plot of the recurrence matrix (1) are known as recurrence quantification analysis (RQA) Zbilut and Webber (1992); Marwan and

Kurths (2002); Marwan et al. (2007). These measures are useful in characterising the dynamics and tracing transitions in the underlying time series. The concept of recurrence plots have been extended to complex network perspective by defining an adjacency matrix associated with equation (1) as

$$\mathcal{A}_{ij}^{B} = \mathcal{R}_{ij}^{B}(\varepsilon_b) - \delta_{ij}, \tag{3}$$

where $\delta_{i,j}$ denote Kronecker's delta ($\delta_{i,j} = 1$ if $i = j$, otherwise $\delta_{i,j} = 0$). The adjacency matric can be viewed as the recurrence matrix with self-loops removed. The equation (3) defines the recurrence network of an underlying data (Marwan et al. (2009); Donner et al. (2010b, 2011b)). These networks have been successfully used in the identification of dynamical transitions in marine palaeoclimate records (Donges et al. (2011)). The first application of recurrence networks and its associated network measures in economics was in Addo (2015). The feasibility of this network approach in studying spatial dependencies, and tracing dynamic transitions in sovereign credit default swaps and government bond yields prior and during the European debt crisis was introduced in Addo (2015). In this work, we focus on an inter-sectoral analysis by the means of inter-system recurrence networks as a new extension to the application of recurrence networks in economics.

Using the definition of cross-recurrence matrix (2) and recurrence network (3), the inter-system recurrence network is defined by

$$\mathcal{A}(\varepsilon) = \mathcal{ISR}(\varepsilon) - \mathcal{I}_N, \tag{4}$$

where $\mathcal{ISR}$ is the inter-system recurrence matrix given by

$$\mathcal{ISR}(\varepsilon) = \begin{pmatrix} \mathcal{R}^B(\varepsilon_b) & \mathcal{CR}^{BS}(\varepsilon_{bs}) \\ \mathcal{CR}^{SB}(\varepsilon_{bs}) & \mathcal{R}^S(\varepsilon_s) \end{pmatrix} \tag{5}$$

with $\varepsilon = \begin{pmatrix} \varepsilon_b & \varepsilon_{bs} \\ \varepsilon_{bs} & \varepsilon_s \end{pmatrix}$, $N = N_b + N_s$, $\mathcal{I}_N$ is the N-dimensional identity matrix, and $\mathcal{CR}^{BS}$ denoting the cross-recurrence matrix between the banking sector and the insurance sector. It is worth pointing out that $\mathcal{R}^B = \mathcal{CR}^{BB}$, $\mathcal{R}^S = \mathcal{CR}^{SS}$, $\mathcal{CR}^{SB} = [\mathcal{CR}^{BS}]^T$ by definition (Feldhoff et al. (2012)). The threshold ε for each sector is chosen to be equal to $\sigma/10$, where σ is the fluctuation level in signal (Letellier (2006); Schinkel et al. (2008)), with ε_{bs} chosen to be the $\min\{\varepsilon_b, \varepsilon_s\}$. Given the presence of noise in the macro-financial time series, and following a confirmed rule of thumb for RQA (Schinkel et al. (2008)), the recurrence threshold ε is chosen such that the link density is close to 0.05 with the internal recurrence rates $\lesssim 10\%$ (Donner et al. (2010a); Schinkel et al. (2008)). From a complex network perspective, the inter-system recurrence network (4) provides a novel way of studying the mutual inter-relationships between different sectors. Unlike other methods of time series analysis including recurrence plot and RQA, recurrence networks rely on geometric considerations and do not require time information. This feature is essential in the area of economics & finance where variables of interest could have different sampling frequency. For instance, in studying the coupling direction between macroeconomic indices (usually sampled quarterly) verses financial sector indices sampled at relatively higher frequencies. We now discuss how measures associated with the inter-system recurrence network will be useful in identifying coupling direction between the banking sector and insurance sector. In Table (2), the expected signatures of inter-system recurrence network measures in different coupling situation is provided (Feldhoff et al. (2012); Donges et al. (2012)). The coupling directions are based on the definitions of global cross-clustering coefficient and cross-transitivity coefficient presented in Table (1). In general, the transitivity coefficient is a more robust measure than the global clustering coefficient especially in short time series (Newman (2002); Saramaki et al. (2007); Donner et al. (2010b); Donges et al. (2011)).

Name	Definition
cross-degree	$k_v^{BS} = \sum_{q \in V_S} \mathcal{A}_{vq}$
local cross-clustering coefficient	$\mathcal{C}_v^{BS} = \frac{1}{k_v^{BS}(k_v^{BS}-1)} \sum_{p,q \in V_S} \mathcal{A}_{vp}\mathcal{A}_{pq}\mathcal{A}_{qv}, \quad \mathcal{C}_v^{BS} = 0 \text{ iff } k_v^{BS} < 2$
global cross-clustering coefficient	$\mathcal{C}^{BS} = \langle \mathcal{C}_v^{BS} \rangle_{v \in V_B}$
cross-transitivity	$\mathcal{T}^{BS} = \frac{\sum_{v \in V_B; p,q \in V_S} \mathcal{A}_{vp}\mathcal{A}_{pq}\mathcal{A}_{qv}}{\sum_{v \in V_B; p,q \in V_S} \mathcal{A}_{vp}\mathcal{A}_{vq}}$

Table 1: Measures for inter-system recurrence network (Feldhoff et al. (2012); Donges et al. (2012)) based on the adjacency matrix (4), where $v \in V_B$ and $p, q \in V_S$ denote vertices of intra-recurrence network of Banking Sector and Insurance Sector respectively. $\langle \cdot \rangle_{v \in V_B}$ denotes the average over all vertices $v \in V_B$ in Sector B. Similarly $\mathcal{C}^{SB}$ and $\mathcal{T}^{SB}$ can be obtained by definition.

2.3. Implementation

In the implementation of the recurrence networks and calculation of complex network measures, we make use of the `Python` programming language, and in particular the package "`pyunicorn`". The `Python` packages

Relation	Coupling direction
$\mathcal{T}^{BS} \approx \mathcal{T}^{SB}, \quad \mathcal{C}^{BS} \approx \mathcal{C}^{SB}$	no coupling
$\mathcal{T}^{BS} \approx \mathcal{T}^{SB}, \quad \mathcal{C}^{BS} \approx \mathcal{C}^{SB}$	$B \longleftrightarrow S$
$\mathcal{T}^{BS} > \mathcal{T}^{SB}, \quad \mathcal{C}^{BS} > \mathcal{C}^{SB}$	$S \longrightarrow B$
$\mathcal{T}^{BS} < \mathcal{T}^{SB}, \quad \mathcal{C}^{BS} < \mathcal{C}^{SB}$	$B \longrightarrow S$

Table 2: Signatures of Coupling based on the global cross-clustering coefficient and cross-transitivity recurrence network measures. $\mathcal{T}^{SB}$ and $\mathcal{C}^{SB}$ denotes the cross transitivity and global cross-clustering coefficient of S with respect to B respectively. The unidirectional coupling is denoted by the arrow "$\longrightarrow$", whilst the arrow "$\longleftrightarrow$" denotes a bidirectional coupling. See Donges et al. (2012); Feldhoff et al. (2012) for a detailed discussion.

"`NetworkX`" and "`PyGraphviz`" have been used for the visualization of network graphs. Following Addo (2015), we make use of the Los Alamos National Laboratory (lanl) internet routes algorithm for the graphical representation of the complex networks based on the adjacency matrices.

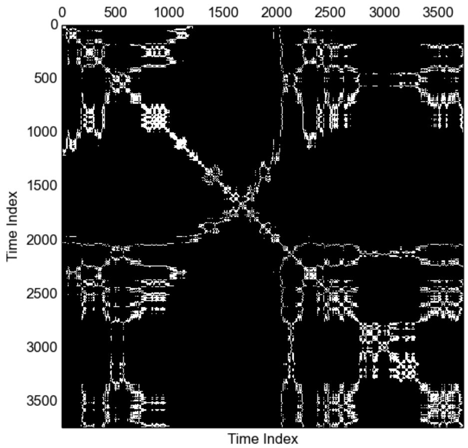
In the section that follows, we will present the results on detecting coupling directions in banking and insurance sectors by means of inter-system recurrence networks described in Section (2.2). A discussion of the feasibility and relevance of the approach in studying "two–way" (bivariate) risk connections among sectors is then presented.

3. Discussion of Results & Concluding Remarks

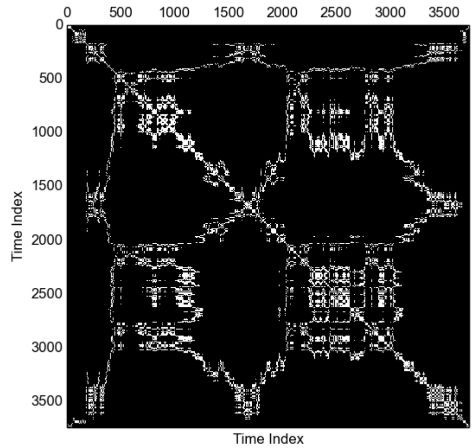
In this section, we present results on the empirical application of inter-system recurrence networks in detecting coupling direction between two sectors of the European financial sector. Figure 1 shows the plot of the daily

EMU MSCI Bank sector equity total return index and Insurance sector equity total return index over the period (29/12/2000–23/04/2015). In general, the banking sector returns were relatively higher compared to the insurers especially between year 2003–2009. From this figure, it is evident that the banking sector was strongly hit during the recent global financial crisis. This could be due to risk exposures arising from banking operations on the interbank market and banking assets. The recurrence plots associated with the banking and insurance sectors are displayed in Figure 2a and Figure 2b respectively. We refer to these plots as the "intra-sectoral" recurrence plots. The butterfly-like structures on the diagonal of the recurrence plots in Figure 2 mark times of distress in these financial sectors of the economy (Addo et al. (2013)). Figure 3 shows the cross recurrence plot for the sectors and the graphical representation of the inter-sector recurrence network. The cross recurrence plot displays times that observations in both sectors simultaneously recur. The recurrence plot of the inter-sector recurrence matrix is provided in Figure 4a and the associated degree rank plot in Figure 4b. The recurrence network measures in Table 3 indicates the presence of assortativity patterns with variations in the average path length implying dynamic transitions in the financial system. The results on the coupling direction for the banking and insurance sector across time is presented in Table 4. Overall, we find a coupling direction from the banking sector to the insurance sector which implies the direction of risk transmission between these sectors.

The correct identification of coupling direction in financial sectors of the economy is one of the main challenges in studying in the high degree of interdependence in the financial system. In this paper, we consider a structural



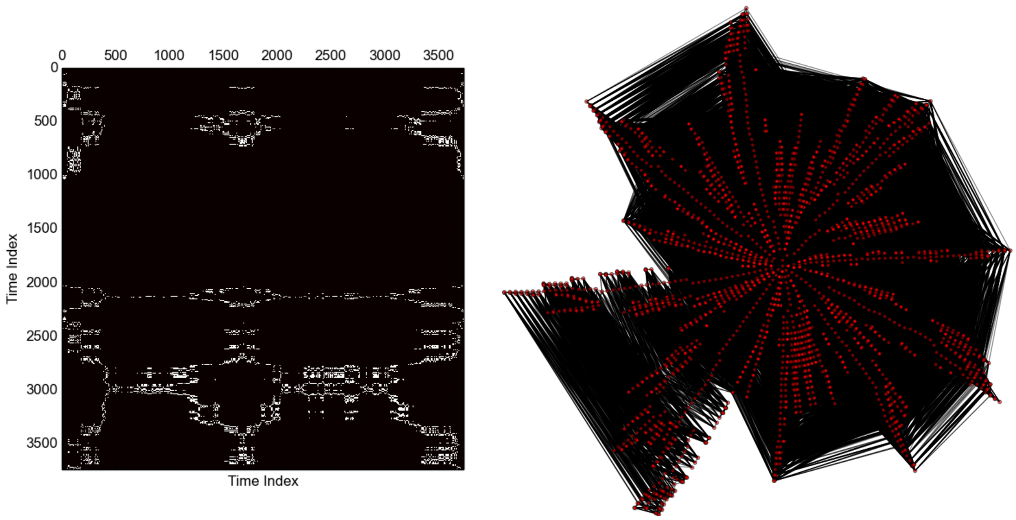
(a) Bank Sector Recurrence Plot



(b) Insurance Sector Recurrence Plot

Figure 2: The recurrence plot of the adjacency matrices of the recurrence network associated with the Banking and Insurance Sectors respectively over period 29/12/2000–23/04/2015. This can also be referred to as the "intra-sectoral" recurrence plots. The time indexes corresponds to the following calender dates: "500"= 11/28/2002, "1000" = 10/28/2004, "1500"= 9/28/2006, "2000"= 8/28/2008, "2500"= 7/29/2010, "3000"= 6/28/2012, "3500"= 5/29/2014.

characterisation of non-stationary multivariate data based on geometrical closeness of observations in providing insights to uncovering transitions and causal interdependencies. Unlike the wide class of methods which are based on the quantification of temporal interrelationships between observations, recurrence networks takes into account the mutual proximity relationships of observations and does not require stationarity or any pre-processing of the original data (Addo (2015)). We have shown the usefulness of recurrence networks in identifying dynamical transitions (regime/structural change) (see

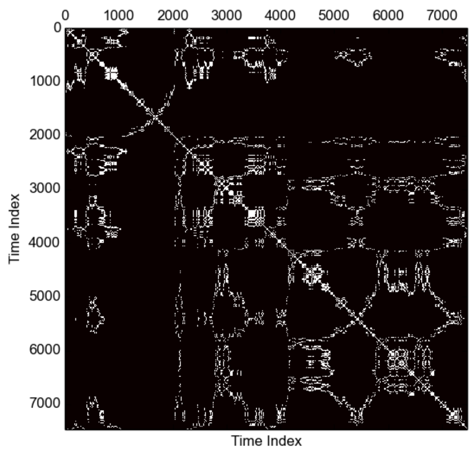


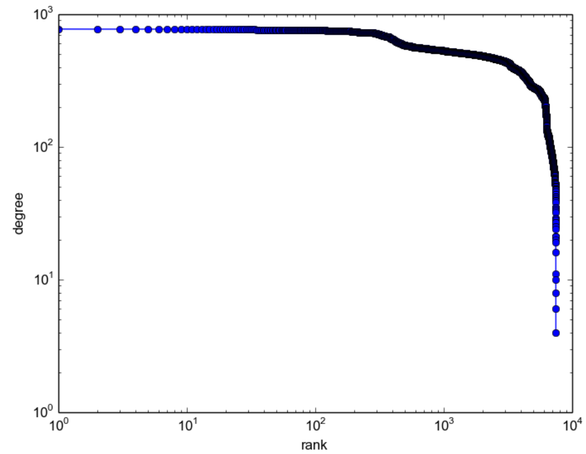
(a) Bank and Insurance Sector Cross-Recurrence Plot

(b) Graphical representation of the inter-sector recurrence network.

Figure 3: The recurrence plot of the cross-recurrence of the Banking and Insurance Sectors over period 29/12/2000–23/04/2015. The time indexes corresponds to the following calender dates: "500"= 11/28/2002, "1000" = 10/28/2004, "1500"= 9/28/2006, "2000"= 8/28/2008, "2500"= 7/29/2010, "3000"= 6/28/2012, "3500"= 5/29/2014. Figure (3b) is the recurrence network with the Internet lanl Routes representation.

Figure 2 and Table 3), which can serve as systemic risk indicators or early warning measures. Specifically, we have provided a comprehensive feasibility of the application of inter-system recurrence networks in identifying coupling direction in the field of economics. Without providing a verdict on whether banks should be designated as systemically important, our analysis indicates that the EMU banking sector is relatively more important than the EMU insurance sector when it comes to its contribution to systemic risk transmission. In other words, our findings suggest that risk transmissions have





(a) Recurrence Plot of the inter-sector recurrence matrix.

(b) Degree rank plot of the inter-sector recurrence network.

Figure 4: A graphical representation of the inter-sector recurrence matrix and the degree rank plot.

Dates	Assortativity	Link density	Average path length	RR^B, RR^S
– 2007	0.8476	0.0469	15.5910	(0.0709, 0.0785)
2007–2009	0.8042	0.0421	13.9078	(0.0728, 0.0687)
2007–2012	0.6827	0.0538	10.5838	(0.0825, 0.0767)
2007–2014	0.6515	0.0590	7.2976	(0.0937, 0.0710)
2007–2015*	0.6851	0.0608	7.3827	(0.0948, 0.0719)

Table 3: Recurrence network measures for the inter-sector interconnectedness of banks and insurers shown in Figure 4a. RR^B, RR^S in the last column denotes the internal recurrence rate for the bank sector and insurance sector respectively. For detailed background on these measures, we refer the reader to Newman (2002, 2003); Donner et al. (2010b); Addo (2015).

Dates	$\mathcal{T}^{BS}$	$\mathcal{T}^{SB}$	$\mathcal{C}^{BS}$	$\mathcal{C}^{SB}$	Coupling direction
– 2007	0.7875	0.9434	0.5491	0.4627	Bank $\hookrightarrow$ Insurance
2007–2009	0.7702	1.000	0.1854	0.9119	Bank $\longrightarrow$ Insurance
2007–2012	0.7565	1.000	0.3724	0.9738	Bank $\longrightarrow$ Insurance
2007–2014	0.7601	1.000	0.4858	0.9804	Bank $\longrightarrow$ Insurance
2007–2015*	0.7620	1.000	0.5907	0.9820	Bank $\longrightarrow$ Insurance
2010–2012	0.7525	1.000	0.3538	0.9923	Bank $\longrightarrow$ Insurance
2010–2014	0.7645	0.8379	0.6712	0.8331	Bank $\longrightarrow$ Insurance
2010–2015*	0.7688	0.7704	0.7729	0.7670	Bank $\hookrightarrow$ Insurance

Table 4: Coupling direction of the banking and insurance sector across time. The date " – 2007" denotes the start date of the sample until the last recorded value for year 2006. The time window of the format "20AA"–"20BB" denotes the period from the start date of year "20AA" to the end date of year "20BB". The last recorded date for the analysis is 2015-04-23 denoted by "2015*". Coupling directions are based on the signatures presented in Table (2). Coupling direction based on only the cross-transitivity network measure $\mathcal{T}$ is represented by the hook arrow "$\hookrightarrow$".

mainly been from the banking sector to the insurance sector and not the vice versa.

To conclude, possible extensions and applications of the approach to systemic risk would be to formulate systemic dependence between two sectors conditional on dependencies among other sectors. In other words, the introduction of a conditional inter-system recurrence network and associated measures to investigate systemic dependencies between two financial subsystem (sectors) in the presence of other sectors. In addition, an introduction of a possible statistical tests on the expected relation associated with coupling direction could serve as a new topic for research. In terms of empirical applications, the proposed approach is not only useful for sectoral systemic dependencies, it could be extended to cross-regional/border analysis to provide insights to systemic risk.

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