

Sovereign-Bank Nexus: Sovereign Debt Shocks Propagation and Their Role in Forecasting Episodes of Financial Distress

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SGH

Why does Sovereign-Bank Nexus (SBN) matter?

Sovereign-Bank Nexus in a nutshell

*When the sovereign debt market experiences periods of stress, the **lending capacity of local banks tends to be impaired**. The resulting **credit crunch** leads to a deterioration of the economy, which eventually ends up **exacerbating the stress in the sovereign debt market** even further.*

Albertazzi, Cimadomo, and Maffei-Faccioli (2022)

Sovereign-Bank Nexus from a policy perspective

*We must also break the **vicious cycle** of banks hurting sovereigns and sovereigns hurting banks. **This works both ways**. Making banks stronger (...) stops banks from hurting sovereigns (...) and restoring confidence in sovereign debt helps banks, which are important holders of such debt*

Christine Lagarde (2012)

My research in a nutshell

- **What's the problem?** Sovereign debt shocks (SDS) can generate periods of elevated systemic distress¹. **Empirical literature hasn't reached consensus on how to identify them econometrically**
- **What do I do?**
 - ① Building upon Antolín-Díaz and Rubio-Ramírez (2018), I develop a novel **identification scheme**: Sign-Restricted Narrative Approach (SRNA)
 - ② Propagation schemata derived from SRNA (IRFs) are put into a **macroprudential early-warning logit (EWL)** as input scenarios to study **impact on systemic stress**
- **What do I find?** Estimation of a SVAR model documents several sovereign-bank nexus-related phenomena:
 - ① Substantial role of SDS in shaping supply of loans
 - ② Significance of the balance sheet transmission channel
 - ③ Heavy build-up of systemic stress following a SDS incident, up to 3.74% in a 12M horizon

¹Due to the vicious circle of sovereign debt valuation and the financial sector (Sovereign-Bank Nexus, SBN).

Agenda

1 SDS identification in the empirical literature

2 SRNA step 1: proxy for SDS

3 SRNA step 2: sign restrictions

4 Macroprudential early-warning logit (EWL)

5 Findings & empirical experiments

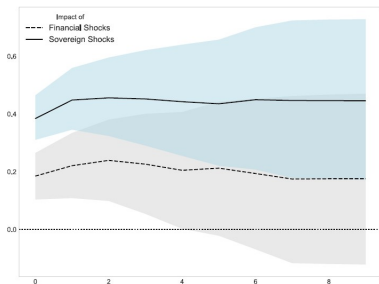
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6 Appendix

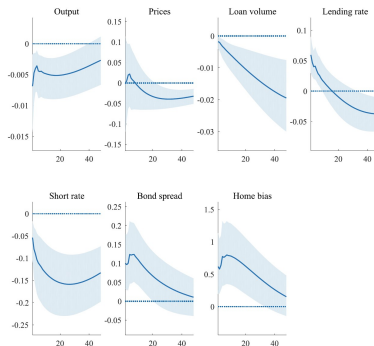
SDS identification: state of the game

- 1 Empirical literature on SDS identification: **no consensus**
- 2 Two **most notable** identification approaches:
 - ▶ **Narrative Approach:**
 - ★ Extremely versatile
 - ★ Allows for detailed examination of the known shock periods
 - ▶ **Sign restrictions**
 - ★ Easy alignment of the model to stylised facts and theoretical findings
 - ★ Ambiguous in character, minimally restrictive
- 3 Building on Antolín-Díaz and Rubio-Ramírez (2018), I aim to **reconcile** both those identification schemes and **apply them jointly** to the empirical study of SBN in seven EA countries.

SDS identification: excerpts from the literature



(a) Manzo and Picca (2018)



(b) Palmén (ibid.)

Figure: SDS IRFs identified with narrative methods (LHS) and sign restrictions (RHS).

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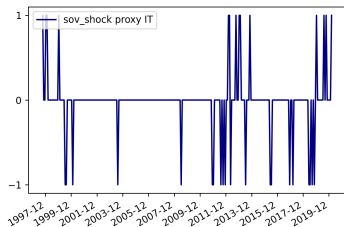
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SRNA step 1: SDS proxy estimation (1/2)

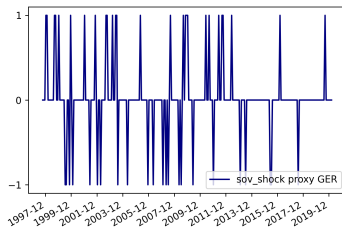
SDS proxy is derived from in-sample forecast errors of long-term (10Y maturity) sovereign debt interest rate (LTI) using an ARIMA model. Derivation goes **country by country** as to fully capture **cross-country heterogeneity**.

- 1 Take series of monthly, country-specific LTI data and fit the ARIMA forecasting model. Choose AR, I, and MA orders which minimises Bayesian Schwarz information criterium (BIC, see Schwarz, 1978)
- 2 After ARIMA estimation, conduct in-sample forecast
- 3 Compute forecast errors
- 4 Fix a cut-off point at a country-specific level. Identify periods with absolute errors above the chosen cut-off and label them as shock periods
- 5 Label periods with highest positive errors as negative shocks (-1) and periods with highest absolute negative errors as positive shocks (+1). All other periods take value 0.

SRNA step 1: SDS proxy estimation (2/2)



(a) Italy



(b) Germany

Figure: SDS proxy based on ARIMA in-sample forecast LTI errors with 80% cut-off threshold.

Appendix: Why country-specific thresholds?

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SRNA step 2: sign restrictions (1/2)

Assumption: SDS transmitted *via* balance sheet channel have:

- **Positive (+)** impact on:
 - ▶ Domestic bonds portfolio (*home bias*)
 - ▶ Credit supply
- **Negative (-)** impact on:
 - ▶ Foreigns bonds portfolio (*run to quality*)

Assumption: SDS regardless of transmission channel have:

- **Positive (+)** impact on:
 - ▶ Credit supply

SRNA step 2: sign restrictions (2/2)

Identification matrix B_0^{-1} is defined as follows:

$$B_0^{-1} = SH \quad (1)$$

$$S = \text{chol}(\Sigma) \quad (2)$$

$$H : (HH^T = \mathcal{I}) \text{ and sign restrictions satisfied} \quad (3)$$

There are infinitely many matrices H satisfying this definition. Sampling algorithm is following:

- 1 Take $S = \text{chol}(\Sigma)$
- 2 Draw $M_{n,n}$ such that $\forall_{1 \leq i, j \leq n} M_{i,j} \sim \mathcal{N}(0, 1)$
- 3 Make QR decomposition and normalise: $M = QR$

Appendix: Normalisation of diagonal

- 4 Let $H = Q$.
 - ▶ If in given periods k impulse responses of variable i to SDS $(\mathbb{A}_{[i,1]}^k \cdot SH)$ satisfy restrictions: iteration successful
 - ▶ Else go back to step 2 (draw new matrix M)

SRNA step 3: SVAR specification and estimation

Model specification (all variables in logs but for the SDS proxy):

$$Y_t = [\text{proxy}_t \quad BH_t^{\text{dom}} \quad BH_t^{\text{for}} \quad L_t \quad rGDP_t]' \quad (4)$$

Estimation of a reduced-form SVAR:

$$Y_t = \sum_{j=1}^p A_{t-j} Y_{t-j} + \epsilon_t \quad (5)$$

Baseline specification has $p = 5$ lags as indicated by AIC.

Data overview

The dataset includes **monthly** data spanning from late 90s to the end of 2023, i.e. **306-314 observations per country**. The dataset includes **GIPS, Germany, France, and the Netherlands**. Data sources:

- **ECB SDW** (balance sheet entries and credit supply: BSI, LTI: IRS)
- **FRED** (real GDP)

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EWL specification and estimation

- I estimate probability of a financial crisis outbreak with **country-specific logits**. Common tendencies come from a **panel**
- Benchmark specification comprised credit gap as the sole regressor².
- Alternative specification selected additional controls from a broad pool proposed by Jarmulska (2020). [More on controls](#)

$$ProbSys_t = \alpha_0 + \alpha_1 Basel_t + \sum \beta_i Control_{i,t} \quad (6)$$

- For the purpose of EW, lag distribution has been applied:

$$ProbSys_t = \alpha_0 + \sum_{i=1}^I \alpha_i Basel_{t-i} + \sum_j^J \sum_k^K \beta_{j,k} Control_{j,t-k} \quad (7)$$

Data overview

- **Dependent variable** comes from ESRB Financial Crisis Database (Lo Duca et al., 2017) which comprises detailed data on systemic stress spells in the Euro Area. The series is of **monthly** frequency, spanning from early 70s to 2017.

Bridging SVAR to the EWL *via* cIRF

*Note: for simplicity it is assumed that a SDS has **no impact** on GDP. Empirical findings support this assumption.*

Note: post-SDS values are apostrophed (')

Given that SVAR is estimated in logs, cumulative IRf of credit supply is given by:

$$cIRF_t = \log L'_t - \log L_t = \log \frac{L'_t}{L_t} \quad (8)$$

$$gap'_t = gap_t \times e^{cIRF_t} \quad (9)$$

Eventually — given that **contemporaneous credit gap is the sole driver of systemic stress**, as in the baseline specification — we have:

$$\Delta p_{systemic} = \frac{dy}{dx} \times gap_t (e^{cIRF_t} - 1) \quad (10)$$

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Findings — SDS transmission *via* balance sheet channel

- *Home bias* **present** in **all economies** — yet peak impact timing differs tremendously IRF
- *Run to quality* **measures resistance to SDS** — it's **permanently negative** in fiscally weakest economies (Greece), **indifferentiable from zero** in the most austere (Germany, the Netherlands), in other cases **transitory** IRF
- **Credit** IRF to SDS **similar in all countries** (instantaneous impact approx. 0,005, wanes out in a year) IRF
- Impact on **GDP**: actually **insignificant**; notably, **confidence bands converge over time** IRF

Review of the robustness checks

Findings — systemic stress build-up

country group	country	0M effect [%]	12M effect [%]
GIPS (non-austere)	Greece	0.39	3.74
	Italy	0.04	0.34
	Portugal	0.20	3.30
	Spain	0.33	1.72
non-GIPS (austere)	Germany	0.38	2.61
	France	0.34	3.32
	Netherlands	0.32	1.86

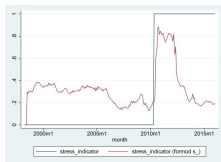
Table: Increment in probability of a systemic crisis outbreak following a sovereign yield shock (baseline specification)

More on marginal effects

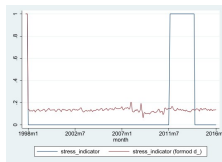
AUROC statistics

Panel estimates

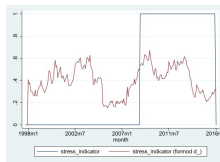
EWL: in-sample forecasting capacity



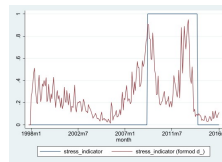
(a) Greece



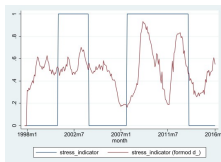
(b) Italy



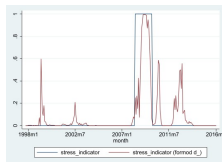
(c) Portugal



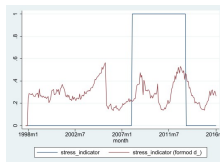
(d) Spain



(e) Germany



(f) France



(g) Netherlands

Figure: EWL performance in an in-sample forecasting exercise

Findings: — balance sheet channel vs other channels

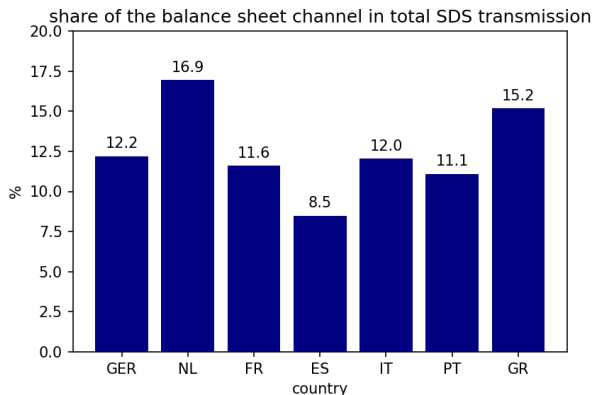


Figure: Ratio of acceptance ratios (3 sign restrictions vs 1)

Findings — cross-country contagion

	GR	IT	PT	ES	GER	FR	NL
GR	1.00	0.08	0.33	0.12	-0.07	-0.04	-0.04
IT		1.00	0.38	0.62	0.27	0.45	0.38
PT			1.00	0.42	0.17	0.22	0.21
ES				1.00	0.45	0.59	0.55
GER					1.00	0.81	0.83
FR						1.00	0.90
NL							1.00

Table: Correlations between country-specific SDS indicators

All in all, despite **heavy GIPS-to-GIPS and austere-to-austere SDS proxy correlations**, overall contagion effects seem limited. [More](#)

SRNA robustness checks

SRNA identification scheme has been subject to various robustness checks:

- ① **More selective SDS threshold:** In line with Antolín-Díaz and Rubio-Ramírez (2018), narrative identification of SDS has been based on extremely rare events (approx. 3 per country) [More](#)
- ② **Rolling 3M sum of SDS proxy:** This method takes into account possible cumulation of subsequent shocks [More](#)
- ③ **One-sided SDS proxy:** Ultimately, one-sided proxy allows for non-symmetric IRFs to positive and negative shocks

Results **do not diverge** from the baseline findings.

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Conclusions

Regarding **impact on the systemic risk in the EA**:

- 1 **Significant, instantaneous effect** on systemic stress with **rapid build-up** of risk

Regarding **Sign-Restricted Narrative Approach (SRNA)**:

- 1 My method allows to **document particular SBN-related phenomena** in the EA:
 - ▶ balance sheet phenomena (*home bias, run to quality*)
 - ▶ nominal phenomena (impact on the supply of credit)
 - ▶ real (no impact on real GDP)
- 2 It shows the role of **balance sheet channel** in SDS identification. This channel is responsible for approx. **20% of the overall transmission**

Regarding **Sovereign-Bank Nexus (SBN)**:





- 1 SDS have significant impact on credit supply
- 2 No **direct impact** on real GDP

Thank you for your attention!
Any remarks are more than welcome!




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Threshold selection — discussion

- **Heterogeneity** across LTI processes in different Eurozone countries is **clearly visible**
- **Relative approach** addresses the issue of cross-country heterogeneity — there **does not exist a single, absolute cut-off** that could fit both austere economies and GIPS countries

country group	country	SD
GIPS (non-austere economies)	Greece	0.9222
	Italy	0.2732
	Portugal	0.3084
	Spain	0.2301
non-GIPS (austere economies)	Germany	0.1601
	France	0.1685
	Netherlands	0.1626

Table: In-sample LTI one-period-ahead forecast error standard deviation

Normalisation of H diagonal

- QR decomposition of a given matrix is **indefinite**
 - ▶ In particular, it is **indefinite wrt sign**
- QR algorithm implementation (both R and Python) **forces** $Q[1, 1] < 0$ and thus **is biased towards** negative diagonal
- **Solution:** Normalisation of Q columns with negative diagonal numbers

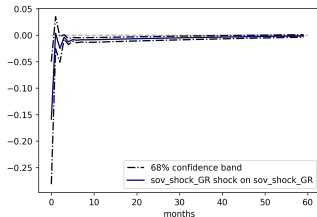


Figure: Non-normalised Q matrix: unexpected IRF (Greece) [Back](#)

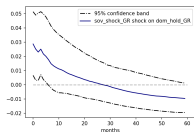
Selection of additional controls in EWL with LASSO

In line with Jarmulska (2020), a pool of additional controls consisted of five sub-groups:

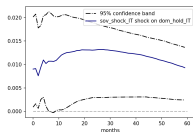
- **Global macro:** US policy rate, US GDP, Chinese GDP, Brent oil price index
- **Local macro & competitiveness:** GDP growth rate, GDP PC, current account balance (net), net exports, consumption, investment, CPI, index of housing prices
- **Financial:** EURUSD exchange rate
- **Fiscal:** general government debt and balance, implicit interest rate
- **Labour market:** rate of unemployment

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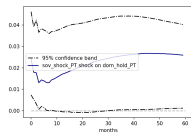
Home bias: IRF



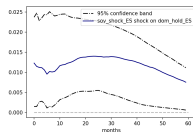
(a) Greece



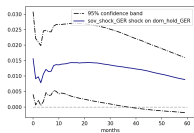
(b) Italy



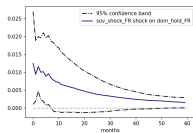
(c) Portugal



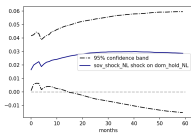
(d) Spain



(e) Germany



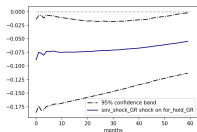
(f) France



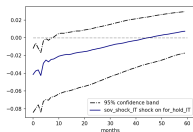
(g) Netherlands

Figure: *Home bias* — IRFs of domestic bond holdings in response to a sovereign debt shock (balance sheet transmission channel) [Back](#)

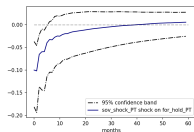
Run to quality: IRF



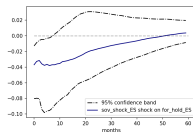
(a) Greece



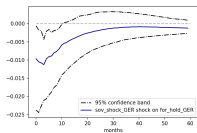
(b) Italy



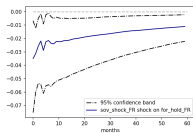
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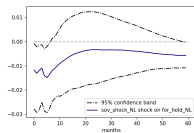
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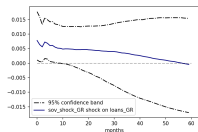
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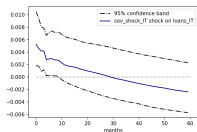
(g) Netherlands

Figure: Run to quality — IRFs of foreign bond holdings in response to a sovereign debt shock (balance sheet transmission channel) [Back](#)

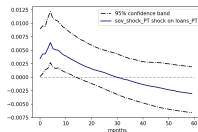
Credit supply: IRF



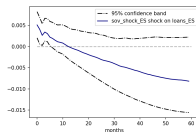
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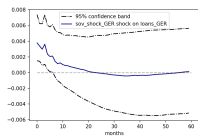
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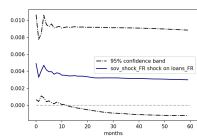
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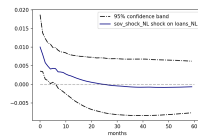
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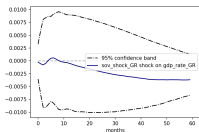
(f) France



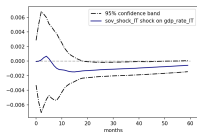
(g) Netherlands

Figure: IRFs of loan supply in response to a sovereign debt shock (balance sheet transmission channel) [Back](#)

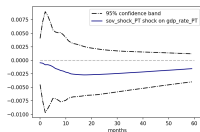
GDP: IRF



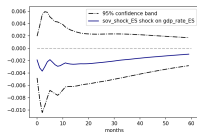
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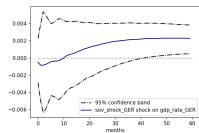
(b) Italy



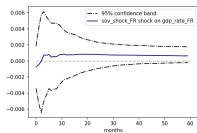
(c) Portugal



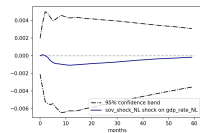
(d) Spain



(e) Germany



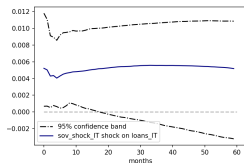
(f) France



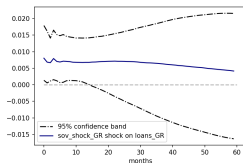
(g) Netherlands

Figure: IRFs of real GDP in response to a sovereign debt shock (balance sheet transmission channel) [Back](#)

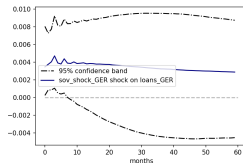
SRNA: Narrative Approach using extremely rare events



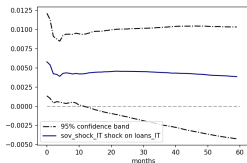
(a) IT (rare events)



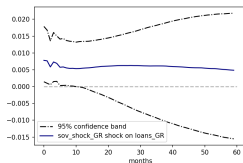
(b) GR (rare events)



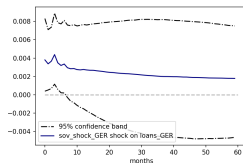
(c) GER (rare events)



(d) IT (standard)



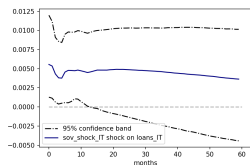
(e) GR (standard)



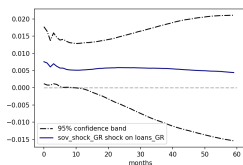
(f) GER (standard)

Figure: IRFs of loan supply in response to a sovereign debt shock (all transmission channels) — narrative approach comparison [Back](#)

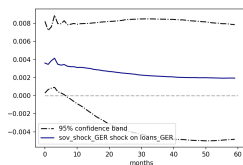
SRNA: Narrative Approach using rolling sum of proxy



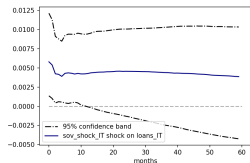
(a) IT (rollsum)



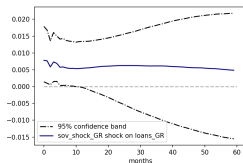
(b) GR (rollsum)



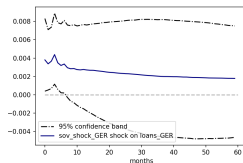
(c) GER (rollsum)



(d) IT (standard)



(e) GR (standard)



(f) GER (standard)

Figure: IRFs of loan supply in response to a sovereign debt shock (all transmission channels) — narrative approach comparison [Back](#)

EWL: marginal effects at means

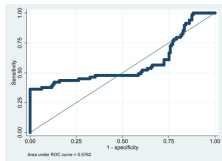
country group	country	$\frac{dy}{dx}$
GIPS (non-austere economies)	Greece	0.5034***
	Italy	0.0853
	Portugal	0.5714***
	Spain	0.6487***
non-GIPS (austere economies)	Germany	1.0083***
	France	0.6964***
	Netherlands	0.3240***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

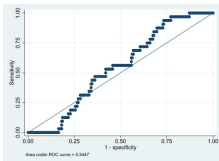
Table: Marginal effects calculated at means under baseline specification

Back

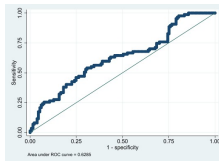
EWL: Area Under Receiver Operating Curve



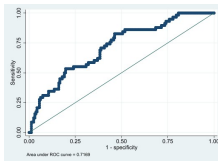
(a) Greece



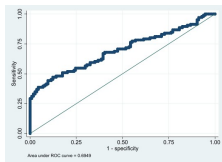
(b) Italy



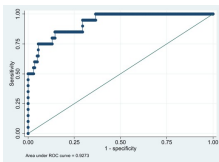
(c) Portugal



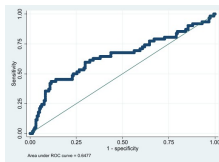
(d) Spain



(e) Germany



(f) France



(g) Netherlands

Figure: Area under ROC for country-specific early-warning logit models under baseline specification [Back](#)

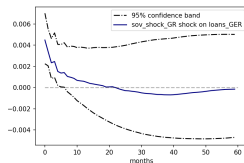
EWL: common tendencies (panel estimation)

model	controls	$\frac{dy}{dx}$	OR
pool	no	0.5018***	
LASSO	yes		4.5921***
FE	no	0.6458***	

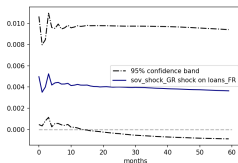
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table: Marginal effects calculated at means/odds ratios under various panel specifications [Back](#)

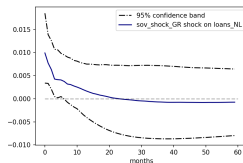
Greece-to-austere contagion: IRF



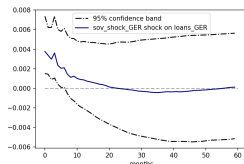
(a) GR to GER



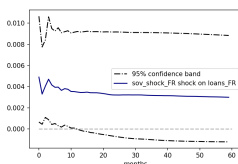
(b) GR to FR



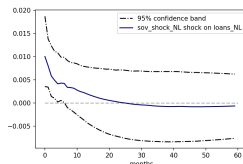
(c) GR to NL



(d) GER



(e) FR



(f) NL

Figure: SDS contagion coming from Greece — loans [Back](#)