Table 3: Geographical connectedness and financial linkages

	(1) Financial → Non-Financial	(2) Sovereign → Non-Financial
Bilateral bank claims		
(i) All sectors	0.244***	0.034
	(0.065)	(0.086)
(ii) Non-bank private sector	0.341***	0.124
	(0.113)	(0.155)

Note: The table reports the results of regressing the pairwise cross-country connectedness measures on bilateral bank claims from the consolidated banking statistics database of the Bank for International Settlements (BIS). We differentiate between (i) bilateral bank claims of country i to all sectors of country j, and (ii) bilateral bank claims of country i to the non-bank private sector of country j. We divide bilateral bank claims by country j's GDP to control for economy size. The BIS consolidated banking statistics measure banks' country risk exposures by capturing the claims of banks' foreign affiliates (ultimate risk basis). This consolidation approach is consistent with our strategy of aggregating the connectedness measures by the geographical location of a bank's headquarter. Each OLS regression includes a constant and country dummies. Standard errors are in parentheses. *** denotes significance at the 1% level.

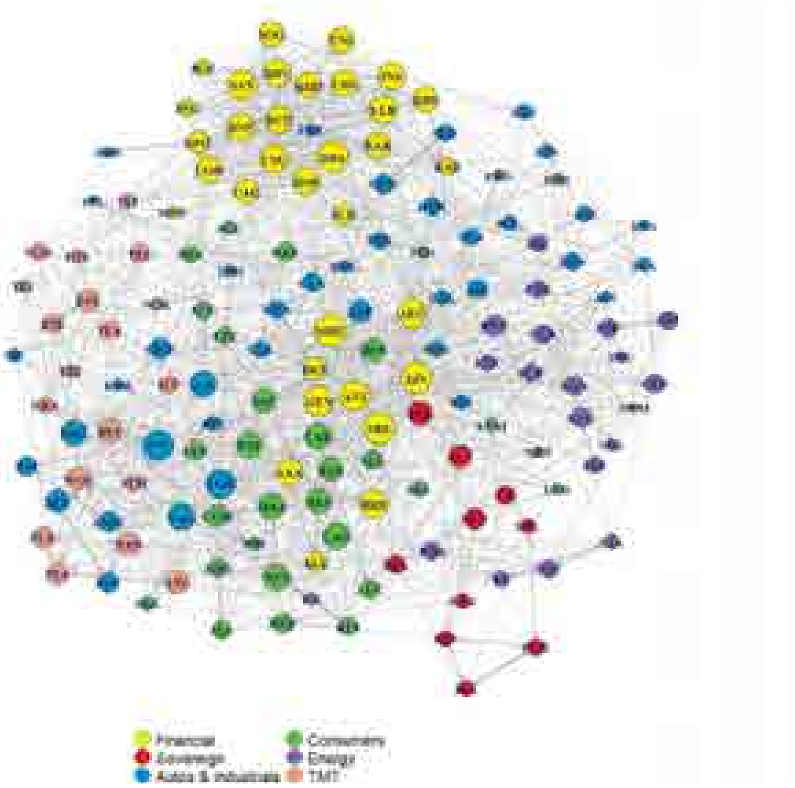
Table 4: Out-of-sample forecast results

	Autos & Industrials	Consumers	Energy	TMT	Financial	Sovereign	**Total**
Optimal Elastic Net	4.2726	2.5729	2.7713	2.8523	8.2922	5.8820	**4.5380**
Constant mean	4.2926	2.5783	2.7243	2.8725	8.3319	5.7668	**4.5424**
AR(1)	4.3141	2.5795	2.8296	2.8735	8.2759	5.8282	**4.5528**
Ridge	4.2950	2.5853	2.7799	2.8611	8.3120	5.9312	**4.5561**
Constant Elastic Net	4.2826	2.5799	2.7806	2.8610	8.3226	5.8725	**4.5503**

Note: The in-sample period is 23/10/2006 - 31/12/2014, the out-of-sample period corresponds to 02/01/2015-28/07/2017. The table shows the mean squared error (MSE) of our baseline elastic net model (first row) by sector and compares it to a number of competitor models. Our optimal elastic net model (first row) chooses optimal α and λ jointly in the shrinkage and selection process. The constant mean model uses the in-sample mean of each variable as forecasts. The AR(1) model conducts forecasts based on the fitted values from a persistent process. Ridge regression applies shrinkage in the VAR with $\alpha = 1$ and constant elastic net uses a fixed elastic net mixing parameter of $\alpha = 0.5$ and chooses only the optimal λ in the penalty function.

Figure 6: CDS network before and after Lehman Brother's bankruptcy

(a) Before: September 1, 2008



(b) After: November 6, 2008

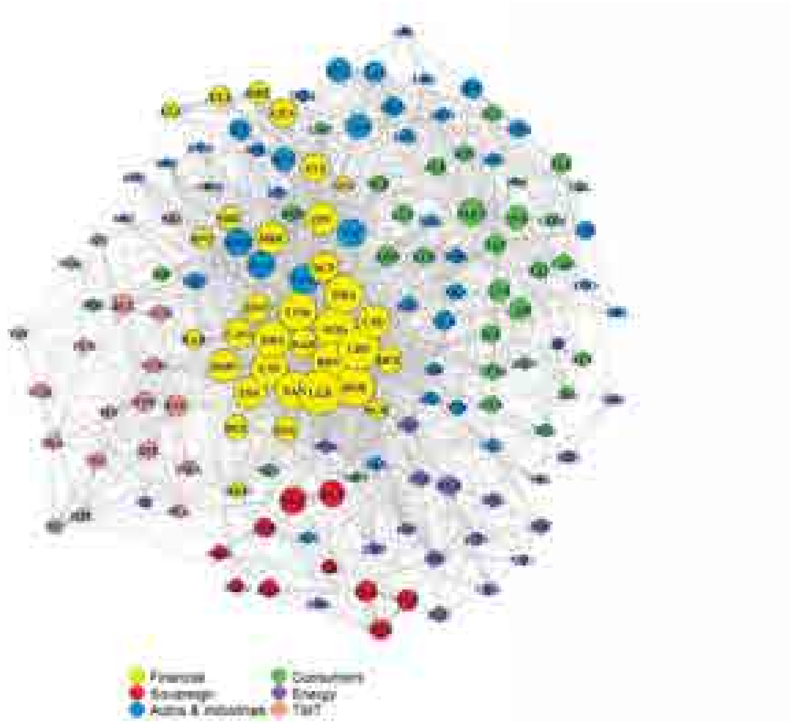
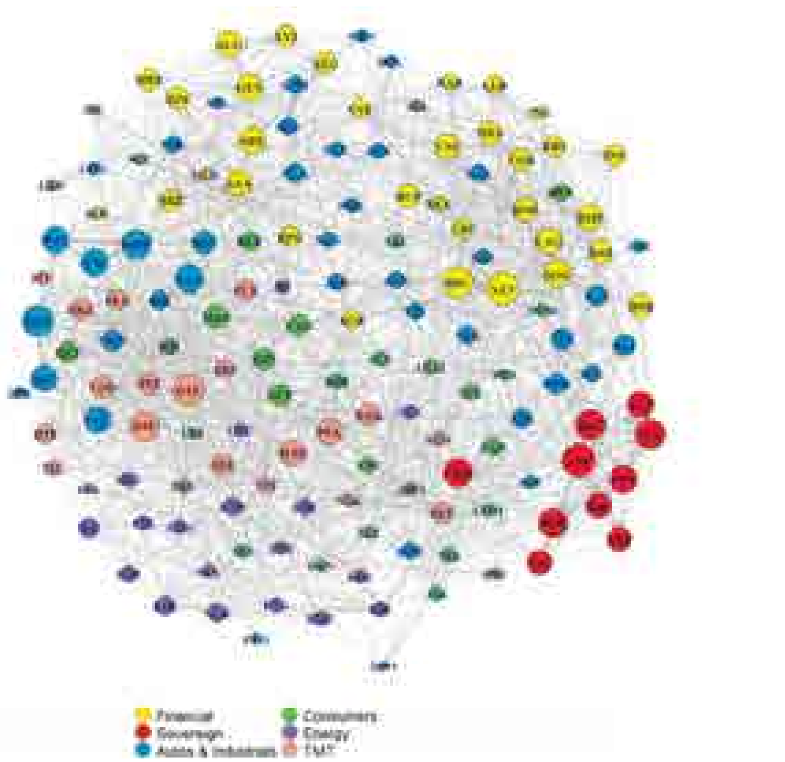


Figure 7: CDS network before and after the onset of the sovereign debt crisis

(a) Before: December 30, 2009



(b) After: May 5, 2010

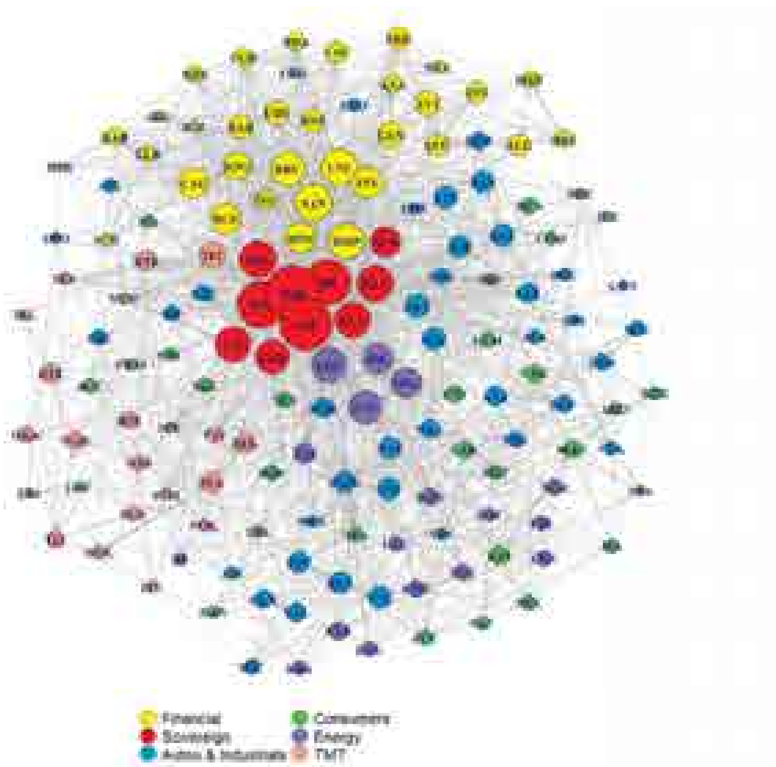
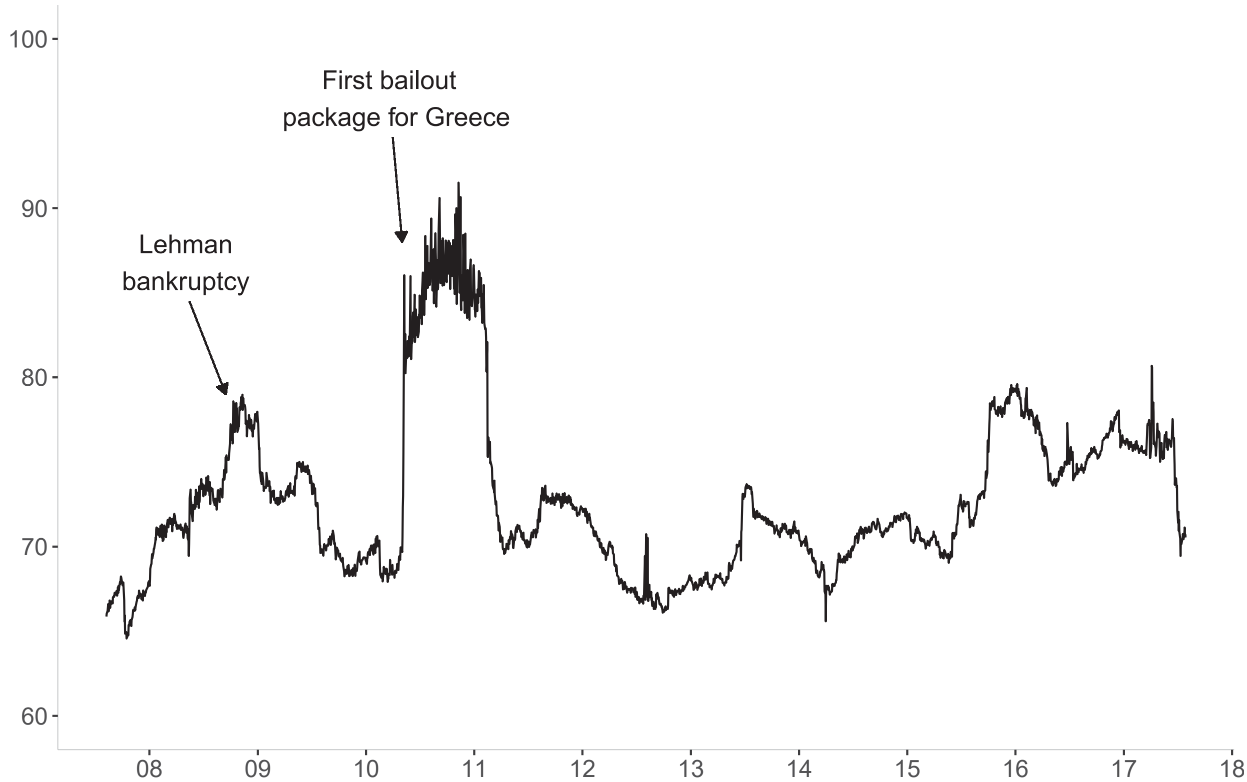
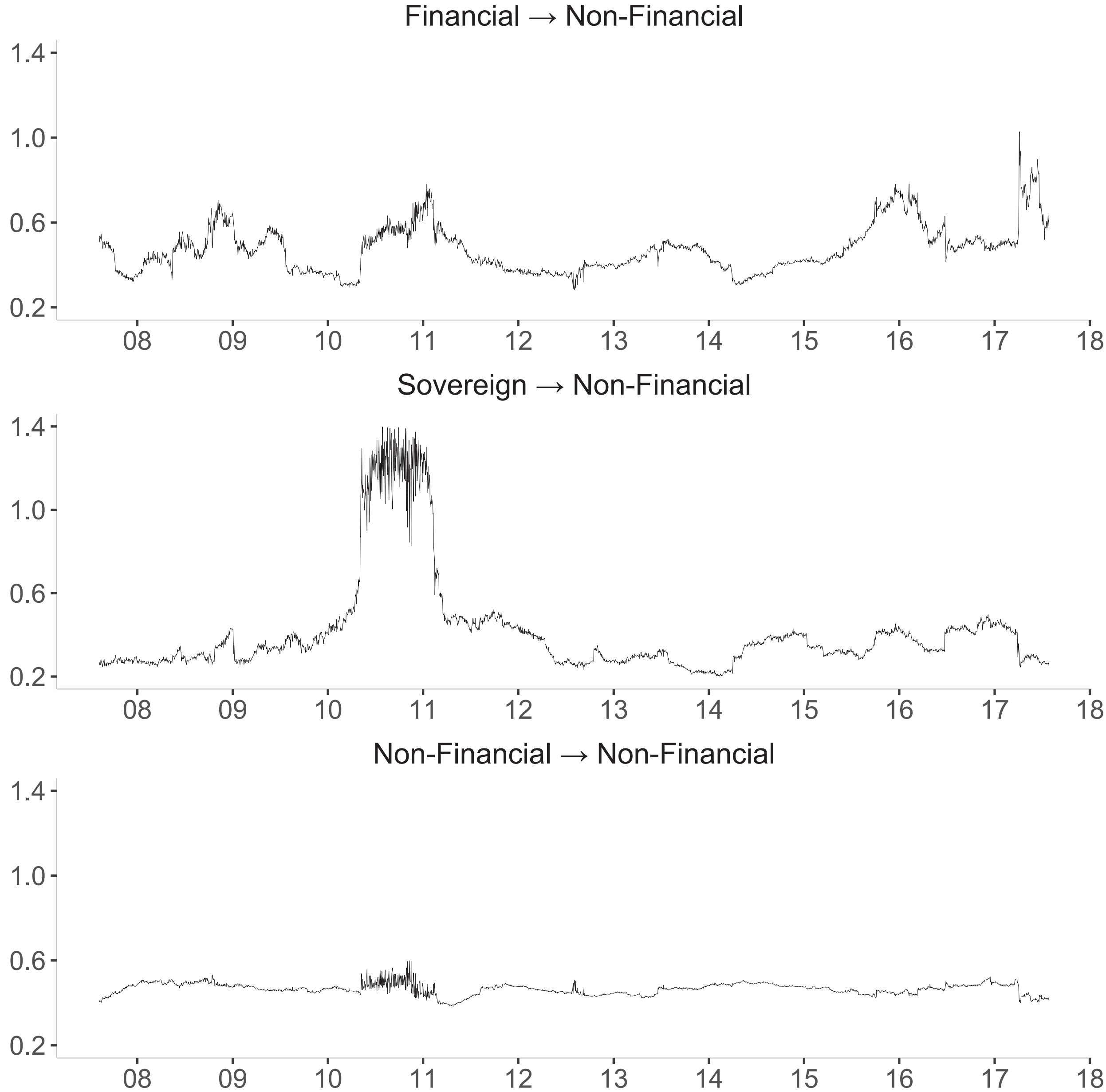


Figure 8: Dynamic system-wide connectedness



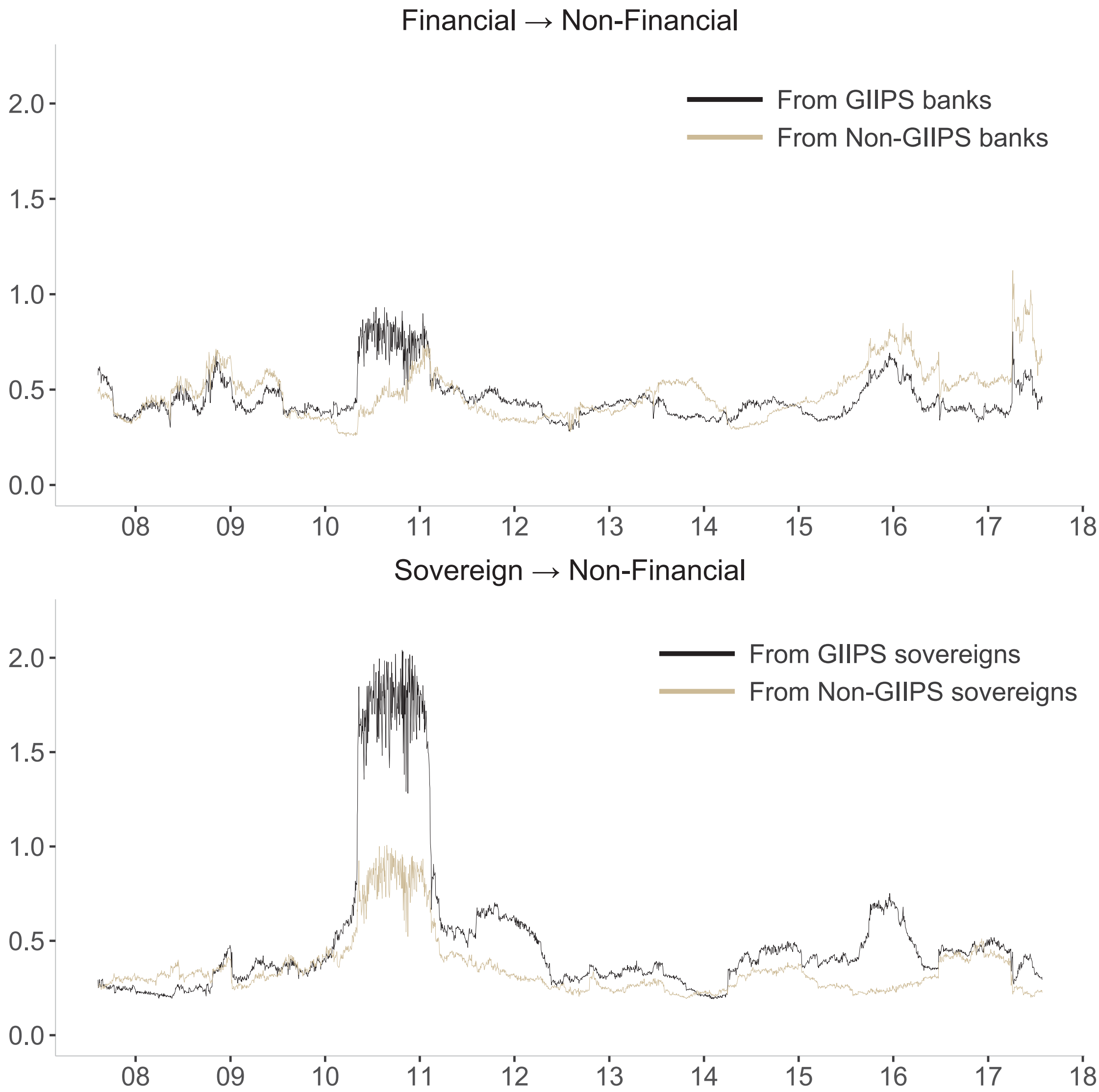
Note: The above figure shows the results from calculating time-varying parameters of the overall connectedness measure written in Eq. (7), using a rolling-window of 200 days.

Figure 9: Dynamic cross-sectoral connectedness



Note: The above figure shows the results from calculating time-varying parameters of the connectedness measure aggregated by sector, using a rolling-window of 200 days. Each measure is normalized by the number of entities so that the graph shows the average impact for each sector.

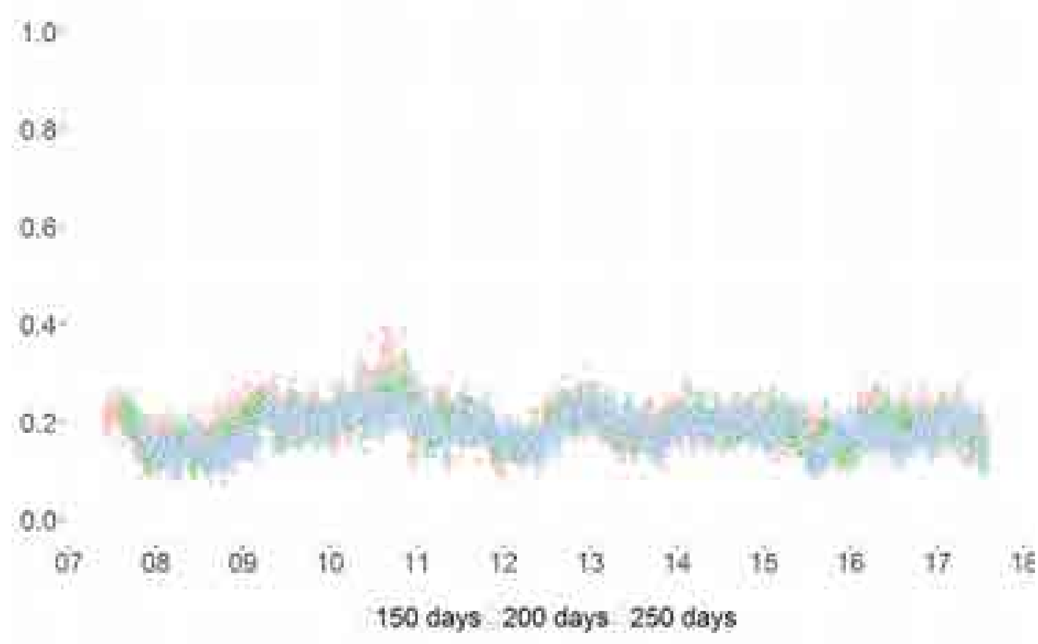
Figure 10: Dynamic network connectedness across country groups



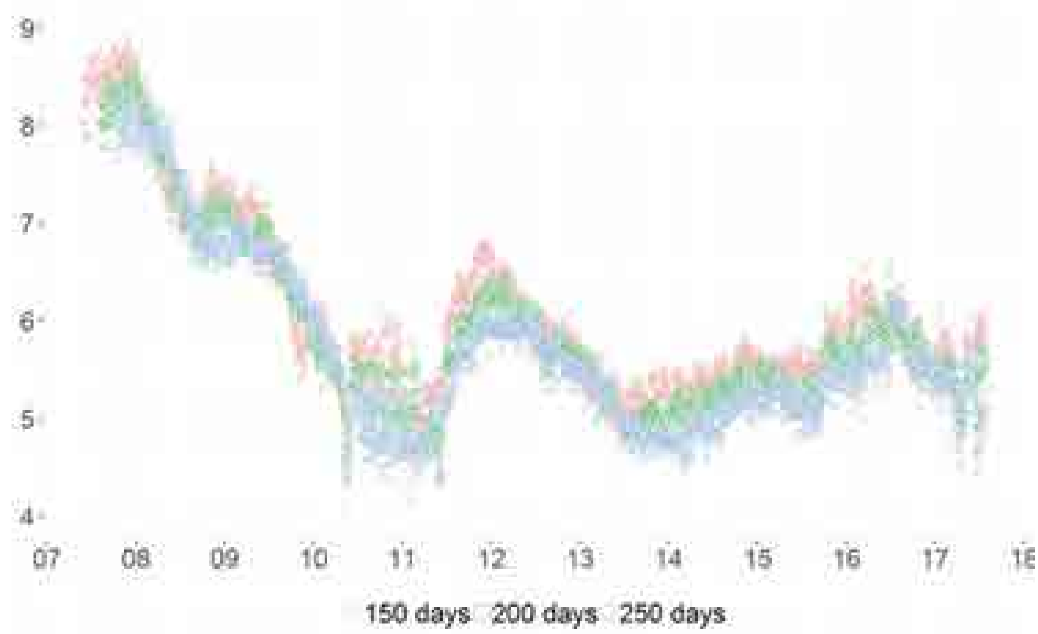
Note: The above figure shows the results from calculating time-varying parameters of the connectedness measure aggregated by country group, using a rolling-window of 200 days. (G)IIPS countries are Ireland, Italy, Portugal and Spain (Greece is exluded due to data availability). Each measure is normalized by the number of entities so that the graph shows the average impact for each group of countries.

Figure 11: Distribution of elastic net parameters for different window sizes

(a) Mixing parameter α

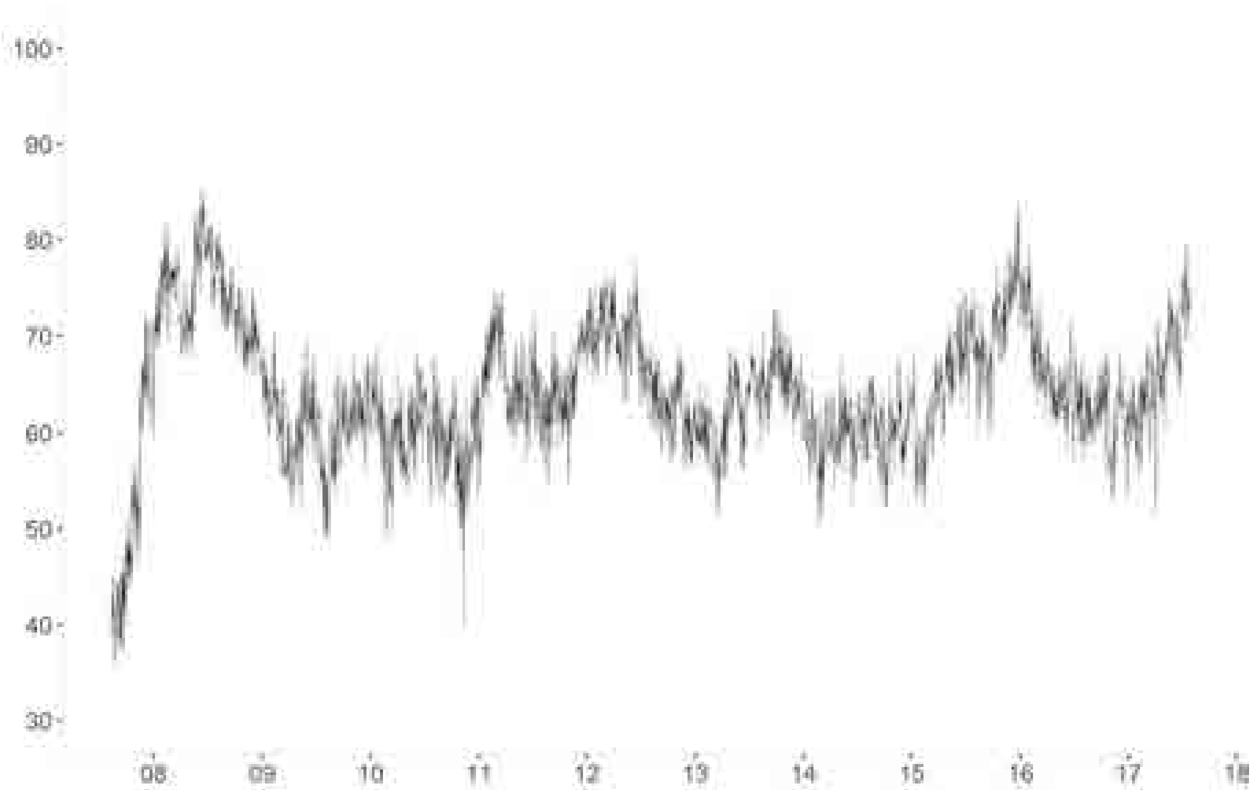


(b) Penalty tuning parameter λ



Note: Figure (a) shows the evolution of the elastic net mixing parameter α for the dynamic VAR framework over the sample period for different window sizes in the rolling-regression. Figure (b) depicts the corresponding values (log scale) for the penalty tuning parameter λ. Each observation for α and λ represents the average value across all 152 VAR equations for each window.

Figure 12: Dynamic Granger-causality connectedness



Note: The figure shows the share of Granger-causality linkages between CDS entities, i.e. it presents the share of non-zero links relative to the total number of possible links. The underlying VAR is estimated with a rolling-window of 200 days. The above figure is the analogue to the system-wide connectedness measure depicted in Figure 8 which is based on variance decompositions.

Appendix

Table A.1: List of CDS Entities

Entity Name	Sector	Sub-Sector	Country	Name Code
Adecco	Non-financial	Autos & Industrials	Switzerland	ADE
Volvo	Non-financial	Autos & Industrials	Sweden	VOL
Akzo Nobel	Non-financial	Autos & Industrials	Netherlands	AKN
Alstom	Non-financial	Autos & Industrials	France	ALS
Anglo American	Non-financial	Autos & Industrials	UK	ANA
Astrazeneca	Non-financial	Autos & Industrials	UK	ASZ
Atlantia	Non-financial	Autos & Industrials	Italy	ATL
Bae Systems	Non-financial	Autos & Industrials	UK	BAE
BASF	Non-financial	Autos & Industrials	Germany	BAS
Bayer	Non-financial	Autos & Industrials	Germany	BAY
BMW	Non-financial	Autos & Industrials	Germany	BMW
Bouygues	Non-financial	Autos & Industrials	France	BOU
Clariant	Non-financial	Autos & Industrials	Switzerland	CLA
Saint-Gobain	Non-financial	Autos & Industrials	France	SAG
Michelin	Non-financial	Autos & Industrials	Switzerland	MIC
Continental	Non-financial	Autos & Industrials	Germany	CON
Daimler	Non-financial	Autos & Industrials	Germany	DAI
Deutsche Post	Non-financial	Autos & Industrials	Germany	DPO
Evonik	Non-financial	Autos & Industrials	Germany	EVO
Finmeccanica	Non-financial	Autos & Industrials	Italy	FME
GKN Holding	Non-financial	Autos & Industrials	UK	GKN
Glencore	Non-financial	Autos & Industrials	Switzerland	GLC
Koninklijke DSM	Non-financial	Autos & Industrials	Netherlands	DSM
Air Liquide	Non-financial	Autos & Industrials	France	AIR
Lanxess	Non-financial	Autos & Industrials	Germany	LAX
Linde	Non-financial	Autos & Industrials	Germany	LIN
Peugeot	Non-financial	Autos & Industrials	France	PEU
Renault	Non-financial	Autos & Industrials	France	REN
Rentokil Initial	Non-financial	Autos & Industrials	UK	REI
Rolls-Royce	Non-financial	Autos & Industrials	UK	ROR
Sanofi-Aventis	Non-financial	Autos & Industrials	France	SAA
Siemens	Non-financial	Autos & Industrials	Germany	SIE
Stora Enso Oyj	Non-financial	Autos & Industrials	Finland	SEO
Solvay	Non-financial	Autos & Industrials	Belgium	SOL
ThyssenKrupp	Non-financial	Autos & Industrials	Germany	THK
UPM-Kymmene Oyj	Non-financial	Autos & Industrials	Finland	UPM
Valeo	Non-financial	Autos & Industrials	France	VAL
Vinci	Non-financial	Autos & Industrials	France	VIN
Volkswagen	Non-financial	Autos & Industrials	Germany	VOL
Wendel	Non-financial	Autos & Industrials	France	WEN
Accor	Non-financial	Consumers	France	ACC
Electrolux	Non-financial	Consumers	Sweden	ELE
Auchan	Non-financial	Consumers	France	AUC
Alliance Boots	Non-financial	Consumers	UK	ALL
Carrefour	Non-financial	Consumers	France	CAR
Casino Guichard	Non-financial	Consumers	France	CAG
Compass	Non-financial	Consumers	UK	COM
Danone	Non-financial	Consumers	France	DAN
Lufthansa	Non-financial	Consumers	Germany	LUF
Diageo	Non-financial	Consumers	UK	DIA
Experian Finance	Non-financial	Consumers	UK	EXF

(Table A.1 continued)

Entity Name	Sector	Sub-Sector	Country	Name Code
Henkel	Non-financial	Consumers	Germany	HEN
Ladbrokes	Non-financial	Consumers	UK	LAD
Imperial Brands	Non-financial	Consumers	UK	IMB
ISS Global	Non-financial	Consumers	Denmark	ISS
J Sainsbury	Non-financial	Consumers	UK	JSA
Kering	Non-financial	Consumers	France	KER
Kingfisher	Non-financial	Consumers	UK	KIN
Koninklijke Ahold Delhaize	Non-financial	Consumers	Netherlands	AHO
Koninklijke Philips	Non-financial	Consumers	Netherlands	PHI
LVMH	Non-financial	Consumers	France	LVM
Marks & Spencer	Non-financial	Consumers	UK	M&S
Metro	Non-financial	Consumers	Germany	MET
Nestlé	Non-financial	Consumers	Switzerland	NES
Next	Non-financial	Consumers	UK	NEX
PernodRicard	Non-financial	Consumers	France	PER
Safeway	Non-financial	Consumers	UK	SAF
Svenska Cellulosa	Non-financial	Consumers	Sweden	SCE
Swedish Match	Non-financial	Consumers	Sweden	SWM
Tate & Lyle	Non-financial	Consumers	UK	T&L
Tesco	Non-financial	Consumers	UK	TES
Unilever	Non-financial	Consumers	UK	UNI
BP	Non-financial	Energy	UK	BP
Centrica	Non-financial	Energy	UK	CEN
EON	Non-financial	Energy	Germany	EON
Edison	Non-financial	Energy	Italy	EDI
Energias de Portugal	Non-financial	Energy	Portugal	EDP
Electricité de France	Non-financial	Energy	France	EDF
ENBW	Non-financial	Energy	Germany	ENB
ENEL	Non-financial	Energy	Italy	ENE
ENGIE	Non-financial	Energy	France	ENG
Fortum OYJ	Non-financial	Energy	Finland	FOY
Gas Natural SDG	Non-financial	Energy	Spain	SDG
Iberdrola	Non-financial	Energy	Spain	IBE
National Grid	Non-financial	Energy	UK	NGR
Royal Dutch Shell	Non-financial	Energy	Netherlands	RDS
RWE	Non-financial	Energy	Germany	RWE
Statoil	Non-financial	Energy	Norway	STA
Total	Non-financial	Energy	France	TOT
United Utilities	Non-financial	Energy	UK	UNU
British Telecom	Non-financial	TMT	UK	BTE
Deutsche Telekom	Non-financial	TMT	Germany	DTE
Hellenic Telecom	Non-financial	TMT	Greece	HTE
ITV	Non-financial	TMT	UK	ITV
Nokia	Non-financial	TMT	Finland	NOK
Orange	Non-financial	TMT	France	ORA
Pearson	Non-financial	TMT	UK	PEA
Publicis	Non-financial	TMT	France	PUB
Relx	Non-financial	TMT	UK	REL
St Microelectronics	Non-financial	TMT	Switzerland	STM
Ericsson	Non-financial	TMT	Sweden	ERI
Telefonica	Non-financial	TMT	Spain	TEF

(Table A.1 continued)

Entity Name	Sector	Sub-Sector	Country	Name Code
Telekom Austria	Non-financial	TMT	Austria	TEA
Telenor	Non-financial	TMT	Norway	TEL
Telia	Non-financial	TMT	Sweden	TEI
Vivendi	Non-financial	TMT	France	VIV
Vodafone	Non-financial	TMT	UK	VOD
Wolters	Non-financial	TMT	Netherlands	WOL
WPP	Non-financial	TMT	UK	WPP
Aegon	Financial		Netherlands	AEG
Allianz	Financial		Germany	ALL
Generali	Financial		Italy	GEN
Aviva	Financial		UK	AVI
AXA	Financial		France	AXA
Hannover Rueck	Financial		Germany	HRE
Munich RE	Financial		Germany	MRE
Swiss RE	Financial		Switzerland	SRE
Zurich Insurance	Financial		Switzerland	ZIN
Dexia	Financial		Belgium	DEX
BNP Paribas	Financial		France	BNP
Crédit Agricole	Financial		France	CAG
Société Générale	Financial		France	SOG
Deutsche Bank	Financial		Germany	DBA
Commerzbank	Financial		Germany	COB
Bank of Ireland	Financial		Ireland	BOI
Intesa Sanpaolo	Financial		Italy	INS
Banca Monte Di Paschi	Financial		Italy	BMP
Banca Popolare	Financial		Italy	BPO
Unicredit	Financial		Italy	UNI
Mediobanca	Financial		Italy	MED
ING	Financial		Netherlands	ING
Rabobank	Financial		Netherlands	RAB
Banco Comercial Port.	Financial		Portugal	BCP
Santander	Financial		Spain	SAN
BBVA	Financial		Spain	BBV
Royal Bank of Scot.	Financial		UK	RBS
HSBC Bank	Financial		UK	HSB
Barclays Bank	Financial		UK	BAB
Lloyds Bank	Financial		UK	LLB
Standard Chartered	Financial		UK	SCH
UBS	Financial		Switzerland	UBS
Credit Suisse	Financial		Switzerland	CSU
Austria	Sovereign		Austria	AUT
Belgium	Sovereign		Belgium	BEL
France	Sovereign		France	FRA
Germany	Sovereign		Germany	GER
Ireland	Sovereign		Ireland	IRE
Italy	Sovereign		Italy	ITA
Netherlands	Sovereign		Netherlands	NED
Portugal	Sovereign		Portugal	POR
Spain	Sovereign		Spain	ESP
UK	Sovereign		Spain	UK

Online Appendix[1]

A. Determining the number of common factors

Hallin and Liška (2007) propose a consistent information criterion for determining the number of q common dynamic shocks in Forni et al.'s (2000) generalized dynamic factor model. The criterion builds on the (n,T)-asymptotic properties of the eigenvalues for the spectral density matrix of the observable variables Y_{nt}. The spectral density matrix is denoted by $\mathbf{\Sigma}_n(\theta)$, where $\theta \in [-\pi, \pi]$, and its corresponding eigenvalues in decreasing order of magnitude are denoted by $\kappa_{n1}(\theta), ..., \kappa_{nn}(\theta)$. As $n \to \infty$ it can be shown that the projection $X_{it}^{(n)}$ of Y_{it} onto the space spanned by $\mathbf{\Sigma}_n(\theta)$'s first q dynamic principal components provides a consistent reconstruction of X_{it}, where the number q is equivalent to the number of diverging eigenvalues of $\mathbf{\Sigma}_n(\theta)$. As illustrated by Hallin and Liška (2007) the q dynamic principal components and the $X_{it}^{(n)}$'s are the solutions to an optimization problem in which the expected mean of squared residuals is minimized.

Accordingly, Hallin and Liška (2007) propose that the estimated number of factors, for given (n,T) and a maximum number of common factors q_{max}, is determined by minimizing the following information criterion:

$$IC_{2;n}^{T}(k) = log\left[\frac{1}{n}\sum_{i=k+1}^{n}\frac{1}{2M_T+1}\sum_{l=-M_T}^{M_T}\kappa_{ni}^{T}(\theta_l)\right] + kp(n,T), \qquad \text{(OA.1)}$$

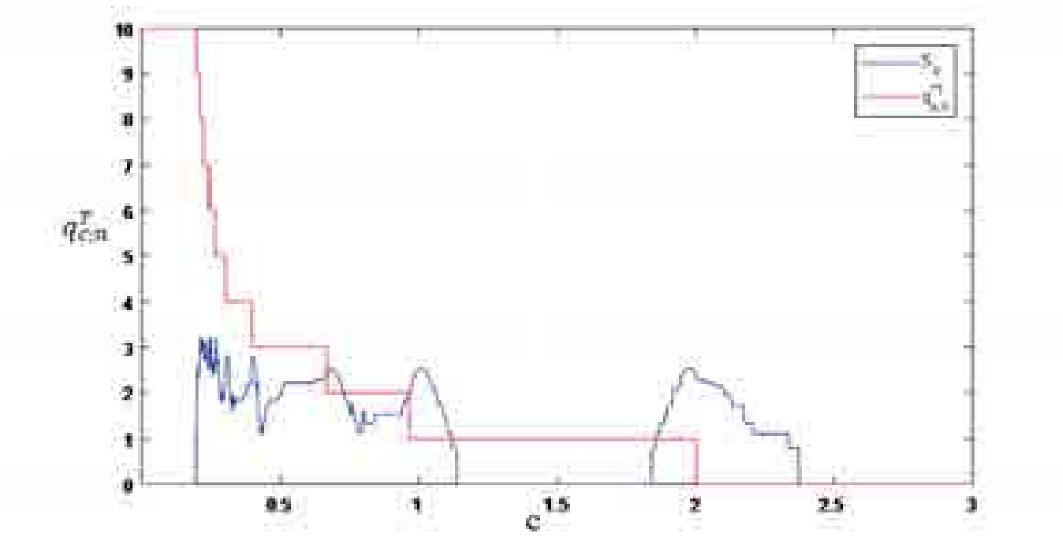
where $0 \leq k \leq q_{max}$.

$M_T > 0$ is a truncation parameter and $p(n,T)$ is an appropriate penalty function whose conditions and properties are discussed in detail by Hallin and Liška (2007). Provided that $p(n,T)$ is an appropriate penalty function, then multiplying the penalty with an arbitrary positive real constant c, i.e. $cp(n,T)$, is also appropriate. The uncertainty regarding the choice of c is exploited by Hallin and Liška (2007) to derive a practical guide for the selection of q, which is based on a mapping of $c \to q_{c,n}^T$ and $c \to S_c$ in a joint plot. $q_{c,n}^T$ denotes the number of factors resulting from applying the IC_2 criterion in Eq. (OA.1) and S_c captures

[1]Not for publication.

the variability among the J values of $q^{T_j}_{c;n_j}, j = 1, ..., J$ in a sample with fixed n and T and allows for an assessment of the stability of the factors for a given c.

Figure OA.1: Hallin and Liška (2007) IC_2 criterion



Note: The figure shows the joint mapping of $c \rightarrow q^T_{c,n}$ and $c \rightarrow S_c$ for the panel of 152 CDS returns. $q^T_{c,n}$ is derived from applying the IC_2 criterion as shown in (OA.1) using a penalty function of $p(n,T) = (M_T^{-2} + M_T^{0.5}T^{-0.5} + n^{-1})\log(\min[n, M_T^2, M_T^{-0.5}T^{0.5}])$.

Figure OA.1 depicts the joint mapping for our sample of 152 CDS series. As can be seen the values for S_c are 0 in several intervals of c, which are called "stability intervals" in the terminology of Hallin and Liška (2007), while the values for S_c fluctuate heavily in other regions of c (hence they are called "instability intervals"). For values of c close to 0, the first "stability interval" typically yields the maximum possible numbers of common factors $\hat{q} = q_{max}$. Since low values of c are associated with severe underpenalization Hallin and Liška (2007) propose to choose the number of factors $\hat{q} = q^T_{\hat{c},n}$ by considering the $c \rightarrow S_c$ mapping where $\hat{c}$ belongs to the second "stability interval". In Figure OA.1 this is the case for the interval $c = [1.15, 1.84]$ which corresponds to $q = 1$, hence the criterion clearly identifies one common factor in our sample and higher-order factor model specifications are not supported.

B. Dataset of CDS spreads

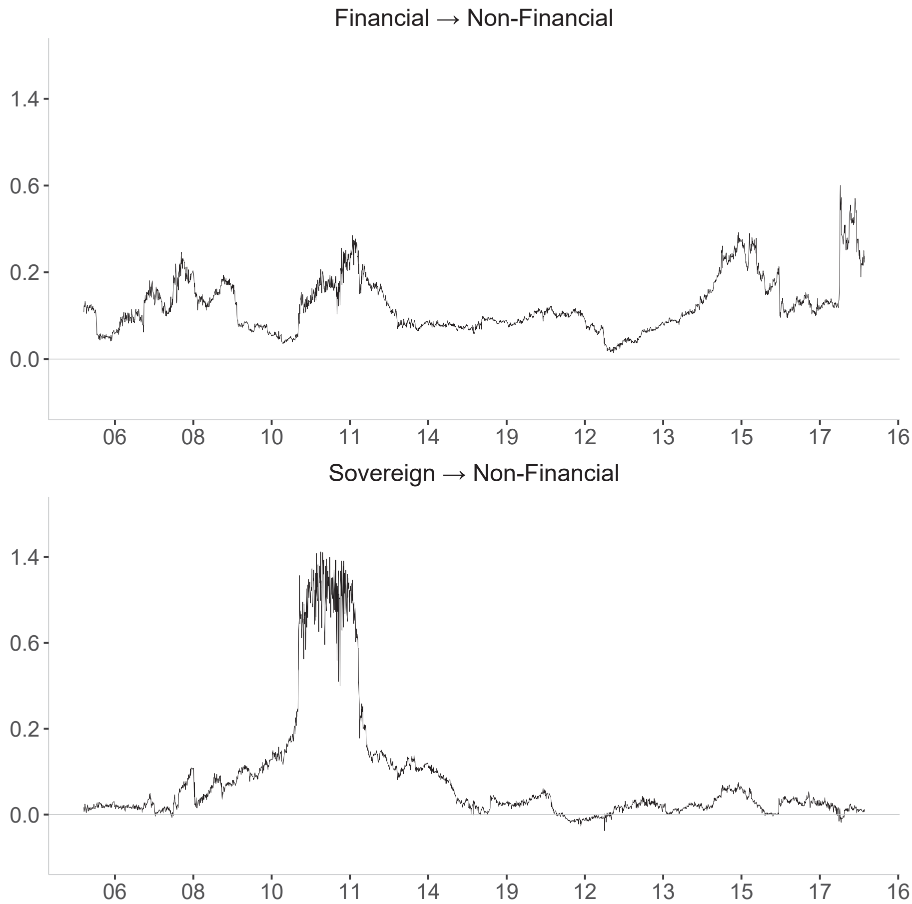
Table OA.1: Summary statistics of CDS data by country

Panel A: CDS non-financial corporations		Raw returns				Idiosyncratic returns			
Country	Entities	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Austria	1	0.00	3.12	-24.76	25.16	0.00	2.03	-12.76	18.34
Belgium	1	0.04	3.33	-24.99	27.46	0.00	2.20	-13.46	26.59
Denmark	1	-0.04	3.65	-83.40	38.09	0.00	3.25	-82.86	32.30
Finland	4	0.04	3.43	-83.81	37.77	0.00	2.61	-84.21	33.87
France	24	0.02	3.34	-58.90	60.05	0.00	2.32	-59.10	56.89
Germany	19	0.02	3.41	-33.47	103.03	0.00	2.36	-32.10	104.47
Greece	1	0.06	4.68	-33.14	44.11	0.00	3.69	-26.79	44.37
Italy	4	0.05	3.71	-53.65	33.74	0.00	2.73	-52.62	31.62
Netherlands	6	3.29	0.032	-77.98	80.75	0.00	2.41	-80.11	78.10
Norway	2	0.02	3.14	-25.62	29.90	0.00	2.36	-16.90	26.71
Portugal	1	0.06	4.13	-39.00	29.34	0.00	2.76	-29.63	19.28
Spain	3	0.03	4.03	-39.99	30.53	0.00	2.64	-19.22	30.17
Sweden	6	0.02	2.96	-28.86	51.84	0.00	2.11	-24.43	51.71
Switzerland	6	0.02	3.57	-44.11	44.11	0.00	2.60	-36.85	38.27
UK	30	0.03	3.39	-127.01	140.46	0.00	2.56	-129.97	139.87
Panel B: CDS financial institutions		Raw returns				Idiosyncratic returns			
Country	Entities	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Belgium	1	0.11	4.47	-35.06	86.61	0.00	4.23	-34.17	86.82
France	4	0.05	4.80	-43.96	62.68	0.00	3.24	-22.58	42.14
Germany	5	0.05	4.96	-47.63	61.34	0.00	3.32	-37.74	40.60
Ireland	1	0.08	5.84	-86.90	60.45	0.00	5.61	-86.73	58.79
Italy	6	0.08	4.76	-53.99	75.37	0.00	3.38	-53.62	55.22
Netherlands	3	0.07	4.44	-38.22	67.65	0.00	3.38	-32.84	62.16
Portugal	1	0.10	4.31	-35.41	40.67	0.00	3.40	-17.93	47.57
Spain	2	0.05	4.79	-45.72	32.54	0.00	3.07	-16.60	20.17
Switzerland	4	0.05	4.51	-41.03	56.25	0.00	3.06	-33.50	30.57
UK	6	0.06	4.80	-70.69	65.79	0.00	3.44	-61.27	56.97
Panel C: CDS sovereigns		Raw returns				Idiosyncratic returns			
Country	Entities	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Austria	1	0.09	10.42	-200.14	153.14	0.01	10.17	-197.03	153.23
Belgium	1	0.06	4.46	-28.76	30.59	0.00	3.93	-28.04	31.58
France	1	0.07	10.17	-200.14	153.14	0.00	9.97	-197.37	153.24
Germany	1	0.07	9.45	-133.50	154.04	0.01	9.27	-133.93	154.23
Ireland	1	0.08	16.40	-208.63	207.18	0.00	16.33	-208.23	207.81
Italy	1	0.07	4.21	-36.27	33.12	0.00	3.55	-33.11	25.59
Netherlands	1	0.10	6.25	-65.92	65.92	0.00	6.12	-65.35	69.46
Portugal	1	0.11	4.60	-51.27	27.99	0.00	4.05	-34.40	25.59
Spain	1	0.06	5.24	-57.05	57.05	0.00	4.87	-58.66	56.74
UK	1	0.09	4.44	-40.54	93.60	0.00	4.21	-40.90	92.17

Note: The table shows descriptive statistics of CDS raw and idiosyncratic returns by country and sector. Raw CDS returns have been demeaned prior to computation of the common and idiosyncratic returns.

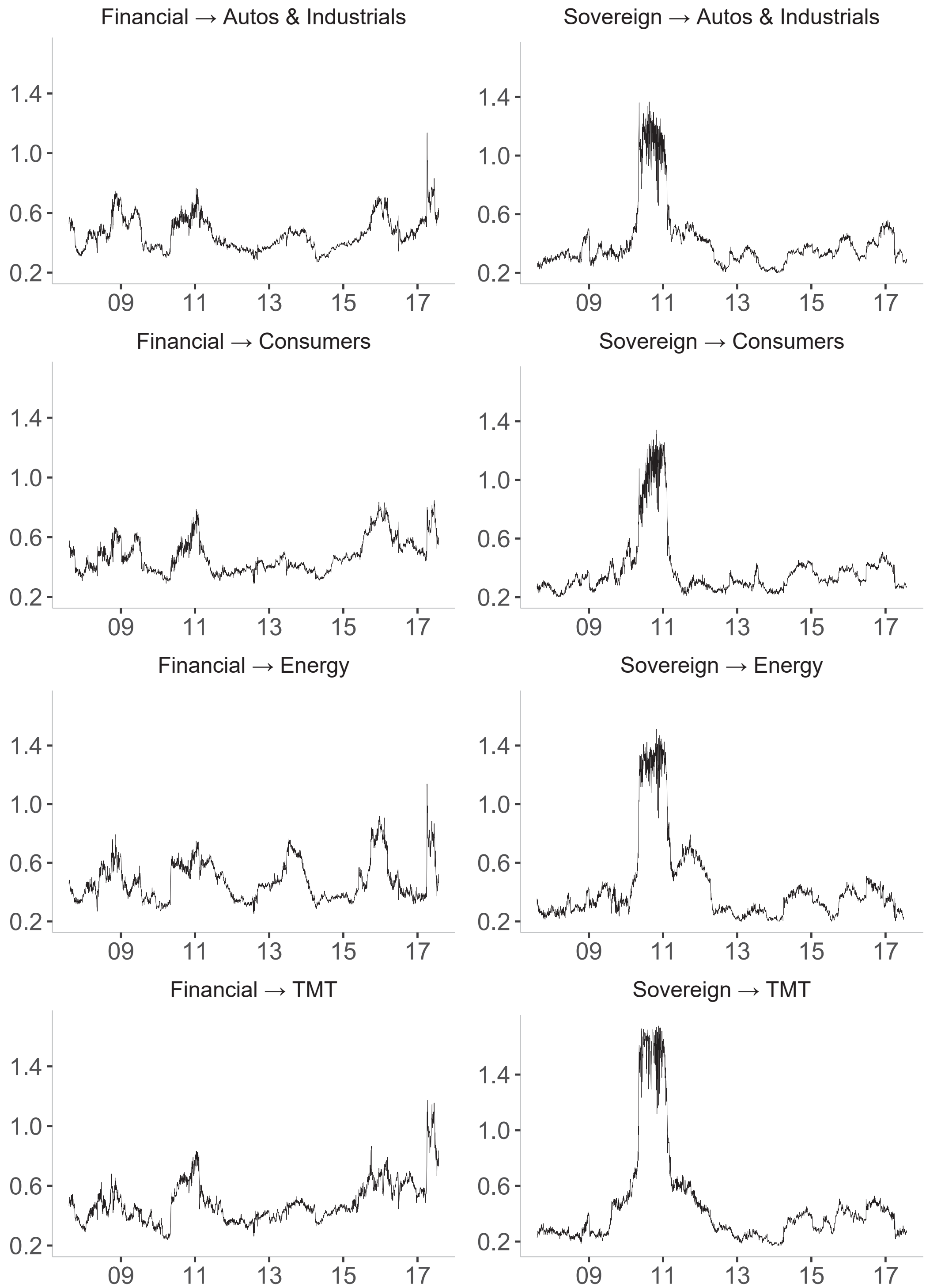
C. Additional results for cross-sectoral connectedness

Figure OA.2: Dynamic cross-sectoral connectedness, net contribution



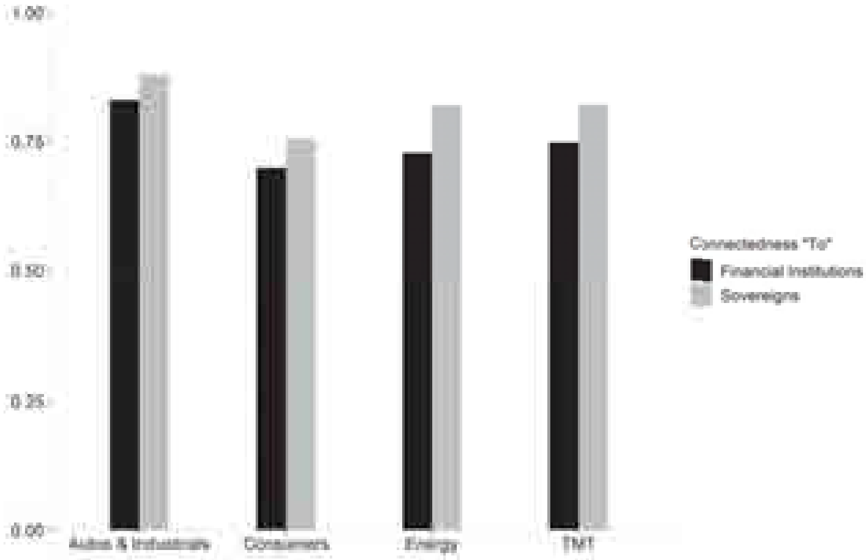
Note: The above figure shows aggregate net contribution of the financial and sovereign sector, respectively, to the non-financial sector in a dynamic framework (rolling window of 200 days). Net contribution of the financial sector is "aggregate connectedness from financial institutions to non-financial corporations" *minus* "aggregate connectedness from non-financial corporations to financial institutions". Net contribution of the sovereign sector is "aggregate connectedness from sovereigns to non-financial corporations" *minus* "aggregate connectedness from non-financial corporations to sovereigns". Each measure is normalized by the number of entities so that the graph shows the average impact for each sector.

Figure OA.3: Dynamic cross-sectoral connectedness, sub-sectors



Note: The above figure shows the results from calculating time-varying parameters of the connectedness measure aggregated by sub-sectors, using a rolling-window of 200 days. Each measure is normalized by the number of entities so that the graph shows the average impact for each sub-sector.

Figure OA.4: Static Granger-causality cross-sectoral network connectedness



Note: The figure shows the share of Granger-causality linkages between sectors, i.e. it presents the share of non-zero links relative to the total number of possible links across sectors.

D. Robustness checks results

Figure OA.5: Network with forecast horizon $h = 5$

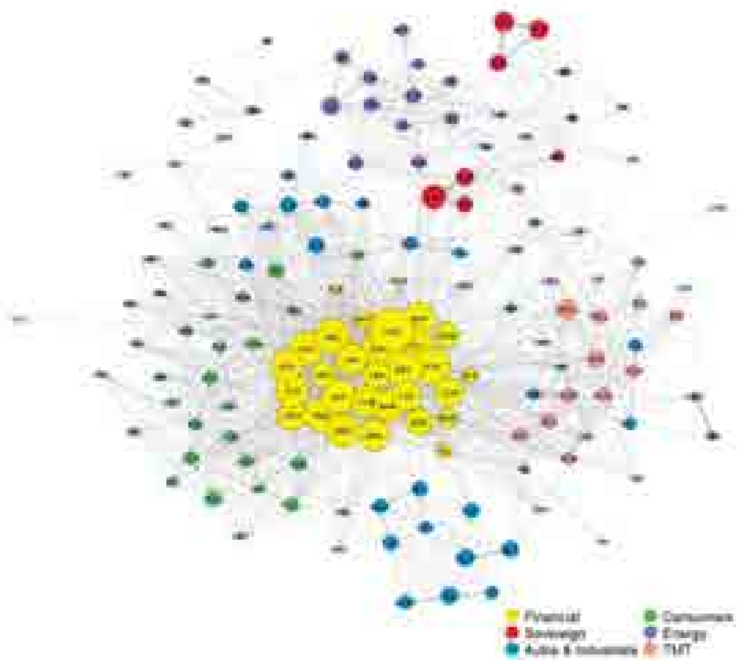


Figure OA.6: Network with forecast horizon $h = 15$

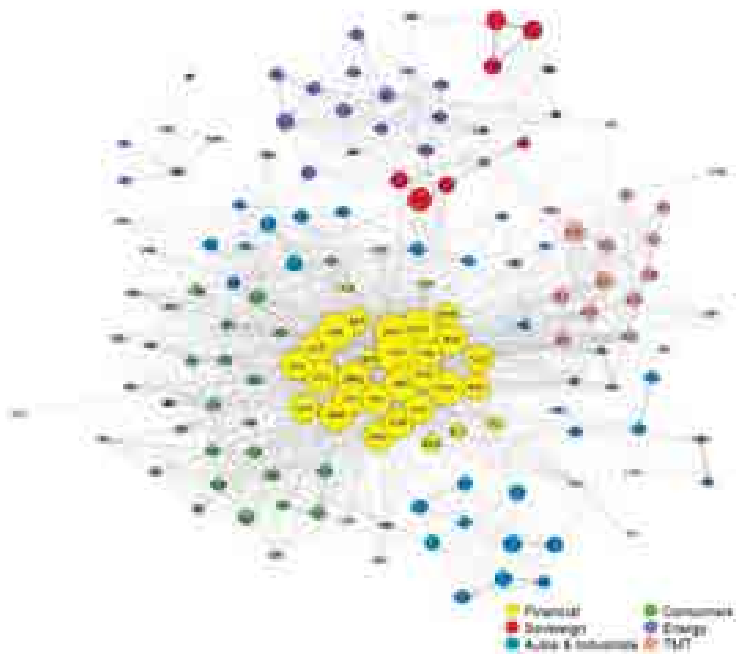


Figure OA.7: Network with forecast horizon $h = 20$

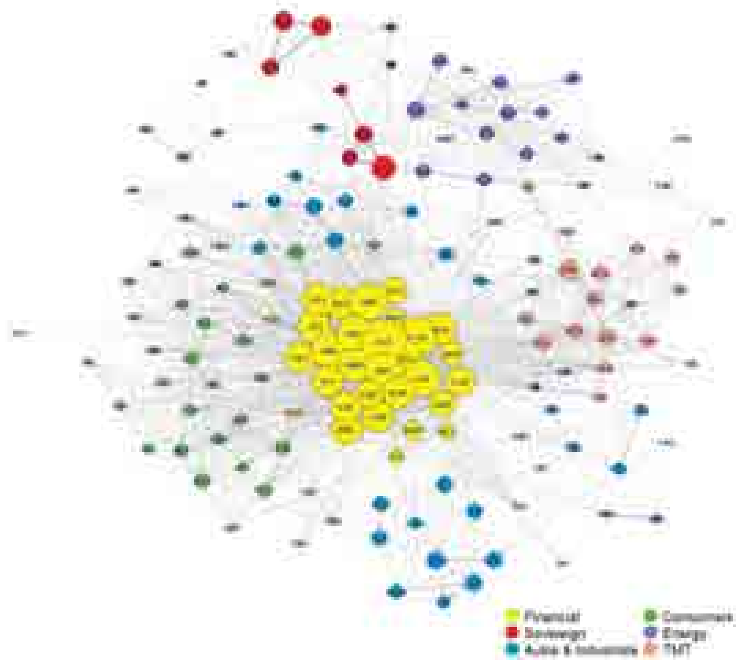


Figure OA.8: Network based on 2-factor model

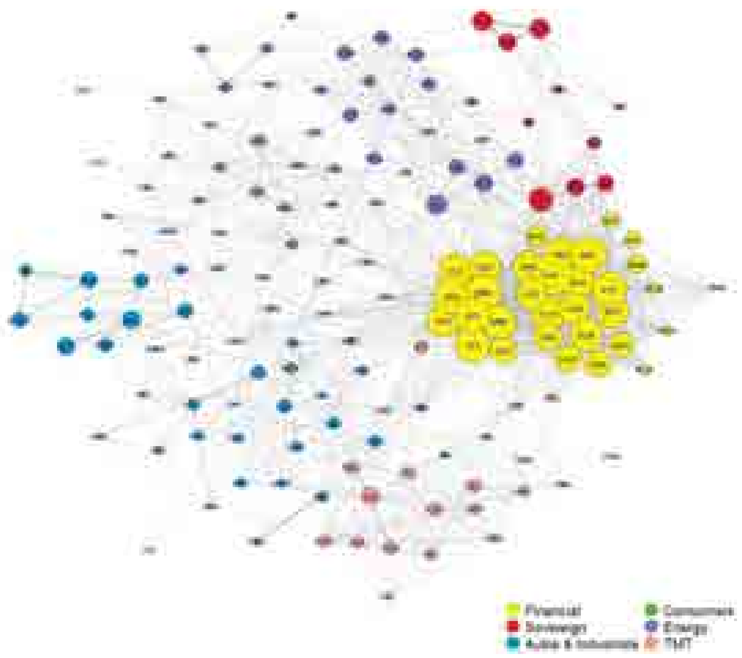


Table OA.2: Rank correlation coefficients between baseline model (1 factor, 10 days forecast horizon) and alternative specifications

(a) Financial → Non-Financial

	Ranking of Senders	Ranking of Receivers
Forecast horizon		
5 days	0.997***	0.997***
15 days	0.981***	0.996***
20 days	0.997***	0.997***
2 common factors	0.812***	0.439***

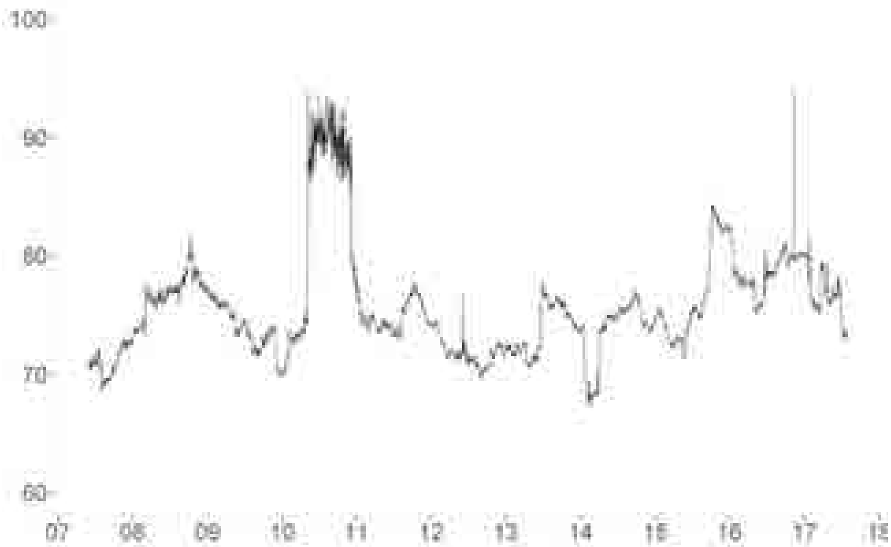
(b) Sovereign → Non-Financial

	Ranking of Senders	Ranking of Receivers
Forecast horizon		
5 days	0.987***	0.989***
15 days	1.000***	0.993***
20 days	0.987***	0.989***
2 common factors	0.988***	0.809***

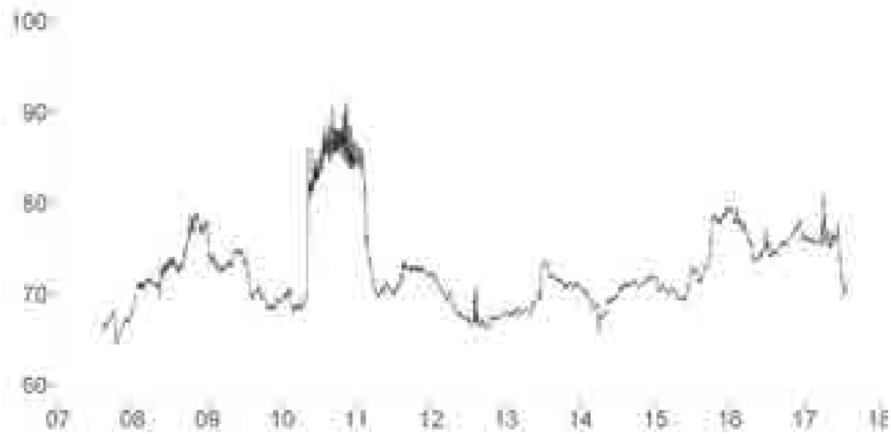
Note: The table reports rank correlation coefficients for rankings of receivers/senders based on different specifications of the underlying VAR model. The comparison is always the ranking resulting from the baseline model with one common factor and a 10 days forecast horizon as reported in Table 2. A value of 1 indicates that the ranking is exactly equal between the baseline model and the alternative model.

Figure OA.9: Dynamic system-wide connectedness for different window sizes

(a) 150 days



(b) 200 days



(c) 250 days