

Structural Estimation of Time-varying Spillovers: an Application to International Credit Risk Transmission

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Introduction – Motivation

- Numerous econometric models to gauge financial spillovers (Dungey *et al.*, 2005).

Main issue: endogeneity of asset prices.

- Among them, **Diebold and Yilmaz** (2009, DY) allow for the construction of time-varying spillovers, from pairwise to systemwise.
- Yet, DY-approach relies on identified SVAR, and empirical research:
 - Either **circumvents** identification-issues (Cholesky, GIRF, Claeys and Vašíček, 2014).
 - Or has attractive identification, but **no time variation** of spillovers **outside of rolling window estimation** (Ando *et al.*, 2018, De Santis and Zimic, 2018, 2019).

Introduction – Overview of our approach

General idea:

- Exploit time-varying FEVDs as measures of spillovers (Diebold-Yilmaz).

Data:

- 9 EZ sovereign CDS: BE DE ES FR GR IE IT NL PT.
- 7 corresponding EZ bank CDS, apart for GR and IE. Daily since 2008.

Econometric roadmap:

- 1 Filter CDS series from **common shocks**.
- 2 Estimate a SVAR-GARCH on the residuals, **identified by heteroskedasticity**.
- 3 **Economic identification** by contribution, validated by matching structural shocks with historical events.
- 4 TV variances from GARCH processes allow construction of TV FEVDs.

① Methodological Contribution

- Identified orthogonal shocks even in a **16-variable** SVAR.
- Our contagion indices appear **more reactive** than other methods used in the literature (Granger-causality).
- Pairwise spillovers **better identify** the sources of shocks.

② Economic Validation

- Our estimates match both **the narratives of spillovers** during the EZ debt crisis...
- ...and **the theoretical channels** of credit risk spillovers.

Model – Identification by Heteroskedasticity

$$\begin{array}{ll} \text{Reduced form VAR} & \text{Structural VAR} \\ \mathbf{y}_t = \mathbf{A}(\mathbf{L}) \mathbf{y}_{t-1} + \boldsymbol{\mu}_t & \rightarrow \mathbf{B}_0 \mathbf{y}_t = \mathbf{B}(\mathbf{L}) \mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t \end{array}$$

Assume:

$$E(\boldsymbol{\mu}_t \boldsymbol{\mu}_t') = \begin{cases} \boldsymbol{\Sigma}_1 & \text{if } t \leq T \\ \boldsymbol{\Sigma}_2 & \text{if } t > T \end{cases} \quad E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t') = \begin{cases} \mathbf{I} & \text{if } t \leq T \\ \boldsymbol{\lambda} & \text{if } t > T \end{cases}$$

Then, fully identified system:

$$\boldsymbol{\Sigma}_1 = \mathbf{B}_0 \mathbf{B}_0^{-1} \quad \text{and} \quad \boldsymbol{\Sigma}_2 = \mathbf{B}_0 \boldsymbol{\lambda} \mathbf{B}_0^{-1}$$

Works also with more than two volatility regimes (as in our case)

Model – SVAR-GARCH

Assume:

$$\epsilon_{k,t} = \sigma_{k,t|t-1} e_{k,t} \quad \text{where} \quad \mathbf{e}_t \sim \text{i.i.d. } N(\mathbf{0}, \mathbf{I}_N) \quad \text{and} \quad (1)$$

$$\sigma_{k,t|t-1}^2 = (1 - \gamma_k - g_k) + \gamma_k (\epsilon_{k,t-1})^2 + g_k \sigma_{k,t-1|t-2}^2 \quad (2)$$

Model – SVAR-GARCH

Assume:

$$\epsilon_{k,t} = \sigma_{k,t|t-1} e_{k,t} \quad \text{where} \quad \mathbf{e}_t \sim \text{i.i.d. } N(\mathbf{0}, \mathbf{I}_N) \quad \text{and} \quad (1)$$

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Then, we can express the reduced form shocks as:

$$\boldsymbol{\mu}_t = \mathbf{B}_0^{-1} \boldsymbol{\lambda}_{t|t-1}^{\frac{1}{2}} \mathbf{e}_t \quad (3)$$

where:

$$\boldsymbol{\lambda}_{t|t-1} = \begin{bmatrix} \sigma_{1,t|t-1}^2 & & 0 \\ & \dots & \\ 0 & & \sigma_{N,t|t-1}^2 \end{bmatrix} \quad (4)$$

Model – SVAR-GARCH

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Statistical identification:

$$\boldsymbol{\Sigma}_{u,t|t-1} = \mathbf{B}_0^{-1} \boldsymbol{\lambda}_{t|t-1} \mathbf{B}_0^{-1'} \quad (5)$$

Model – Diebold-Yilmaz Index (sum-up)

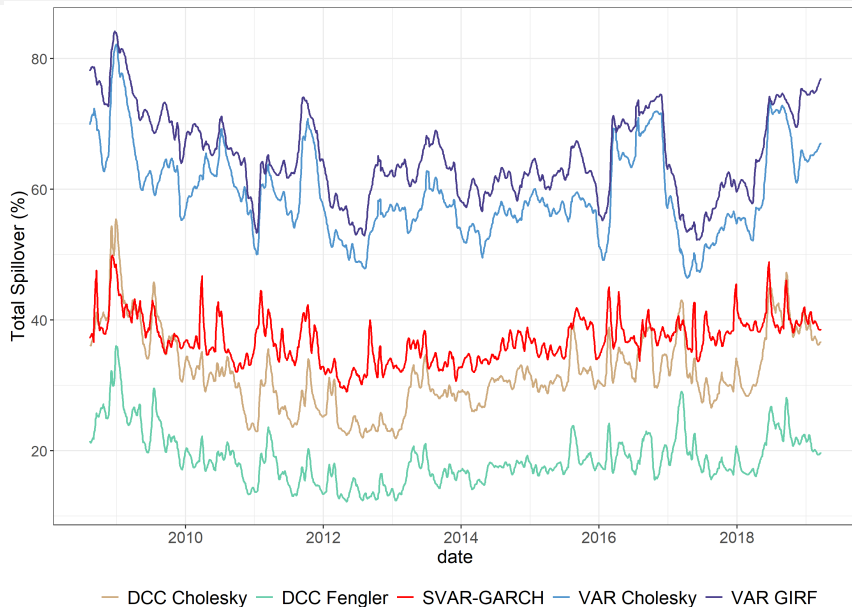
- ❶ VAR: $\mathbf{y}_t = \mathbf{A}(\mathbf{L}) \mathbf{y}_{t-1} + \boldsymbol{\mu}_t$
- ❷ Identification: $\mathbf{B}_0 \mathbf{y}_t = \mathbf{B}(\mathbf{L}) \mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t$ and $E_{t-1}(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t') = \boldsymbol{\lambda}_{|t-1}$
- ❸ Use of FEVD as connectedness tables:

	y_1	y_2	\cdots	y_N	To Others
y_1	d_{11}^H	d_{12}^H	\cdots	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H, j \neq 1$
y_2	d_{21}^H	d_{22}^H	\cdots	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H, j \neq 2$
\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
y_N	d_{N1}^H	d_{N2}^H	\cdots	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H, j \neq N$
From Others	$\sum_{\substack{i=1 \\ i \neq 1}}^N d_{i1}^H$	$\sum_{\substack{i=2 \\ i \neq 2}}^N d_{i2}^H$	\cdots	$\sum_{\substack{i=3 \\ i \neq N}}^N d_{i3}^H$	$\frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^N d_{ij}^H$

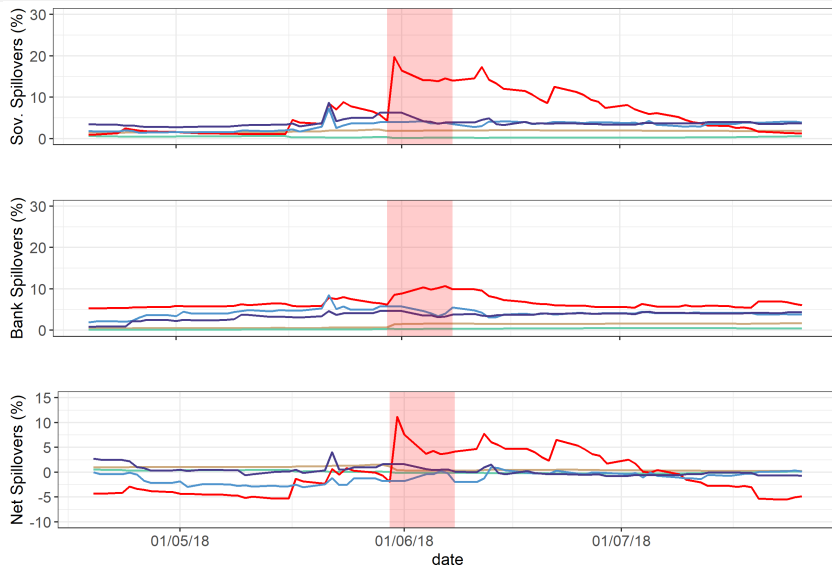
Economic Identification – FEVD

	BE_bk	FR_bk	DE_bk	IT_bk	NL_bk	ES_bk	PT_bk	DE	BE	FR	GR	NL	ES	IT	PT	IE
BE_bk	81%	1%	3%	0%	2%	0%	0%	2%	1%	1%	0%	1%	0%	0%	0%	1%
FR_bk	0%	54%	5%	2%	0%	6%	0%	2%	16%	11%	1%	2%	4%	6%	3%	5%
DE_bk	3%	9%	78%	3%	2%	3%	1%	4%	11%	7%	2%	4%	11%	8%	10%	10%
IT_bk	3%	5%	1%	83%	17%	16%	4%	0%	1%	0%	5%	0%	2%	2%	3%	0%
NL_bk	1%	2%	0%	5%	61%	1%	1%	3%	3%	3%	3%	7%	19%	4%	9%	4%
ES_bk	2%	23%	3%	1%	1%	56%	1%	10%	4%	3%	1%	1%	1%	1%	1%	4%
PT_bk	2%	1%	0%	1%	0%	1%	84%	0%	0%	1%	2%	0%	1%	1%	2%	1%
DE	4%	1%	1%	0%	2%	2%	0%	70%	13%	8%	2%	10%	4%	5%	3%	6%
BE	0%	2%	0%	0%	1%	1%	1%	1%	34%	0%	1%	3%	1%	2%	2%	5%
FR	1%	2%	0%	0%	1%	2%	1%	0%	5%	61%	1%	1%	1%	3%	1%	1%
GR	0%	0%	0%	0%	1%	0%	0%	1%	0%	0%	76%	0%	1%	0%	0%	1%
NL	1%	0%	0%	1%	1%	2%	0%	2%	9%	3%	1%	68%	1%	2%	1%	7%
ES	1%	0%	6%	2%	8%	8%	1%	1%	0%	1%	0%	1%	50%	7%	15%	1%
IT	0%	0%	0%	0%	1%	1%	0%	1%	1%	1%	2%	1%	2%	58%	3%	2%
PT	0%	0%	0%	0%	0%	0%	1%	0%	1%	0%	2%	1%	2%	1%	40%	0%
IE	1%	0%	0%	1%	0%	0%	3%	1%	0%	1%	0%	0%	1%	1%	8%	53%

Model Comparison – Total Spillovers



Model Comparison – Identification (i)



— DCC Cholesky — DCC Fengler — SVAR-GARCH — VAR Cholesky — VAR GIRF

Model Comparison – Identification (ii)

	DCC Fengler	DCC Cholesky	VAR GIRF	VAR Cholesky	SVAR - GARCH
(i) Subset of sovereign events	11.0	22.0	44.0	39.0	78.0
(ii) Total sovereign events	30.8	33.3	33.3	38.5	64.1
(iii) Total sovereign and bank events	34.2	36.8	39.5	47.4	68.4
(iv) Candelon et al. (2011)	36.3	45.4	36.4	44.6	63.6
(v) Alexandre et al. (2016)	12.5	25.0	75.0	0.5	75.0

Note: This table reports the percentage of correct event identifications by each model.

Economic Validation – Theoretical channels (i)

- Do estimates also match with **theoretical contagion channels**?
- We turn to panel analysis, regressing:
 - $\bar{\omega}_{i \rightarrow j, t}$ quarterly average pairwise spillover from i to j .
 - On \mathbf{D}_{ijt} distance variables between i and j , e.g.: similarity in debt/GDP.
 - And on $\mathbf{E}_{j \rightarrow i, t}$, exposure variables of j on i , e.g.: trade links.
- We assess **various potential channels**, such as:
 - Trade links between sovereigns.
 - Similar portfolio channel between banks.
 - Implicit bailout channel from banks to sovereigns.
 - Balance sheet channel from sovereigns to banks...

Economic Validation – Theoretical channels (ii)

$$\bar{\omega}_{i \rightarrow j, t} = \beta_i + D_{ijt} \beta_1 + E_{j \rightarrow i, t} \beta_2 + \alpha_t + \epsilon_{ij, t} \quad (6)$$

Regression		Expected channels	Significant channels
Sov. - Sov.		Distance: Business Cycle, D/GDP Exposure: Trade, Investment	D/GDP (+), Trade (+), Investment (+)
Bank - Bank		Distance: NPLs, Capital ratios Exposure: Sim. portfolios, bank claims	Capital ratios (+), Sim. portfolios (+)
Bank - Sov.	<i>High debt</i>	Vulnerability: Capital ratio, D/GDP,	Cap ratio (-), D/GDP (+)
	<i>Low debt</i>	Current account, GDP growth Exposure: domestic sovereign / domestic NFC	Cap ratio (-), D/GDP (-), NFC (+)
Sov. - Bank	<i>High debt</i>	Vulnerability: NPLs, Capital ratio, Liquidity	NPLs (+), Liquidity (-), Sovereign debt (+)
	<i>Low debt</i>	Exposure: domestic sovereign / domestic NFC	Liquidity (-), Sovereign debt (+), NFCs (+)

Conclusion

- Model: **Structural version** of DY based on a SVAR-GARCH with **up-to-date spillovers**.
- Methodological Results:
 - **Economic identification** enabled, even in a 16-variable system.
 - **Outperforms other models** in terms of timeliness and narrative fit.
 - Validation further supported by regression analysis: **estimates match theoretical channels**.
- Further research:
 - **Trade-off** between daily reactive estimates and time-varying B_0 .
 - Fewer constraints than usual SVAR: could be used for alternative datasets (e.g. liquidity contagion).

THANK YOU

BACKUP SLIDES

Annex – FEVD build-up

- With the MA representation of \mathbf{Y}_t :

$$\mathbf{Y}_{t+H} - \mathbf{Y}_{t+H|t} = \sum_{i=0}^{H-1} \mathbf{\Theta}_i \boldsymbol{\epsilon}_{t+H-i} \quad (7)$$

- FEVD is a function of MSPE:

$$\begin{aligned} MSPE_t(H) &= E_t(\mathbf{Y}_{t+H} - \mathbf{Y}_{t+H|t})(\mathbf{Y}_{t+H} - \mathbf{y}_{t+H|t})' \\ &= \sum_{i=0}^{H-1} \mathbf{\Theta}_i \boldsymbol{\lambda}_{t+H-i|t}^* \mathbf{\Theta}_i' \end{aligned} \quad (8)$$

- So connectedness may come from 2 sources, propagation mechanisms ($\mathbf{\Theta}_i = \mathbf{J} \mathbf{A}^i \mathbf{J}' \mathbf{B}_0^{-1}$) or volatility ($\boldsymbol{\lambda}_{t+H-i|t}^*$). Volatility being projected at each t with the GARCH structure of the SVAR.

Annex – Theoretical channels, between sovereigns

$$\bar{\omega}_{i \rightarrow j,t}(h) = \beta_i + \alpha_t + \beta_2 d_{ij,t}^{GDP} + \beta_3 d_{ij,t}^{\frac{D}{GDP}} + \beta_4 \text{exposure}_{j \rightarrow i,t}^k + \epsilon_{ij,t} \quad (9)$$

	(1)	(2)	(3)
Similar BC	-0.00005 (0.001)	-0.002 (0.001)	-0.001 (0.001)
Similar D/GDP	0.021*** (0.002)	0.007*** (0.002)	0.014*** (0.002)
Trade exposure		0.433*** (0.020)	
Investment exposure			0.236*** (0.028)
Time fixed effects?	Yes	Yes	Yes
i fixed effects?	Yes	Yes	Yes
Observations	3,240	3,240	3,171
R ²	0.448	0.598	0.490
Adjusted R ²	0.438	0.591	0.481

*p<0.05; **p<0.01; ***p<0.001

Annex – Theoretical channels, between banks

$$\bar{\omega}_{i \rightarrow j, t}(h) = \beta_i + \alpha_t + \beta_2 d_{ij, t}^{NPL} + \beta_3 d_{ij, t}^{Lev.R.} + \beta_4 \text{exposure}_{j \rightarrow i, t}^k + \epsilon_{ij, t} \quad (10)$$

	(1)	(2)	(3)
Similar NPLs	-0.001 (0.003)	-0.003 (0.003)	-0.001 (0.003)
Sim. Capital ratios	0.037*** (0.009)	0.029** (0.010)	0.040*** (0.010)
Similar portfolio		7.304*** (1.355)	
Bank claims			-0.013 (0.009)
Time fixed effects?	Yes	Yes	Yes
i fixed effects?	Yes	Yes	Yes
Observations	1,812	1,812	1,812
R ²	0.434	0.439	0.435
Adjusted R ²	0.417	0.422	0.417

* p<0.05; ** p<0.01; *** p<0.001

Annex – Theoretical channels, bank to sovereign

$$\bar{\omega}_{bank_i \rightarrow sov_i, t}(h) = \beta_0 + \alpha_t + \beta_1 v_{bank_i, t}^{Lev.R.} + \beta_2 v_{sov_i, t}^{D/GDP} + \beta_3 v_{sov_i, t}^{CA} + \beta_4 v_{sov_i, t}^{gGDP} + \beta_5 exposure_{sov_i \rightarrow bank_i, t}^k + \epsilon_{bank_i, sov_i, t} \quad (11)$$

	<i>High debt countries</i>			<i>Low debt countries</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Capital	-0.91*** (0.21)	-0.91*** (0.21)	-1.01** (0.31)	-5.01*** (1.04)	-5.07*** (1.05)	-3.88*** (1.07)
Debt to GDP	1.00*** (0.17)	1.01*** (0.17)	0.88*** (0.21)	3.74** (1.29)	3.56** (1.28)	3.50** (1.22)
Current Account	0.13 (0.20)	0.13 (0.26)	0.23 (0.28)	-0.63 (1.26)	-0.62 (1.28)	0.16 (1.31)
GDP growth	-0.06 (0.22)	-0.05 (0.23)	-0.05 (0.22)	-0.29 (0.66)	-0.31 (0.66)	-0.28 (0.68)
Sov. exposure		0.06 (1.92)			2.94 (9.63)	
Non-bank exposure			-0.88 (1.50)			20.52*** (6.02)
Time fixed effects?	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	174	174	174	123	123	123
R ²	0.74	0.74	0.74	0.93	0.93	0.94
Adjusted R ²	0.64	0.64	0.64	0.89	0.89	0.90

*p<0.05; **p<0.01; ***p<0.001

Annex – Theoretical channels, sovereign to bank

$$\bar{\omega}_{sov_i \rightarrow bank_{i,t}}(h) = \beta_0 + \alpha_t + \beta_1 v_{bank_{i,t}}^{NPL} + \beta_2 v_{bank_{i,t}}^{Lev.R.} + \beta_3 v_{bank_{i,t}}^{Liq.R.} + \beta_5 \text{exposure}_{bank_{i,t} \rightarrow sov_i}^k + \epsilon_{sov_i, bank_{i,t}} \quad (12)$$

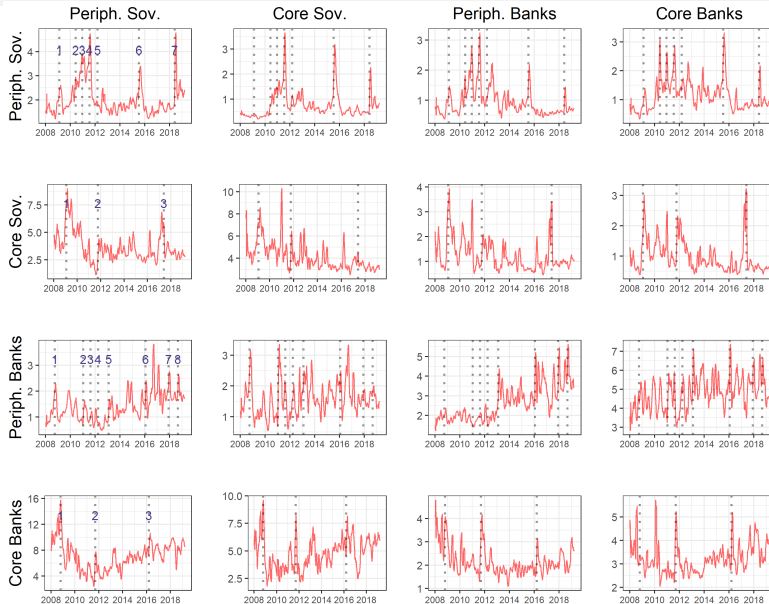
	<i>High debt countries</i>			<i>Low debt countries</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
NPLs	2.61** (0.81)	2.24** (0.81)	2.74** (0.84)	-0.10 (0.18)	-0.12 (0.17)	-0.19 (0.17)
Capital	-1.38 (0.77)	-0.80 (0.76)	-2.49 (1.31)	-0.06 (0.23)	0.34 (0.23)	0.41 (0.31)
Liquid assets	-4.03*** (0.48)	-6.17*** (1.01)	-4.60*** (0.69)	-0.92*** (0.18)	-0.11 (0.29)	-0.43 (0.29)
Exposure domestic gov. debt		0.18** (0.07)			0.18*** (0.05)	
Exposure domestic NFCs			-0.04 (0.03)			0.05** (0.02)
Time fixed effects?	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	174	174	174	121	121	121
R ²	0.54	0.55	0.54	0.88	0.89	0.88
Adjusted R ²	0.37	0.38	0.37	0.80	0.82	0.81

*p<0.05; **p<0.01; ***p<0.001

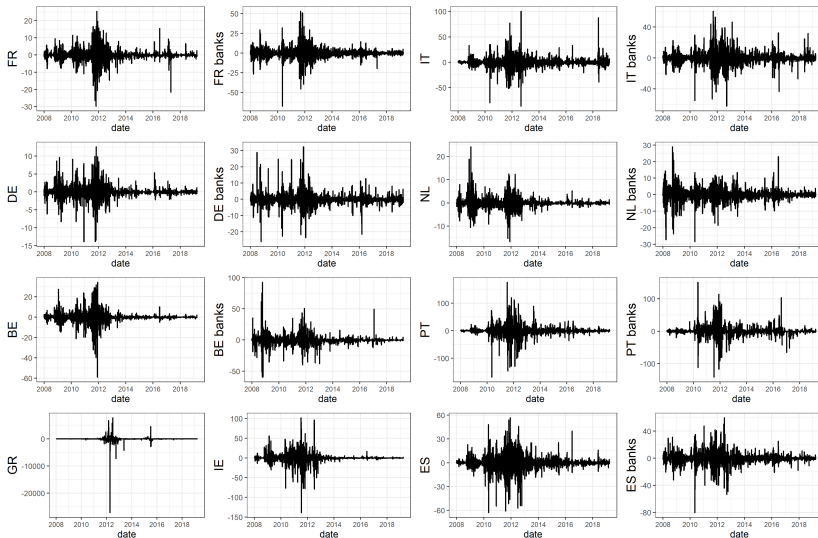
Annex – Granger causality

H_0 : SVAR-GARCH does not Granger cause:	F - test	p-value
<i>Rolling window estimated models</i>		
VAR Cholesky	14.91	3.627e-07***
VAR GIRF	6.0492	0.002391 **
<i>GARCH-related models</i>		
DCC Cholesky	1.0527	0.3491
DCC Fengler	1.3641	0.2558
H_0 : SVAR-GARCH is not Granger caused by:	F - test	p-value
<i>Rolling window estimated models</i>		
VAR Cholesky	0.5159	0.597
VAR GIRF	0.9483	0.3875
<i>GARCH-related models</i>		
DCC Cholesky	0.4206	0.6567
DCC Fengler	8.8071	0.0001539***

Annex – Pairwise spillovers



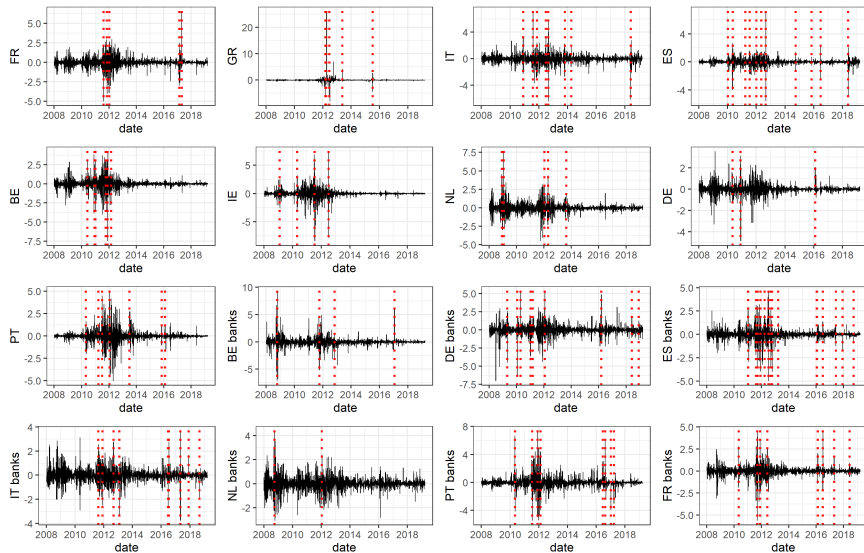
Annex – Inputs



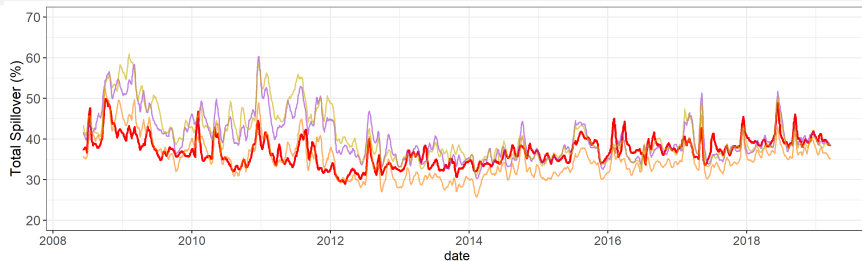
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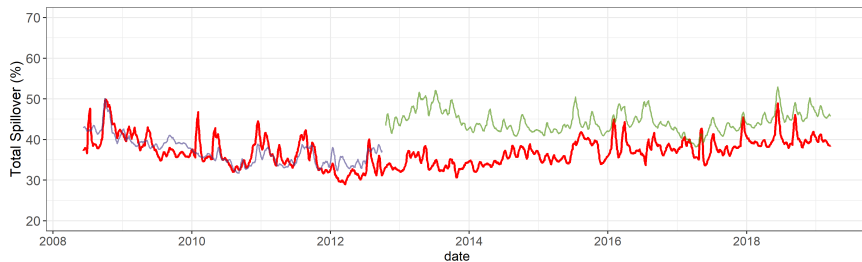
Annex – Events



Annex – Robustness



— Citi-Oil-US & UK sov. — Citi-Oil-US & UK sov.-US & UK banks — Citi-Oil-US sov.-US banks — SVAR-GARCH



— Fratzscher et al. 1 — Fratzscher et al. 2 — SVAR-GARCH

Annex – Test identification

h under H_0	$Q_1(1)$	df	p-value
1	124.3405	1	$< 10^{-5}$
2	113.4685	1	$< 10^{-5}$
3	85.0733	1	$< 10^{-5}$
4	66.6269	1	$< 10^{-5}$
5	60.7231	1	$< 10^{-5}$
6	46.2298	1	$< 10^{-5}$
7	38.0658	1	$< 10^{-5}$
8	35.8007	1	$< 10^{-5}$
9	25.3033	1	$< 10^{-5}$
10	16.2284	1	5.615e-05
11	13.3168	1	0.000263
12	12.6034	1	0.000385
13	517.7083	1	$< 10^{-5}$
14	185.0355	1	$< 10^{-5}$
15	154.8558	1	$< 10^{-5}$