Temporal networks in the analysis of financial contagion

Presenter:
Angelos Vouldis
European Central Bank

Co-authored with:

Fabio Franch
European Central Bank

Luca Nocciola
European Central Bank

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Network analysis of financial contagion

- **Financial contagion features:**
  - Originating shocks into segments of the financial system
  - Propagation
  - Amplification & further transmission

⟶ Requires node-level analysis, rather than examination of aggregates only. Time-changing network representations is a natural tool to employ (constant set of nodes remain, evolving set of edges i.e. time-changing topology)

Nodes: Entities participating into the contagion episodes (financial institutions, financial instruments, country-level aggregates)

Edges: Bilateral exposures (stocks), flows of exposures, dependence (e.g. based on correlations), impact (e.g. based on causality tests).

- **Network-based analysis of financial contagion** requires a focus on temporal dimensions to study the dynamics of the phenomenon. However, existing studies employ ‘static’ tools, which analyse the information content of each topology separately.

Limitations of static network analysis

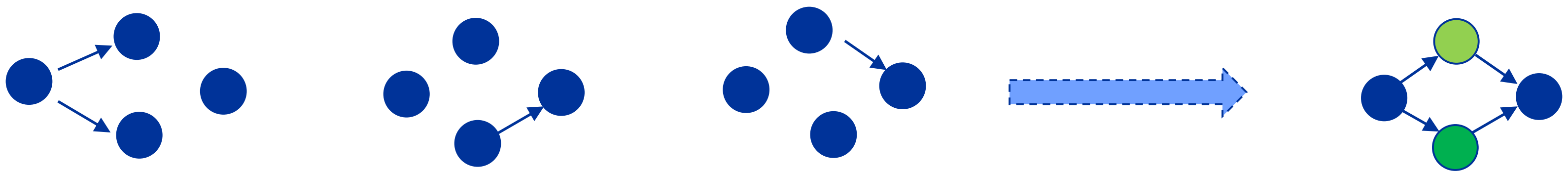
Case 1: use of network snapshots

Snapshot at *t* Snapshot at *t+1*

When each snapshot is examined separately, the transmitting role of the orange node cannot be identified.

Case 2: use of aggregated networks

Snapshot at *t* Snapshot at *t+1* Snapshot at *t+T* **Aggregate network**



The aggregate network depicts the two green nodes as equivalent transmitters, however if *T>>1* this is misleading, as the upper node is most probably a source of a new shock rather than a transmitter of shock originating from the leftward node.
In this case, the aggregate network conflates two different contagion episodes by neglecting the time scale which characterizes each contagion episode and identifies a node as a transmitter when it is actually a source.

Indicative literature review on network analysis of contagion

- **Theoretical literature:** Allen and Gale 2000 (JPE), Acemoglu et al. 2015 (AER)

- **Empirical literature**

  - ***Using bilateral exposures:*** Cocco et al. 2009 (JFI); Bech et al. 2010 (JME); Battiston et al. 2012 (SR); Hale 2012 (JIE); Silva et al. 2018 (JEDC)
  - ***Using yields/returns:*** Lee and Yang 2014 (IRFA); Caporin et al. 2018 (JFS), Corsi et al. 2018 (JFS)
  - ***Using dependence/causality metrics:*** Billio et al. 2012 (JFE); Billio et al. 2016 (WP); Brownlees et al. 2021 (JME)
  - ***Comparing physical and dependence networks:*** Brunetti et al. 2019 (JFE)

- **Surveys:** Bardoscia et al. 2021 (WP)

A taxonomy of tools and applications / aim of the paper

Feature/type of network	**Physical networks**	**Dependence networks**
Edges represent:	Stocks / flows	Dependence of prices/causality
Data used	Bilateral contracts (e.g loans)	CDSs / EDFs / returns / yields
Time-dependence	Persistent	Dynamic
Amenable to static analysis	Sometimes	No

Aim of the paper: We propose a method to identify node centrality incorporating information of multiple, temporally ordered topologies using time-respecting paths and enabling the identification of sources, transmitters and targets of financial contagion. We adopt relevant tools developed for use in other fields (Scholtes et al. 2016 *European Physical Journal B*; Scholtes et al. 2014 *Nature Communications*) in the financial contagion context .

Overview of the paper - methodology

- **We use expected default frequency (EDF) data** provided by *Moody's Analytics*, pertaining to the main segments of the financial sector (banks, insurance firms and shadow banking entities).
  - aggregated for 16 advanced countries (daily data, spanning the period January 2006 to February 2018).

- **Then, a temporal sequence of networks is constructed**, connecting 16 x 3 country-sector pairs.
  - The networks reflect bilateral contagion transmission, in a statistical sense, utilizing the shocks derived after accounting for persistence and heteroskedasticity (through GARCH-based modelling) and conducting model-averaged Granger causality-in-risk tests.

- **Both static and temporal centrality metrics** are computed for each node in the network (betweenness, out-closeness, in-closeness).

Overview of the paper - findings

- **Tight interconnectedness between banks and shadow banks,** with insurance companies less connected with the remaining financial system. Bi-directional feedback loops between banks and shadow banks occur most frequently than other types of links.

- **Role of financial entities during contagion:** based on the ‘chains of contagion’ computed through the second-order aggregated network (time-respecting paths of length 2), we find that
  - **banks** act mainly as sources and transmitters of financial stress
  - **shadow banks** as sources and
  - **insurance firms** as receivers.

- **Temporal centrality metrics** offer more intuitive results compared to static centrality metrics, identifying more clearly the role of financial segments during contagion episodes (e.g. banks vs. shadow banks and insurers).

Definitions (temporal networks & time-respecting paths)

Temporal network: $G^T = (V, E^T)$

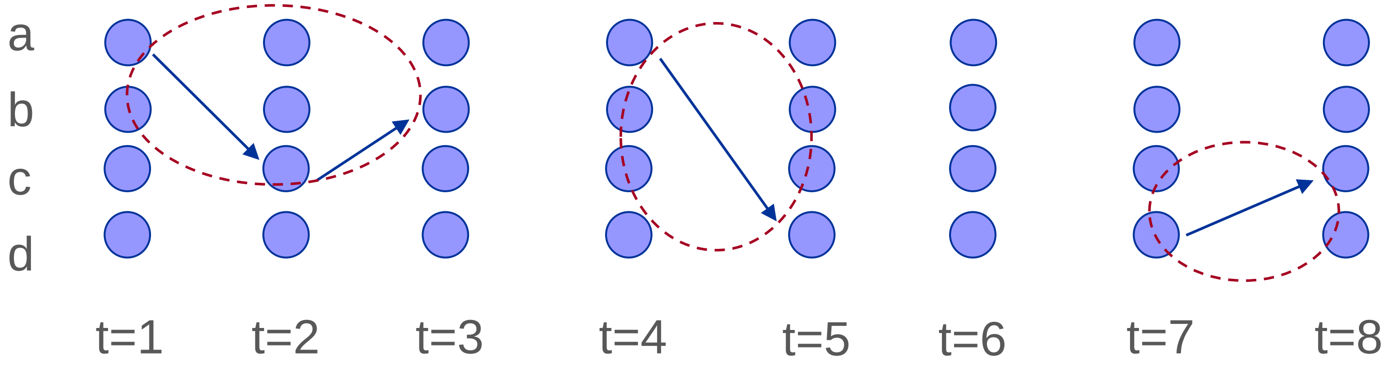
Edges: $E^T \subseteq V \times V \times [0, T]$

Each edge $(x, y; t)$ represents an edge existing during $[t, t + \Delta t]$

Time scale: Δt (reflects time scale of the phenomenon analysed)

Static centrality metrics: $C_t(v) = f(G_t)$ (considers only one snapshot)

Time-respecting paths (given δ, a multiple of Δt)



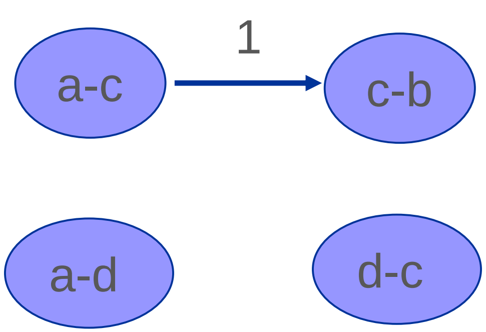
With *δ=1*, only a → c→b, a → d, d→c are time-respecting paths.
a → d→c is not (too long time distance)!

Definitions (n-th order aggregated network)

The concept of a n-th order aggregated network is a Markovian representation of non-Markovian temporal network and enables the computation of temporal centrality metrics for each node.

A n-th order aggregated network $G^{(n)}$ comprises n-th order nodes $V^{(n)} \subseteq V^n$ and n-th order edges $E^{(n)} \subseteq V^{(n)} \times V^{(n)}$.

A n-th order edge (v, ω) exists if the two nodes form a path of length *n* in the original network: $(v_1, v_2 = \omega_1; t_1), \ldots, (v_n, v_{n-1} = \omega_n; t_n)$



A *n*-th order aggregated network accommodates non-Markovian features, as the *n*-th edge of a time-respecting path of length *n* depends on the previous *n-1* edges.

Definitions (temporal centrality metrics)

Second-order betweenness centrality:

$$BC^{(2)}(v) = \sum_{\substack{x \neq y \in V, \\ u - x \in V^{(2)}, \\ y - w \in V^{(2)}}} |\{p \in P^{(2)}(u - x, y - w; v) : len(p) = dist^{(2)}(u, w)\}|$$

Second-order out-closeness centrality (distances *to* all other nodes):

$$CC^{(2)}(v) = \sum_{u \neq v} \frac{1}{dist^{(2)}(u, v)}$$

For the second-order in-closeness centrality, we sum distances *from* all other network nodes.

Scope of data

- 16 advanced economies (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Portugal, Slovakia, Spain, Sweden, United Kingdom, United States)

- 3050 daily observations (January 2006 – February 2018) of EDFs, representing forward-looking probabilities of default (based on Vasicek's formulation of option contracts).

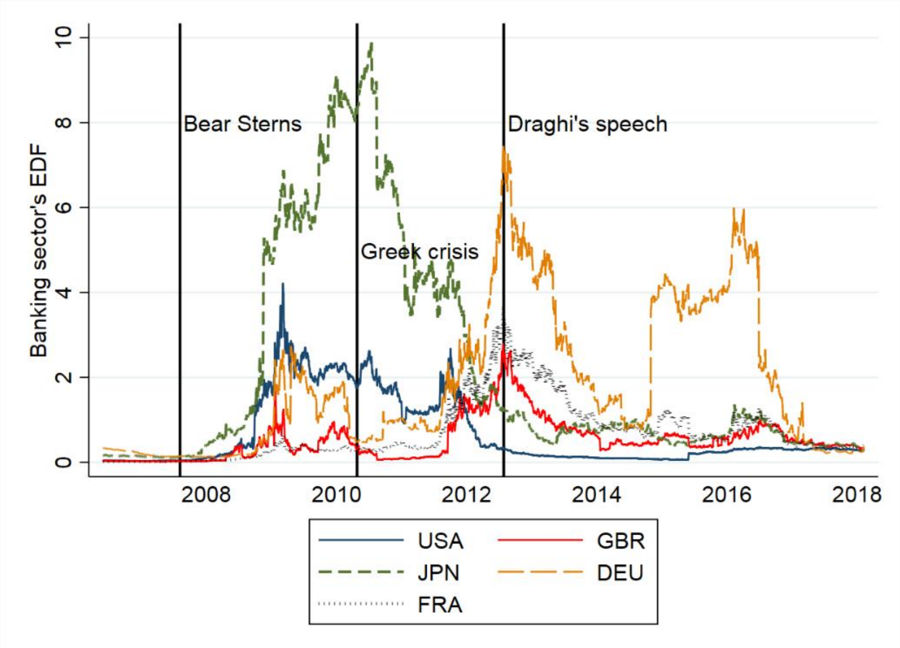
- Three segments of the financial system: banks, shadow banks, insurers. We aggregate the data at the country level, weighted by assets.

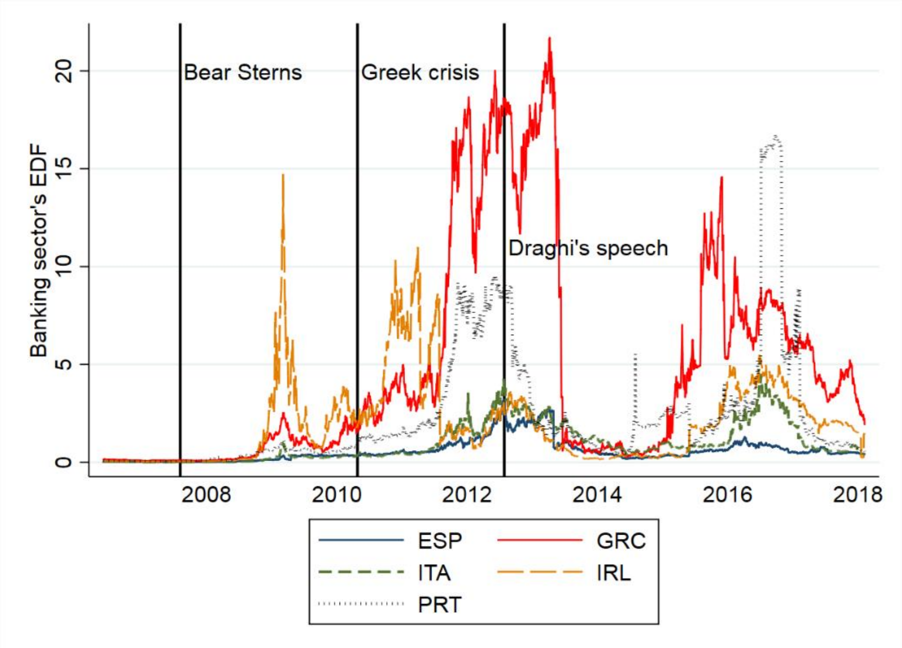
- Rolling-window approach leads to the construction of 90 snapshots corresponding to 30-day steps and 360 days of duration.

- Changing composition of sample.

Descriptive statistics

EDFs for banks (separately for large and distress countries)

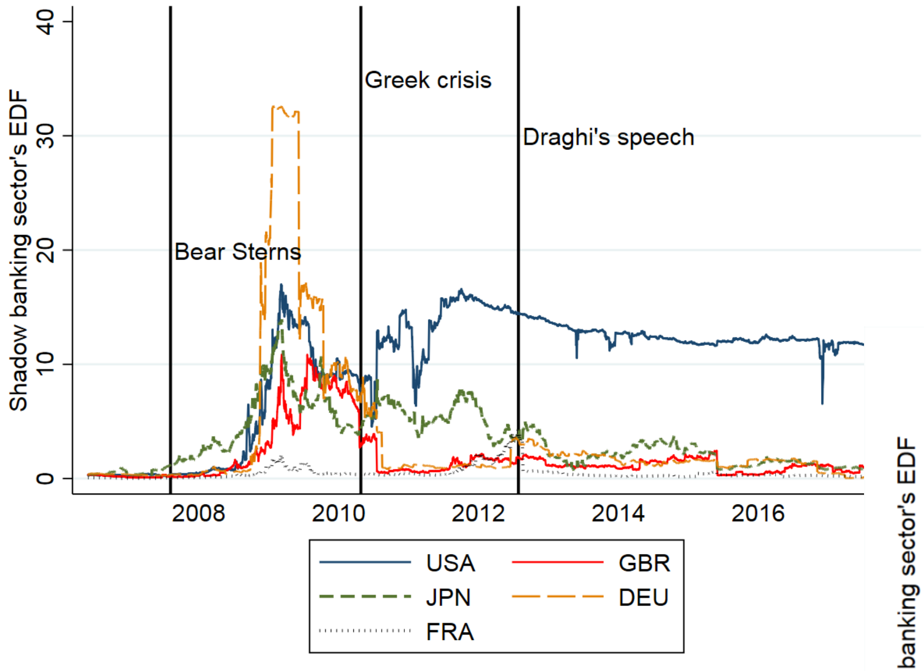


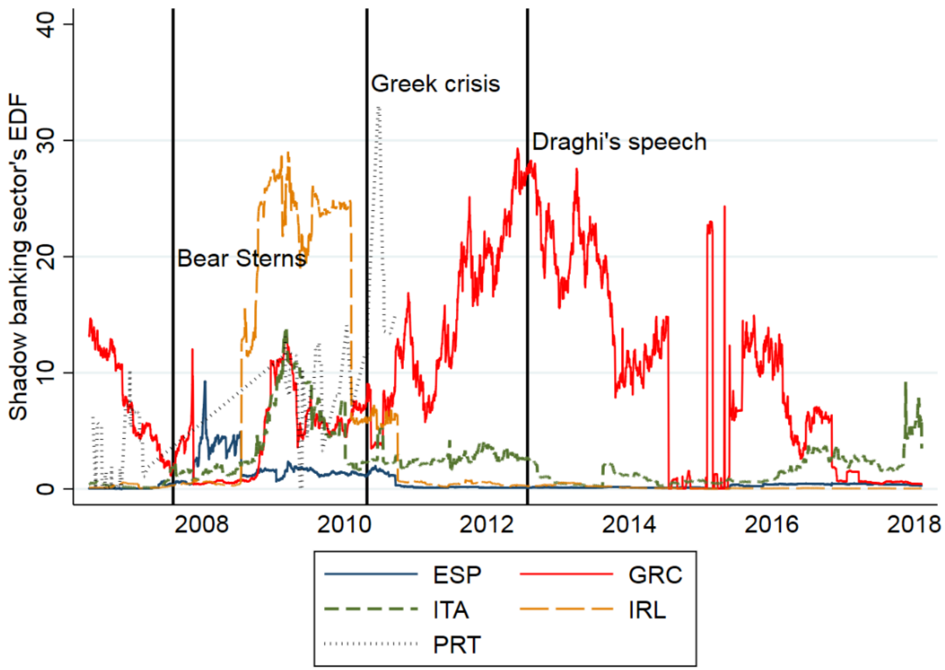


Overall, the most elevated risk levels were observed during the global and the European financial crises, with bouts of financial stress occurring after Mario Draghi's speech in 2012 especially in the banking sectors of 'distress' countries after 2015. A significant degree of heterogeneities across countries and financial institutions is apparent.

Descriptive statistics

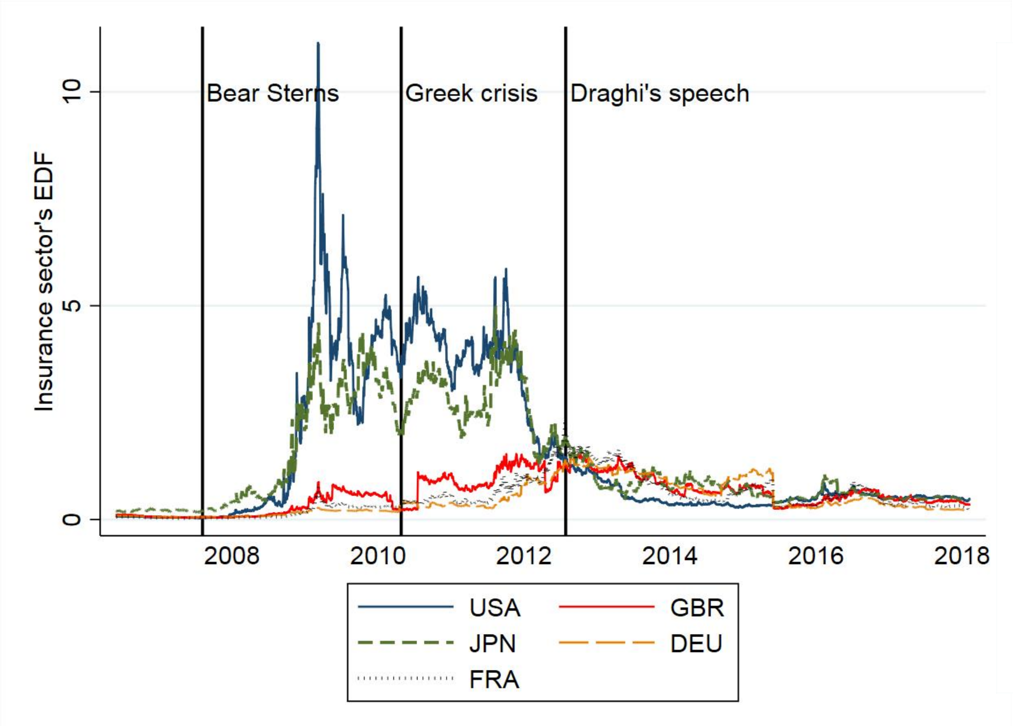
EDFs for shadow banks (separately for large and distress countries)

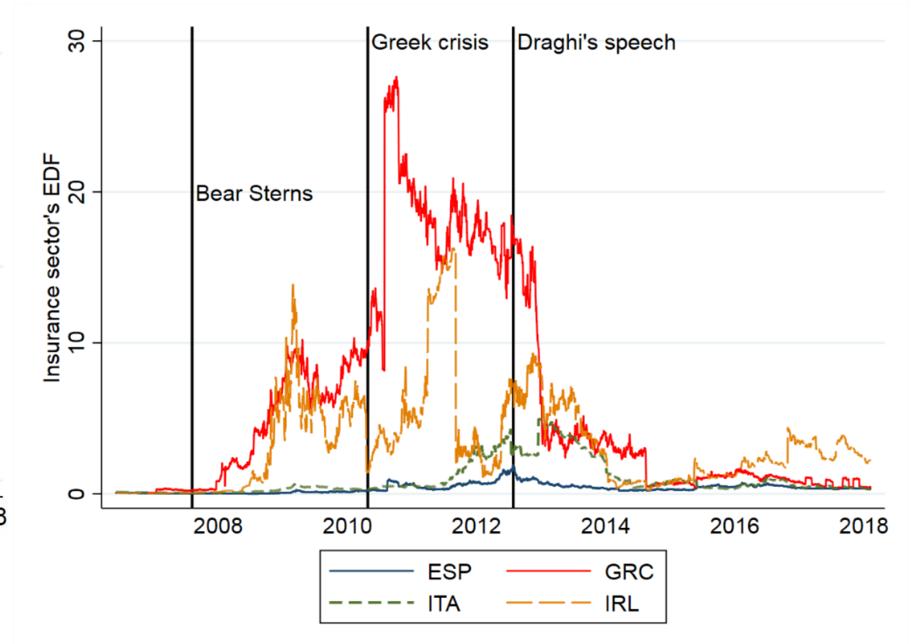




Descriptive statistics

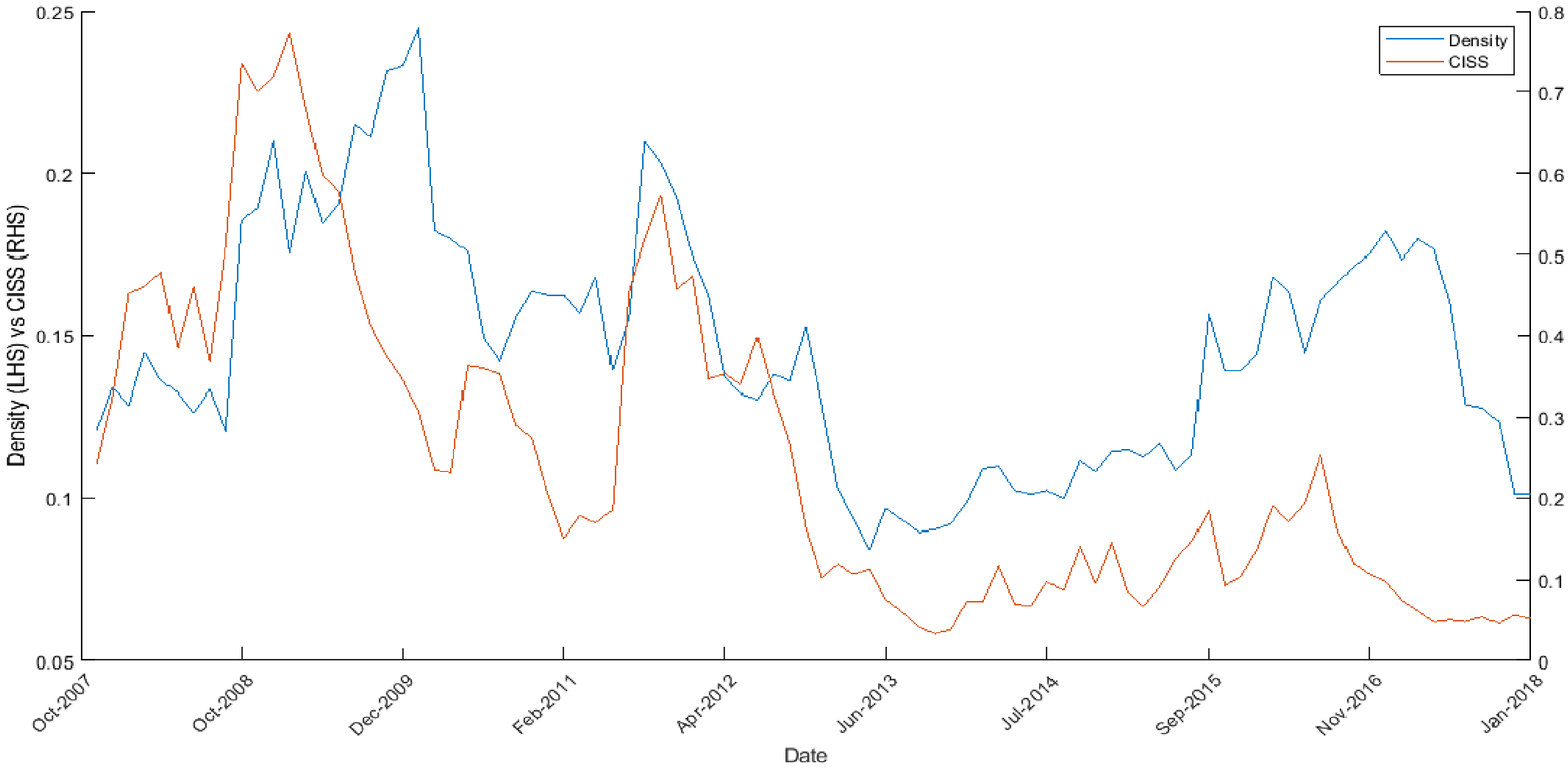
EDFs for insurance firms (separately for large and distress countries)





Network density across time

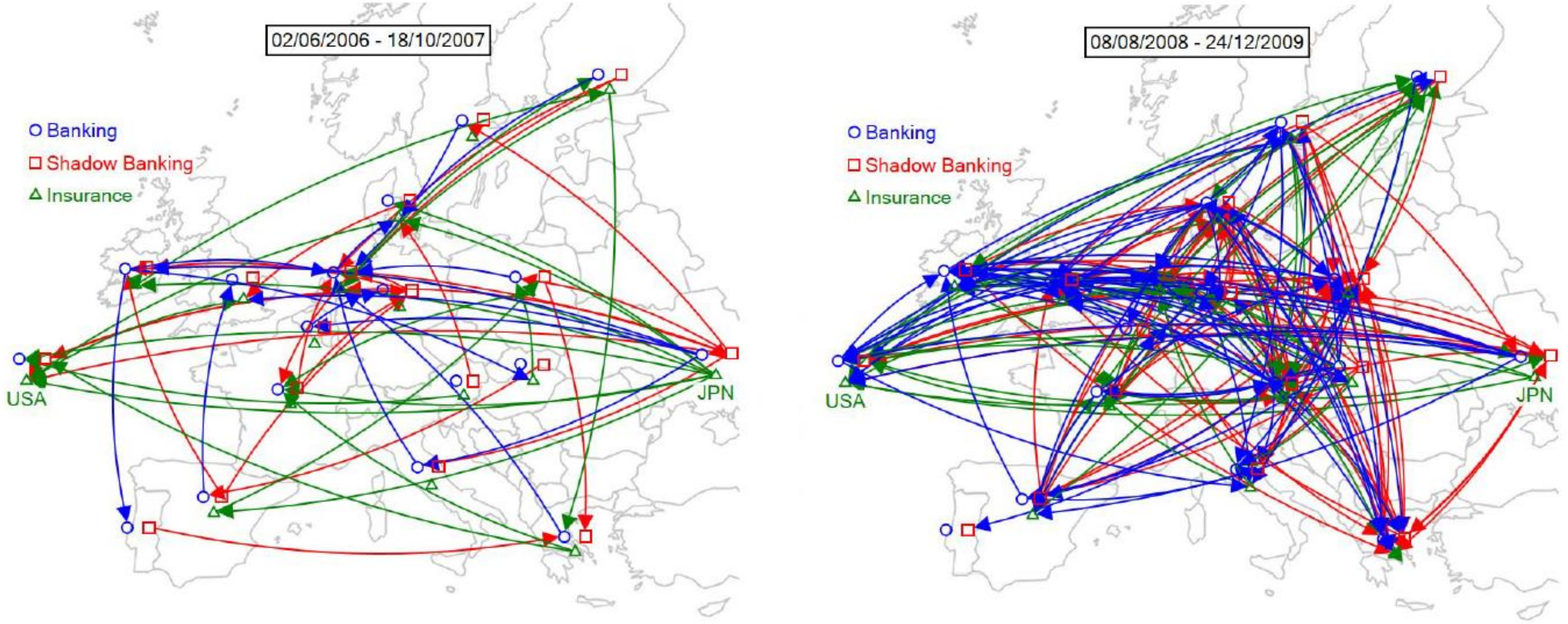
Comparison with CISS



Higher density during periods of stress. The two indicators are relatively synchronized.

Network snapshots across time

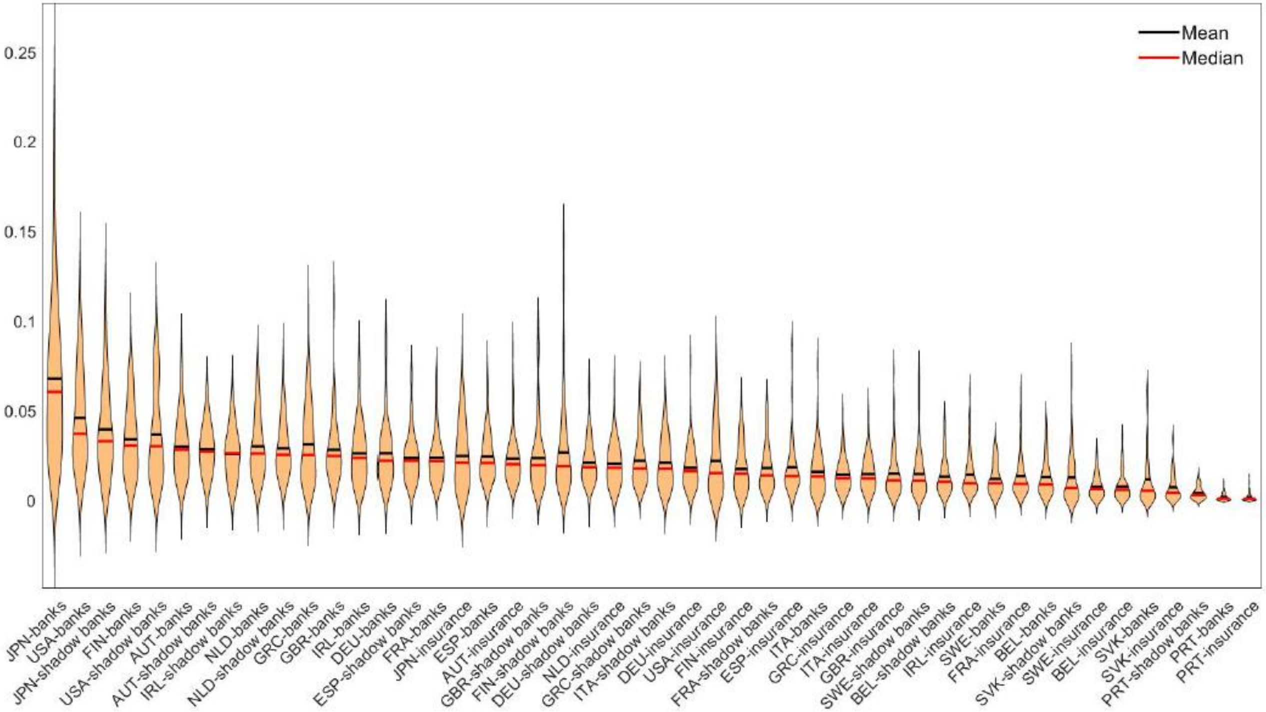
Topology changes significantly across time. For example, during the period marking the outbreak of the global financial crisis:



The increasing density during periods of elevated financial stress has been noted in the literature (e.g. see Brunnetti et al. 2019 for correlation networks).

Centrality of nodes: betweenness

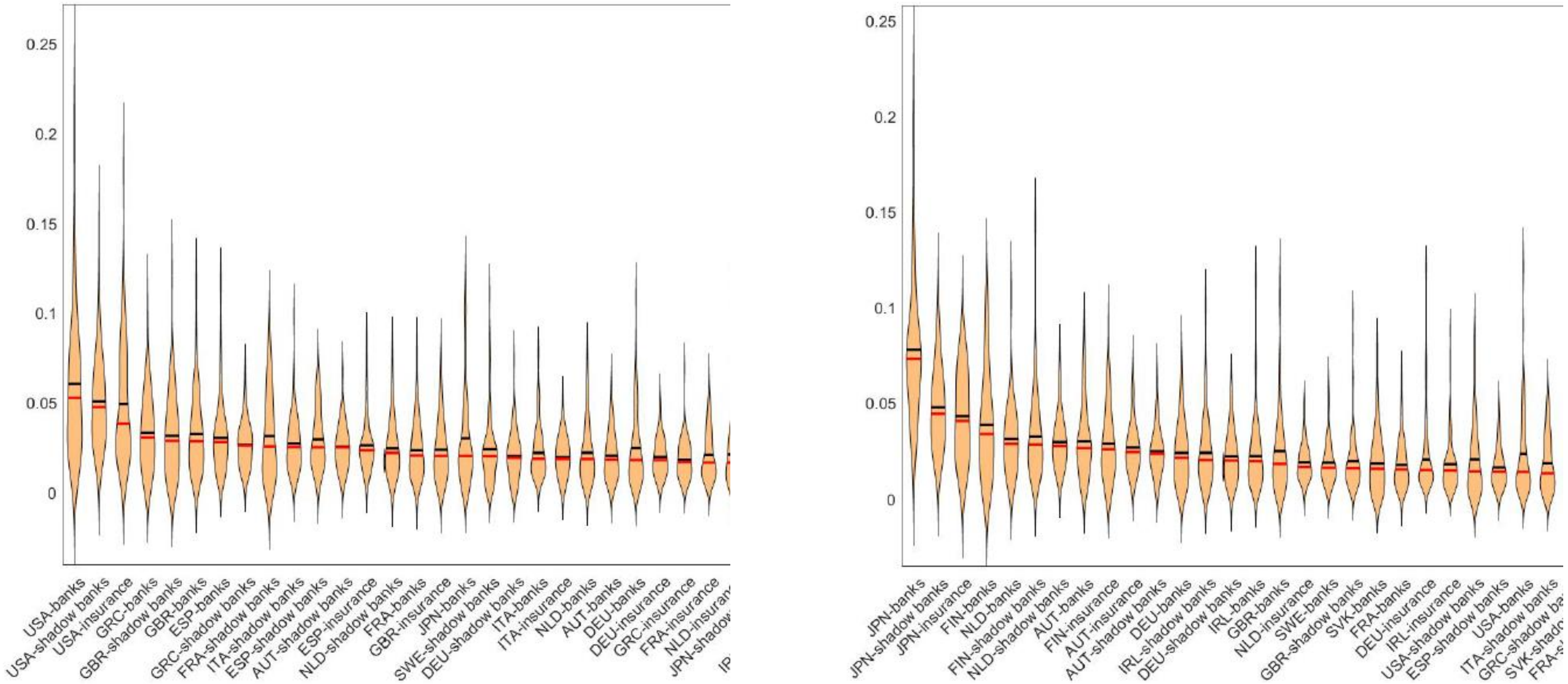
Static metrics are computed first. Ranking is done based on the median as these metrics are calculated separately for each snapshot (→ 90 values each).



The banking sectors of the two largest countries (US, JP) are ranked the highest. Betweenness metric does not distinguish between transmitters and receivers → both crisis-hit and countries with stronger fundamentals are high.

Centrality of nodes: out- and in-closeness

Extended forms of out- and in-degree metrics. Large and crisis-hit countries are high on the out-closeness based ranking. ‘Safer’ countries are ranked higher when the in-closeness metric is used.



Banks and shadow banks tend to rank higher than insurers.

Centrality of nodes: temporal metrics

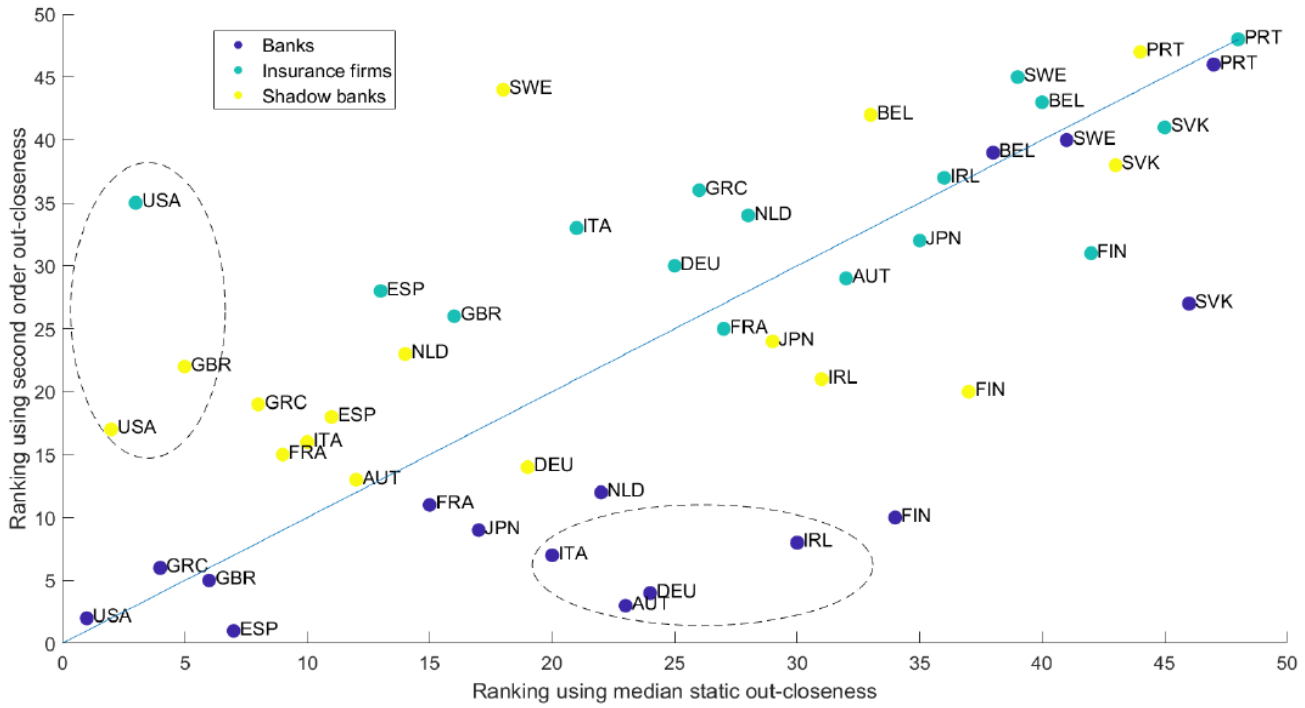
The corresponding temporal metrics attain one value for each country-sector pair, as they consider all 90 topologies.

Out-closeness		In-closeness		Betweenness	
USA-B	59	GBR-B	59	JPN-B	88.9
ESP-B	59	IRL-B	58.5	BEL-Ins	59.5
GRC-B	58.5	JPN-B	58	IRL-Sb	45.1
AUT-B	58.5	AUT-B	58	FIN-B	41.6
GBR-B	58.5	FIN-B	58	GRC-B	36.5
ITA-B	58.5	NLD-B	57.5	NLD-B	24.7
DEU-B	58.5	GRC-B	57.5	DEU-B	23.5
JPN-B	58	DEU-B	57.5	JPN-Ins	22.5

The banking sector is more clearly distinguished when the temporal metrics are used, based on the 2nd order aggregated network.
Also, shadow banks represent more clearly the second most important sector and insurance comes last.

Centrality of nodes: comparison between static and temporal metrics

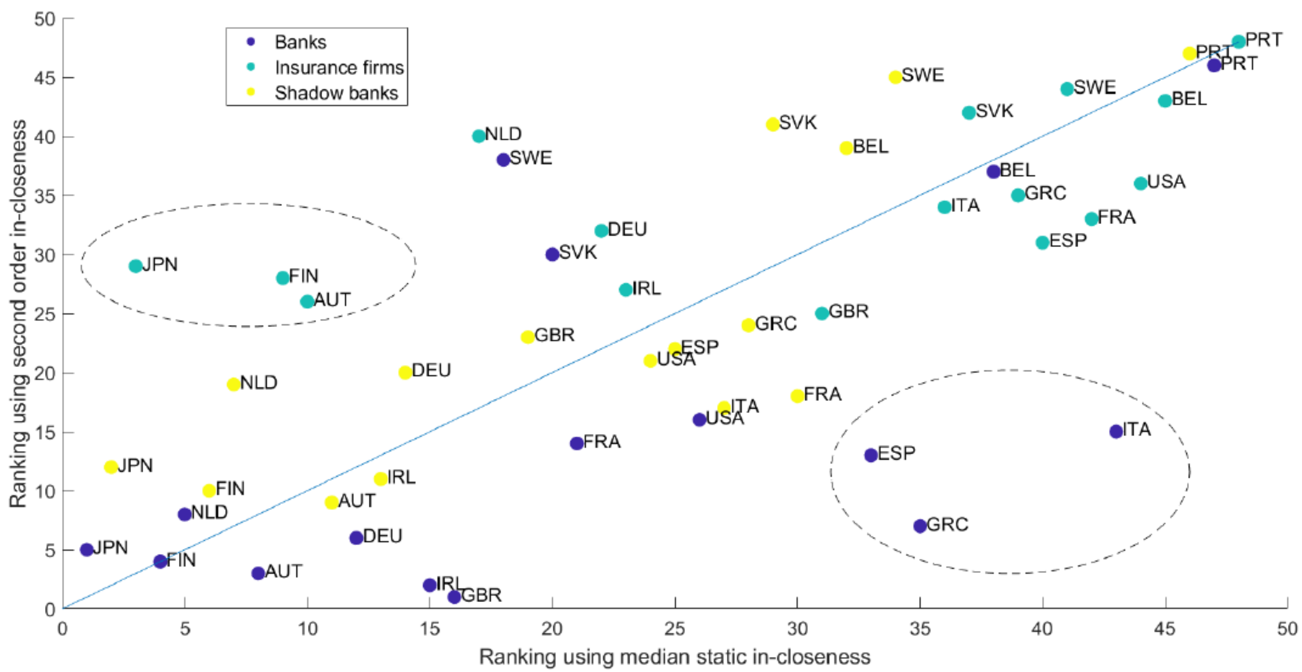
The comparison of out-closeness centralities shows that the banking sectors of crisis-hit countries, such as Italy and Ireland, and also of Germany and Austria, feature higher values when the temporal metric is used.



By contrast, the shadow banking sector of US, JP and the insurance sector of the UK are ranked lower when the second-order out-closeness centrality is used.

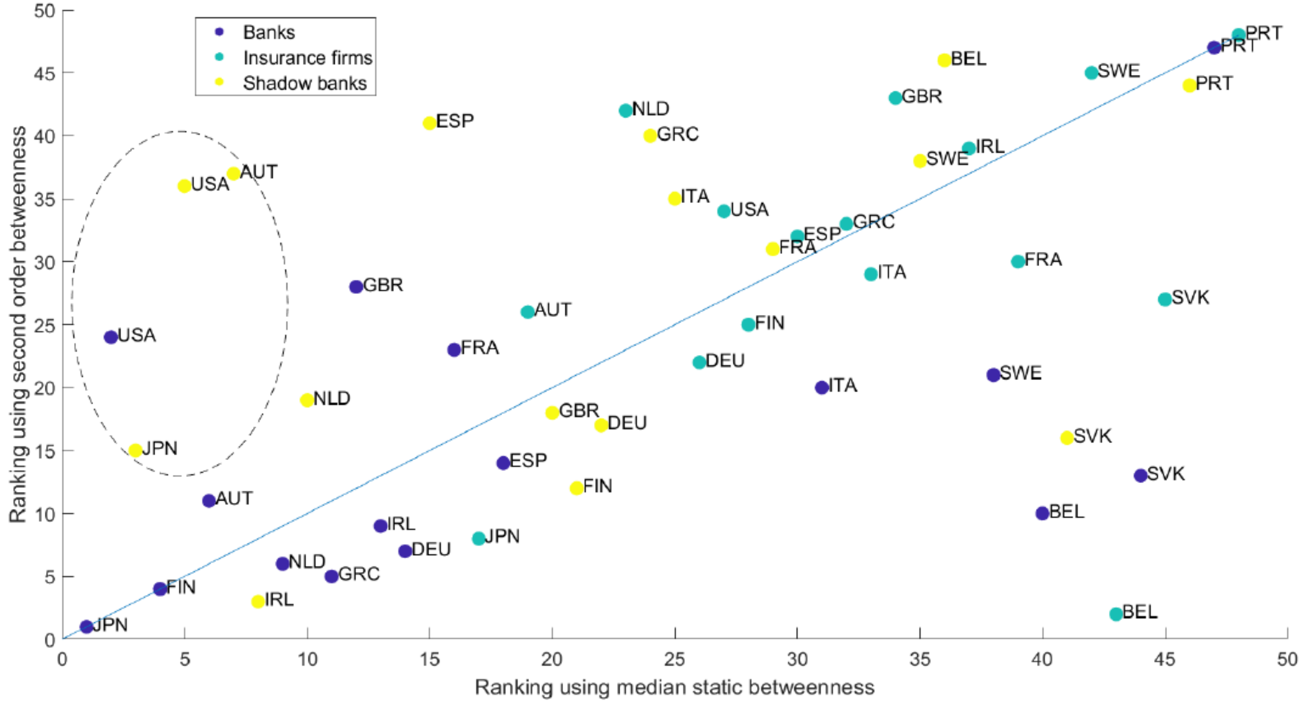
Centrality of nodes: comparison between static and temporal metrics

Similarly, when we compare the rankings obtained with the in-closeness centrality metrics, the banking systems of Spain, Italy and Greece are ranked higher with the second-order approach.



Centrality of nodes: comparison between static and temporal metrics

Finally, the comparison of the betweenness-based rankings shows that the United States (banks and insurance) and Japan are ranked much lower by the second-order measure compared to the static one.



Cross sectoral contagion

We analyse paths of contagion episodes of length larger than one, using the 2nd-order aggregate network.

Contagion path	Jan06 - Aug07	Aug07 - Apr10	Apr10 - Jul12	Jul12 - Feb18
Banks → banks → banks	**298**	**737**	401	**926**
Shadow banks → banks → banks	237	**759**	**601**	**896**
Banks → shadow banks → banks	**308**	595	**429**	**889**
Insurers → banks → banks	152	**682**	390	841
Shadow banks → shadow banks → shadow banks	**276**	475	**551**	811
Insurers → shadow banks → shadow banks	252	470	380	724
Banks → insurers → banks	236	600	386	682
Shadow banks → insurers → banks	175	583	403	561

- Tight interconnectedness between the banking and the shadow banking sectors.
- Contagion chains with insurers as the source of stress are found to occur much less often → the insurance sector acts mainly as a receiver rather than the origin of stress.
- The banking sector functions far more frequently as an intermediary node compared to the shadow banking and insurance sectors.

Conclusions

- The use of the newly introduced concepts from temporal networks theory seem to be well-fitted to analyse financial contagion as they consider the sequence of topologies and each node’s role in this sequence.

- Temporal centrality measures distinguish much more clearly the role of each financial sector segment in a contagion phenomenon.

- Overall, based on the 2nd order aggregated network, the average crisis event starts either from the banking or the shadow banking sector, while insurers are sometimes affected at a later stage.

- Our analysis is statistical in nature, and we do not seek to distinguish transmissions channels operating during crises e.g. due to direct exposures and indirect exposures. This extension would be of great interest for future research.