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Beyond spreads: measuring sovereign market stress in the euro area

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Abstract

In this paper we propose a composite indicator that measures multi-dimensional sovereign bond market stress in the euro area as a whole and in individual euro area member states. It integrates measures of credit risk, volatility and liquidity at short-term and long-term bond maturities into a broad measure of sovereign market stress. The statistical framework builds on that of the ECB's Composite Indicator of Systemic Stress (CISS) developed by Holló, Kremer and Lo Duca (2012), so that we call our metric the Composite Indicator of Systemic Sovereign Stress or "SovCISS". We implement the SovCISS for eleven euro area member states and also present four options of a SovCISS for the entire monetary union. In addition, we suggest a linear decomposition of the SovCISS, singling out contributions of the different components and of the time-varying correlations across these components. Comparing develoments in the SovCISS and the CISS over the crisis period clearly illustrates the usefulness of the latter for the real-time monitoring of systemic instabilities in the financial system as a whole. Finally, an application of the country-specific SovCISS indicators to the VAR-based spillover literature suggests that stress mainly originates from a few euro area countries, and that spillover patterns vary over time.

Keywords: financial stress index; systemic risk; sovereign debt crisis; spillover index

JEL classification: C43, E44, F45, G01, H63

Non-technical summary

Quantifying stress in sovereign bond markets is a relevant task since such tensions can easily spill over to other important financial market segments, raising the odds of a systemic crisis in the financial system as a whole. The so-called sovereign-bank nexus is a case in point for one possible transmission mechanism via which sovereign market stress may become systemic. In the literature sovereign stress is usually measured in terms of either the yield spread of a particular government bond against a "safe" benchmark bond, or by the spread of a credit default swap written on government debt. Both indicators are usually interpreted as a measure of the (excess) default risk premium embedded in the price of a more risky government bond.

In this paper we develop a composite indicator of sovereign market stress which is based on a wider set of stress symptoms that includes, apart from yield spreads, a measure of yield volatility and bid-ask spreads. We also use country information from both the short and the long end of the yield curve. All these different measures of sovereign stress are aggregated into a composite indicator based on the methodology of the ECB's Composite Indicator of Systemic Stress, CISS (see Holló, Kremer, and Lo Duca, 2012). In order to recognise this affinity, we call our indicator the Composite Indicator of Systemic Sovereign Stress, or just SovCISS. Accordingly, the SovCISS results as a correlation-weighted average of its components which are homogenised in a particular way before the aggregation step. The basic idea is that the overall level of sovereign stress increases (decreases) with a stronger (weaker) correlation between the different measures of stress symptoms. We compute the SovCISS both for euro area member states individually and for the euro area as a whole. The latter provides a yardstick for quickly gauging the extent to which sovereign stress is a more local or a more widespread phenomenon within the euro area.

In an empirical application of our SovCISS indicators, we follow the spillover model as developed by Diebold and Yilmaz (2009 and 2012). We use their model to estimate directional spillover patterns across eleven sovereign bond markets of the euro area between September 2000 and April 2018. Evidence points to little actual contagion from smaller (and less liquid) countries to the remaining (and more liquid) euro area economies during the most acute phases of the sovereign debt crisis.

1 Introduction

This paper proposes a composite indicator of sovereign bond market stress in the euro area: the Composite Indicator of Systemic Sovereign Stress (SovCISS). Sovereign stress is important to quantify as tensions in sovereign bond markets—due to their benchmark status and sheer size—can easily spill over to other market segments and thereby create systemic risks for the financial system as a whole. Sovereign market stress is most often measured by the yield spread between a country's bond and a safe reference security ("credit spread"). However, sovereign market stress can also reveal itself in higher price volatility and lower liquidity in bond trading; incorporating these two stress symptoms along with a credit spread into an overall (composite) measure of sovereign market stress thus makes sense to begin with.

We construct a SovCISS for the euro area as a whole that aggregates information from eleven member states. This makes it possible to monitor euro area wide sovereign bond market tensions with one single indicator. In addition, we decompose the euro area indicator into eleven country-specific ones. The SovCISS builds on the methodological concept of the Composite Indicator of Systemic Stress (CISS) from Holló, Kremer, and Lo Duca (2012) who apply basic principles of portfolio theory to the aggregation of market-specific stress indicators into a composite index. Following this framework, the SovCISS represents a correlation-weighted average of homogenised individual stress indicators, with correlation-weights which vary over time. The basic idea is that sovereign stress is overall stronger the more symptoms of stress the market displays at the same time.

To our best knowledge, the SovCISS is the first (and one) of its kind by combining different symptoms of sovereign stress into a composite indicator.[1] Since its first publication, the SovCISS has been regularly shown and

[1] Partially building on the CISS methodology, Broto and Lamas (2017) compute a

commented on in the ECB's Financial Stability Review and in the European Systemic Risk Board's (ESRB) Risk Dashboard.[2] Monthly updates of the SovCISS for the euro area as a whole as well as for a broad range of euro area and non-euro area EU countries are available online from the ECB's Statistical Data Warehouse.[3]

In an empirical application, we adopt the framework proposed by Diebold and Yilmaz (2009, 2012) to assess sovereign stress spillovers across euro area countries. While the literature identifies spillover patterns separately for returns (or risk spreads) and volatilities (e.g., Diebold and Yilmaz, 2009), the SovCISS enables an integrated analysis of the cross-country transmission of both stress symptoms. In line with previous studies, we find that the nature and the intensity of spillovers varies across time in general and during the financial and sovereign debt crisis in particular (see, e.g., Alter and Beyer, 2014; and Cronin, Flavin and Sheenan, 2016). This notwithstanding, the spillover patterns for the SovCISS differ markedly from those obtained when using plain yield spreads.

2 Statistical methodology and data

The construction of the SovCISS involves three major steps, namely the selection of the input series, their transformation, and their aggregation into the composite index (see Holló, Kremer, and Lo Duca, 2012).

composite indicator of market liquidity in the US fixed income markets, combining different liquidity measures from the US Treasury and corporate bond markets.

[2]It is shown, along with the CISS, as Figure 1.1 of the ESRB Risk Dashboard (https://www.esrb.europa.eu/pub/rd/html/index.en.html).

[3]Monthly updates of the SovCISS for the euro area as a whole and a broad range of indidvidual European countries can be obtained as part of the CISS index family from the ECB's Statistical Data Warehouse (SDW) at http://sdw.ecb.europa.eu/browse.do?node=9689686.

2.1 Data

The SovCISS consists of a range of indicators capturing certain symptoms of a market in distress. We measure stress symptoms along three dimensions: (i) *risk spreads* capture the pricing of credit and liquidity risk of the underlying bonds; (ii) *yield volatilities* measure the degree of fragility and uncertainty prevailing in the market; and (iii) *bid-ask spreads* reflect transaction costs and market liquidity conditions more generally. These three stress dimensions are not completely independent from each other. However, for our purpose it suffices that they tend to correlate more strongly in crisis times than under normal circumstances. In fact, such time-varying correlation patterns provide the rationale for the portfolio-theoretic aggregation applied in this paper.

Risk spreads are measured as the absolute difference between a government bond yield and the euro interest rate swap rate for 2-year and 10-year contracts. Whenever 2-year bonds are not available (Finland, Greece and Ireland), we use 3-year yields instead.[4] *Volatility* is computed as absolute daily yield changes for both maturities. *Bid-ask spreads* for 2-year and 10-year bonds show as mid-price percentages. All indicators are computed as weekly averages. Raw interest rates are collected from Datastream, bid and ask prices from Reuters.

This selection yields six stress components for each of eleven euro area members states, namely Austria (AT), Belgium (BE), Germany (DE), Spain (ES), Finland (FI), France (FR), Greece (GR), Ireland (IE), Italy (IT), The Netherlands (NL) and Portugal (PT). Our data spans from September 2000 to April 2018.

[4]As from March 2012, the Greek SovCISS includes only three input series derived from 10-year bonds since 3-year bonds stopped being traded.

2.2 Transformation

We transform each input series by applying the probability integral transform (PIT). The theorem of the PIT states that for any continuous random variable X with cumulative distribution function (CDF) $F(x)$, the random variable defined by $Y = F(X)$ has a standard uniform distribution regardless of the form of the original distribution (Cassela and Berger, 2002): $Y = F(X) \sim U(0, 1)$.

In practice we work with the discontinuous sample analogue of the CDF, the empirical CDF. Assume we have a sample of T observations of a raw indicator $x = (x_1, x_2, ..., x_T)$. The observations are first ranked in ascending order, i.e. $x_{[1]} \leq x_{[2]} \leq ... \leq x_{[T]}$, where $x_{[1]}$ represents the sample minimum and $x_{[T]}$ the maximum. The transformed indicators y_t result from replacing each original observation x_t with its respective empirical CDF value $F(x_t)$. That value can be computed as the ranking number r of observations not exceeding a particular value x_t, divided by the total number of observations T:

$$y_t = F(x_t) := \begin{cases} \frac{r}{T} \text{ for } x_{[r]} \leq x_t < x_{[r+1]}, r = 1, 2, ..., T-1 \\ 1 \text{ for } x_t \geq x_T. \end{cases} \tag{1}$$

In the case of tied observations, that is when m identical observations share the same rank r, the functional value assigned to each of them is computed as $((r + 1) + (r - m))/2T$. All transformed indicators are unit-free and approximately uniform distributed over the range $(0, 1]$.

The PIT possesses the distinct advantage that whatever is the original distribution of the raw indicators, the transformed indicators are homogenous in terms of scale and distribution. Since it involves the use of order statistics, the PIT also robustifies the composite indicator against the addition of outliers in sub-sample computations. This property is important as we compute the SovCISS "in real time" over an expanding data window as from 25 December 2006. Moreover, the distributional homogeneity helps avoid that the dynamics of the composite indicator is dominated by those components whose original distribution function is likely to produce more observations far away from the sample mean. On the downside, the PIT implies losing the extra information contained only in the cardinal scale of the original data.

2.3 Aggregation 1: SovCISS for individual countries

The SovCISS for country $c = AT, ..., PT$ is computed as:

$$SovCISS_{c,t} = (w \circ s_{c,t})'\Omega_{c,t}(w \circ s_{c,t}), \tag{2}$$

with $w = (1/6, \ldots, 1/6)'$ a 6×1 vector of equal indicator weights, $s_{c,t}$ a 6×1 vector containing the transformed stress indicators $s_{c,i,t}$ with $i = 1, ..., 6$ and country index c; $w \circ s_{c,t}$ denotes the element-wise product of both vectors; and $\Omega_{c,t}$ the symmetric 6×6 matrix collecting time-varying (Spearmans) rank-correlations between the $s_{c,i,t}$ for country c. The SovCISS can also be expressed in "volatility-equivalent" terms by taking the square root of its "variance-equivalent" quadratic form of equation 2:[5]

$$SovCISS^{vola}_{c,t} = \sqrt{(w \circ s_{c,t})'\Omega_{c,t}(w \circ s_{c,t})}. \tag{3}$$

The time-varying cross-correlations are computed from an exponentially-weighted moving average (EWMA) estimate of the variance-covariance matrix $H_{c,t}$ of the demeaned stress indicators $\widetilde{s}_{c,t} = (s_{c,t} - 0.5)$, where the smoothing parameter or decay factor λ is set at 0.93 which is rather conven-

[5]The difference between both variants of the SovCISS is analogous to the difference between a variance and a standard deviation (or volatility) as a statistical measure of dispersion.

tional for daily and weekly data (see Engle 2002):

$$H_{c,t} = \lambda H_{c,t-1} + (1-\lambda)\widetilde{s}_{c,t}\widetilde{s}'_{c,t}. \tag{4}$$

The elements $\omega_{c,ij,t}$ of correlation matrix $\Omega_{c,t}$ are simply computed from the elements $h_{c,ij,t}$ of $H_{c,t}$ as $\omega_{c,ij,t} = h_{c,ij,t}/\sqrt{h_{c,ii,t}}\sqrt{h_{c,jj,t}}$.

2.4 Aggregation 2: SovCISS for the euro area as a whole

The SovCISS for the euro area as a whole is computed basically in the same way, stacking all the country-specific individual stress indicators into a 1×66 vector $s_{EA,t}$ and estimating the *full* 66×66 matrix $\Omega_{EA,t}$ of cross-correlations between all of them:

$$SovCISS^{full}_{EA,t} = (w \circ s_{EA,t})'\Omega_{EA,t}(w \circ s_{EA,t}) \tag{5}$$

The weights w_j attached to each $s_{EA,j,t}$ are set to $1/66$ in case of equal weights, or to $(1/6) \cdot (\overline{GDP}^r_c / \sum_{k=AT,\ldots,PT} \overline{GDP}^r_k)$ for a SovCISS with real GDP weights; the real GDP weights are held constant and proportional to the average relative real GDP of each country from 1999:Q1 to 2012:Q4. Two alternative variants of a SovCISS for the euro area as a whole are obtained by simply taking the GDP-weighted or the equally-weighted *average* of the eleven country-specific SovCISS indices, thereby ignoring the cross-country correlations between the individual components of each country-specific SovCISS:

$$SovCISS^{average}_{EA,t} = \sum_c w_c \cdot SovCISS_{c,t}, \tag{6}$$

with $w_c = \overline{GDP}^r_c / \sum_{k=AT,\ldots,PT} \overline{GDP}^r_k$ in the case of GDP weights and $w_c = 1/11$ in the case of equal weights.

3 Empirical implementation

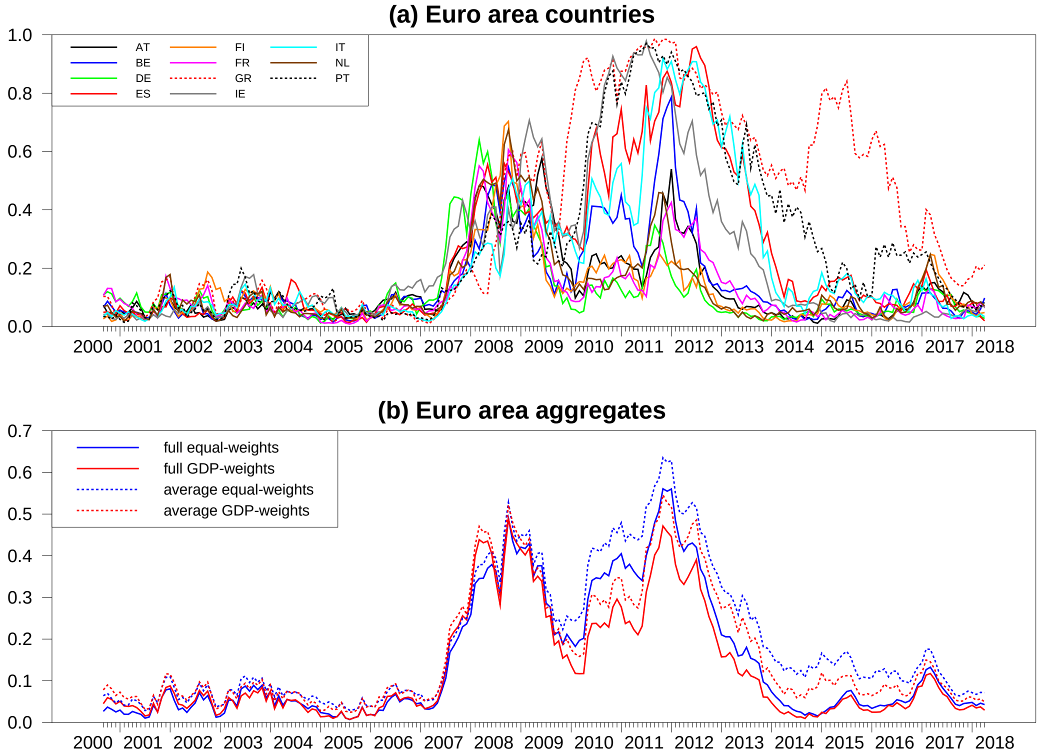
Figure 1 plots the SovCISS for eleven euro area countries—panel (a)—and for the euro area as a whole—panel (b). The upper panel illustrates the rather homogeneous path of sovereign stress across euro area countries from the beginning of the sample until around mid-2009. Subsequently, developments in sovereign stress were much more dispersed, partly following opposing trends. The lower panel displays the aggregate euro area SovCISS computed in four different ways as described in the previous section. The first two apply the full 66×66 matrix of cross-correlations $\Omega_{EA,t}$ according to equation 5, one using real GDP-weights for the cross-country aggregation (black line) and the other equal weights (blue line). The two series began to diverge as from early 2010 when the sovereign debt crisis started and hit some of the smaller countries particularly hard. Towards the end of the sample period, this gap closed again at around pre-crisis levels of the SovCISS, which suggests a general convergence and dissipation of sovereign stress across euro area member states. However, simple averages of the eleven country SovCISS indices computed according to equation 6 - with either equal weights (red) or GDP-weights (green) - recognise the continued elevated stress levels prevailing in a few smaller countries like Greece and Portugal.[6]

3.1 Index decomposition

It may sometimes be useful to know by how much each component contributed to certain developments in the SovCISS. However, decomposing the SovCISS into the contributions of credit spreads, yield volatility or bid-ask

[6]The SovCISS computed as equation 5 equals the simple country-average in the special case of perfect cross-country correlations. Hence, whenever the fully-fledged euro area SovCISS differs more markedly from its simple country-average counterpart, it indicates generally rather low cross-country correlations between individual stress factors.

Figure 1: Composite Indicator of Systemic Sovereign Stress (SovCISS) for the euro area



Notes: Monthly averages of weekly data, Sept. 2000 to April 2018. Source: ECB Statistical Data Warehouse spreads is not a trivial task due to the nonlinear aggregation scheme and the fact that the direction of causality in the contemporaneous correlations between index components is not identified. In order to circumvent the problem of identification, we segregate the overall contribution from all rank correlations as a separate factor. To this end we restate equation 2 as a double-summation (dropping the country subscript for ease of exposition):

$$SovCISS_t = \frac{1}{n^2} \sum_i \sum_j s_{i,t} s_{j,t} \omega_{ij,t} \tag{7}$$

and build on the special case of perfect correlation between all components assuming $\omega_{ij,t} = 1 \; \forall \; i, j = 1, ..., n$, and $n = 6$.[7] Factorisation leads to the following expression of the SovCISS under the assumption of perfect correlation ($SovCISS_t^{p.c.}$):

$$SovCISS_t^{p.c.} = \frac{1}{n^2} \sum_i \sum_j s_{i,t} s_{j,t} = \left(\frac{1}{n} \sum_i s_{i,t} \right)^2 . \tag{8}$$

In this special case the relationship between the individual index components (within the bracket) becomes that of a simple average and thus easy to decompose. Based on this result, we can derive the intended decomposition by starting from the difference between the general SovCISS and its perfect-correlation equivalent:

$$\begin{aligned} SovCISS_t - SovCISS_t^{p.c.} &= \frac{1}{n^2} \sum_i \sum_j s_{i,t} s_{j,t} \omega_{ij,t} - \frac{1}{n^2} \sum_i \sum_j s_{c,i,t} s_{c,j,t} \\ &= \frac{1}{n^2} \sum_i \sum_j s_{i,t} s_{j,t} (\omega_{ij,t} - 1) \end{aligned}$$

[7]This assumption implies that the matrix $\Omega_{c,t}$ becomes an all-ones matrix (with all elements being equal to one) for all t.

$$
\begin{aligned}
SovCISS_t &= SovCISS_t^{p.c.} - \frac{1}{n^2}\sum_i\sum_j s_{i,t}s_{j,t}(1-\omega_{ij,t}) \\
SovCISS_t &= \left(\frac{1}{n}\sum_i s_{i,t}\right)^2 - \frac{1}{n^2}\sum_i\sum_j s_{i,t}s_{j,t}(1-\omega_{ij,t}) \\
SovCISS_t &= \sqrt{SovCISS_t^{p.c.}}\left(\frac{1}{n}\sum_i s_{i,t}\right) - \frac{1}{n^2}\sum_i\sum_j s_{i,t}s_{j,t}(1-\omega_{ij,t})
\end{aligned}
$$

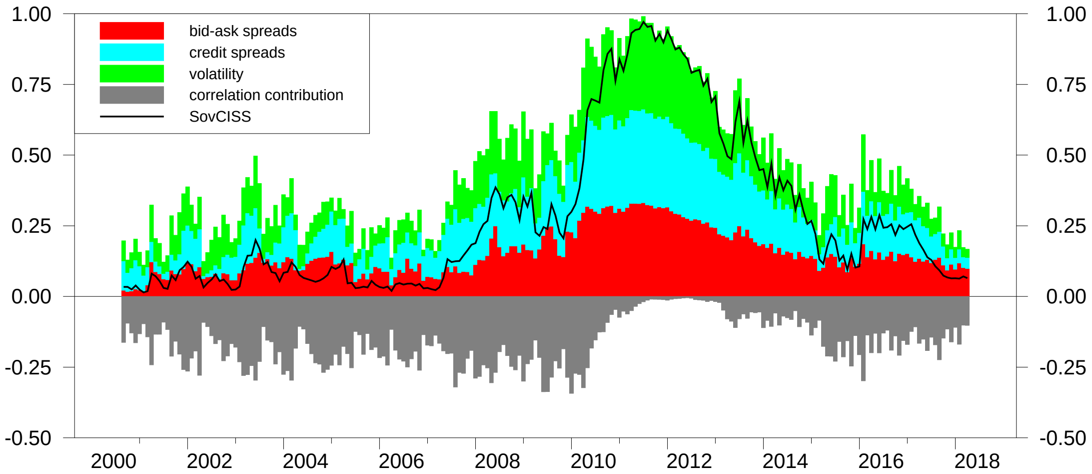
$$
SovCISS_t = \sum_i \frac{\sqrt{SovCISS_t^{p.c.}}}{n} s_{i,t} - \left(\frac{1}{n^2}\sum_i\sum_j s_{i,t}s_{j,t}(1-\omega_{ij,t})\right). \quad (9)
$$

The final equation 9 thus decomposes the SovCISS into $n+1$ different parts, namely the sum of the scaled contributions from each of the n index components $\left(\sqrt{SovCISS_t^{p.c.}}/n\right) s_{i,t}$ minus the term $\frac{1}{n^2}\sum_i\sum_j s_{i,t}s_{j,t}(1-\omega_{ij,t})$ which is negative (at most zero in case of perfect correlation) and decreases, ceteris paribus, with decreasing correlations $\omega_{ij,t}$.[8]

Figure 2 shows such a decomposition for the Portugues SovCISS. The contributions from bid-ask spreads, credit spreads and volatility are computed as averages from those of short- and long-maturity bonds. While the aggregate contribution from (imperfect) correlations between the components of the Portugues SovCISS is typically sizeable—indicating relatively weak correlations between credit spreads, bid-ask spreads and bond volatility under normal circumstances—, it became virtually zero for about two years during the height of the European debt crisis in 2011 and 2012. During this period the SovCISS and its perfect-correlation counterpart therefore basically coincided. Figure 2 also reveals that the bid-ask spread became the dominant factor behind the level of the Portugues SovCISS as from the last quarter 2017 onwards against the background of significant gradual declines in the contributions from both credit spreads and yield volatility.

[8]Note that this term just equals the difference between the SovCISS and the SovCISS under perfect correlation.

Figure 2: Decomposition of the SovCISS for Portugal



Notes: SovCISS for Portugal. Monthly averages of weekly data, Sept. 2000 to April 2018. Source: ECB and authors' calculation.

3.2 Stress in sovereign bond markets and the financial system as a whole

As mentioned above, the SovCISS builds on the methodology of the CISS developed by Holló, Kremer, and Lo Duca (2012). Despite their computational similarity, the two indicators are economically very different from each other, i.e. in terms of what they are supposed to measure. While the SovCISS exclusively measures sovereign bond market stress, the CISS quantifies the stress level in the financial system as a whole and thus the level of *systemic stress*. For this purpose, the CISS—as computed for the euro area—aggregates information from five different market segments, namely money, bond, equity, banking and foreign exchange markets, comprising in total 15 market-specific stress measures.[9] As a matter of fact, there is only a marginal overlap between the components of the SovCISS and the CISS for the euro area. The volatility of the German 10-year government bond yield as well as the spread between the 10-year swap interest rate and the German Bund yield appear both in the SovCISS and the CISS, but in the case of the SovCISS these are only two out of 66 components. Furthermore, the bond market subindex of the CISS also includes a corporate bond spread as a third component, which is why this CISS subindex can differ materially even from the SovCISS for Germany (which has a larger overlap with the CISS—namely two out of six indicators—than the euro area aggregate SovCISS).[10]

[9] For the time being the CISS is available for the euro area, the United States, the UK and China. Weekly updates of the euro area CISS are published in the ECB's SDW as one element of the CISS index family: http://sdw.ecb.europa.eu/browse.do?node=9689686. Data for the US, UK and Chinese CISS are available upon request from one of the authors (manfred.kremer@ecb.europa.eu). A chart of the US CISS is shown in Kremer (2016).

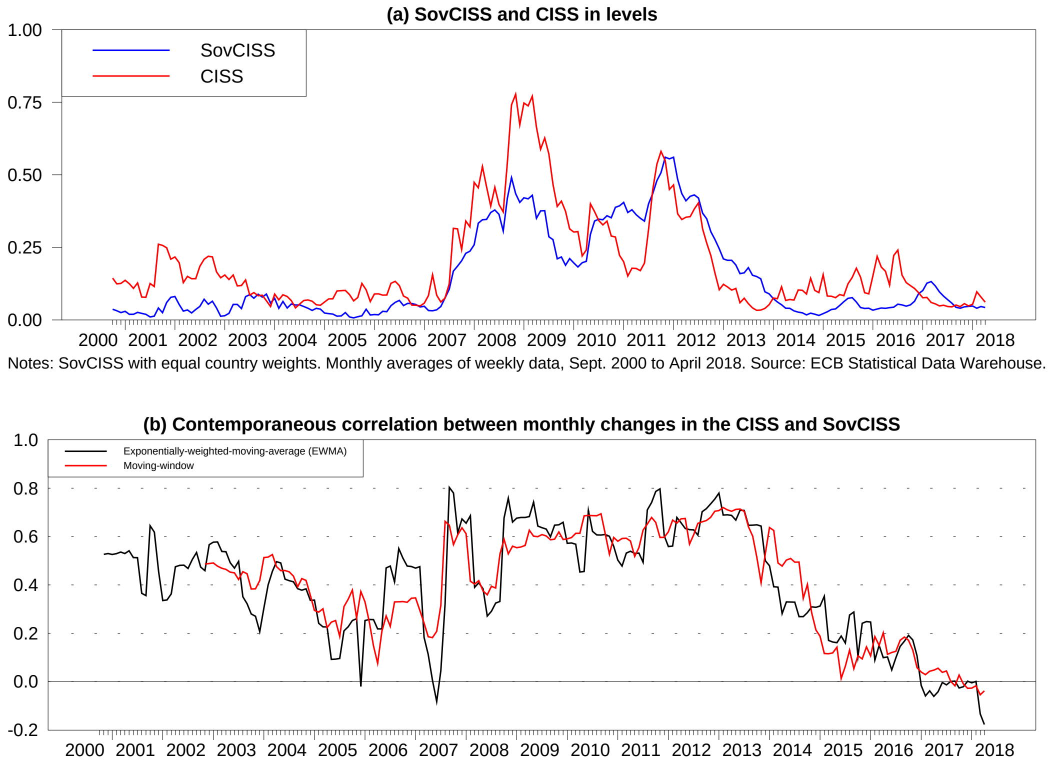
[10] One further difference is that the yield spread between a 10-year government bond and the euro (identidal to the German) 10-year swap interest rate enters the SovCISS in absolute terms, assuming that any larger yield wedge between the long-term government bond of a euro area country and the benchmark swap interest rate for the euro area as a whole indicates bond market stress reflecting market concerns about default risk and

A visual comparison of the SovCISS with the CISS provides an informal idea as to whether sovereign market stress may be related to systemic stress, i.e. to the level of stress prevailing in the financial system as a whole. In principle, this relationship can run both ways, with sovereign stress increasing in the wake of a systemic banking crisis, for example, or sovereign debt problems triggering widespread financial stress. Both directions of causality are likely behind the strong comovement between the SovCISS and the CISS during the Great Recession and the subsequent sovereign debt crisis in the euro area, reflecting—to a large extent—the so-called sovereign-bank nexus (see, e.g., Acharya, Drechsler and Schnabl, 2014). Panel (a) of Figure 3 displays both stress indicators for a common data sample running from October 2000 to April 2018, while panel (b) shows—for robustness reasons—two estimates of time-varying correlation between monthly changes in the SovCISS and the CISS, respectively. Before the onset of the financial turmoil in August 2007, the average correlation was rather weak. It increased markedly in that month and remained at such elevated levels (of about 0.7) until around mid-2013 when both sovereign and financial system stress had fallen back to pre-crisis levels. While sovereign stress was likely driven up by general financial system and banking stress over the first part of that period, causality seem to have reversed in the latter part, with sovereign market stress spilling over to the rest of the financial system. From mid-2013, however, the correlation between changes in sovereign and system stress dropped gradually and hovered at values of around zero in 2017 and the first months of 2018, indicating that the sovereign-bank nexus has become largely inactive.

All in all, comparing developments of the SovCISS with those of the CISS nicely illustrates the latter's character as a *systemic* financial stress index. Whereever financial stress may originate—i.e., even if strains become first

liquidity risk of the respective sovereign bond. In the case of the CISS, in contrast, the spread is computed as the 10-year swap interest rate less the German 10-year Bund yield with the aim to capture general flight-to-safety and flight-to-liquidity effects in times of stress for the euro area as a whole.

Figure 3: Euro area CISS and SovCISS



Notes: SovCISS with equal country weights. Monthly averages of weekly data, Sept. 2000 to April 2018. Source: ECB Statistical Data Warehouse.

Notes: EWMA estimate from a bivariate monthly GARCH model. Moving correlation over 24-month window. Source: Authors' calculation.

apparent in new and/or hard to monitor market segments—the CISS starts reacting at the moment when stress in a particular market segment spills over to the major market segments covered by the CISS, i.e. at the moment when initially idiosyncratic stress becomes widespread and thus systemic. This is an essential feature of the CISS as a tool to regularly monitor systemic risk and financial (in-)stability.

4 Empirical application: cross-country spillovers

The risk of contagion was at the very fore of the sovereign debt crisis in the euro area. At the time, the risk of excessive stress spillovers across euro area sovereign bond markets loomed large. Such spillover effects were likely to further spread to the banking sector and other market segments, posing systemic risk for the euro area economy as a whole. In order to mitigate systemic risk, far-reaching policy measures were taken to directly address the risk of contagion, such as the announcement of the ECB's Outright Monetary Transactions (OMT) programme and the establishment of the Banking Union. Against this background, an empirical tool to monitor stress spillovers in the euro area sovereign debt markets appears useful.

In two influential papers, Diebold and Yilmaz (2009 and 2012) introduce an econometric framework to monitor asset market spillovers. It is based on forecast error variance decompositions in linear VAR models. We apply the Diebold-Yilmaz framework to study patterns of sovereign stress spillovers across eleven euro area countries, running a VAR with two lags and the (square root of the) national SovCISS indicators as the endogenous model variables. Following Diebold and Yilmaz (2012), we produce forecast error variance decompositions (FEVDs) from the *generalised* VAR framework as originally proposed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1999). The main advantage of using generalised FEVD (GFEVD) is that the results are independent of variable orderings. Technical details of how to compute the GFEVDs are provided in the Appendix.

Table 1 provides comprehensive information about directional—bilateral and aggregate—spillover patterns estimated over the whole sample of available data running from September 2000 to April 2018.[11] The columns report the percentage forecast error variance contributions from a "sending" country to all "receiving" countries including the sender itself. The sums of the contributions to other countries (*spillovers*) are listed in the row labelled "Contribution to others;"adding *own shock contributions* gives rise to the row labelled "Contribution incl. own." The column sums can take any value between zero (in which case the shocks of one country would contribute nothing neither to its own forecast error variance nor to that of any other country) and 1100 (in which case the shocks of one country would explain 100% of its own forecast error variance as well as 100% of the forecast error variance of all the ten other countries. Row-wise summation aggregates the contributions received by a country from other countries. The "Net spillovers" are obtained by subtracting, for each country, the sum of the contributions received ("from others") from the sum of contributions sent ("to others"), such that positive entries indicate a country that sends more stress than it receives, and vice versa. The value of the overall spillover index is highlighted in bold. It means that on average 72.7% of the forecast error variances across all countries reflect shocks received from other euro area countries.

[11] All estimations are performed using codes available in RATS. The formulas behind all entries in Table 1 can be found in the Appendix.

Table 1: Spillover of sovereign stress across euro area countries

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT	From Others	Net spillover
AT	15.1	12.3	20.3	6.1	8.8	4.5	2.5	8.3	3.7	13.6	4.8	85	-47
BE	4.7	27.0	14.2	7.6	7.4	3.3	4.0	10.4	4.2	9.2	7.9	73	35
DE	3.8	6.4	38.0	5.5	8.7	5.8	2.4	7.5	4.1	12.0	5.7	62	77
ES	3.7	12.8	13.6	19.8	5.0	3.7	6.5	12.7	7.8	4.5	9.8	80	5
FI	2.7	11.0	22.3	4.9	26.1	1.9	5.4	3.8	2.0	11.9	7.9	74	-6
FR	4.7	11.6	20.4	7.0	8.2	17.0	3.6	5.0	5.8	11.1	5.7	83	-50
GR	1.4	4.1	3.7	12.9	4.7	0.8	47.4	6.9	1.2	7.8	9.2	53	-1
IE	3.4	16.7	8.0	9.0	5.7	0.8	3.3	40.3	2.6	3.8	6.5	60	26
IT	3.5	11.0	9.0	14.6	5.2	6.6	7.0	11.1	18.3	6.3	7.5	82	-46
NL	7.2	8.1	22.6	4.2	12.1	4.2	4.7	5.4	2.2	21.8	7.5	78	4
PT	2.5	14.2	5.1	13.8	2.0	1.2	12.8	15.0	2.7	1.8	29.0	71	2
Contribution to others	38	108	139	85	68	33	52	86	36	82	73	800	0
Contribution incl. own	53	135	177	105	94	50	99	127	55	104	102	**72.7%**	= (800/11)

Germany is by far the largest average gross and net sender of sovereign stress during our sample period. In gross terms, shocks in the German SovCISS contribute 139% to the forecast error variance of the remaining countries, which means that German stress is responsible for 13.9% of the prediction error variance *per country* on average. Germany's net spillover contributions add up to 77% or, put differently, to 7.7% on a cross-country average. This sort of "German dominance" affects most countries except Greece, Ireland and Portugal where the German contribution remains well below double-digit numbers.[12] When interpreting these findings, however, one has to bear in mind that the estimated stress spillovers from one country to another do not necessarily reflect a causal role of the sender country in a *structural* sense. For instance, during the first crisis years, stress in the German bond market reflected largely price impacts of global flight-to-safety and flight-to-liquidity capital flows[13]—in some episodes probably even related to emerging concerns about debt sustainability in some other euro area countries—rather than shocks fundamentally of German origin. And due to its superior liquidity status, the German government bond market may react more strongly and quickly to common shocks than other euro area sovereign bond markets, thereby contributing to the large estimated spillovers from Germany to most other member states of the monetary union. Other important net originators of stress are Ireland and Belgium. The set of the largest net receivers of stress comprise Austria, France and Italy. Interestingly, Greece and Portugal influence each other but not other countries. When we employ plain yield spreads instead of the SovCISS we get materially different spillover patterns. For instance, Germany no longer emerges as

[12]Several empirical papers from the early 1990s found a similar dominant role of German interest rates within the European Monetary System, i.e. before the euro was introduced as the common currency. However, evidence on this "German dominance hypothesis" was generally mixed (see Kirchgässner and Wolters, 1993; and Katsimbris and Miller, 1993).

[13]See Baele, Bekaert, Inghelbrecht and Wei (2018) on how the prices of safe and liquid bonds are typically affected during flight-to-safety episodes.

a main originator of stress neither in gross nor in net terms.[14]

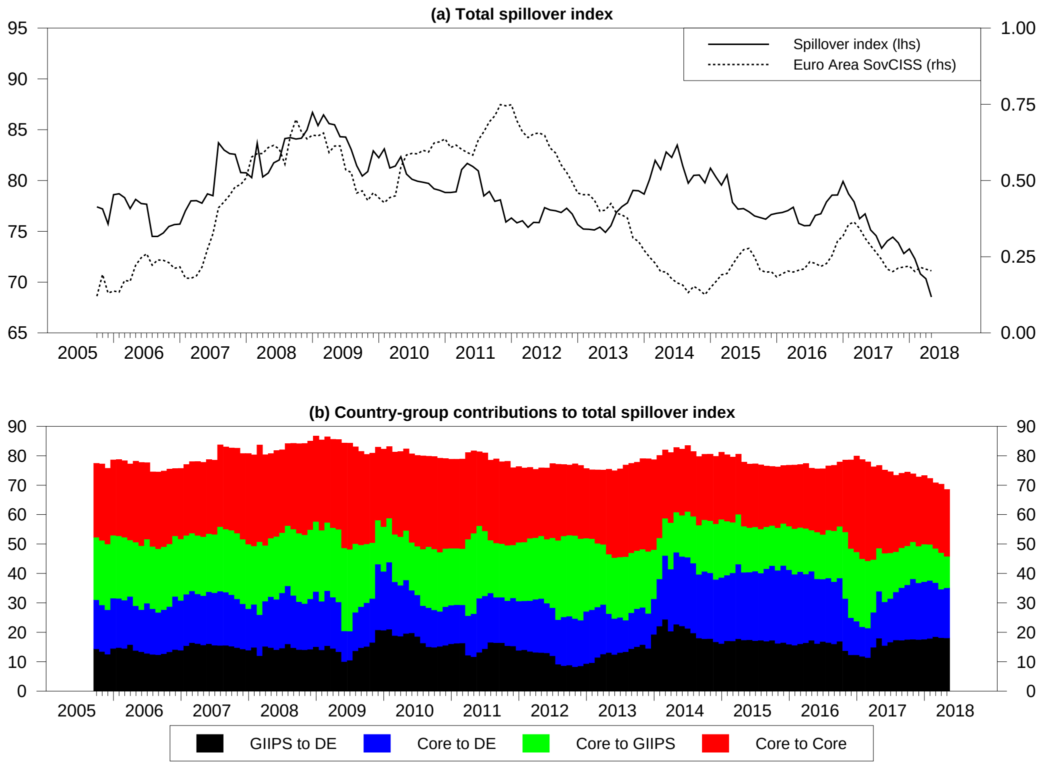
Splitting the total spillover index (72.7%) into contributions from the countries that were hit hard by the sovereign debt crisis (the "GIIPS" countries Greece, Ireland, Italy, Portugal and Spain) and the rest (the "core" countries Austria, Belgium, Germany, Finland, France and The Netherlands) tells us that 41.2 percentage points originate from the core countries and 31.5 percentage points from the GIIPS countries. However, almost one third (27 percentage points) of all spillovers take place within core countries; the spillovers from GIIPS to core, from GIIPS to GIIPS and from core the GIIPS countries all amount to between 15 and 16 percentage points.

In order to capture potentially important structural and cyclical movements in spillovers, we follow Diebold and Yilmaz (2009) and estimate the model using 60-month rolling samples.[15] Panel (a) of Figure 4 plots the time-varying spillover index together with a measure of average sovereign stress in the euro area. Two distinct phases can be distinguished: First, from 2005 until the start of the European debt crisis in early 2010, both series co-moved quite closely and peaked shortly after the collapse of Lehman Brothers. This co-movement may suggest that sovereign stress during this period was more strongly driven by common shocks such as changes in global risk aversion, an interpretation also consistent with an increasing share of spillovers from (the

[14]This finding may reflect an inherent asymmetry in the relationship between German and other euro area countries' yield spreads owing to the role of the German Bund as an international safe-haven instrument. While the German and, say, the Italian yield spread tend to comove under normal circumstances, they became negatively correlated during the European sovereign debt crisis. In a linear VAR such asymmetry cannot be properly captured and may actually blur the estimated dynamic interactions between the two government bond yield spreads. Since the sovereign yield spread against an interest rate swap rate enters the SovCISS in absolute terms, such asymmetric correlation patterns appear much less likely. The table showing the detailed spillover results for the case of plain yield spreads is available upon request.

[15]Referring, i.a., to Pesaran and Timmermann (2007), Thiem (2018) suggests using averages over a range of different window-sizes instead of a single window-size within the Diebold-Yilmaz spillover framework. In our case, results turn out rather robust to different widths of the rolling estimation window.

Figure 4: Time-varying Spillover Index for euro area countries and country groupings



Notes: Estimates based on VAR with 2 lags estimated over moving 60-month window, 12-month ahead FEVD.

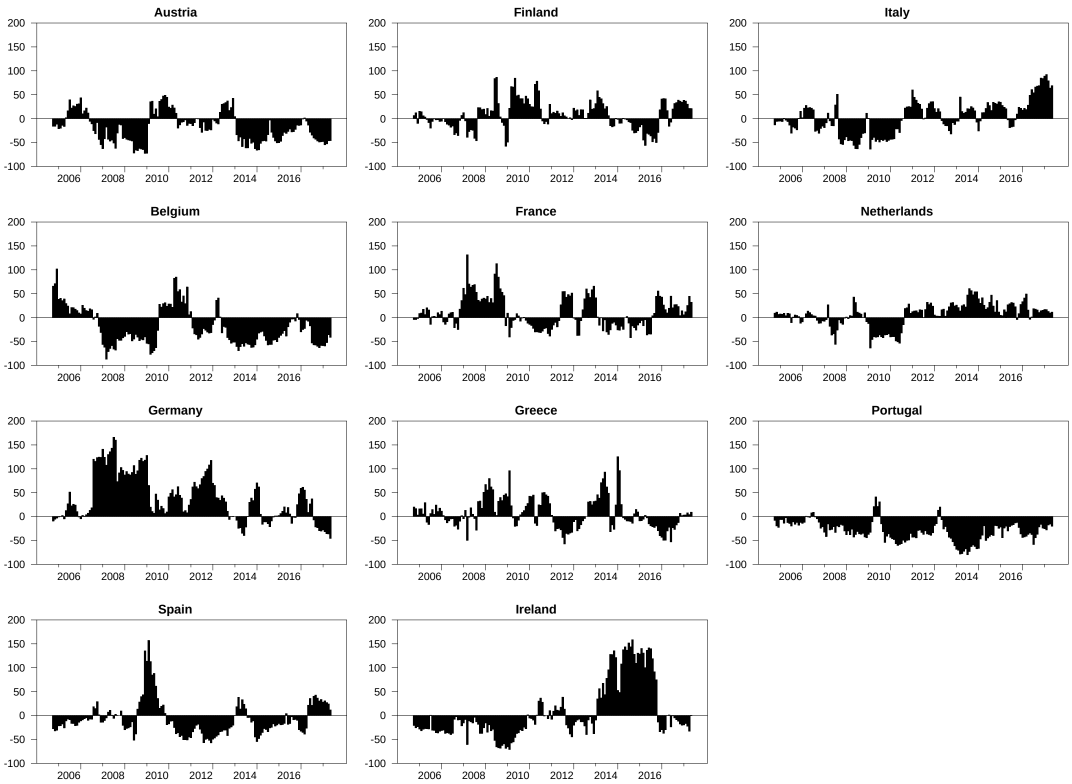
most liquid large) core countries to other (smaller) core and GIIPS countries (see panel (b) of Figure 4).

Second, from early 2010 to mid-2013, the spillover index and the euro area SovCISS moved in opposite directions. This decoupling may suggest that idiosyncratic shocks, or shocks common to only a small group of mostly smaller countries, played a larger role during that period. According to this interpretation, actual contagion of stress from strained countries was rather limited during the height of the sovereign debt crisis (see also panel (b) of Figure 4). The subsequent increase in the spillover index mainly reflects increased spillover contributions from GIIPS countries to other GIIPS and core countries (responsible for about half of total spillovers). This time, however, increased spillovers worked in favour of stability conditions in almost all euro area sovereign markets (except Greece). This likely reflects a broad-based unravelling of stress symptoms and related risk premia.

Figure 5 provides more details regarding the distribution of time-varying net spillovers across countries. We can see, for instance, that the strongly positive German net contribution mainly stems from the first few years after the start of the crisis in the summer of 2007; in that period, German bond yields were moved relatively strongly by flight-to-safety and flight-to-liquidity considerations among euro area and global investors. In contrast, Italy became a significant net sender of stress only in the most recent period starting from early 2017. For most of the time between 2014 and 2016, Ireland contributed very substantially to the forecast error variance of sovereign stress in the other countries; since the Irish SovCISS hovered consistently around rather low levels during this period, the Irish net contribution to the forecast error variance in other euro area countries reflects Ireland's mitigating contributions to average sovereign stress in the euro area, i.e. Ireland's increasing role as a stabilising force within the monetary union.

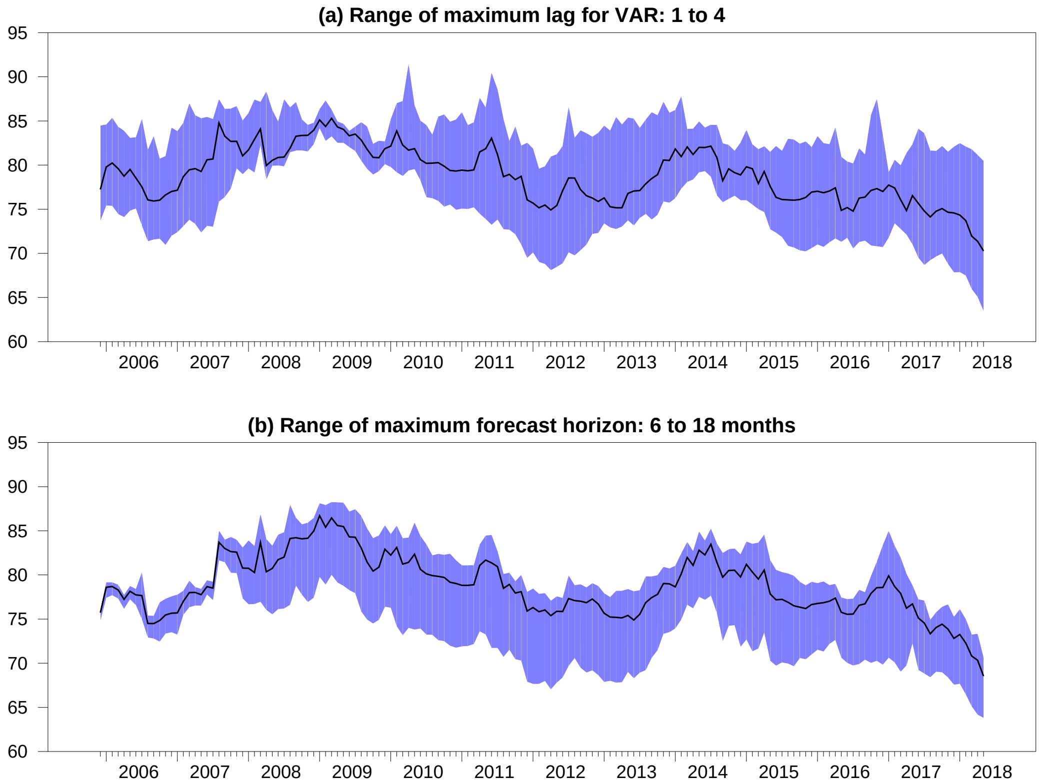
Addressing issues of robustness, Figure 6 plots the range of estimates for

Figure 5: Time-varying Net Spillover Index for euro area countries



Notes: Estimates based on VAR with 2 lags estimated over moving 60-month window, 12-month ahead FEVD.

Figure 6: Sensitivity analysis for time-varying Total Spillover Index



the time-varying spillover index (from the VAR estimated over a moving 60-month window) for different lag length—panel (a)—and for different forecast horizons—panel (b). Estimating the VAR with one up to six lags produces a range of spillover indices (minimum to maximum) with width of about ± 5 percentage points around the benchmark index computed with two lags. During the height of the financial crisis, however, the estimation range tightens significantly, indicating more uniform coefficient estimates across different maximum lags. Varying the forecast horizon from six to 18 months results in a relatively narrow minimum-maximum range for the spillover index, with spillovers generally increasing with the forecast horizon.

Appendix: The Diebold-Yilmaz spillover framework

This appendix briefly describes how the various spillover metrics are computed following the approach suggested by Diebold and Yilmaz (2012). According to this approach, spillover indices are derived from generalised forecast error variance decompositions (GFEVD) as proposed by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1999).[16] The starting point is a standard vector autoregression (VAR) model with $l = 2$ lags and the $N = 11$ country-specific SovCISS indices collected in the $N \times 1$ vector z_t: $z_t = \sum_{i=1}^{l} \Phi_i z_{t-i} + \varepsilon_t$, $t = 1, 2, \ldots, T$, with $N \times N$ coefficient matrices Φ_i and potentially correlated shocks ε_{it} collected in the $N \times 1$ vector ε_t; the disturbances are assumed to be multivariate normal distributed with $\varepsilon_t \sim N(0, \Sigma)$, i.e., with $E(\varepsilon_t) = 0$, $N \times N$ positive-definite variance-covariance matrix $E(\varepsilon_t \varepsilon_t') = \Sigma$ for all t and $\Sigma = \{\sigma_{ij}, i, j = 1, 2, \ldots, N\}$ and $E(\varepsilon_t \varepsilon_{t'}') = 0$ for all $t \neq t'$.

Assuming covariance stationarity of the VAR process, it can be written as the infinite moving average representation $z_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$ where the $N \times N$ coefficient matrices A_i obey the recursive relations: $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_l A_{i-l}$, $i = 1, 2, \ldots$,with $A_0 = I_N$ (an N-dimensional identity matrix).

The basic idea of the generalised VAR analysis is that when shocking one element of ε_t, say $\varepsilon_{jt} = \delta_j > 0$, the effects of the other potentially correlated shocks ε_{it} (with $i \neq j$) are integrated out using, in our case, the estimated error distribution under the assumption of multivariate normality: $E(\varepsilon_t | \varepsilon_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \ldots, \sigma_{Nj})' \sigma_{jj}^{-1} \delta_j = \Sigma e_j \sigma_{jj}^{-1} \delta_j$ where e_j is an $N \times 1$ selection vector with unity as its jth element and zeros elsewhere. The GFEVD is defined as the proportion of the h-step ahead forecast error variance of variable i which

[16] The following exposition of the generalised VAR approach draws on Pesaran and Shin (1998).

is accounted for by thus defined shocks in variable j, denoted as $\theta_{ij}^{g}(h)$:

$$\theta_{ij}^{g}(h) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{h}(e_i' A_k \Sigma e_j)^2}{\sum_{k=0}^{h} e_i' A_k \Sigma A_k' e_i}, \; i, j = 1, ..., N, \text{ and } h = 0, 1, 2, ...$$

In the denominator, the expression $\sum_{k=0}^{h} A_k \Sigma A_k'$ represents the variance-covariance matrix of the h-step ahead forecast errors. If the shocks were orthogonalised, the row sum of the decomposition matrix $\{\theta_{ij}^{o}(h), i, j = 1, 2, \ldots, N\}$ would by construction be $\sum_{j=1}^{N} \theta_{ij}^{o}(h) = 1$. For the generalised decomposition, however, it generally holds that $\sum_{j=1}^{N} \theta_{ij}^{g}(h) \neq 1$. The decomposition results shown in Section 4 are therefore normalised by dividing each entry of the decomposition matrix by its corresponding row sum:

$$\widetilde{\theta}_{ij}^{g}(h) = \frac{\theta_{ij}^{g}(h)}{\sum_{j=1}^{N} \theta_{ij}^{g}(h)}.$$

Hence, by construction we have $\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(h) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(h) = N$. The total spillover index $S^g(h)$ for horizon h, as depicted in Figure 4 and Figure 6, is computed as:

$$S^g(h) = \frac{\sum_{i,j=1 \wedge i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(h)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(h)} \cdot 100 = \frac{\sum_{i,j=1 \wedge i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(h)}{N} \cdot 100.$$

The directional stress spillovers received by country i from all other countries $j \neq i$ is measured by:

$$S_{i\bullet}^{g}(h) = \frac{\sum_{j=1 \wedge i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(h)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(h)} \cdot 100 = \frac{\sum_{j=1 \wedge i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(h)}{N} \cdot 100.$$

Accordingly, the directional stress spillovers transmitted by country i to all other countries $j \neq i$ results as:

$$S^g_{\bullet i}(h) = \frac{\sum_{j=1 \wedge i \neq j}^{N} \widetilde{\theta}^g_{ji}(h)}{\sum_{i,j=1}^{N} \widetilde{\theta}^g_{ji}(h)} \cdot 100 = \frac{\sum_{j=1 \wedge i \neq j}^{N} \widetilde{\theta}^g_{ji}(h)}{N} \cdot 100,$$

such that the net stress spillover index $S^g_i(h)$ per country (see Figure 5) or per country-grouping (see panel (b) of Figure 4) is defined as:

$$S^g_i(h) = S^g_{\bullet i}(h) - S^g_{i \bullet}(h).$$

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This is an expanded version of the article published under the same title in Economics Letters (Garcia-de-Andoain and Kremer, 2017). Apart from data updates and smaller editorial changes, the present version adds Sections 3.1 and 3.2, proposing a decomposition framework and comparing the SovCISS with ECB's CISS indicator, respectively. Section 4 now also contains results of net spillovers at the country level and a visual sensitivity analysis. A new Appendix describes in detail the Diebold-Yilmaz spillover VAR approach. We thank Thomas Kostka for very helpful suggestions and Francesca Barbiero for excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank.

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