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

Lukas Boeckelmann[1], Arthur Stalla-Bourdillon[2]

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Abstract

We propose a novel approach to quantify spillovers on financial markets based on a structural version of the Diebold-Yilmaz framework. Key to our approach is a SVAR-GARCH model that is statistically identified by heteroskedasticity, economically identified by maximum shock contribution and that allows for time-varying forecast error variance decompositions. We analyze credit risk spillovers between EZ sovereign and bank CDS. Methodologically, we find the model to better match economic narratives compared with common spillover approaches and to be more reactive than models relying on rolling window estimations. We find, on average, spillovers to explain 37% of the variation in our sample, amid a strong variation of the latter over time.[3]

Keywords: CDS, spillover, sovereign debt, systemic risk, SVAR, identification by heteroskedasticity.

JEL classification: C58, G01, G18, G21

[1] Paris School of Economics and Banque de France, lukas.boeckelmann@banque-france.fr
[2] Université Paris Dauphine and Banque de France, arthur.stalla-bourdillon@banque-france.fr
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NON-TECHNICAL SUMMARY

Assessing spillovers between financial assets is a difficult exercise. When a shock occurs in one market and then spreads to others, prices of those markets are affected in a quasi-contemporary manner. It is difficult then, ex post, to identify the source of the shock and thus to distinguish correlation from causality in the movement of financial time series.

Moreover, the magnitude of the transmission of such shocks is not stable over the observed period. Therefore, a good spillover model should not only succeed in identifying the shocks in question, but also take into account the time-varying effects they have on other markets. Several papers in the literature have proposed to solve this problem by estimating models on rolling windows. However, this methodology has downsides: in rolling windows new observations have little weight compared to past observations, so that such model lack in responsiveness.

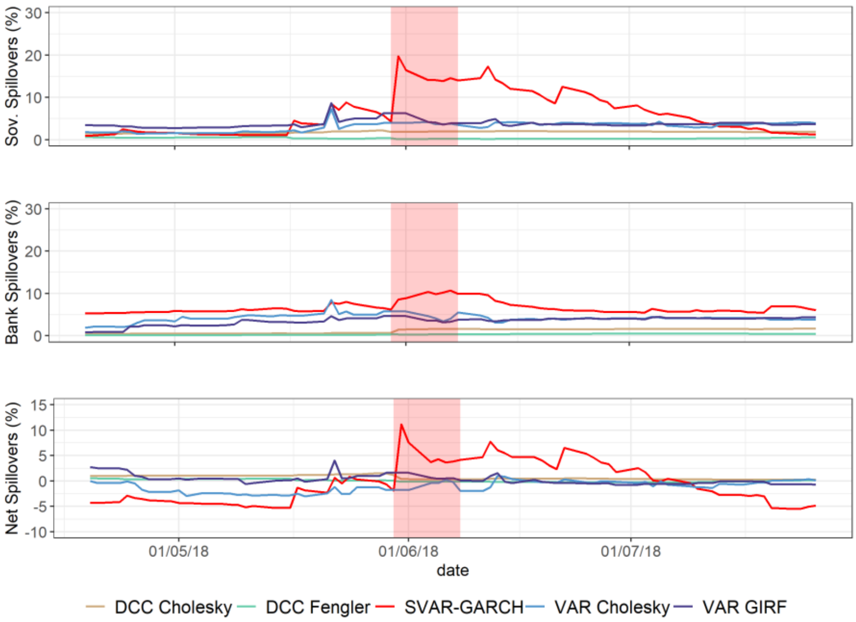
In this paper, we propose a novel model to quantify spillovers based on the work of Diebold and Yilmaz (2009) and Lütkepohl and Milunovich (2016). We estimate this model on sovereign and bank Credit Default Swaps (CDS) in the Eurozone. More specifically, we use this methodology to assess the national and international propagation of credit risk shocks and to analyze the extent of the sovereign-bank nexus across countries.

Our main results are methodological. By comparing our estimates with those of other models used in the literature, we observe a superior performance of our methodology with respect to the two issues mentioned: the identification of shocks and the reactivity to new events. Concerning the identification of shocks, we compare the capacity of the models to clearly distinguish between bank and sovereign shocks. For example, during the Italian political crisis of May 2018, Italian bank and sovereign CDS spreads increased significantly at the same time, thus reinforcing the likelihood for any spillover model to mistake this sovereign shock for a bank shock. As shown in the graph below, for this particular event the SVAR-GARCH model we propose is the only one correctly identifying the shock. Analysing the performance more generally on a large list of bank and sovereign events, the SVAR-GARCH compares favourable to competing models. Concerning the reactivity of spillover estimates, we compare the different methodologies by performing Granger causality tests. We find that the estimates produced by the SVAR-GARCH model are more reactive, especially compared to models estimated on rolling windows.

We also present economic results that further support our identification strategy: The spillovers the model produces retrace well the Eurozone crisis; for example by underlining the importance of Irish shocks at the beginning of the crisis, followed by a rise of Italian and Spanish shocks. Moreover, we find that the spillover estimates are positively associated with channels of credit risk transmission that the theoretical and empirical literature suggests.

All in all, the model we propose appears well suited for estimating spillovers between CDS markets, combining an attractive identification approach with time variation in the spillover estimates, while contributing to the active literature on methodologies for spillover estimations. Moreover, to the extent that our model imposes relatively few restrictions, it lends itself to be a useful tool for the analysis of spillover dynamics on a broad set of financial markets, instruments and variables.

Spillover indices from Italian shocks (sovereign and bank)



Note: The upper and middle parts of the graph represent spillover indices from Italian sovereign and bank shocks (i.e. how much the latter affect the variances of other variables). The lower part of the graph represents the difference between Italian sovereign and bank spillovers. The vertical red bar highlights the period of May 2018, when Italy was rattled by political turmoil. The models represented correspond to the following references: our paper (SVAR-GARCH), Diebold and Yilmaz (2009, VAR Cholesky), Diebold and Yilmaz (2012, VAR GIRF), Fengler and Herwartz (2018, DCC Fengler), and a contagion model built on Engle (2002, DCC Cholesky).

Estimer de manière non-constante les contagions financières : une application à la transmission de chocs sur le risque de crédit

RÉSUMÉ

Nous proposons une nouvelle méthodologie pour estimer les contagions financières à l'aide d'une version structurelle de l'approche de Diebold-Yilmaz. Le cœur de notre approche repose sur un modèle SVAR-GARCH qui est identifié par hétéroscédasticité et par la contribution maximale des chocs, et qui permet d'obtenir des décompositions non-constantes de la variance des erreurs de prévision. Nous analysons les contagions entre les CDS souverains et bancaires de la Zone Euro. En termes de méthodologie, nous trouvons que notre modèle permet de mieux identifier les chocs par rapport aux autres approches de la littérature, et qu'il est aussi plus réactif que les modèles estimés sur fenêtres glissantes. Nous trouvons, en moyenne, que la contagion explique 37% de la variation des séries de notre échantillon, avec toutefois de fortes variations dans le temps.

Mots-clés : CDS, contagion, dette souveraine, risque systémique, SVAR, identification par hétéroscédasticité.

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1 Introduction

Assessing financial spillovers between different markets can be highly challenging. To evaluate how a specific shock propagated from one market to another requires first to identify this shock. Yet, this task may cause significant difficulties as asset prices contemporaneously affect each other and thus co-move significantly. As for numerous asset classes, this problem applies to spillovers of credit risk; itself a topic of substantial interest for both researchers and policy makers due to their pivotal role in the European debt crisis (Coeuré (2018)).

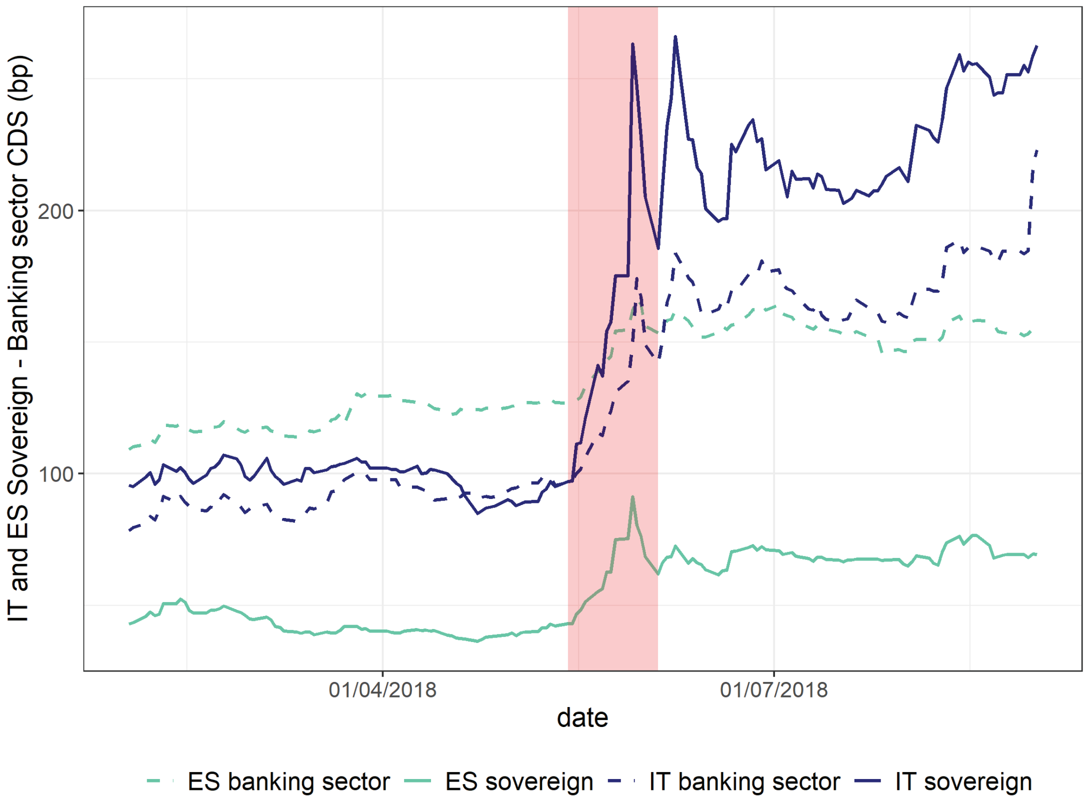
A recent example for credit risk contagion[1] that has lead to asset price comovement is the political turmoil in Italy and heightened fear of a referendum on the Euro membership in May 2018[2]. The event, which can be interpreted as a sovereign Italian shock, led to a considerable surge in the Italian sovereign CDS spreads, a proxy for credit risk. This shock then propagated to Italian bank CDS as well as to CDS of other Euro Area sovereigns and banking sectors, for example in Spain (Figure 1 presents daily CDS of the Euro Area sovereigns and banking sector, the red bar indicates the peak of the political turmoil). As can be seen from Figure 1 the daily CDS series increased simultaneously, therefore a mere visual analysis of Figure 1 cannot help to identify the source of the upsurge: was it a sovereign or a bank shock, and originating from which country? This example highlights the two main needed features of an econometric model with the aim to capture credit risk spillovers. First, the estimated model should be able to handle endogeneity and strong asset co-movements. Second, spillover estimates need to reflect the time variation in financial spillovers as these latter are unlikely to stay constant over time.

The main contribution of this paper is to combine an attractive identification approach

[1] Here, we use the terms spillover and contagion interchangeably. Section 2 differentiates more clearly between the concepts.

[2] See FT: https://www.ft.com/content/eed97b90-6306-11e8-90c2-9563a0613e56

Figure 1: Sovereign and bank CDS spreads for Italy and Spain



On the graph are represented the CDS spreads from the Italian and Spanish sovereign and banking sectors (dashed lines). The red bar indicates the peak of the Italian political turmoil. The sources of the data and the underlying methodology can be found in Section 4.

for a set of endogenous variables with time variation in the estimates of the spillovers. To do so, we rely on a SVAR-GARCH approach combined with the framework of Diebold and Yilmaz (2009). As an application, we estimate the model on a sample of 16 banking sector and sovereign CDS series in the Eurozone (EZ), including the CDS series presented in Figure 1. First, we show that economic identification of the shocks is feasible in this framework, even in a 16-variable system. Second, we test and validate that the economic channels behind the estimates fit economic theories on financial contagion.

The seminal work by Diebold and Yilmaz (2009), as well as a large number of subsequent papers (Alter and Beyer (2014); Claeys and Vašíček (2014); De Santis and Zimic

(2018); Demirer et al. (2018)), propose to base spillover estimates on the off-diagonal entries of forecast error variance decompositions (FEVDs) of rolling window structural vector autoregressions (SVARs). While the approach allows for the construction of mutual consistent spillovers, the literature faces the econometric challenge of identification (De Santis and Zimic (2018)). Earlier papers rely on short-run zero restrictions for the coefficients of the SVAR. However this assumption is unlikely to hold with very reactive financial data (see Alter and Beyer (2014)). Later papers sidestep any structural identification by using reduced form shocks in the form of Generalized FEVD analysis (GFEVD, see Pesaran and Shin (1998)). Yet, reduced form shocks have no economic interpretation and cannot be used for quantifying causal relationships of the data (Kilian and Lütkepohl (2017)). Other standard identification approaches are not appealing either: sign restrictions (Fry and Pagan (2011)), for example, are not exploitable as we do not want to restrict the impacts of the shocks *a priori*. De Santis and Zimic (2018) and De Santis and Zimic (2019) propose attractive identification schemes using magnitude restrictions. However, as most of the literature, they rely on rolling window estimations in order to generate time variation in their spillover estimates. Such rolling window estimations come with a significant drawback: at each point in time they deliver average effects over large time spans where new events are drown in past data. Spillover estimates therefore do not represent up-to-date information.

We propose a novel approach on handling such econometric modeling choices by exploiting a SVAR-GARCH model that is statistically identified by the heteroskedasticity in the data (Lütkepohl and Milunovich (2016)). We show that this modelization is also attractive as it yields time-varying FEVDs based on the conditional variances of estimated structural errors. To the best of our knowledge, we are the first to exploit the time-varying properties of the conditional variances for Diebold-Yilmaz spillover estimates in a SVAR-GARCH setting. Moreover, we show that it is feasible to achieve economic identification between structural shocks and financial market variables in a nontrivial one-to-one relationship, even in a system of 16 variables. We label shocks with a maximum contribution to the forecast error variance of a variable as a shock of precisely that variable (following the 3 to 4-variable identification of Grosse Steffen and Podstawski (2016) and Dungey et al. (2010)). Due to the GARCH component in our estimation, spillover estimates are up-to-date (as in Fengler and Herwartz (2018)) and not drown in a moving window average (as in Diebold and Yilmaz (2009, 2012, 2014)).

We present both methodological as well as economic results. First on the methodological side, we show that the identification of the SVAR-GARCH model yields shock estimates that fit known economic and market events, thus supporting the initial maximum contribution identification. We manage to match major shocks to credit risk to 117 news events, either for bank or for sovereign CDS. In a second step, building either on this list of events or on the lists used in Candelon et al. (2011) and Alexandre et al. (2016), we compare the economic match of the spillovers implied by the SVAR-GARCH to a wide range of different DY-models. We find that the SVAR-GARCH outperforms, on this measure, identification schemes used in Fengler and Herwartz (2018), Diebold and Yilmaz (2009) or Diebold and Yilmaz (2012). Third, we show that the SVAR-GARCH yields more up-to-date spillover estimates compared to traditional moving window estimates as it Granger causes the latter.

Economically, we find cross-section results that corroborate our identification strategy as spillover estimates match (i) the economic narratives of the EZ debt crisis and (ii) economic contagion channels proposed by the theoretical and empirical literatures. For example, we find that during the European debt crisis, spillovers from periphery countries increased markedly, while elevated spillovers from core countries are more centered around the 2008/09 financial crisis. As for the underlying economic channels, we find *international* credit risk spillovers between sovereigns to be higher when the two countries have stronger ties in trade and portfolio investments, in line with the business cycle network literature (Foerster et al. (2011)). We also find *international* credit risk spillovers between banking systems to be higher when they exhibit more similar portfolios; yet we find spillovers not to be significantly associated with bank cross-holdings (as suggested in Brunetti et al. (2019)). Concerning the national sovereign-bank nexuses, we find that (i) a lower capital ratio and higher debt to GDP ratio increase *domestic* bank to sovereign spillovers in both low and high debt countries; while (ii) reliance of the non bank sector on domestic bank funding is significantly associated with domestic bank to sovereign spillovers only in low debt countries. In turn, we find *domestic* sovereign to bank spillovers to be higher for countries with a stronger bank exposure to domestic government debt. Moreover, we find that in high debt countries *domestic* sovereign to bank spillover are stronger when the domestic banking sector shows higher non-performing loan ratios and disposes of a lower share of liquid assets to short term liabilities.

Overall, we find credit risk in the Euro Area to be less integrated than suggested by estimates based on the more standard Diebold-Yilmaz style VAR models. We estimate that, on average, credit risk spillovers explain about 37% of the total variation in our sample. Yet, we show that the importance of spillover fluctuates distinctively, peaking at 61%.

2 Estimating Contagion in the Literature

Throughout this paper, we define spillovers as the degree to which exogenous shocks to one CDS market drive the variation of CDS spreads in other markets, in line with the FEVD-analysis of Diebold and Yilmaz (2009). Note however, that the definition of spillovers may differ in the literature. De Santis and Zimic (2018) characterize spillovers as the impulse response of one shock to another variable (hence taking into account the sign and not only the magnitude of the impact) while they label FEVD-estimates as "connectedness" and the coefficient estimates of their SVAR purged from the size-effect of the shocks as "contagion". Similarly, Claeys and Vašíček (2014) and Dungey et al. (2015) term contagion as significant changes in the propagation mechanism, not the propagation mechanism itself.

Diebold and Yilmaz (2009, 2012, 2014) propose in a set of papers a prominent approach to quantify time-varying spillovers on financial markets. The model is widely reused in the literature (e.g. Claeys and Vašíček (2014), Alter and Beyer (2014), Fengler and Gisler (2015), Diebold et al. (2018), Hale and Lopez (2018), Greenwood-Nimmo et al. (2017) or Greenwood-Nimmo et al. (2019)). Yet the Diebold-Yilmaz approach relies on orthogonalized SVARs and the identification of the latter is challenging.

Three different streams of the contagion-literature do offer attractive identification strategies. First, De Santis and Zimic (2018) and De Santis and Zimic (2019) apply a methodology close to ours. They gauge the interconnectedness among sovereign debt markets or between medium-term interest rates with a Diebold-Yilmaz approach based on a SVAR that is identified by "magnitude restrictions", that is by imposing that a shock stemming from one country impacts the most its own country. Second, Ando et al. (2018) add numerous exogenous variables to their vector autoregressions with the aim to purge their variables from common factors. Once this filtering is done, they obtain (quasi) orthogonal shocks. Finally, several papers focusing on financial spillovers (Ehrmann et al. (2011), Dungey et al. (2015), Ehrmann and Fratzscher (2017), Fratzscher and Rieth (2019)) apply the idea of Rigobon (2003) and rely on the identification by heteroskedasticity. The authors use the variations in the variance-covariance matrix of the reduced form shocks to identify the structural shocks.

However, the time variation in the first two streams of the literature comes from a rolling window estimation. These papers use relatively long window length in order to have a sufficient accuracy in their parameter estimates. Nevertheless, with this feature, their models will lack responsiveness as past observations mitigate the effect of new ones. The third stream of the literature focuses on specific sub-periods (e.g. Ehrmann and Fratzscher (2017) or Dungey et al. (2015)) and do not provide a continuous estimation of their spillover indices.

In contrast, a recent literature has exploited MGARCH models that are capable of generating up-to-date spillovers (Fengler and Herwartz (2018), Strohsal and Weber (2015)). However, these models lack attractive identification approaches for structural analysis[3]. The same drawback applies to variation of the approach using time-varying VARs as in Geraci and Gnabo (2018) or in Korobilis and Yilmaz (2018).

3 Methodology

3.1 Measuring spillovers

We follow the key idea of Diebold and Yilmaz (2009, 2012, 2014) and base a set of mutual consistent spillover measures, from pairwise to system wise, on FEVDs. Table 1 depicts a FEVD which is amended with an additional bottom row that captures the off-diagonal column sums, an additional column on the right that captures the off-diagonal row sums and a bottom right element that captures the grand average of either off-diagonal column or row sums.

The FEVD is populated by elements d_{ij}^H, which give the proportion of the H step forecast error variance of variable y_j that is driven by an orthogonal shock to y_i. Following

[3]For example, in Fengler and Herwartz (2018) the orthogonalisation is based on the square root of the variance-covariance matrix of the reduced form shocks. Thus it does not rely on economic intuition and therefore makes the interpretation of the structural shocks difficult.

Table 1: Diebold-Yilmaz Spillover Table

	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	$\sum_{i=1}^N d_{i1}^H$ $i \neq 1$	$\sum_{i=2}^N d_{i2}^H$ $i \neq 2$	$\cdots$	$\sum_{i=3}^N d_{i3}^H$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1}^N d_{ij}^H$ $i \neq j$

Diebold and Yilmaz (2009, 2012, 2014) we define d_{ij}^H as a *pairwise directed spillover* from i to j:

$$S_{i \to j}^H = d_{ij}^H. \tag{1}$$

The pairwise spillovers allow to construct more aggregated spillover indices. For example, the off-diagonal column sums indicate to which degree the H step forecast error variation of variable y_j is driven by other variables in the system. Diebold and Yilmaz (2009, 2012, 2014) define therefore *inward spillovers* as:

$$S_{j \leftarrow \bullet}^H = \sum_{\substack{i=1 \\ i \neq j}}^N d_{ij}^H. \tag{2}$$

Vice versa, the off-diagonal row sums indicate to what degree variable y_j drives the variation of all other variables in the system. *Outward spillovers* are therefore defined as:

$$S_{j \to \bullet}^H = \sum_{\substack{i=1 \\ i \neq j}}^N d_{ji}^H. \tag{3}$$

Total spillovers in the system are finally defined as average of *inward* or *outward spillovers*.

$$S^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} d_{ij}^H. \tag{4}$$

As underlined above, Diebold and Yilmaz (2009, 2012, 2014) estimate time-varying FEVDs based on moving window estimations of vector autoregressions, and identify the SVARs with orthogonalization strategies that can be challenged. The remainder of the paper outlines an approach that allows for a structural estimation of VAR parameters as well as for time-varying FEVDs that do not rely on rolling window estimations.

3.2 Description of the Model

For the development of a structural version of the Diebold-Yilmaz index, we rely on a SVAR model with a GARCH error structure and an identification by heteroskedasticity, similar in spirit to Normandin and Phaneuf (2004). We choose the model for the following reasons: first, a GARCH error structure appears a natural choice given that first differences of CDS, alike many other financial variables, show clustering of volatility over time and is therefore well approximated by GARCH processes. Second, the model has the property of time-varying conditional volatility of the errors, given the GARCH structure of the model. This property is crucial for the identification of structural shocks (Rigobon (2003)). Third, still relying on this property, we can construct time-varying FEVDs. This last feature allows us to estimate the model over the whole period, thus enabling more responsiveness compared to a time-varying FEVD based on a rolling estimation.

SVAR identification through heteroskedasticity

We base the empirical model on a structural vector autoregression of order p, that allows our variables to be determined simultaneously.

$$\boldsymbol{B}_0\boldsymbol{Y}_t = \boldsymbol{\gamma} + \boldsymbol{B}_1\boldsymbol{Y}_{t-1} + ... + \boldsymbol{B}_p\boldsymbol{Y}_{t-p} + \boldsymbol{\epsilon}_t \tag{5}$$

where $\boldsymbol{Y}_t$ is a vector containing the endogenous variables of interest, typically sovereign and bank sector CDS time series. The matrices $\boldsymbol{B}_i$ contain the contemporaneous and lagged effects of the endogenous variables. $\boldsymbol{\epsilon}_t$ denote structural errors with zero mean and an unconditional diagonal variance covariance matrix $\boldsymbol{\lambda}_\epsilon$. As the SVAR cannot be estimated directly, we first estimate a reduced form VAR:

$$\boldsymbol{Y}_t = \boldsymbol{\beta} + \boldsymbol{A}_1\boldsymbol{Y}_{t-1} + ... + \boldsymbol{A}_p\boldsymbol{Y}_{t-p} + \boldsymbol{\mu}_t \tag{6}$$

where the reduced form shocks $\boldsymbol{\mu}_t$ have zero mean and a non-diagonal variance covariance matrix $\boldsymbol{\Sigma}_\mu$. The structural errors $\boldsymbol{\epsilon}_t$ are then defined through $\boldsymbol{\mu}_t$ and the contemporaneous interaction matrix $\boldsymbol{B}_0$:

$$\boldsymbol{\epsilon}_t = \boldsymbol{B}_0\boldsymbol{\mu}_t \quad \Leftrightarrow \quad \boldsymbol{\mu}_t = \boldsymbol{B}_0^{-1}\boldsymbol{\epsilon}_t \tag{7}$$

The well known VAR identification problem arises as we try to obtain estimates for the contemporaneous interaction matrix $\boldsymbol{B}_0$ from the relationship $\boldsymbol{\Sigma}_\mu = \boldsymbol{B}_0^{-1}\boldsymbol{\lambda}_\epsilon\boldsymbol{B}_0^{-1\prime}$. Yet without further restrictions $\boldsymbol{B}_0$ is not identified since $\boldsymbol{\Sigma}_\mu$ provides only $\frac{N(N+1)}{2}$ equations for N^2 unknowns if we normalize $\boldsymbol{\lambda}_\epsilon = I$.

The SVAR-GARCH model we are using relies on Rigobon (2003) identification scheme that exploits the general heteroskedasticity in financial data. Suppose that the variances (or conditional variances) of $\boldsymbol{\mu}_t$ vary over time - implying that the structural error variance does too - while $\boldsymbol{B}_0$ is constant [4]. This feature implies that there is more than one volatility regime in the data, defined by a different reduced form variance-covariance

[4] In Annex A.6 we relax this assumption.

matrix $\boldsymbol{\Sigma}_\mu(m)$. If there are M different volatility regimes, then we have:

$$\boldsymbol{\Sigma}_\mu(1) = \boldsymbol{B}_0^{-1}\boldsymbol{B}_0^{-1\prime}, \quad \boldsymbol{\Sigma}_\mu(m) = \boldsymbol{B}_0^{-1}\boldsymbol{\lambda}_m\boldsymbol{B}_0^{-1\prime}, m = 2, ..., M \tag{8}$$

where $\boldsymbol{\lambda}_m$ are the diagonal matrices of the structural shocks ($\boldsymbol{\lambda}_1$ is normalized to $\boldsymbol{I}$). Lanne and Saikkonen (2007) show that $\boldsymbol{B}_0$ is locally uniquely determined if $\forall(k,\ l)$ $\in \{1, ..., K\}^2$, $k \neq l$, there is an index $j \in \{2, ..., M\}$ such that $\lambda_{jk} \neq \lambda_{jl}$, *i.e.* there is sufficient heterogeneity in the volatility changes.

SVAR-GARCH

Conditional heteroskedasticity can be modeled in different ways (see Lütkepohl and Netšunajev (2017a)). We rely on the methodology first proposed by Normandin and Phaneuf (2004) and assume that it is driven by GARCH processes. Similar models have been applied in Bouakez and Normandin (2010), Lütkepohl and Milunovich (2016) and Lütkepohl and Netšunajev (2017a).

We assume that the structural shocks are orthogonal and that their variances follow a univariate GARCH(1,1) process:

$$\epsilon_{k,t} = \sigma_{k,t|t-1}e_{k,t} \quad \text{where} \quad \boldsymbol{e}_t \sim \text{i.i.d. N}(\boldsymbol{0}, \boldsymbol{I}_N) \quad \text{and} \tag{9}$$

$$\sigma^2_{k,t|t-1} = (1 - \gamma_k - g_k) + \gamma_k(\epsilon_{k,t-1})^2 + g_k\sigma^2_{k,t-1|t-2} \tag{10}$$

where $\gamma_k > 0, g_k \geq 0, \gamma_k + g_k < 1, 1 \leqslant k \leqslant N$ so that the GARCH(1,1) processes are non-trivial.

Then, we can express the reduced form shocks as:

$$\boldsymbol{\mu}_t = \boldsymbol{B}_0^{-1}\boldsymbol{\lambda}^{\frac{1}{2}}_{t|t-1}\boldsymbol{e}_t \tag{11}$$

where:

$$\boldsymbol{\lambda}_{t|t-1} = \begin{bmatrix} \sigma^2_{1,t|t-1} & & 0 \\ & \dots & \\ 0 & & \sigma^2_{N,t|t-1} \end{bmatrix} \tag{12}$$

is a (N x N) diagonal matrix with the univariate GARCH processes on the diagonal. Therefore, the distribution of $\boldsymbol{\mu}_t$ conditional on past information has mean zero and a covariance matrix:

$$\boldsymbol{\Sigma}_{\mu,t|t-1} = \boldsymbol{B}_0^{-1}\boldsymbol{\lambda}_{t|t-1}\boldsymbol{B}_0^{-1\prime} \tag{13}$$

Rigobon (2003) shows that for full (local) statistical identification, 2 different volatility regimes is enough. With a SVAR-GARCH we have T (number of observations) different volatility "regimes". In this study, using daily CDS data between 2008 and 2019, this translates into more then 2800 regimes. We estimate the parameters of the SVAR-GARCH model by Maximum Likelihood as in Lütkepohl and Milunovich (2016).

Forecasts for FEVD

Estimates for time-varying conditional variance-covariance matrices allow us to construct FEVDs for each time period, i.e. for each day. Note that for the computation of FEVDs in each period t, one cannot take the actual estimated structural variances $\hat{\boldsymbol{\lambda}}_{t|t-1}$. Instead, we need to compute, by definition of the FEVD, in-sample forecasts for the structural variances $\boldsymbol{\lambda}^*_{t+h|t}$ conditional on the information set in t, as in Fengler and Herwartz (2018). Contrary to the approach in the latter, our matrix $\boldsymbol{B}_0$ is constant over time, so that the only change between a classic SVAR-FEVD and our approach is the computation of future structural variances.

We have with Equation 10:

$$\sigma^2_{k,t+h|t+h-1} = (1-\gamma_k - g_k) + \gamma_k(\epsilon_{k,t+h-1})^2 + g_k\sigma^2_{k,t+h-1|t+h-2} \tag{14}$$

Taking conditional expectation at time t, with $h \geq 2$:

$$E_t\sigma^2_{k,t+h|t+h-1} = (1-\gamma_k-g_k) + \gamma_k\sigma^2_{k,t+h-1|t} + g_k E_t\sigma^2_{k,t+h-1|t+h-2} \tag{15}$$

Using the law of iterated expectations, we get:

$$E_t\sigma^2_{k,t+h|t} = (1-\gamma_k-g_k) + \gamma_k\sigma^2_{k,t+h-1|t} + g_k E_t\sigma^2_{k,t+h-1|t} \tag{16}$$

That is:

$$\sigma^2_{k,t+h|t} = (1-\gamma_k-g_k) + (\gamma_k+g_k)\sigma^2_{k,t+h-1|t} \tag{17}$$

We thus obtain $\boldsymbol{\lambda}^*_{t+h|t}$ for each h as this matrix is diagonal and is only composed of the different $\sigma^2_{k,t+h|t}$. To build the FEVDs, we then first compute the MSPE. The $\boldsymbol{\Theta}_i$ matrices come from the Moving Average (MA) representation of the SVAR as detailed in Kilian and Lütkepohl (2017):

$$\boldsymbol{Y}_{t+H} - \boldsymbol{Y}_{t+H|t} = \sum_{i=0}^{H-1} \boldsymbol{\Theta}_i \boldsymbol{\epsilon}_{t+H-i} \tag{18}$$

With the structural variances estimated, we get:

$$\begin{aligned} MSPE_t(H) &= E_t(\boldsymbol{Y}_{t+H} - \boldsymbol{Y}_{t+H|t})(\boldsymbol{Y}_{t+H} - \boldsymbol{Y}_{t+H|t})' \\ &= \sum_{i=0}^{H-1} \boldsymbol{\Theta}_i \boldsymbol{\lambda}^*_{t+H-i|t} \boldsymbol{\Theta}'_i \end{aligned} \tag{19}$$

We can then evaluate the contribution of shock j to MSPE of y_{kt} with the usual MSPE-formula, the only difference with a classic SVAR is that variances of structural shocks are no longer normalized to 1. With $\theta_{kj,h}$ the kj^{th} element of $\mathbf{\Theta}_h$:

$$MSPE_{j,t}^{k}(H) = \theta_{kj,0}^{2}\sigma_{j,t+H|t}^{2} + ... + \theta_{kj,H-1}^{2}\sigma_{j,t+1|t}^{2} \tag{20}$$

With:

$$MSPE_{t}^{k}(H) = \sum_{j=1}^{K} MSPE_{j,t}^{k}(H) \tag{21}$$

We get:

$$FEVD_{j,t}^{k}(H) = \frac{MSPE_{j,t}^{k}(H)}{MSPE_{t}^{k}(H)} \tag{22}$$

Eventually the time-varying FEVDs enable to build the time-varying spillover indices, as explained in Section 3.1.

4 Data and filtering for common shocks

4.1 Data

We focus on credit risk of major EZ sovereigns and banks. We attempt to strike a balance between a sufficiently high coverage of important CDS markets and the limited number of variables our empirical approach allows. As a result, we limit the sample to 9 countries (Greece, Ireland, Italy, Portugal, Spain, Germany, France, Belgium and Netherlands). For each country we include two variables in the sample, sovereign credit risk and credit risk in the banking sector, except for Ireland and Greece where we lack banking credit risk series due to data constraints[5]. This leaves us with 16 variables all together.

As standard in this literature (see Greenwood-Nimmo et al. (2019)), we measure credit

[5]See Acharya et al. (2014) and Fratzscher and Rieth (2019).

risk using CDS spreads on senior unsecured debt, modified-modified restructuring, mid spread and a maturity of 5 years[6]. We retrieve CDS spreads for non-US sovereigns and US banks denominated in USD while CDS spreads for the US sovereign and European banks are denominated in EUR. Our sample covers daily data between January 2008 and March 2019, covering the GFC, European debt crisis and several sovereign and banking turbulence such as the Italian political turmoil of May 2018. We construct country banking variables as an unweighted average of bank CDS from that country as in Greenwood-Nimmo et al. (2017). In the selection of banks, we follow Alter and Beyer (2014) (while we exclude those banks that defaulted over the observation period). In line with the rest of the literature we first-difference the CDS series. A detailed list of the considered banks as well as descriptive graphs of the CDS series can be found in Annex A.2.

4.2 Filtering for common shocks

The literature agrees that global and regional variables may exert a common influence on credit spreads (Longstaff et al. (2011)). Ignoring such common shocks that have a simultaneous effect on different variables in an econometric analysis may result in an overestimation of contagion patterns. We would falsely attribute common shocks to the propagation of idiosyncratic shocks. We therefore follow Alter and Beyer (2014) in including the following set of pan-European credit risk factors, including (i) the *Itraxx Europe index* (which comprises investment grade rated European entities, reflecting the overall credit performance of the European real economy), (ii) the *Itraxx Crossover index* (which comprises below investment grade rated European entities, reflecting the lower-end credit performance of the European real economy), and (iii) the spread between the

[6] We combine data from three sources: we use principally Thomson Reuters Datastream and extend the sample backwards using growth rates extracted from CDS series from CMA. In case of missing values in the resulting data set, we retrieve growth rates on CDS spreads from Bloomberg.

3-month EURIBOR and the *3-month EONIA* swap (a proxy for funding liquidity conditions equivalent to the TED spread). Moreover, we control for the *Eurostoxx 50* (the European stock market index), the *VIX index* (as a proxy for investors' risk aversion) and US and UK sovereign and banking CDS series (to account for foreign shocks).

We account for common shocks in a two-step approach. First, we regress each CDS series individually on a vector of common factors and then we run the SVAR-GARCH model specified in Section 3.2 on the obtained residuals, as in Dungey et al. (2010)[7]. That is, in a first step, we filter first differences bank and sovereign CDS series by the following OLS regression:

$$\Delta z_{jt} = \alpha_j + \Delta \boldsymbol{X}_t' \boldsymbol{\beta}_j + y_{jt} \tag{23}$$

where Δz_{jt} represents the first difference of a CDS series j in the sample, α_j is a constant and $\Delta \boldsymbol{X}_t$ is a vector of common factors in first differences. y_{jt} contains the residuals of the regression and serves as input data for the SVAR-GARCH. Annex A.6 reports robustness checks using a smaller set of exogenous variables.

5 Results

In this section we present the results for the SVAR-GARCH model outlined above. We estimate the model with 2 lags as indicated by the information criteria from a simple VAR estimated on the same dataset. Moreover, in line with Diebold and Yilmaz (2009, 2012, 2014), we choose a forecast horizon for the FEVD of 10 days. In Section 5.1 we present the results of our identification approach, that is the labeling of structural shocks, as well as comparisons of timeliness and of identification performances between competing models. In Section 5.2 we present the economic results of our application.

[7]This approach is similar to including a vector of exogenous variables directly into the SVAR. Alter and Beyer (2014) find similar results between the two approaches. In our case, a two-step approach is preferable as we found that including a vector of exogenous variables in the SVAR-GARCH significantly increases the time to convergence.

5.1 Econometric results

5.1.1 Statistical and economic identification

Statistical identification is achieved when the number of univariate GARCH components underlying the GARCH structure are larger or equal to N-1. That means that for full local identification we may have at most one series that is not well approximated by a GARCH process in order to have sufficient heteroskedasticity in the structural shocks. We follow the identification test proposed by Lanne and Saikkonen (2007) and reject fewer than N-1 GARCH processes in our sample (see Annex A.1).

However, full local identification implies only statistical identification up to sign changes and ordering. To make the orthogonal shocks economic meaningful we need to label them, ideally in such a way that each orthogonal shock corresponds to a different variable. In line with Grosse Steffen and Podstawski (2016), we label shocks with the maximum contribution to the forecast error variance of a variable as a shock from this particular variable (for example the German banking sector). Exact economic identification is obtained if for each CDS series there is only one structural shock with a maximum contribution to the forecast error variance of that specific CDS series. As we estimate one FEVD for each day we focus on average shock contributions over time. However the labelling would be exactly the same if we focus, at each point in time, on individual FEVDs. Table 2 reports a FEVD that is averaged over all time periods and for which shocks are labelled accordingly. It is clear from the diagonal of the table that each shock has a maximum contribution to a different CDS series, allowing a clear labelling of the orthogonal shocks.

Our economic identification approach receives further confirmation from the fact that the estimated structural time series of shocks ($\hat{\epsilon}_t$ in Equation 5) correspond to a large

Table 2: Forecast error variance decomposition, average over time (%)

	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**

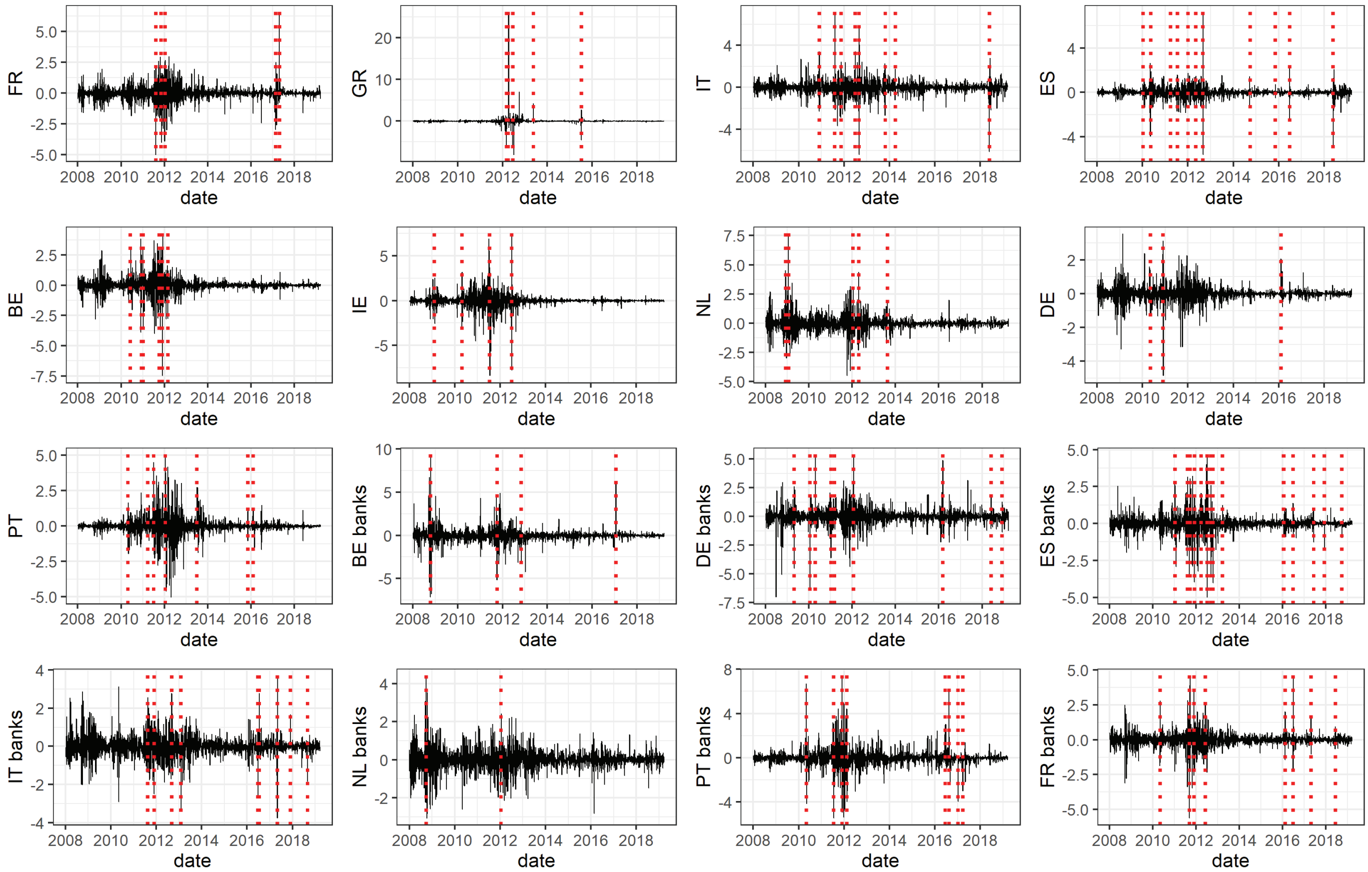
This table represents the average over time of the FEVDs obtained with the SVAR-GARCH. We can see that the originating shocks (in line) impact the most their own variables (in column).

number of historical events. In the spirit of Antolín-Díaz and Rubio-Ramírez (2018), we compare major shocks with historical economic and market events[8]. We define major shocks as those shocks that are higher than 6 times their own standard deviations. Of the 79 shocks that meet this criteria, we are able to match 62 events (covering 78% of major shocks)[9]. On Figure 2 we present the time series of the estimated structural shocks (in black) along with the timing of the matched events (red vertical lines). Figure 2 shows also isolated events of spillovers that fall short of the threshold for major events. Again, we are able to match a large amount of such shocks to economic and financial events, extending the list of events to 117 items. The identified events are typically rating downgrades or political shocks (for sovereigns) or bank stress episodes (for banking sectors). Annex A.3 reports the exhaustive list of events. This exercise suggests that our identification strategy based on major shock contribution is further supported by the event-analysis on structural shocks of Figure 2, something which is rarely performed in the SVAR literature.

[8] More precisely, for days with a large structural shock surge, we investigate the existence of major market events in the financial press.

[9] We consider that a peak is identified if we can match it with an event 5 days before or after the date of the peak. This ratio is robust to changes in the threshold value as well to changes in the number of days considered.

Figure 2: Structural Shocks and Events



On the different graphs above are represented the estimated structural shocks of the model ($\hat{\epsilon}_t$) as well as identified historical events for each variable represented in vertical red lines. The list of events used is available in Annex A.3.

5.1.2 Total Spillover Comparison

How reactive is our model to new events? To assess its timeliness, we compare total spillovers (S^H in Equation 4) from our SVAR-GARCH model with total spillover estimates from other Diebold-Yilmaz approaches of the literature. More precisely, we estimate S^H for the following 4 models[10]:

[10]Note that a comparison with the De Santis and Zimic (2018) model is unfeasible here as this latter does not yield daily estimates, due to heavy computation time, and cannot be compared with in a daily event-analysis.

Model 1 A SVAR estimated on a rolling window and identified by Cholesky decomposition (as in Diebold and Yilmaz (2009), labeled here VAR Cholesky);

Model 2 A SVAR estimated on a rolling window and identified by GIRF/GFEVD (as in Diebold and Yilmaz (2012), labeled here VAR GIRF);

Model 3 A DCC-GARCH identified by Cholesky decomposition and estimated over the entire sample, labeled here DCC Cholesky. More precisely, we estimate a DCC GARCH as a reduced form VAR, that is:

$$\boldsymbol{Y}_t = \boldsymbol{\beta} + \boldsymbol{A}_1\boldsymbol{Y}_{t-1} + ... + \boldsymbol{A}_p\boldsymbol{Y}_{t-p} + \boldsymbol{\mu}_t$$

with:

$$\boldsymbol{\mu}_t \sim N(\boldsymbol{0}, \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t) \text{ and } \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t = \boldsymbol{H}_t$$

following the notations of Engle (2002). We then switch to the structural form with a Cholesky decomposition at each period t: $\boldsymbol{B}_{0t}^{-1}\boldsymbol{B}_{0t}^{-1\prime} = \boldsymbol{H}_t$;

Model 4 Similarly to Model 3, we estimate a VAR-GARCH based on a DCC-GARCH, but with the identification of Fengler and Herwartz (2018): $\boldsymbol{B}_{0t}^{-1} = \boldsymbol{H}_t^{1/2}$[11]. The model is labeled DCC Fengler.

Figure 3 plots the different S^H. First, the figure suggests that the SVAR-GARCH evaluates credit risk in the EZ to be significantly less integrated than VAR Cholesky and VAR GIRF. This may be linked to the fact that GIRF identification tends to overestimate total spillovers (as shown in De Santis and Zimic (2018)[12]). In the same time, Cholesky

[11] Here, as in Fengler and Herwartz (2018), the square root of a symmetric positive definite matrix $\boldsymbol{H}$ is defined as $\boldsymbol{H}_t^{1/2} = \boldsymbol{\Gamma}\boldsymbol{\Lambda}^{1/2}\boldsymbol{\Gamma}'$ where the columns of $\boldsymbol{\Gamma}$ contain the eigenvectors of $\boldsymbol{H}$ and $\boldsymbol{\Lambda}^{1/2}$ is diagonal with the positive square roots of the eigenvalues on its diagonal.

[12] As De Santis and Zimic (2018) show, when contemporaneous interaction effects between variables are not equal to 0, the estimated standard errors of structural shocks obtained with GIRF are biased upwards, equally biasing upwards spillovers estimates based on FEVDs. The 0 restrictions the Cholesky identification introduces are likely to be at odds with the data generating process. In a numerical exercise De Santis and Zimic (2018) show that also this DY-model is likely to misspecify estimated spillovers.

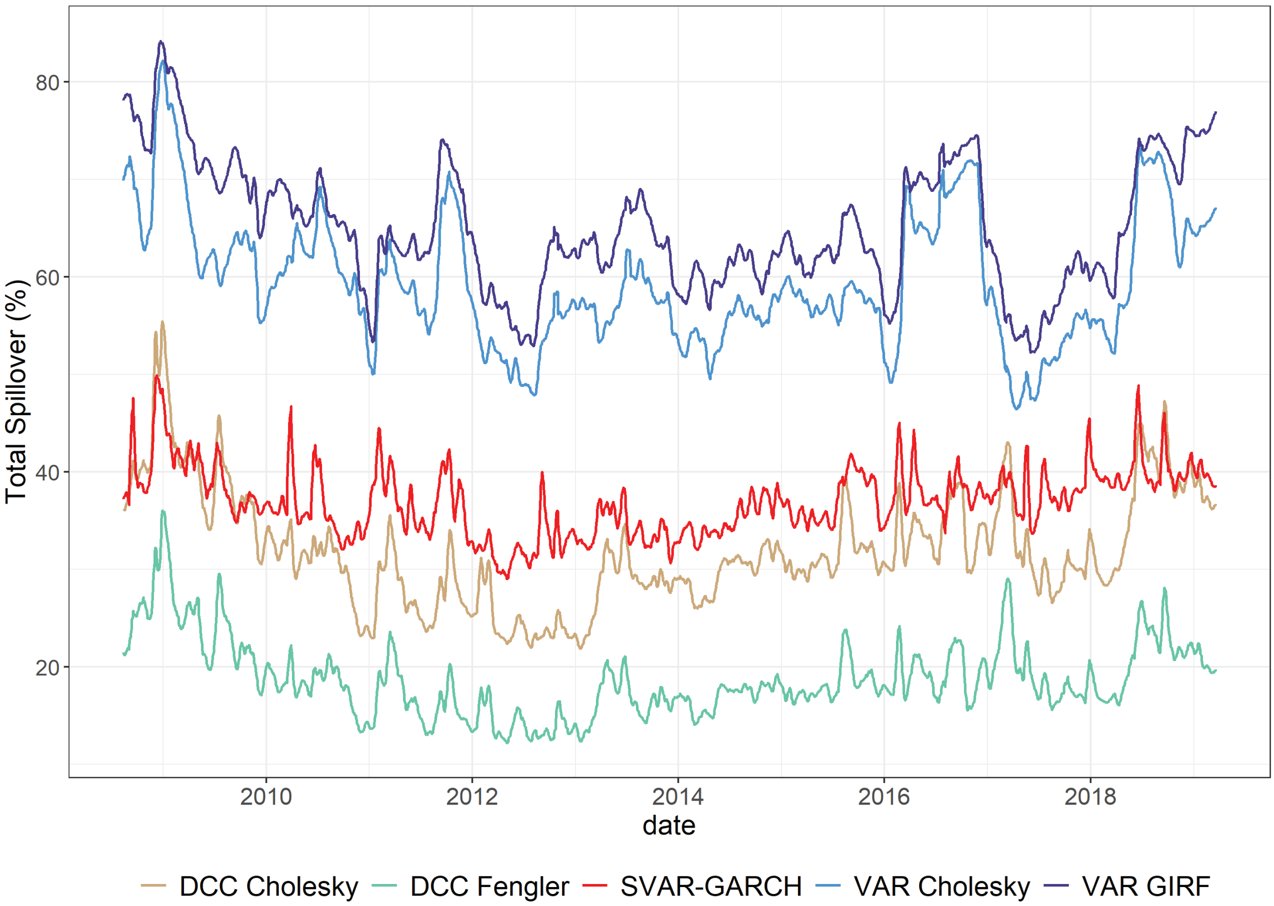
identification imposes restrictions that are likely to be at odds with the data generating process. SVAR models relying on this identification are thus susceptible to over- or underestimate total spillovers. We come back more formally on this point in Annex A.4.

Second, we see across all modelizations the 2010-2012 the “financial fragmentation” of the EZ. Indeed, each total spillover index is U-shaped: declining during those years, before increasing again afterwards. Ehrmann and Fratzscher (2017) and De Santis and Zimic (2018), who find similar shapes of total spillovers, argue that the latter decreased over 2010-2012 since shocks from peripheric countries had a decreasing impact on core countries.

Third, intuitively, indices relying on a rolling window estimation should be less responsive to new events compared to the SVAR-GARCH. However, there is no clear distinction *a priori* in responsiveness between the different models with a GARCH-component.

This intuition is confirmed by a Granger causality analysis between the different S^H given in Table 3. Indeed S^H from the SVAR-GARCH does Granger cause S^H indices from the rolling window estimated models (VAR GIRF and VAR Cholesky), but not the indices stemming from a DCC-GARCH (DCC Cholesky and DCC Fengler). When we reverse the perspective, SVAR-GARCH is only Granger caused by DCC Fengler and not by VAR Cholesky or VAR GIRF. In that sense, S^H index estimated by DCC Fengler appears to be the most responsive to new events. However, as we show in the next section, the underlying pairwise spillovers estimated by DCC Fengler and DCC Cholesky are at odds with economic narratives. So that, contrary to the SVAR GARCH, these models fulfill the second condition of a good contagion model (responsiveness) but not the first one (good identification of the events).

Figure 3: Total Spillover Indices from different Models



The different lines represent the Total Spillover indices S^H built from the five different models outlined above. The rolling window models are estimated on a 100-day period, as standard in this strand of literature. For readability we show 10 day moving averages of the indices.

5.1.3 Spillover Comparison and Narrative Events

To evaluate the performance of our identification strategy compared to other models, we analyze how the different spillovers evolve along well-known narrative events.

To showcase our approach, we focus on the May 2018 political turmoil in Italy. At that time, the formation of a Eurosceptic coalition brought about a sharp increase in Italian

Table 3: Granger causality between the models (First difference, lags=2)

H_0 : **SVAR-GARCH does not Granger cause...**	**F - test**	**p-value**
Rolling window estimated models		
VAR Cholesky	14.91	3.627e-07***
VAR GIRF	6.0492	0.002391 **
GARCH-related models		
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**
Rolling window estimated models		
VAR Cholesky	0.5159	0.597
VAR GIRF	0.9483	0.3875
GARCH-related models		
DCC Cholesky	0.4206	0.6567
DCC Fengler	8.8071	0.0001539***

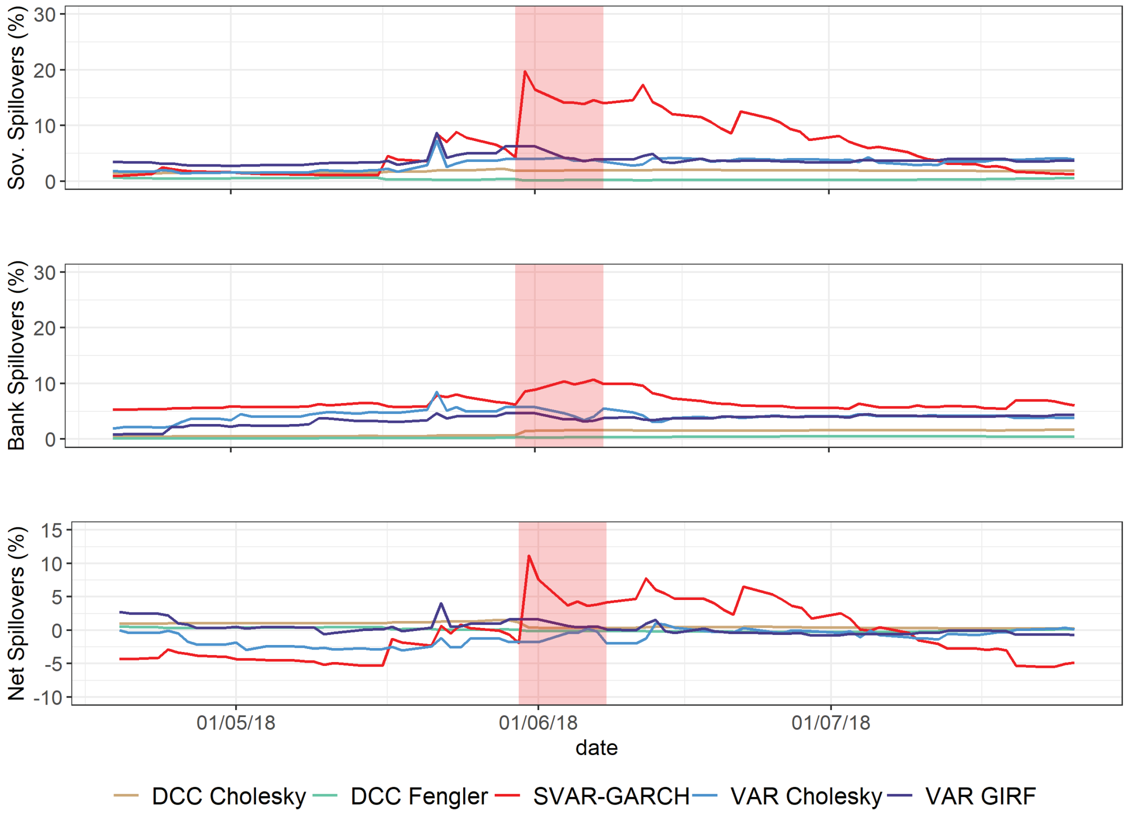
*This table indicates the results from the Granger causality tests between the S^H of the different models. Only three Granger causality relationships appear significant: SVAR-GARCH on VAR Cholesky and VAR GIRF, and DCC Fengler on SVAR-GARCH. The marks *, **, *** indicate, respectively, the following significance levels: 0.1, 0.05 and 0.01*

sovereign CDS[13]. We argue that this event should be interpreted as sovereign shock, not as a bank shock. In that regard, one would expect an increase in outward spillovers ($S^H_{j\to\bullet}$ of Equation 3) from the Italian sovereign at the time of the events. Yet, the upper part of Figure 4 shows that only the spillover estimates from the SVAR-GARCH do so during this period (highlighted in red), while other methodologies' spillovers remain subdued.

Moreover, as CDS spreads tend to comove a lot (Longstaff et al. (2011)), especially

[13]see https://www.ft.com/content/eed97b90-6306-11e8-90c2-9563a0613e56, or Reuters https://www.reuters.com/article/us-eurozone-bonds/italian-bonds-suffer-worst-day-in-more-than-25-years-idUSKCN1IU16G

Figure 4: Outward Spillovers from Italian sovereign and bank shocks



The two upper parts of the graph represent the Outward Spillover Index ($S^H_{j\rightarrow\bullet}$) from, respectively, the Italian sovereign and the Italian banks, built from the five different models outlined above. The bottom part of the graph represents the "net" spillovers (outward sovereign spillovers minus outward bank spillovers). The periods highlighted in red represent the May 2018 Italian political turmoil.

between sovereign and bank CDS series from the same country, there is a high risk that a model confuses bank shocks with their corresponding sovereign shocks. Accordingly, at the time of a sovereign event, outward spillovers from the country's banking sector should remain flat or decrease. Therefore, for a sovereign event to be correctly identified, not only the sovereign spillovers should increase, they should also increase by more than the corresponding bank spillovers. On the middle and lower parts of Figure 4 we display the outward spillovers from Italian banks as well as the difference between sovereign and bank outward spillovers ("net" spillovers). While most of the models exhibit flat or negative net spillovers, only the SVAR-GARCH manages well to identify this specific event on this measure.

To evaluate on a more systematic basis the identification strategies of the different models, we replicate the analysis of Figure 4 over the set of our identified events available in Annex A.3. We estimate that a sovereign (bank) event is well identified if, 5 days around the day of the event, the spillover estimate stemming from the sovereign (banking sector) increases more than the spillover estimate from the banking sector (sovereign) in the same country. We evaluate the identification performance of the models on different sets of events: (i) a subset of the least contestable sovereign events (i.e. only elections, sovereign rating downgrades, or political events) of the list identified in Section 5.1.1 and shown in Annex A.3 covering 18 events, (ii) all sovereign events in Annex A.3 covering 54 events and (iii) all events, bank and sovereign, in Annex A.3 covering 117 events. As the sets of events (i), (ii) and (iii) are generated from our model, we corroborate the analysis with two exogenous lists of sovereign events, from (iv) Candelon et al. (2011) which covers 11 events and (v) Alexandre et al. (2016) that includes 8 events.

Table 4 suggests that the SVAR-GARCH outperforms, on every set of events, the other models in terms of identification. Note also that the competing models barely exceed the 50% threshold of identification, meaning that they tend to confuse more sovereign events with banking events than a random selection [14].

[14]Results reported in Table 4 are robust to a large number of specifications (by analysing the % change instead of absolute changes, with different window lengths or with pairwise spillovers instead of outward spillovers).

Table 4: Percentage of good event-identification by model

	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. E.g. we consider a sovereign event to be correctly identified if, 5 days around the event, the outward spillover stemming from the sovereign increases more than the outward spillover stemming from the corresponding banking sector. The results are reported for (i) uncontroversial sovereign events (sovereign rating downgrades and votes) (ii) all the sovereign events previously identified (iii) all the sovereign and banking events identified (iv) the sovereign event list of Candelon et al. (2011) (v) the sovereign event list of Alexandre et al. (2016).

5.2 Economic results

Figure 3 on total spillover indices shows that we estimate credit risk to be less integrated than other models would suggest. According to our S^H estimates, on average about 37% of the variation in the filtered CDS rates can be explained by spillovers. Yet, we find substantial variation in this magnitude over time. To investigate the sources of heightened spillovers, this section analyses first the time-variation of both bank and sovereign spillovers from the EZ countries, and then the economic channels behind the spillovers we estimate. As our estimates match both the narrative of spillovers in the EZ debt crisis (Section 5.2.1) and the theoretical channels of credit risk spillovers (Section 5.2.2), we interpret these economic results as a further validation of our identification strategy.

5.2.1 Group pairwise spillovers

In this section, we analyse credit risk spillovers in terms of (i) timing, (ii) magnitude and (iii) origin. Given, that we estimate spillovers between 16 CDS series, presenting the resulting 240 pairwise spillovers is not feasible. We focus therefore on pairwise spillovers from different sets of countries/banking sectors. In the "Peripheric" group are included the high-debt countries at the time of the EZ debt crisis: Italy, Spain, Portugal, Greece, Belgium and Ireland[15]. The "Core" group, on the reverse, is constituted by Germany, France and the Netherlands. The "Peripheric banks" and "Core banks" include the corresponding banking sectors. However, as indicated in Section 4, due to data-constraints the group "Peripheric banks" does not include Greek and Irish banking sectors.

Figure 5 presents estimates of group pairwise spillovers for each variable sets defined above. In line with Section 3.1 we define the group pairwise spillover from group G_1 to group G_2 as the average outward spillovers from $G1$ restricted to the variables of G_2. More formally we have:

$$S^H_{G_1 \to G_2} = \frac{1}{N_{G_1} N_{G_2} - N_{G_1} \mathbb{1}_{\{G_1 = G_2\}}} \sum_{i \in G_1} \sum_{\substack{j \in G_2 \\ j \neq i}} d^H_{ij} \tag{24}$$

With N_{G_1} and N_{G_2} the number of variables in G_1 and G_2[16]. Each line represents by how much shocks from a variable set drive the variation of other variable sets on average. The analysis of time-varying spillovers here differs from the presentation of snapshots spillovers around narrative events in Section 5.1.3 (as we focus here on a much broader time period) and also from the presentation of the shocks in Section

[15]Note that we include Belgium in the Periphery-group as the country exhibited high public debt/GDP ratio. However the results are very similar if we define Belgium as a Core country.

[16]Contrary to Equations 2 and 3, we divide here the index by the number of pairwise directed spillovers considered. Likewise the different indices of Figure 5 are expressed in the same unit, that is: by how much, on average, a single variable of G_1 has an impact on a single different variable of G_2.

5.1.1. This is because spillover estimates in our DY-framework are not only functions of the time-varying variances of structural shocks ($\boldsymbol{\lambda}_t$), but also of the interaction matrix ($\boldsymbol{B}_0$) and of the VAR coefficients ($\boldsymbol{A}_i$). Therefore a large structural shock does not necessarily translate into a large spillover if it is associated with low coefficients in the corresponding matrices or if the magnitude of the shock is low relatively to other shocks' variances.

Figure 5 can be read in two ways, either from a *shock to* perspective by rows, or from a *shock from* perspective by columns. In the following, we take the *shock to* perspective. Figure 5 shows significant variation across time and groups. We find, in line with conventional wisdom, sizeable effects of sovereign periphery shocks to the rest of the EZ clustered around the beginning of the debt crisis in 2010. For example, at the height of the EZ debt crisis around mid-December 2010 when Moody's put Spain's rating on review, single variables from periphery sovereign shocks explained on average 4% and 3.5% of the variation of single variables from periphery sovereign and periphery banking groups respectively. Other major events of spillovers from periphery sovereigns include the Irish request for financial support to the EU's Financial Stability Facility and the IMF, the EU finance minister gathering to decide Greece's fate in 2015 or the 2018 Italian election crisis amid fears of new elections and voter support for Eurosceptics (see the subcaption of Figure 5 for exact dates). Figure 5 suggests that periphery sovereign shocks affect strongest CDS rates in other sovereign periphery countries followed by periphery banking sectors. Yet, core sovereigns and banks were also significantly affected periphery sovereign shocks.

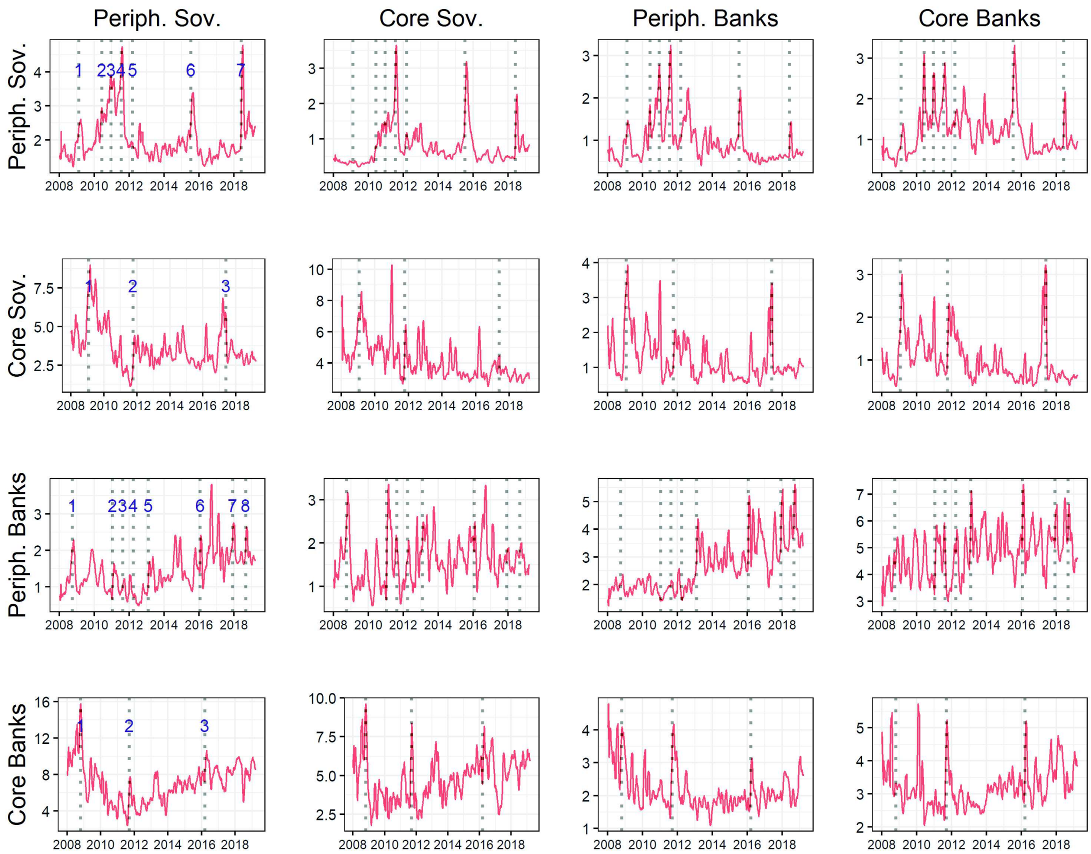
We also find sizable spillovers from the periphery banking sector to other blocks in the EZ. For example, Figure 5 shows elevated spillovers at the beginning of 2013, when investors worried about the health of the Italian banking sector (due to high NPL ratios amid excessive reliance on debt), as well as at the beginning of 2016, when again concerns about NPLs and the lack of credibility in the Italian banking sector heightened. We also find increased spillovers around dates between 2011 and mid-2012 when the Spanish banking sector signaled problems.

While we find spillovers from periphery EZ countries to increase with the beginning of the Euro debt crisis, we find spillovers from core EZ countries to be stronger during 2008/09 financial crisis. As such, we estimate strong sovereign core spillovers in January 2009 when the Dutch government announced plans to provide a backup facility to cover the risks of the ING's securitised mortgage portfolio. Moreover, Figure 5 shows increased sovereign core spillovers around dates that coincide with a downgrade of France by SP as well as the second round presidential election stand-off between Emmanuel Macron and Marine Le Pen. Finally, we find strong core bank spillovers, for example around the dates when ING received 10bn EUR from the Dutch government or when BNP entered a liquidity crunch when the bank was no longer able to borrow in USD. Overall, compared to their periphery counterparts, we find sudden increases of spillovers from core countries to be less frequent.

5.2.2 What economic channels explain spillovers?

While in the previous section we discussed the sources and time-variation of outward and total spillovers, this section focuses on the economic channels underlying the pairwise spillovers we estimate. More specifically, given a shock to a sovereign or banking sector in our sample, we vet whether the resulting pairwise spillovers match the economic channels proposed by the theoretic and empirical literature as an additional test for our identification strategy. We focus here on four different types of spillovers: (i) *international* sovereign to sovereign spillovers, (ii) *international* bank to bank spillovers, (iii) *national* bank to sovereign spillovers and finally (iv) *national* sovereign to bank spillovers.

Figure 5: Outward spillovers from peripheric EZ countries (%)



The different lines represent group pairwise spillovers ($S^H_{G_1 \rightarrow G_2}$) for the 4 groups: Peripheric sovereigns, Core Sovereigns, Peripheric banks, Core banks. For readability we show 30 day moving averages of the indices. ***Peripheric Sovereigns****: 1) Ireland recapitalizes its two main banks 11/02/09, 2) Belgium struggles to raise debt among political uncertainty 07/06/10, 3) Moody's puts Spain's ratings on review 15/12/10, 4) Market pressure on Spanish and Italian sovereigns 17/07/11, 5) ISDA declares Greece in default 09/03/12, 6) EU finance minister gathering to decide Greece's fate 11/07/15, 7) Italy election crisis spreads as CB chief warns about investor trust 30/05/18,* ***Core Sovereigns****: 1) Dutch government announces plans to rescue banks 26/01/09, 2) SP mistakenly downgrades France 10/11/11, 3) French elections, spike in sovereign CDS 24/05/17,* ***Peripheric Banks****: 1) Dexia bailed out 30/09/08, 2) Concerns on Spanish banks 14/01/11, 3) Trading suspension for Italian bank IS 17/08/11, 4) Need for Spanish bailout is underlined by EU officials 28/03/12, 5) MPS asks for 3.9bn bailout 01/02/13, 6) Market sentiment turns against Spain's banking sector 21/01/16, 7) ECB undernlines Italian banks' NPL problems 29/11/17, 8) UniCredit and IS fall on news of increased political uncertainty 31/08/18* ***Core Banks****: 1) ING receives 10 bn from Dutch government 19/10/08, 2) BNP can no longer borrow USD 13/09/11, 3) Deutsche and UBS defeated in UK tax avoidance case 10/03/16.*

International spillovers

First, we address the following question: given a sovereign shock in country i, what factors are the international spillovers to the sovereign risk in country j associated with? We follow broadly the regression approach by De Santis and Zimic (2018) and regress the credit risk spillover of sovereign i on sovereign j in quarter t on a set of regressors that can be divided into two main groups: distance and exposure. We estimate:

$$\bar{\omega}_{i\to j,t}(h) = \beta_i + \alpha_t + \beta_2 d^{GDP}_{ij,t} + \beta_3 d^{\frac{D}{GDP}}_{ij,t} + \beta_4 \text{exposure}^k_{j\to i,t} + \epsilon_{ij,t} \tag{25}$$

where $\bar{\omega}_{i\to j,t}(h)$ is the average spillover from i to j at forecast horizon h over the quarter t, all variables d are distance measures that include (i) the squared difference between country i and country j's GDP growth in t and (ii) the squared difference between country i and country j's government debt to GDP ratio in t[17]. Exposure$^k_{j\to i,t}$ is the exposure of country j to country i in respect of either the share of exports or portfolio assets (equity and bonds). The choice of those exposure variables follows the empirical work by De Santis and Zimic (2018) and the theoretical work by Foerster et al. (2011), see Annex A.5 for data sources and construction of the explanatory variables. We use time fixed effects and, following De Santis and Zimic (2018), fixed effects for the origin of the sovereign shock.

The results, reported in Table 5 suggest that similarity in business cycles cannot explain spillovers in sovereign risk. Instead, we find that similar credit risk in terms of similar debt to GDP ratios as well as both stronger trade and portfolio exposure are significantly related to higher sovereign risk spillovers. This finding supports the business cycle network literature (such as Foerster et al. (2011)) which models contagion channels through exactly those two exposure variables[18].

[17] We multiply difference variables by -1, such that the indicators increase in similarity.

[18] As the use of generated dependent variables in the regression can induce heteroskedasticity (see De

Table 5: Factors associated with spillovers from sovereigns to sovereigns

	(1)	(2)	(3)
Similar BC	-0.00005	-0.002	-0.001
	(0.001)	(0.001)	(0.001)
Similar D/GDP	0.021***	0.007***	0.014***
	(0.002)	(0.002)	(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

We repeat the same exercise to investigate the determinants of a spillover from the banking sector in country i to the banking sector in country j. Similar to Equation 26, we regress pairwise banking spillovers on a fixed effect for the shocking banking sector, as well as distance and exposure variables.

$$\bar{\omega}_{i\to j,t}(h) = \beta_i + \alpha_t + \beta_2 d_{ij,t}^{NPL} + \beta_3 d_{ij,t}^{Lev.R.} + \beta_4 \text{exposure}_{j\to i,t}^{k} + \epsilon_{ij,t} \tag{26}$$

The distance variables include credit risk distances which we estimate by the squared difference between country i and country j's banking sector's non-performing loans and capital ratios in period t[19]. In terms of exposures we test for two economic channels that are frequently used to model financial institution linkages: cross asset holdings and similarities in portfolios across banking sectors (see Giudici et al. (2020), Brunetti et al. (2019), Greenwood et al. (2015)). We construct bank sector portfolios from BIS

Santis and Zimic (2018)), we report White heteroskedasticity-consistent standard errors.

[19]Here again, we multiply difference variables by -1, such that the indicators increase in similarity.

Consolidated Banking Statistics data, following Greenwood et al. (2015), and calculate squared differences of those portfolios for each time period t. Cross asset holdings between banking systems are measured as the share of banks claims of country j vis-à-vis country i.

The results, shown in Table 6, suggest that cross-asset holdings are not significantly linked to the bank to bank spillovers. We do find however, that portfolio similarities are significantly associated with bank to bank spillovers. Both these findings are in line with the literature (Brunetti et al. (2019)). Similarly to the sovereign regressions, risk distances have some explicative power: we find that international bank spillovers are significantly associated with similar capital ratios for pairs of banking systems. However, similar NPL ratios turn out not to be of statistical significance.

Table 6: Factors associated with spillovers from banks to banks

	(1)	(2)	(3)
Similar NPLs	-0.001	-0.003	-0.001
	(0.003)	(0.003)	(0.003)
Sim. Capital ratios	0.037***	0.029**	0.040***
	(0.009)	(0.010)	(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

Spillovers in the national sovereign - bank nexus

While in the previous two regression sets we have focused on international spillovers, we investigate in the next two regressions the economic determinants of the national sovereign bank-nexus. In this section, we differentiate between high debt (Belgium, Italy, Portugal and Spain) and low debt (France, Germany and the Netherlands) countries as in the European debt crisis periphery and core countries experienced substantially different degrees of sovereign-bank nexuses (Podstawski and Velinov (2018)).

We focus first on the economic transmission channels of domestic spillovers from banks to sovereigns. First, one reason for higher spillovers may simply be a more vulnerable economy. We include in the regression measures of debt to GDP ratios, current account and GDP growth as predictor variables. Second, bank risk may also affect domestic sovereign risk through the "bailout channel", that is explicit or implicit public guarantees, in case of distress of the banking sector (Alter and Schüler (2012)). To proxy this effect, we add as a predictor the capital ratio of the banking sector. Intuitively, the bailout channel should be significant if domestic banks are undercapitalized and in potential need of public support. Third, another potential channel of spillovers is that when a banking sector is in distress, it can trigger fire sales of the government bonds it holds, increasing in turn the credit risk of the sovereign issuer. Fourth, distress for banks may affect their lending activity and therefore impact sovereign risk through a slowdown in economic growth (Podstawski and Velinov (2018)). For the third and fourth channels, we therefore include two exposure variables in the regression set: the share of domestic government bonds and the share of domestic non-bank assets that the banking sector holds. Denoting v_s^k the vulnerability variable k for sector s, Equation 27 restates the OLS regressions we estimate:

$$\begin{aligned}\bar{\omega}_{bank_i \to sov_i,t}(h) = \beta_0 + \alpha_t + \beta_1 v^{Lev.R.}_{bank_i,t} + \beta_2 v^{D/GDP}_{sov_i,t} + \beta_3 v^{CA}_{sov_i,t} + \beta_4 v^{gGDP}_{sov_i,t} \\ + \beta_5 \text{exposure}^k_{sov_i \to bank_i,t} + \epsilon_{bank_i,sov_i,t}\end{aligned} \tag{27}$$

Note that for the vulnerability variables, we use dummies instead of continuous variables contrary to Equations 25 and 26 [20]. We define high and low realisations of the variables with regards to their overall sample mean [21]. Since the sample is split according to debt levels, using the mean debt/GDP as threshold for the construction of a debt dummy does not yield much variation in the high debt subsamples. We therefore use the subsample mean for the high debt country group, and the overall sample mean for the low debt country group [22].

We find in Table 7 that low capital ratios and high debt to GDP ratios are significantly associated with stronger domestic spillovers from banks to sovereigns. This suggests that the "bailout channel" may indeed be important in explaining the sovereign-bank nexus (Fratzscher and Rieth (2019)), as is higher sovereign indebtedness. Moreover, we find that neither the capital account nor GDP growth is significantly associated with the spillovers we estimate. While the vulnerability variables yield similar results concerning the significance of the indicators across country groups, the results for the exposure variables differ. For high debt countries, both the dependence of the domestic non-bank corporate sector and government on domestic bank lending are not significant. In contrast, we find for low debt countries that higher non-bank exposure to domestic lending is significantly associated with higher domestic bank to sovereign spillover, suggesting that reduced lending activity in the case of a banking shock may indeed feed through the corporate sector into sovereign risk (see Pagano (2018)). As for high debt countries, we also find non-significant effects of sovereign debt exposure to domestic bank for low

[20]The underlying reason for using continuous variables for Equations 25 and 26 is that investors on the CDS markets may pass the shock of one sovereign (bank) to the price of another sovereign (bank) CDS if they judge them as similar. However for bank-to-sovereign or sovereign-to-bank regressions we cannot rely on such similarity metrics as the giving and the receiving variables are of different types. Therefore for Equations 27 and 28 we consider that investors pass the shock of a bank (sovereign) to a sovereign (bank) CDS if they judge the receiving variable as not resilient enough. This kind of reasoning is discrete, therefore we turn to dummy variable so as to illustrate the threshold that investors may consider.

[21]Defined by 15.2% for the capital ratio, 0.5% for the capital account and 0.3% for real GDP growth.

[22]We use the overall sample mean (86.5 %) for the low debt group, and not the subsample mean (70%) as crossing the latter is unlikely to appear as warning signal for investors. Indeed, Germany has crossed this threshold between 2009 and 2016 while keeping its status as safe heaven. The subsample mean is at 101.7 % for the high debt group

debt countries.

Table 7: Factors associated with spillovers from banks to sovereigns in same country

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

Finally, we investigate the determinants of domestic credit risk spillovers from a country's sovereign to its banking sector (see Equation 28). We test the following hypotheses: First, are domestic spillovers to banks stronger if the banking sector is more vulnerable? We proxy here bank vulnerability with capital ratio, liquidity (measured by liquid assets to short term liabilities) and NPL ratios. Second, are spillovers stronger if the domestic banking sector holds more domestic government debt, expressed in % of total assets (the "balance sheet channel" as described in Angeloni and Wolff (2012) and Buch et al. (2016))? Third, are spillovers stronger if the domestic banking sector holds more assets of domestic non-financial firms, expressed in % of total assets (the "real economy channel"[23])? Here again, we express vulnerability variables in terms of dummies, where

[23]The underlying rationale for this hypothesis is that a sovereign shock can feed into the real sector

the thresholds between high and low realisations are set to sample averages [24]. We estimate:

$$\bar{\omega}_{sov_i \to bank_i,t}(h) = \beta_0 + \alpha_t + \beta_1 v^{NPL}_{bank_i,t} + \beta_2 v^{Lev.R.}_{bank_i,t} + \beta_3 v^{Liq.R.}_{bank_i,t} + \\ + \beta_5 \text{exposure}^k_{bank_i \to sov_i,t} + \epsilon_{sov_i,bank_i,t} \tag{28}$$

Table 8: Factors associated with spillovers from sovereigns to banks in the same country

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

The results in Table 8 suggest that, in line with the literature, the "balance sheet channel" plays a major role for both high and low debt countries, as underlined by the positive and significant coefficients associated with government bond exposures. On the contrary,

and then affect domestic banks, e.g. through increased taxes and less consumer spending, or through a downgrade of non-financial companies. This last channel occurs because of the "rating channel": companies cannot have a better rating than their own sovereigns, so when the sovereign is downgraded this also affects private companies, Arezki et al. (2010).

[24] NPL ratios of 3.6%, 15.2% for capital ratios, 80.0% for liquid assets to short term liabilities.

the "real economy channel" seems to matter only for low debt countries (positive and significant coefficient for NFC exposures). Concerning the role of bank vulnerability, we find mixed results across country groups: For high debt countries, both higher NPL and lower liquidity ratios are significantly associated with higher domestic sovereign to bank spillovers in contrast to the capital ratio, which we find not to be significantly linked to the latter. For low debt countries, we find both NPL and capital ratios not to be significantly linked to spillovers, while we find lower liquidity ratios to be significantly associated with higher spillover only in one out of three regressions.

6 Conclusion

We propose a novel approach of the popular Diebold-Yilmaz framework by exploiting a SVAR-GARCH model that is statistically identified by the heteroskedasticity in the data. We show that this identification approach is attractive as it yields time-varying FEVDs based on the conditional variances of estimated structural errors. Moreover, we show that it is feasible to achieve economic identification between structural shocks and financial market variables in a nontrivial bijective relationship, even in a system of 16 variables. We show the advantages of this methodological contribution by comparing the results with other common identification approaches used in the time-varying spillover literature. Overall, the identification scheme is supported by the fact that the results outperform other models in terms of timeliness and narrative fit. Additionally, we show that the obtained pairwise spillovers match theoretical contagion channels.

This study has some limitations that could be addressed in future search. First, our identification approach relies on a constant $\boldsymbol{B}_0$ matrix over the full sample period[25]. In principal, this constraint can be relaxed by estimating the model on shorter subsamples,

[25]That implies that while varying shock sizes may generate time variation in spillovers, elasticities between the variables stay constant.

for example defined on dates for which the researcher expects a structural break in interdependencies. While in Annex A.6 we allow for a single change in the $\boldsymbol{B}_0$ matrix, we leave a more profound analysis of this avenue for future research. Second, by imposing fewer constraints than previous models, the SVAR-GARCH could be applied to investigate contagion issues on time series that have been less considered in the literature, notably market liquidity data.

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A Annex

A.1 Test for identification and estimated coefficients

We rely on the original test proposed by Lanne and Saikkonen (2007) to test for the identification of $\boldsymbol{B}_0$. The recursive test applied here gives strong evidence for full identification of $\boldsymbol{B}_0$, see Table 9. For a more thorough description of the test, see Lütkepohl and Milunovich (2016). Note that the result of the test can be explained despite the reported low power of this latter, because (i) of the size of our dataset (ii) our 16 GARCH processes have a high persistence ($\gamma_k + g_k$ close to 0.9 $\forall k$) which tends to increase the power of the test.

Table 9: Test for identification in SVAR-GARCH

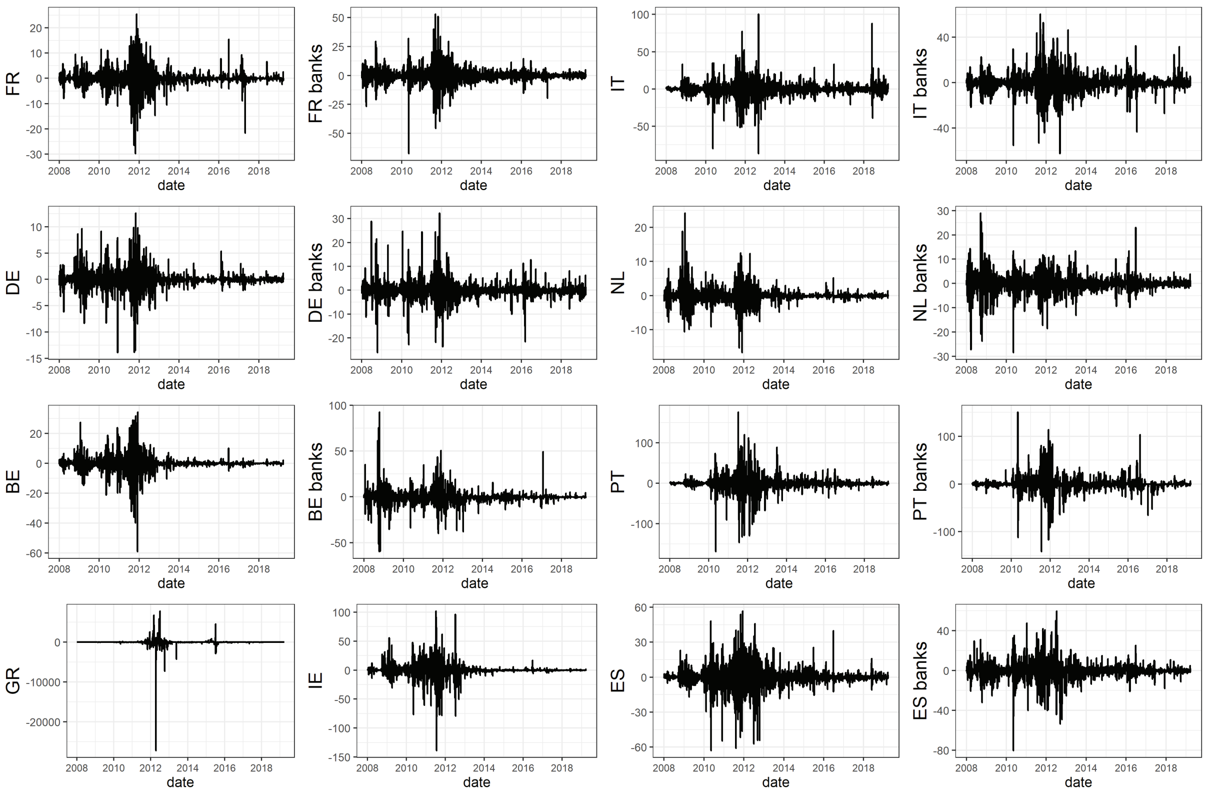
h under H_0	$Q_1(1)$	df	p-value
1	124.3405	1	$< 10^{-5}$
2	113.4685	1	$< 10^{-5}$
3	85.0733	1	$< 10^{-5}$
4	66.6269	1	$< 10^{-5}$
5	60.7231	1	$< 10^{-5}$
6	46.2298	1	$< 10^{-5}$
7	38.0658	1	$< 10^{-5}$
8	35.8007	1	$< 10^{-5}$
9	25.3033	1	$< 10^{-5}$
10	16.2284	1	5.615e-05
11	13.3168	1	0.000263
12	12.6034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

A.2 CDS Data

Table 10: List of banks used in bank sector CDS time series

Country	Banks
BE	Dexia, KBC Bank
FR	BNP, Société Générale, Crédit Agricole
DE	Deutsche Bank, Commerzbank, DZ Bank, Landesbank Baden, Landesbank Hessen, HSH Nordbank, WESTLB
ES	BBVA, Banco pastor, Santander, Sabadell, Banco Popolar Espagnol
NL	Rabobank, ING Bank, SNS Bank
IT	Intesa, Unicredit Spa, Banca Montepaschi, Banco PPO Italiana, Unione di Banche
PT	Banco Comercial Portugues, Banco BPI, Caixa Geral

Figure A.1: CDS time series (bp, first difference)



These graphs represent the raw time series of CDS used in the SVAR-GARCH (before the filtering of common shocks)

A.3 List of Events

Table 11: Historical Events

Variable	Date	Events	Source
ES	12/01/2010	Spain rows back on measures to enforce economic co-operation	FT
ES	13/05/2010	Tough new austerity measures for Spain	FT
ES	15/12/2010	Moody's puts Spain's Aa1 ratings on review for possible downgrade	FT
ES	29/03/2011	Catalan leader Arturo Mas refuses to enforce austerity measures	FT
ES	17/07/2011	Spain and Italy brace for bond market pressure	FT
ES	03/01/2012	Warning over size of Spanish deficit	FT
ES	08/05/2012	Spain set to spend billions on bank rescue	FT
ES	29/08/2012	Catalonia set to call for 5bn bailout	FT
ES	09/11/2015	Catalunya vote for independeence	BBC

Table 11: Historical Events

Variable	Date	Events	Source
ES	27/10/2017	Catalan sparks Madrid showdown	FT
ES	27/05/2018	Spain upheaval deepens Italy market jitters	FT
BE	14/07/2008	Belgium government resigns	le Monde
BE	07/06/2010	Uncertainty on Belgium debt (elections coming)	FT
BE	14/12/2010	SP downgrades Belgium perspective	CNBC
BE	22/11/2011	Belgian spreads enlarge	FT
BE	25/11/2011	SP downgrades Belgium	FT
BE	01/03/2012	Belgian State buys back Dexia	Les Echos
IT	01/12/2010	"Premiums that Italy pay hit fresh highs"	FT
IT	30/06/2012	Markets rebound following EU deal "the agreement allow(...)to buy Italian sovereign bonds"	FT
IT	28/10/2013	Bond yields fall to four-month low as Italy sells 2-year debt	Nasdaq
IT	15/04/2014	"On April 15th yields on ten-year Italian-government bonds fell to 3.11%, the lowest on record"	The Economist
IT	30/05/2018	Italy election crisis spreads as central bank chief warns investor trust is fading	FT
IT	19/12/2018	Italian bonds and stocks rally as government comes closer to EU pact	FT
GR	09/03/2012	ISDA declares Greece in default (impact on CDS, restructuring)	Reuters
GR	09/04/2012	CDS decrease after Greece restructuring	The Economist
GR	19/06/2012	EZ's Greek poll honeymoon short lived	FT
GR	21/05/2013	Significant decrease in Greek sovereign CDS series	
GR	11/07/2015	EZ finance ministers prepare to decide Greece's fate	FT
PT	27/04/2010	Portugal rating downgraded	CNN
PT	29/03/2011	Portugal rating downgraded	FT
PT	06/07/2011	Portugal rating blow	FT
PT	18/01/2012	Moody's warns of second rescue for Portugal	FT
PT	07/02/2012	Speculation on Portugal debt restructuring	Les Echos
PT	09/03/2012	Renew speculation on Portugal debt	Reuters
PT	02/07/2013	Portuguese government at risk of collapse as foreign minister resigns	Telegraph
PT	10/11/2015	Confidence vote againt government, potential left-wing coalition	Business Insider
PT	08/02/2016	Portugal-Germany Yield Spread Widens to Most Since 2014	Bloomberg
IE	11/02/2009	Recapitalisation was carried out at Ireland's two largest banks, Allied Irish Bank (AIB) and Bank of Ireland (BoI)	FT
IE	28/04/2010	Marked increase in Irish 2-year bond yields	The Irish Times
IE	18/07/2011	Record high of Irish CDS in our time series	
IE	06/07/2012	Ireland comes back on sovereign debt markets	FT
FR	11/08/2011	Focus of EZ crisis turns to France	FT
FR	10/11/2011	Standard & Poor's mistakenly announced the downgrade of France's top credit rating on Thursday	Reuters
FR	14/01/2012	SP downgrades France and Austria	FT
FR	22/02/2017	Highest DE-FR spread since 2012	CNBC
FR	28/04/2017	France CDS bounce back after election	IHS Markit
NL	09/10/2008	Governement capital injections into banks	BIS
NL	26/01/2009	Bank comprehensive rescue plans (asset insurance)	BIS
NL	14/01/2012	SP puts Netherlands sovereign on negative outlook	Reuters
NL	23/04/2012	PM Rutte resigns after austerity talks	The Guardian
NL	20/08/2013	Netherland's top rating is affirmed at Fitch amid debt warning	Bloomberg

Table 11: Historical Events

Variable	Date	Events	Source
DE	07/05/2010	German Parliament approves Greek rescue	NYT
DE	29/11/2010	German credit risk jumps to highest since may, debt swaps show	Bloomberg
DE	09/02/2016	Five-year sovereign German CDS rose to almost 22 bps due to hedging activity	Reuters
DE banks	28/04/2009	Profit-taking undermines Deutsche Bank	FT
DE banks	19/04/2010	Bank dividend payments reach record low: Deutsche Bank, plans to pay a dividend of 0.75 for 2009, up from 0.50 in 2008, but still small compared with earnings per share of 7.59	FT
DE banks	11/01/2011	Concerns rise over German bank levy	FT
DE banks	10/03/2011	Sale of stake in Deutsche AM puzzles analysts	FT
DE banks	28/07/2011	Deutsche Bank net revenues in its corporate and investment banking arm fell 27 per cent in the second quarter	FT
DE banks	10/09/2011	Commerzbank hit by 760m Greek writedown	FT
DE banks	24/11/2011	Deutsche bank needs 2 bln to meet EBA's conditions	EBA
DE banks	07/12/2011	SP placed the credit Deutsche Bank and Commerzban under review	Deutsche Welle
DE banks	24/01/2012	Commerzbank buoyant as investors back capital plan	FT
DE banks	10/03/2016	Deutsche and UBS defeated in UK tax avoidance case over bankers' bonuses	BBC
DE banks	03/05/2017	HNA raises stake in Deutsche Bank to nearly 10%	FT
DE banks	01/06/2018	SP downgrades Deutsche Bank	FT
DE banks	04/12/2018	Investor fear raids will hit DB turnaround	FT
FR banks	06/05/2010	BNP Paribas and Société Générale in suffering as the costs of insuring themselves against default rises	FT
FR banks	12/08/2011	French Short-selling ban brings relief for banks	FT
FR banks	13/09/2011	BNP Bank executive says they can no longer borrow USD	WSJ
FR banks	14/10/2011	Big European CDS such as France's BNP Paribas spiked to 291bp	FT
FR banks	07/11/2011	BNP stock price plunges compared to CAC 40p	Les Echos
FR banks	30/11/2011	SocGen, UniCredit and BNP lose some of Monday's gains	FT
FR banks	12/02/2016	SocGen battles to hit targets amid low rates and volatility	FT
FR banks	11/06/2018	France tells its banks to set aside more capital	FT
IT banks	17/08/2011	Shares in Italy's biggest retail bank Intesa Sanpaolo were at one point suspended for excessive losses "European banks at centre of sell-off "	FT
IT banks	30/11/2011	European banks' junior debt under review, including a number of Italian banks "European banks' junior debt under review"	FT
IT banks	01/02/2013	Monte dei Paschi di Siena asks for 3.9bn bailout amid scandal over loss-making derivatives contracts and alleged fraud	the Guardian
IT banks	11/06/2016	Italian banking crisis, heightened by European financial stress tests	FT
IT banks	27/06/2016	Italian banks struggling "Italy resurrects plans to rescue struggling banks"	FT
IT banks	04/05/2017	Monte Paschi CDS time series spike	
IT banks	29/11/2017	European Central Bank has redoubled warnings that the state of EZ banks is a threat to the region's economic recovery, IT banks with biggest problem of sour loans	FT
IT banks	31/08/2018	UniCredit and Intesa Sanpaolo fall on news of increased political uncertainty	FT
PT banks	06/05/2010	Spectre of counterparty risk, focused attention on to smaller banks in Portugal and Spain	FT
PT banks	19/07/2011	BCP fails Espírito Santo Financia almost fails EBA stress test	EBA
PT banks	30/11/2011	BCP's CDS arrive at record level after Fitch downgrade of covered bonds	Bloomberg

Table 11: Historical Events

Variable	Date	Events	Source
PT banks	16/02/2012	Moodys downgrades state guaranteed debt issued by BCP from Ba2 to Ba3 with negative outlook	FT
PT banks	18/08/2016	Portuguese bonds under pressure after rating agency's warning	FT
PT banks	10/01/2017	Fosun to increase its stake in Millennium BCP to 30%	FT
PT banks	28/03/2017	CDS spread of BCP drops sharply	
BE banks	18/09/2008	Speculative rumors against Fortis	La Libre Belgique
BE banks	30/09/2008	Dexia bailed out	The Guardian
BE banks	15/10/2008	Bank rally, Dexia, the Franco-Belgian bank whose borrowings have already had to be guaranteed, dismissed rumours that it faced impending nationalisation by the Belgian government	FT
BE banks	29/12/2008	KBC loses 1 billion on CDOs	La Libre Belgique
BE banks	30/09/2011	Belgium market authority ends short selling ban on Belgian financial institutions	Fed NY
BE banks	05/10/2011	Dexia shares suspended as break-up takes shape	FT
BE banks	02/11/2012	Three banks – Lloyds Banking Group, Commerzbank and Dexia – were dropped from the GSifi list	FT
BE banks	29/12/2012	European commission validates Dexia rescue plan	Le Monde
BE banks	25/01/2017	Repricing of Dexia CDS	FT
ES banks	14/01/2011	Spain seeks to show that it is not another Ireland	FT
ES banks	13/07/2011	Spanish bank IPOs under threat	FT
ES banks	09/08/2011	Investors turn agains spanish financials as they bet against the value of what they see as fragile institutions	FT
ES banks	26/09/2011	News about bank rescue plan: ECB expected to boost bank liquidity. Spanish banks affected in particuliar	FT
ES banks	28/03/2012	EU underlines that Spanish banks need to bailout	FT
ES banks	09/07/2012	Spanish bank bailout talks. Spain to Accept Rescue From Europe for Its Ailing Banks	NYT
ES banks	16/10/2012	Spanish banks rally on hope Madrid ready to request aid	FT
ES banks	25/03/2013	Bankia leads falls across big lenders after EZ comment to toughen bank regime	FT
ES banks	21/01/2016	Market sentiment turns sharply against Spain's banking sector	FT
ES banks	08/06/2017	Emergency funds failed to save Banco Popular from death spiral	FT
ES banks	05/12/2017	Strong drop of CDS of Banco Popular	
ES banks	26/09/2018	Banco Santander changes its chief executive	FT
NL banks	30/09/2008	The Belgian-Dutch Fortis faces state rescue	Reuters
NL banks	19/10/2008	ING receives 10 billion from Dutch government	NYT
NL banks	26/03/2009	Fortis Bank Nederland posts 25.11 billion loss	Reuters
NL banks	16/01/2012	ING benefits from ING gains from Netherlands' credit rating	FT
NL banks	13/06/2012	ING to pay USD 619m to settle sanctions case	FT
NL banks	09/07/2012	Former Rabobank traders fired in LIBOR-scandale	Observer

A.4 IRF assumptions

An additional advantage of our econometric framework is that it imposes less restrictions on the impulse response functions (IRFs) compared to other contagion-models. More specifically, Cholesky-identified SVARs, as used in VAR Cholesky and DCC Cholesky, postulate a recursive structure of the IRFs. Generalized impulse response functions, as used in VAR GIRF, impose that the IRF of a one-unit shock i on variable j has the same initial impact as an IRF from shock j to variable i. Eventually the same criticism applies also to the orthogonalization in Fengler and Herwartz (2018) as used for the model DCC Fengler -see demonstrations below. On the reverse, the SVAR-GARCH framework does not impose such a structure (Lütkepohl and Netšunajev (2017b)). Therefore the level-differences observed on Figure 3 may come from the overly strong assumptions of the competing models, over- or underestimating the spillovers.

Why do the identifications used in VAR GIRF and in DCC Fengler assume symmetrical IRFs? A usual VAR-analysis begins with the reduced form VAR (Equation 6), with the objective to go to the structural form of Equation 5. Under covariance stationarity, Equation 6 is equivalent to its moving average representation:

$$\boldsymbol{Y}_t = \sum_{i=0}^{\infty} \boldsymbol{\Phi}_i \boldsymbol{\mu}_{t-i} \tag{A.29}$$

Which can be rewritten in its structural form:

$$\boldsymbol{Y}_t = \sum_{i=0}^{\infty} (\boldsymbol{\Phi}_i \boldsymbol{B}_0)(\boldsymbol{B}_0^{-1} \boldsymbol{\mu}_{t-i}) = \sum_{i=0}^{\infty} \boldsymbol{\Theta}_i \boldsymbol{\epsilon}_{t-i} \tag{A.30}$$

Generally speaking, the IRF of a vector shock $\boldsymbol{\delta} = (\delta_1, ..., \delta_n)$ on $\boldsymbol{Y}_t$ is defined, at horizon h and with $\boldsymbol{\Omega}_{t-1}$ the information set at t, as:

$$IRF(h, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = E(\boldsymbol{Y}_{t+h}|\boldsymbol{\epsilon}_t = \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) - E(\boldsymbol{Y}_{t+h}|\boldsymbol{\Omega}_{t-1}) \tag{A.31}$$

Due to the orthogonality of the structural shocks, one uses $\boldsymbol{\delta} = (0, ..., 0, \delta_j, 0, ..., 0)$ in order to consider the impact of a single shock. In that case we get, with $\boldsymbol{e}_j$ a vertical vector full of zeros apart for its j^{th} element that is equal to 1: $IRF(h, \boldsymbol{\delta}, \boldsymbol{\Omega}_{t-1}) = \boldsymbol{\Phi}_h \boldsymbol{B}_0 \boldsymbol{\delta} = \boldsymbol{\Phi}_h \boldsymbol{B}_0 \boldsymbol{e}_j \delta_j$

In our SVAR-GARCH setting, $\boldsymbol{B}_0$ is identified by heteroskedasticity and by economic identification (with $\boldsymbol{\Sigma}_\epsilon$ and $\boldsymbol{\Sigma}_\mu$ evolving over time and being equal to, respectively, $\boldsymbol{\lambda}_{t|t-1}$ and $\boldsymbol{\Sigma}_{\mu,t|t-1}$, Equation 13). This identification strategy does not impose any structure on the IRFs. Conversely, in Diebold and Yilmaz (2009), $\boldsymbol{B}_0$ is identified by using the Cholesky decomposition of $\boldsymbol{\Sigma}_\mu$ with $\boldsymbol{B}_0^{-1} \boldsymbol{B}_0^{-1\prime} = \boldsymbol{\Sigma}_\mu$ as in the first equation of Equation 8. Although convenient, this orthogonalization imposes a recursive structure in the Data Generating Process as $\boldsymbol{B}_0$ is then lower-triangular.

Identification by GIRF works differently since, instead of considering structural shocks, the GIRF looks at reduced form shocks. Using the notation $\boldsymbol{\Sigma}_\mu = (\sigma_{ij})_{i,j \in [\![1,n]\!]^2}$, a one standard deviation shock j and the same remaining notations, the GIRF is defined as:

$$GIRF(h, \sigma_{jj} \boldsymbol{e}_j, \boldsymbol{\Omega}_{t-1}) = E(\boldsymbol{Y}_{t+h}|\boldsymbol{\mu}_t = \sigma_{jj} \boldsymbol{e}_j, \boldsymbol{\Omega}_{t-1}) - E(\boldsymbol{Y}_{t+h}|\boldsymbol{\Omega}_{t-1}) \tag{A.32}$$

If one assumes that $\mu_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_\mu)$, then we can write (see Pesaran and Shin (1998)):

$$E(\boldsymbol{\mu}_t|\mu_{jt} = \sigma_{jj}) = [(\sigma_{1j}, ..., \sigma_{mj})' \sigma_{jj}^{-1}] \sigma_{jj} = \boldsymbol{\Sigma}_\mu \boldsymbol{e}_j \tag{A.33}$$

So that the impact of a one standard deviation j shock on variable i at horizon 0 is (with Equation A.29):

$$GIRF_i(0, \sigma_{jj}\boldsymbol{e}_j, \boldsymbol{\Omega}_{t-1}) = \boldsymbol{e}_i'\boldsymbol{\Phi}_0\boldsymbol{\Sigma}_\mu\boldsymbol{e}_j \tag{A.34}$$

As $\boldsymbol{\Phi}_0 = \boldsymbol{I}$ we get:

$$GIRF_i(0, \sigma_{jj}\boldsymbol{e}_j, \boldsymbol{\Omega}_{t-1}) = \boldsymbol{e}_i'\boldsymbol{\Sigma}_\mu\boldsymbol{e}_j = \sigma_{ij} = \sigma_{ij} = GIRF_j(0, \sigma_{ii}\boldsymbol{e}_i, \boldsymbol{\Omega}_{t-1}) \tag{A.35}$$

Similarly, the identification strategy of Fengler and Herwartz (2018) used in DCC Fengler yields also symmetric IRFs on impact. This is because the time-varying matrices $\boldsymbol{B}_{0,t}^{-1}$ (and hence $\boldsymbol{B}_{0,t}$) are symmetric as, $\forall t$ and knowing that $\boldsymbol{\Lambda}_t$ is diagonal and therefore symmetric:

$$(\boldsymbol{B}_{0,t}^{-1})' = (\boldsymbol{\Gamma}_t\boldsymbol{\Lambda}_t^{1/2}\boldsymbol{\Gamma}_t')' = \boldsymbol{\Gamma}_t(\boldsymbol{\Gamma}_t\boldsymbol{\Lambda}_t^{1/2})' = \boldsymbol{\Gamma}_t\boldsymbol{\Lambda}_t^{1/2}\boldsymbol{\Gamma}_t' = \boldsymbol{B}_{0,t}^{-1} \tag{A.36}$$

To conclude, identification with GIRFs or the identification of Fengler and Herwartz (2018) impose a symmetric structure of impulse responses upon impact while identification by Cholesky assumes a recursive one. These assumptions may be controversial when it comes to financial data which tend to respond rapidly to shocks and where variables react asymmetrically to each other.

A.5 Data sources OLS regressions

- Similar Business Cycle : the quarterly squared difference between country i and country j's GDP growth (multiplied by (-1) so that a higher number indicates more similar tendencies) [this is similar to De Santis and Zimic (2018), albeit De Santis and Zimic (2018) sum over over time as they focus on cross sectional effects]; Source: Eurostat

- Similar D/GDP : Same approach for quarterly D/GDP ratios (multiplied by (-1) so that a higher number indicates more similar tendencies); Source: IMF
- Trade exposure: $\frac{\text{Exports}_{j\to i}}{\text{Total exports}_j}$; Source: IMF
- Investment exposure: $\frac{\text{International investment}_{j\to i}}{\text{Total International investment}_j}$; Source: Eurostat
- 'Similar NPLs : the quarterly squared difference between banking sector i and banking sector j's NPLs (multiplied by (-1) so that a higher number indicates more similar tendencies); Source: IMF Financial Soundness indicators and SNL
- Same approach for capital ratios; Source: IMF Financial Soundness indicators and SNL
- 'Similar portfolio: In a first step we construct from CBS data portfolio vectors per quarter for each banking sector as in Greenwood et al. (2015): a vector with the holdings of sovereign debt, non-bank financial institutions, households and non-financial corporations; for a large range of counterparty countries. We then express all portfolio items in % to total assets. And finally, we calculate the sum of the squared difference of those portfolio; Source: BIS CBS
- Bank claim exposure: $\frac{\text{Bank claims of country j vis-a-vis country i}}{\sum_i \text{Bank claims of country j vis-a-vis country i}}$, Source: BIS CBS
- NPLs, capital ratios (regulatory Capital to Risk-Weighted Assets) and liquidity ratios (Liquid Assets to Short Term Liabilities) of banking systems in percent; Source: IMF Financial Soundness indicators and SNL
- Exposure domestic government debt: $\frac{\text{Sovereign debt of country i held by banking system j}}{\text{Total assets of banking system j}}$, Source: IMF IFS
- Exposure domestic government NFCs: $\frac{\text{Non-bank assets of country i held by banking system j}}{\text{Total assets of banking system j}}$, Source: IMF IFS
- 'Sovereign exposure' : $\frac{\text{Sovereign debt of country j held by i}}{\text{Total sovereign debt of country j}}$, Source: BIS CBS

- 'Nonbank exposure' : $\frac{\text{Liabilities of country j's non-banks held by i}}{\text{Total Liabilities of country j's non-banks}}$; Source: BIS CBS
- Debt to GDP, Current account, GDP growth in %, Source: Eurostat, OECD and IMF

A.6 Robustness checks

We perform several checks to assess the robustness of our results. First, with regards to the exogenous regressors: in our main specification we follow Alter and Beyer (2014) and include a significant number of exogenous variables to account for the strong comovement between CDS spreads. However, one might argue that some of them are endogenous to the sovereign and bank CDS. Therefore, we also estimate the model with a more parsimonious set of exogenous variables. In line with De Santis and Zimic (2018) we consider as alternative exogenous variables: oil prices, global macro news provided by Citibank, as well as US and UK CDS spreads. The upper part of Figure A.2 represents total spillover indices S^H from different specifications, including our main one ("SVAR-GARCH"). As can be seen on the graph, some level changes are observable at the beginning of the estimation period, but overall the different indices evolve in a parallel manner.

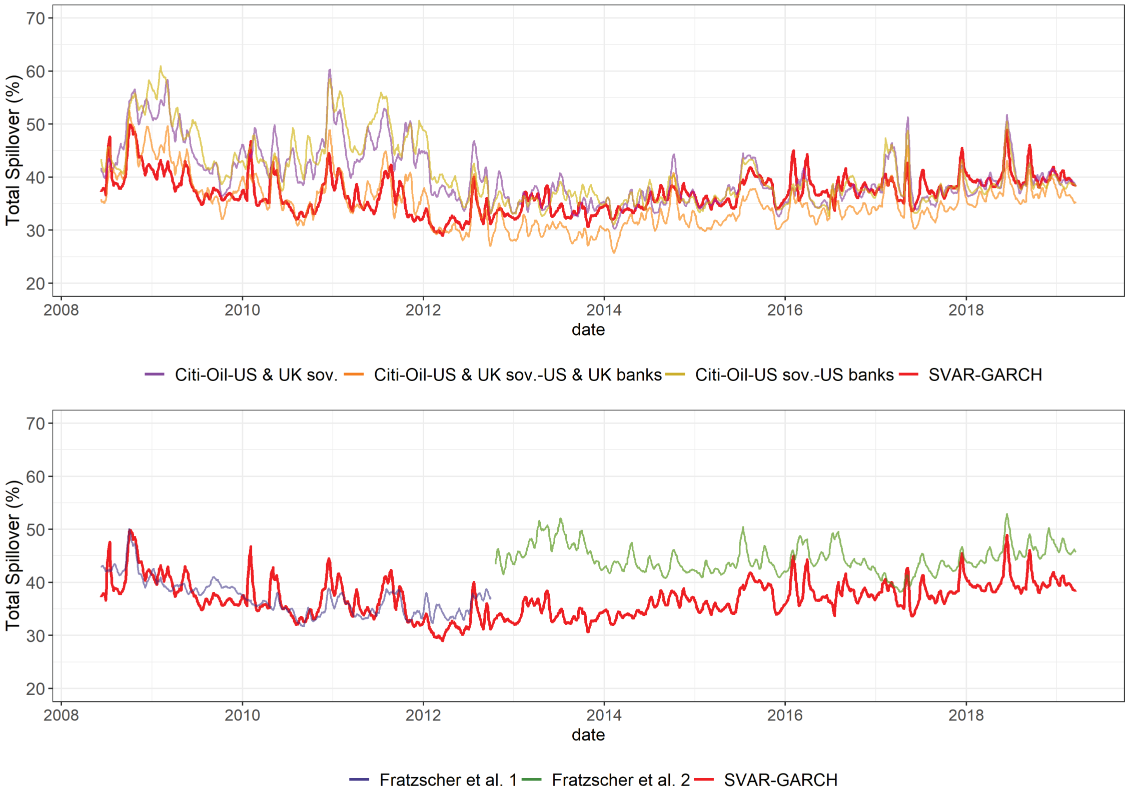
Second, as exposed in Section 3.2, we assume a constant $\boldsymbol{B}_0$ in our study. Some authors argued that the increase in CDS-correlation during the EZ debt crisis came mainly from changes in volatility and not in propagation mechanisms (Caporin et al. (2018)), but this point is disputed (De Santis and Zimic (2018)). To evaluate the robustness of our results to changes in the estimation period, we estimate our model on different subsamples. In line with Ehrmann and Fratzscher (2017), we define two subperiods: a crisis period starting at the beginning of our sample until 01/10/2012 [26], and a post-crisis period

[26] Corresponding to the announcements of the implementation details of the ECB OMT-program

running from 01/10/2012 to the end of our sample [27]. The bottom part of Figure A.2 exhibits total spillover indices S^H from the models estimated over the all sample, or over the two subsamples. Here again, apart from level differences on years 2013-2014, our results appear robust to changes in estimation period.

[27]Note that Ehrmann and Fratzscher (2017) use 3 smaller subperiods, with a "crisis period" for the Greek turmoil that starts in March 2010 and ends in March 2012, and a "post-crisis period" that starts in October 2012. However, to build the total spillover indices S^H, we need the exact identification underlined in Section 5.1.1, i.e. being able to assign each shock to a single variable. This identification is not granted for any subsample, and is hard to achieve on short time intervals. Thus, on Figure A.2 we rely on a large "crisis period" so as to obtain this identification.

Figure A.2: Robustness graphs



The different lines represent the Total Spillover indices S^H built from our main specification ("SVAR-GARCH") as well as from the other specifications outlined above. For the upper part of the graph, the different indices are named according to the exogenous variables included (Oil price, Macro news from Citibank, US and UK bank or sovereign CDS). For the bottom part of the graph, the different indices represent our main specification estimated on subsamples (before and after 01/10/2012 as outlined in Ehrmann and Fratzscher (2017)). For readability we show 10 day moving averages of the indices.