Systemic Risk in European Economies: Deciphering Leading Measures, Common Patterns and Real Effects

Mikhail Stolbov[1], Maria Shchepeleva[2]

Abstract. The paper studies salient features of systemic risk in a sample of 22 European (EU and non-EU) economies. Building on a novel dataset and conducting an empirical horse race, we determine the most influential systemic risk measures across the sample countries. SRISK and volatility indicator tend to lead other metrics, followed by leverage. In contrast to the conventional wisdom, composite systemic risk measures aggregated with the aid of principal and independent component analysis perform worse. The VIX index, TED spread, the Composite Index of Systemic Stress (CISS) and long-term interest rates underlie the leading systemic risk measures. Two clusters within the sample are identified, with CISS and long-term interest rates being crucial to distinguish between them. Standard and nonparametric Granger tests concur as regards causality running from systemic risk to industrial production for Sweden and in the opposite direction – for Hungary and Turkey. Bidirectional linkages are not ruled out for Cyprus and Spain. Both tests underscore no causality at all for Finland, Greece, Luxembourg, Poland and Portugal, providing mixed evidence for the rest.

Keywords: causality, cluster analysis, independent component analysis, principal component analysis, panel vector autoregressions, systemic risk

JEL codes: C32, C38, G01, G32.

---

[1] PhD. in Economics, Associate Professor, Department of Applied Economics, Moscow State Institute of International Relations (MGIMO–University). **Correspondence:** 76 Vernadskogo prospect, Moscow, 119454, Russia. E–mail: stolbov_mi@mail.ru.

[2] Bank of Russia, Department of Monetary Policy.

1 Introduction

Systemic risk has gained momentum over the past years as one of the key macrofinancial concepts. Since the outbreak of the Great Recession, research on systemic risk has intensified, which eventually resulted in a rich academic literature. In the empirical dimension, over thirty measures of systemic risk have been proposed (Bisias et al, 2012). The European financial crisis has become another natural laboratory for putting the metrics into practice. Now regulators in the EU, that is, ECB, EBA and ESRB, are equipped with a multifaceted set of systemic risk measures to monitor financial stability.

In addition to public statistical data on systemic risk, e.g. the European systemic risk dashboard (ESRD), alternative sources are now available. In this paper, we turn to the measures provided by the Center for Risk Management at the HEC Lausanne. Most of them are return-based metrics available at the country level. Our sample covers 22 European economies for the period January 2010 – March 2016. It includes countries which are not EU members but may presumably be of non negligible importance for European financial stability, e.g. Russia and Turkey. The Lausanne systemic risk dataset comprises the indicators which have become popular with scholars and practitioners in the field, namely, the conditional capital shortfall measure (SRISK) and long run marginal expected shortfall (LRMES). However, the ESRD does not convey the two metrics though they can successfully identify fragile institutions and countries with a system-wide impact long before a crisis occurs (Brownlees and Engle, 2016). SRISK also appears to Granger cause industrial production, unemployment and inflation in leading European economies, indicating that such market-based measures of systemic risk can be instrumental in forecasting real sector performance (Engle et al., 2015). Besides SRISK and LRMES, the dataset includes cumulative stock market capitalization, leverage, volatility and correlations with the world stock market. We add two composite systemic risk measures to extract common information from the initial series. The first one is based on the sum of the first three principal components while the second builds on the components obtained by means of the independent component analysis (ICA).

Adopting the extended Lausanne systemic risk dataset, we seek to answer a number of complementary questions:

(i) Which measure plays a pivotal role for each country?

(ii) Which factors underpin these systemic risk measures at the global, regional and national levels?

(iii) Are there any clusters of the European economies based on the underlying determinants?

(iv) Do these measures have any real effects?

We undertake a battery of Granger (no) causality tests to identify leading measures for every country. SRISK and volatility are found to be key systemic risk measures for six countries each. SRISK plays a pivotal role for Belgium, Ireland, Luxembourg, Poland, Portugal, and Switzerland. The volatility indicator is the most significant for Cyprus, Finland, Hungary, Italy, Norway, and Sweden. Leverage is ranked third, leading other measures in the Netherlands, Russia, Spain, and Turkey. Stock market capitalization outperforms the rest of the metrics in France and Germany. LRMES is found to be the leading indicator only in Denmark. In contrast to intuitive expectations, the composite systemic risk measures perform quite modestly. The metric based on the sum of independent components is the leading one for Austria and the UK, while its peer based on principal components is the most salient for Greece. We normalize these most informative systemic risk measures to scale them along the time axis, showing that their dynamics accurately captures all major hikes in financial stress during the observation period.

Then we specify a panel vector autoregression (PVAR) model and conduct corresponding Granger (no) causality tests to examine for exogenous covariates explaining changes in systemic risk across the sample but having no statistically significant feedback from the national systemic risk indicators. The PVAR model adopts the total amount of ECB, Bank of England and the US FED assets as exogenous variables to account for possible effects of unconventional monetary policy. As a result of the PVAR estimation, the VIX index and TED spread appear to be exogenous covariates among the global determinants of systemic risk in our sample. The Composite Index of Systemic Stress (CISS) is the exogenous proxy at the regional level while long-term interest rates (LTRATE) turn out to be the exogenous predictor at the domestic level. We regress the national systemic risk measures on the selected covariates by means of the robust least squares (RLS). The coefficients of determination from the regressions are associated with the relevance of these covariates for each country and are further used in the cluster analysis. The latter reveals two groups of European economies. The first cluster comprises Belgium, France, Germany, Ireland, the Netherlands, and Portugal which heavily depend on the CISS and long term interest rate dynamics. The second cluster consists of the economies which exhibit commensurate dependence on the global, regional and domestic proxies of systemic risk.

We adopt conventional and nonparametric Granger (no) causality tests to investigate if there are any linkages between the leading systemic risk measures and industrial production. There is coincident evidence from the two tests that systemic risk Granger causes industrial production in Sweden while in Hungary and Turkey industrial production is sure to drive systemic risk. The two tests also concur as regards causality running from systemic risk to industrial production for Spain and vice versa – for Cyprus, but do not rule out bidirectional linkages for these countries either. Both tests underscore no causality at all for Finland, Greece, Luxembourg, Poland and Portugal, giving mixed evidence for the rest.

The remainder of the paper is as follows. Section 2 describes the data. In Section 3 we identify leading domestic systemic risk measures, in Section 4 the determinants of these indicators are underscored and the findings related to the cluster analysis are reported. Section 5 assesses the impact of systemic risk on industrial production in the sample countries, while Section 6 concludes.

2 Data

Our research is based on the country level systemic risk measures provided by the Center for Risk Management at the HEC Lausanne. We exploit monthly series of LRMES, SRISK, leverage (LEVERAGE), inverted value of cumulative stock market capitalization (MCAP), volatility (VOLAT), correlations with the world stock market (WMCor) for 22 countries during January 2010 – March 2016[3]. The long run marginal expected shortfall (LRMES) is defined as the sensitivity of a domestic financial institution capitalization to a 40% semiannual world stock market decline. The conditional capital shortfall measure (SRISK) captures the capital shortage which this institution is to experience under the above-mentioned adverse conditions in the world market. To obtain nation-wide LRMES and SRISK, the metrics for individual

[3] The sample includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Russia, Spain,

financial institutions are aggregated[4]. The volatility indicator and correlations with the world stock market are derived from the GARCH models while leverage is the mean of domestic financial institutions' balance sheet based indicator. We slightly modify a single initial measure, using inverted value of cumulative stock market capitalization. By doing so, we ensure that increases in all the series are uniformly interpreted as a systemic risk build-up.

Recent studies on systemic risk, e.g. Kritzman et al. (2011), Billio et al. (2012), Giglio et al. (2016) argue that aggregate measures of systemic risk may be more coherent and informative than individual metrics. In this light, we construct two additional metrics based on the initial series.

The first one (PC) is just the sum of the first three principal components of these indicators. Summing up most informative principal components to derive an aggregate financial stress or systemic risk measure is a firmly entrenched approach. For example, Billio et al. (2012) sum up principal components to examine for individual financial institutions' contribution to systemic risk in the US financial and insurance sectors. Park and Mercado (2014) specifically focus on the sum of the first three principal components to derive financial stress indices for 25 emerging markets and find that they explain from 70 to 80% of the total variance of the input indicators. In our case, the first three components on the average account for 88.6% of the total variance of the series for each country.

However, principal component analysis assumes constant normal multivariate distribution of input indicators (Mardia et al., 1979). It is known that system risk measures tend to exhibit heavy tails. Hence, it is unlikely for a set of such measures to be normally distributed. We test our measures for both univariate and multivariate normality, using the conventional Jarque-Bera and novel Doornik-Hansen (2008) test, respectively. For most of the series across the sample, we strongly reject the null of univariate normality. Against this backdrop, it is no surprise that the null of multivariate normality is also rejected at the 1% level (Table 1).

Sweden, Switzerland, Turkey, the UK. Croatia, the Czech Republic, Malta, Romania, the Slovak Republic and the Ukraine are not considered because of missing data in one or more series.

Table 1. Results of the univariate Jarque-Bera and multivariate Doornik-Hansen normality tests of systemic risk measures

Country	Jarque-Bera test						Doornik-Hansen test
	SRISK	**LRMES**	**LEVERAGE**	**MCAP**	**VOLAT**	**WMCor**	
Austria	2.07	40.67***	15.84***	2.55	30.16***	7.27**	88.04***
Belgium	7.98**	14.25***	4.85*	6.02**	26.74***	8.41**	76.71***
Cyprus	7.25**	0.91	60.19***	30.05***	6.81**	0.66	277.48***
Denmark	2.22	5.03*	4.95*	5.47*	43.89***	1.41	86.27***
Finland	57.90***	9.99***	5.25*	8.11**	24.86***	5.66*	145.05***
France	2.89	8.18**	10.17***	4.41	18.42***	20.83***	88.49***
Germany	5.12*	12.30***	6.17**	3.76	24.48***	120.85***	87.93***
Greece	5.51*	15.70***	14.51***	12.56***	14.75***	2.18	117.94***
Hungary	17.84***	7.31**	1.76	1.87	47.55***	1.44	132.73***
Ireland	7.60**	0.39	18.65***	17.28***	73.46***	0.52	167.95***
Italy	4.90*	2.12	6.89**	3.17	9.21**	7.94**	71.02***
Luxembourg	14.87***	4.51	11.22***	4.82*	27.81***	2.07	98.98***
Netherlands	4.91*	6.71**	4.27	4.75*	39.11***	18.27***	87.65***
Norway	6.89**	30.12***	7.94**	6.04**	46.71***	0.78	105.86***
Poland	95.84***	11.95***	21.67***	3.59	109.81***	0.57	149.01***
Portugal	2.94	4.42	34.34***	10.27***	33.64***	3.38	107.96***
Russia	164.59***	10.08***	3.20	5.53*	198.18***	1.52	147.06***
Spain	4.34	7.27**	19.82***	2.85	13.30***	24.04***	102.92***
Sweden	6.88**	0.73	21.39***	5.06*	51.54***	6.26**	68.03***
Switzerland	3.55	1166.51***	22.41***	90.74***	73.84***	13.94***	127.71***
Turkey	126.08***	2.45	4.40	3.20	2.03	10.17***	140.83***
UK	3.81	5.32*	9.33***	2.93	15.21***	49.97***	49.87***

Note: *, **, *** – significant at the 10, 5 and 1%.

We obtain our second aggregate systemic risk measure (IC) with the aid of independent component analysis, namely, the *fastICA* algorithm. This technique is robust to non-Gaussian multivariate distribution of the data. The ICA generates orthogonal components in both linear and nonlinear settings whereas the PCA cannot rule out nonlinear dependence between components[5]. As far as we know, Fabozzi et al. (2016) appears to be the only study related to financial stability in Europe, building on this conceptual distinction between the ICA and PCA.

In our research, we adopt the sum of the first three independent components to make the IC- and PC-based measures comparable. On the average, they explain 99.5% of the total variance of the input series for each country.

In light of the goals set for this research, we first test all the series for stationarity and signs of nonlinearity using the ADF unit root and BDS tests, respectively (Table 2).

Table 2. Results of the ADF and BDS tests of systemic risk measures

Statistical tests	**SRISK**	**LRMES**	**LEVERAGE**	**MCAP**	**VOLAT**	**WMCor**	**PC**	**IC**
				AUSTRIA				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)

[4] See the methodological note for more details http://www.crml.ch/index.php?id=44

[5] See Hyvärinen et al. (2001) for a detailed description of the ICA theory. Our IC-based aggregate measures have been computed, using the MATLAB code available at the authors' page: https://www.cs.helsinki.fi/u/ahyvarin/. In the *fastICA* algorithm, we select the hyperbolic tangent as the nonlinearity function and set the scale parameter equal to unity.

BDS	NL	NL	NL	NL	NL	NL	NL	NL
				BELGIUM				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				CYPRUS				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				DENMARK				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	L	L	NL	NL
				FINLAND				
ADF	I(0)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(1)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				FRANCE				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				GERMANY				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				GREECE				
ADF	I(1)	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				HUNGARY				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				IRELAND				
ADF	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				ITALY				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(1)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				LUXEMBOURG				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(1)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				NETHERLANDS				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				NORWAY				
ADF	I(1)	I(1)	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	L	NL	NL	NL
				POLAND				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				PORTUGAL				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	L	NL	NL	NL
				RUSSIA				
ADF	I(0)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	L	NL	NL	L
				SPAIN				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				SWEDEN				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				SWITZERLAND				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(1)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				TURKEY				
ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)	I(1)
BDS	NL	NL	NL	NL	NL	NL	NL	NL
				UK				
ADF	I(1)	I(0)	I(1)	I(1)	I(0)	I(1)	I(0)	I(0)
BDS	NL	NL	NL	NL	NL	NL	NL	NL

Notes: I(0) or I(1) indicate the order of integration, i.e. stationary or non stationary; “L” denotes that the series are linear, “NL” means that it has signs of nonlinearity.

The table shows that SRISK, LRMES, leverage and the inverted value of stock market capitalization are mostly I(1) series while volatility, correlations with the world market as well as the aggregate measures tend to be stationary. Almost all the series exhibit signs of nonlinearity.

3 Identification of leading systemic risk measures

We first aim to select leading systemic risk measures for each country. To this end, an empirical horse race in the spirit of Rodríguez-Moreno and Peña (2013) is implemented. They compare macroeconomic (key interbank lending rates) and microeconomic (stock and CDS prices) measures of systemic risk from 2004 to 2009 based on three criteria: (i) Granger (no) causality tests; (ii) information share metrics; (iii) correlation with an index of systemic events and policy actions. In this study, we are unable to rely on the second and third approaches. Information share metrics, like the Gonzalo and Granger (1995) one, can be used only when the series are I(1) and are likely to be cointegrated. As shown in Table 2, 55% of the series are I(0). As for the index of systemic events and policy actions based on the Federal Reserve Bank of St. Louis crisis timeline, it focuses on US rather than European episodes of financial instability and does not go beyond the year 2011. Thus, we opt for extending the first criteria.

In this realm, a battery of Granger (no) causality tests is applied. First, we run bivariate tests for systemic risk measures for each country. They are based on the corresponding vector autoregressions (VAR). We employ the Toda-Yamamoto (1995) approach to estimate the VARs instead of taking first differences to secure stationarity in the data. According to it, a VAR(p) model should be set up in levels, regardless of the orders of integration of the time-series. An appropriate lag length for the variables in the VAR model is then determined based on information criteria. The Bayesian Schwarz Information Criteria (BSIC) is used as a benchmark in this research. The model is also examined for overall stability, i.e. the eigenvalues within the unit circle, and no serial correlation in the residuals. If the maximum order of integration of the variables is m, then the preferred VAR model should be extended to include these m additional lags. For example, if the maximum order of integration is I=1 and the optimal model is VAR(2), the specification that ensures the validity of Granger causality test will be VAR(3). It is important to note that the test should be based on the initial number of lags, i.e. p=2, while the additional lagged variables are necessary to fix up the asymptotics. That is, these lagged variables enter the augmented VAR model exogenously.

Given the detected signs of nonlinearity in the data, we also adopt the Diks-Panchenko nonparametric test for bivariate causality (Diks and Panchenko, 2006). It applies to the levels of the series and runs in both directions for lags from 1 to 5 and for the bandwidth equal to 1.5, taking into account the time series length. Its null hypothesis replicates that of Granger causality test, namely, X does not help predict Y and Y does not help predict X. T-statistic is calculated to test the null at each lag.

Third, we estimate Bayesian VAR (BVAR) models for each country's systemic risk measures and carry out Granger (no) causality tests based on their selected specifications[6]. We select the most appropriate BVAR models with Minnesota/Litterman priors based on the same criteria as unrestricted VARs, i.e. the overall stability, lag length selected in line with the BSIC and absence of serial correlation in the residuals.

The performance of each systemic risk measure is judged by its score in the three causality tests. To obtain the overall score, we just sum up scores across the tests as we assign equal weights to the three methodological approaches, following Rodríguez-Moreno and Peña (2013). To rank the measures we give a score of +1 to measure X if it Granger causes measure Y and give a score of –1 if it is driven by Y in the Granger sense. As a result, the leading measure of systemic risk gets the highest positive score and the worst measure receives the highest negative score. In all the tests we consider causalities significant at least at the 5% confidence level.

The detailed results of the horse race are represented in Tables A1–A3 of the Appendix. Below we only report resulting scores for all countries across all the three tests (Table 3).

Table 3. Results of the horse race identification of leading systemic risk measures

Country	**SRISK**	**LRMES**	**LEVERAGE**	**MCAP**	**VOLAT**	**WMCor**	**PC**	**IC**	**Leading indicator**
Austria	0	-1	-1	-6	3	-3	4	6	IC
Belgium	3	1	2	-5	1	-3	2	-1	SRISK
Cyprus	0	1	0	1	3	-1	2	-5	VOLAT
Denmark	-3	4	0	0	1	-4	0	2	LRMES
Finland	-2	-1	0	0	8	-3	0	-1	VOLAT
France	-6	-10	1	7	4	-2	1	5	MCAP
Germany	-7	-4	0	8	6	-7	1	5	MCAP
Greece	1	1	-3	-6	1	-2	6	2	PC
Hungary	0	-4	0	1	6	0	2	-4	VOLAT
Ireland	6	-2	4	5	2	1	-9	-4	SRISK

[6] We have to employ BVARs to avoid over-parameterization of conventional VAR models as there are 8 variables vs. only 75 observations. For most countries, the lag order of BVARs equal to one has been selected. For BVARs with bigger lag orders, we base our conclusions on impulse-response functions.

Italy	1	0	-2	0	8	-3	6	-9	VOLAT
Luxembourg	5	3	3	0	-2	-5	-2	-2	SRISK
Netherlands	-1	-3	3	2	-1	-2	0	2	LEVERAGE
Norway	3	-4	-4	3	6	-2	2	-4	VOLAT
Poland	5	2	-2	1	0	-5	2	-3	SRISK
Portugal	4	-6	2	3	3	-6	0	1	SRISK
Russia	3	3	4	1	-5	-1	-1	-4	LEVERAGE
Spain	1	-2	3	1	0	1	0	-4	LEVERAGE
Sweden	1	-3	0	3	8	-4	-1	-4	VOLAT
Switzerland	**7**	-6	-2	7	-2	-1	3	-6	SRISK
Turkey	-3	2	6	2	0	0	-6	-1	LEVERAGE
UK	1	-10	3	1	-2	2	1	5	IC
Mean	**0.86**	**-1.77**	**0.77**	**1.32**	**2.18**	**-2.27**	**0.59**	**-1.09**	
Std. deviation	**3.62**	**3.93**	**2.56**	**3.70**	**3.67**	**2.33**	**3.35**	**4.09**	

SRISK and volatility outperform other systemic risk measures in six countries each. SRISK is the leading indicator for Belgium, Ireland, Luxembourg, Poland, Portugal, and Switzerland. Volatility is the most significant measure in Cyprus, Finland, Hungary, Italy, Norway, and Sweden. Leverage is crucial for the Netherlands, Russia, Spain, and Turkey. The inverted value of stock market capitalization is the central measure for Germany and France. LRMES plays a pivotal role only in Denmark. The composite measure based on independent components is the leading metric in Austria and the UK while its peer based on principal components is the key indicator for Greece.

The findings lend support to the view that SRISK is a feasible measure of systemic risk, capturing its different dimensions. However, its leadership is rivaled by volatility. Leverage as a leading measure prevails in big economies where banking sectors exhibit high dependence on external financing. It is noteworthy that LRMES, a popular companion to SRISK, performs by far worse. This result is consistent with the literature which provides evidence of the LRMES tight relationship with market beta (Benoit et al., 2016) and standard balance-sheet metrics, such as Tier 1 solvency ratio (Idier et al., 2014). Therefore, it does not allow for a clear distinction between systemic and systematic risk. Pankoke (2014) compares sophisticated measures of systemic risk, including LRMES and SRISK, with simpler ones such as leverage, market capitalization and correlations with the market index, and also finds that SRISK is superior to LRMES, though does not always outperform simpler measures.

Based on mean scores in Table 3, the systemic risk measures can be divided into two groups. Volatility, the inverted value of stock market capitalization, SRISK, leverage and the aggregate measure based on principal components, on the average, have positive cumulative scores, i.e. mostly lead other metrics. Correlations with the world market, LRMES and the aggregate measure based on independent components are characterized by negative scores, suggesting that they are mostly Granger caused by their peers. Taking into account standard deviation of the scores relative to their mean, one can conclude that volatility demonstrates the least degree of variation, followed by stock market capitalization, leverage, SRISK and the aggregate measure based on principal components.

After obtaining the leading systemic risk measures, we expose them to a conventional normalization to see how well they jointly captures major hikes in financial stress over the observation period. The normalized systemic risk measures are computed as follows:

$$Y_t = \frac{X_t - \bar{X}}{\sigma} \quad (1)$$

where Y_t is the demeaned and standardized series, $\bar{x}$ the mean of the series and σ – standard deviation.

Figure 1 captures hikes in financial stress related to the Greek episode which started to unfold in May 2010, growing concerns that the European crisis could spill over to other regions in September 2011, and the failure to form a coalition government in Greece in May 2012, which further worsened market expectations.

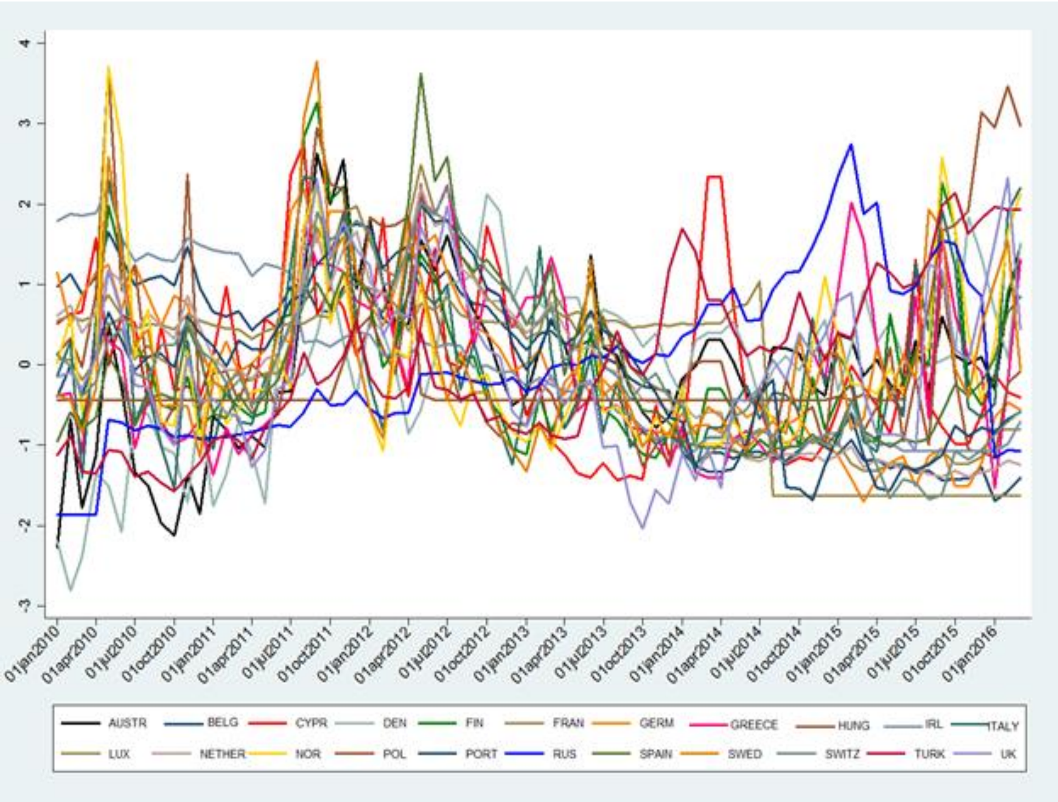

Figure 1. Dynamics of normalized leading systemic risk measures for 22 European countries, January 2010–March 2016.

It also identifies some country-specific hikes such as the outbreak of the Cypriot crisis in late 2012 and deterioration of Russian financial conditions as a response to the escalation of the Ukrainian crisis in late 2014 – early 2015.

Overall, the findings help determine the measures which should be of primary importance for supervisory authorities. In case of EU economies, the leading measures can effectively complement the ESRD indicators. The results implicitly promote the adoption of the Basel III leverage ratio (Tier 1 capital/exposure) as a macroprudential tool in the countries where leverage has been found the leading systemic risk measure[7]. The need for such a cap on leverage would be pressing provided that its adverse impact on real output were revealed. The recent research indicates that this macroprudential tool is significantly more countercyclical than the risk-weighted regulatory capital ratio (Brei and Gambacorta, 2016) and diminishes the likelihood of a bank run when there is imperfect information about real value of bank assets (Dermine, 2015).

4 Patterns of systemic risk

We next aim to decipher common patterns of systemic risk in the sample. Given the diversity of the leading systemic risk measures, our empirical strategy involves two steps. First, we seek to identify underlying determinants of systemic risk in Europe. Based on the factors, we carry out cluster analysis and distil country groups with similar patterns.

Global, regional and country-specific determinants are considered. In line with the extant literature, the VIX index (VIX) as a measure of worldwide volatility and risk aversion and the TED spread (TED) accounting for credit conditions emerge as potential global determinants. González-Hermosillo and Hesse (2011) use these indicators to determine when governments should launch and exit public support programs to mitigate systemic risk. Adrian and Brunnermeier (2016) adopt the VIX index and TED spread as common risk factors to compute delta conditional value-at-risk (ΔCoVaR), a widespread measure of systemic risk. Kinateder (2015) considers the VIX as one of the drivers of changes in equity tail risk in Europe. We add the aggregate IMF commodity price index (COMPR) to the list of potential global determinants of systemic risk as the sample includes countries which financial

[7] In none of such countries in the sample (the Netherlands, Russia, Spain and Turkey), this macroprudential tool was introduced by early 2016.

resilience is largely dependent on commodity prices, e.g. Russia and Turkey. In this regard, Kinda et al. (2016) show that negative shocks to commodity prices tend to weaken the financial sector of resource-rich economies due to a higher level of non-performing loans, insufficient provisions to such loans and lower bank profits.

At the regional level, we take into account the Composite Index of Systemic Stress (CISS), a comprehensive indicator of financial fragility in Europe, proposed by Hollo (2012) and tracked by the ECB, and the VSTOXX index (VSTOXX) as a VIX equivalent for the euro area. Both measures are considered “fear gauges” and can be jointly used to assess financial fragility in Europe, e.g. Byström (2015).

The country-specific determinants encompass the long-term (10-year) interest rates (LTRATE) and short-term (3-month) interbank lending rates (INTBRATE), coming from the OECD database. The two indicators are expected to capture an interplay of sovereign and banking sector fragility during the observation period.

We need to figure out which of these seven factors are exogenous covariates of the leading systemic risk measures identified in Section 3. To this end, a panel VAR (PVAR) model is estimated, using GMM. Since there can be panel unit roots in the data, we take first differences of the normalized leading systemic risk measures (SYSRISKN) as well as global, regional and country-specific determinants to estimate the model. These are endogenous variables. Following Abrigo and Love (2015), we apply a number of model selection criteria to determine an optimal model from first- to third-order PVARs, using the first four lags of the variables as instruments. We also add lagged total assets of the Eurosystem (EUROSYS), Bank of England (BOE) and US Fed (USFED) expressed in US dollars to account for an impact of unconventional monetary policy on the measures of systemic risk and their determinants. They enter the PVAR model as exogenous regressors. The third-order PVAR is represented as a system of linear equations:

$$Y_{it} = A_0 + Y_{it-1}A_1 + Y_{it-2}A_2 + Y_{it-3}A_3 + X_{it-1}B_1 + X_{it-2}B_2 + X_{it-3}B_3 + u_i + e_{it} \quad (2)$$

$$i \in \{1,..,22\},\ t \in \{1,..,74\}$$

where Y_{it} is a vector of eight endogenous variables $\{SYSRISKN, VIX, TED, COMPR, CISS, VSTOXX, LTRATE, INTBRATE\}$, X_{it} is a vector of exogenous regressors $\{EUROSYS, BOE, USFED\}$, A_0 is a vector of constants, A_1, A_2, A_3, and B_1, B_2, B_3 are matrices of coefficients to be estimated, u_i

and e_{it} are vectors of dependent variable-specific panel fixed effects and idiosyncratic errors, respectively.

Based on the moment and model selection criteria (MBIC, MAIC, MQIC) analogous to the BSIC, Akaike and Hannan-Quinn criteria as well as on the value of coefficient of determination and J-statistic (Table 4), we opt for the third-order PVAR model.

Table 4. Lag-order selection criteria for PVAR models

Lag	**Coefficient of determination**	**J-statistic**	**MBIC**	**MAIC**	**MQIC**
1	–4.07	1327.34	–79.09	943.34	562.58
2	–4.72	941.82	4.20	585.82	432.04
3	0.74	579.34	110.53	451.34	324.45

The third-order PVAR model is characterized by the positive coefficient of determination as well as the minimal values of J-statistic and two out of the three moment and model selection criteria (MAIC and MQIC). The preferred PVAR model is found stable (Figure 2) as all eigenvalues lie within the unit circle.

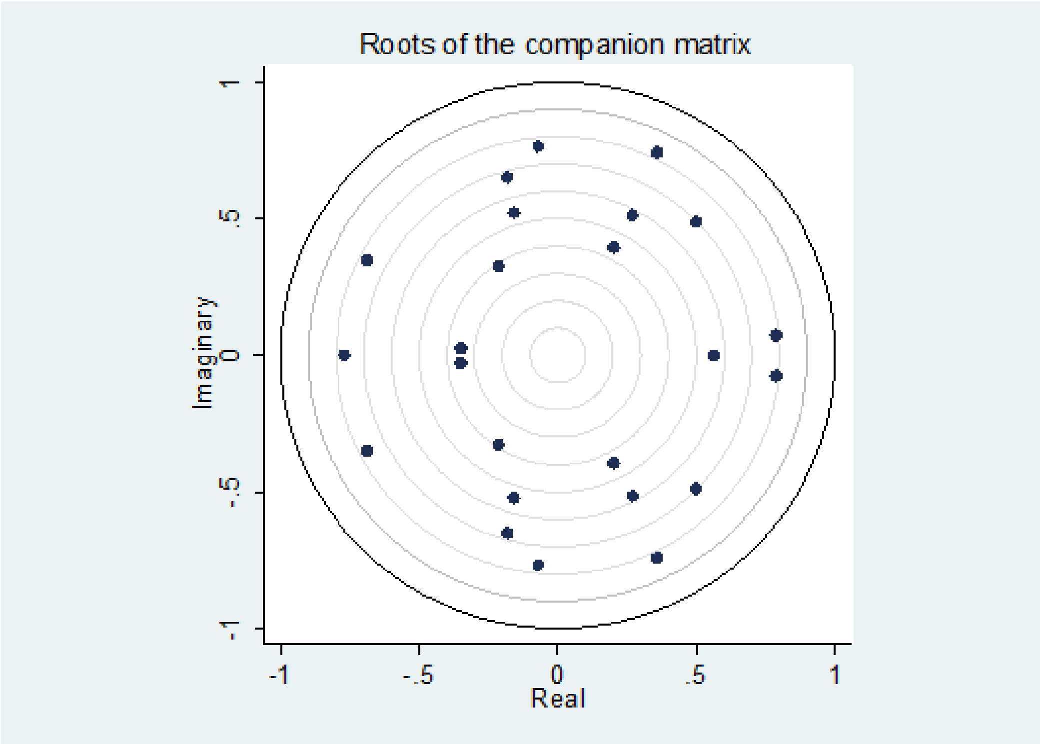

Figure 2. Stability of the PVAR model.

For brevity reasons, we do not report full results of the PVAR estimation here[8], passing to panel Granger (no) causality tests. They enable to determine strongly exogenous covariates of the leading systemic risk measures, i.e. global, regional or country-specific determinants which Granger cause these measures without any statistically significant feedback from them.

Table 5 indicates that all the determinants except short-term interbank lending rates drive the systemic risk measures. We attribute the insignificance of short-term interbank lending rates to the credit risk transfer from the financial sector to the European sovereigns, which occurred before 2010. As a result, interbank lending rates lowered while sovereign bond yields increased substantially. There is evidence that the latter even started to Granger cause the former, e.g. Alter and Schuler (2012), Corzo Santamaría et al. (2014).

The IMF commodity price index and VSTOXX have bidirectional causal linkages with the systemic risk measures. In case of the VIX index, TED spread, CISS and long-term interest rates causality is unidirectional. Thus, global, regional and country-specific exogenous covariates underpin systemic risk in our sample.

Table 5. Results of panel Granger (no) causality tests

Hypothesis	χ^2	**p-value**
SYSRISKN does not Granger cause VIX	3.54	0.32
VIX does not Granger cause SYSRISKN	8.72	0.03
SYSRISKN does not Granger cause TED	3.29	0.35
TED does not Granger cause SYSRISKN	88.55	0.00
SYSRISKN does not Granger cause COMPR	16.20	0.00
COMPR does not Granger cause SYSRISKN	16.41	0.00
SYSRISKN does not Granger cause CISS	1.36	0.72
CISS does not Granger cause SYSRISKN	76.21	0.00
SYSRISKN does not Granger cause VSTOXX	10.20	0.02
VSTOXX does not Granger cause SYSRISKN	21.84	0.00
SYSRISKN does not Granger cause LTRATE	4.61	0.20
LTRATE does not Granger cause SYSRISKN	11.77	0.01
SYSRISKN does not Granger cause INTBRATE	4.98	0.17
INTBRATE does not Granger cause SYSRISKN	1.85	0.60

The normalized leading systemic risk measures are responsive to the lagged changes in the Bank of England and US Fed total assets. The impact of the Eurosystem total assets is borderline by the significance level and observed only at the third lag (Table 6). The composition of the sample may affect this result as nine countries have

[8] They are available from the authors upon request.

national currencies other than the euro. Hence, there may be no direct impact of the ECB monetary policy on them. Moreover, investigating macrofinancial linkages in the euro area, Kremer (2016) also finds only marginal effect of the ECB balance sheet changes on the aggregate systemic risk.

Table 6. The impact of central banks' total assets on leading systemic risk measures

Lag	EUROSYS	BOE	USFED
1	0.25 (0.31)	–26.96*** (4.62)	2.39** (1.07)
2	–0.12 (0.29)	0.12 (4.69)	0.05 (1.04)
3	0.46* (0.25)	–10.96*** (3.93)	–3.16*** (1.00)

Note: *, **, *** – significant at the 10, 5 and 1%; standard errors are in the brackets.

Next, we regress the normalized leading measures of systemic risk on each of the four exogenous covariates, using the robust least squares (RLS). We apply the MM-estimation type in the RLS regressions, accounting for potential outliers in the dependent variable and predictor. We focus on how much these exogenous covariates contribute to the dynamics of the leading systemic risk measures for each country, based on the coefficients of determination from pairwise regressions. These statistics have essentially the same meaning as correlations adjusted for possible outliers (Table 7).

Table 7. Coefficients of determination from pairwise regressions of systemic risk measures on their factors

Country	**Global factors**		**Regional factors**	**Country-specific factors**
	VIX	**TED**	**CISS**	**LTRATE**
Austria	0.05	0.36	0.07	0.08
Belgium	0.22	0.03	0.39	0.68
Cyprus	0.14	0.03	0.32	0.02
Denmark	0.05	0.03	0.05	0.40
Finland	0.44	0.30	0.37	0.00
France	0.18	0.23	0.37	0.32
Germany	0.37	0.12	0.67	0.37
Greece	0.09	0.24	0.15	0.31
Hungary	0.31	0.11	0.27	0.11
Ireland	0.19	0.00	0.29	0.56
Italy	0.28	0.16	0.25	0.03
Luxembourg	0.00	0.06	0.01	0.01
Netherlands	0.23	0.12	0.46	0.38
Norway	0.26	0.06	0.12	0.02
Poland	0.31	0.17	0.25	0.05
Portugal	0.16	0.21	0.39	0.72
Russia	0.13	0.00	0.22	0.21
Spain	0.10	0.22	0.16	0.37
Sweden	0.37	0.18	0.14	0.03
Switzerland	0.15	0.20	0.38	0.10
Turkey	0.03	0.04	0.09	0.13
UK	0.34	0.38	0.35	0.12

Then, we conduct hierarchical cluster analysis to decipher common patterns of systemic risk, building on these goodness-of-fit metrics. Ward's method is used to perform the analysis based on squared Euclidean distances between cluster centers. The clusterization process is represented by the following dendrogram (Figure 3).

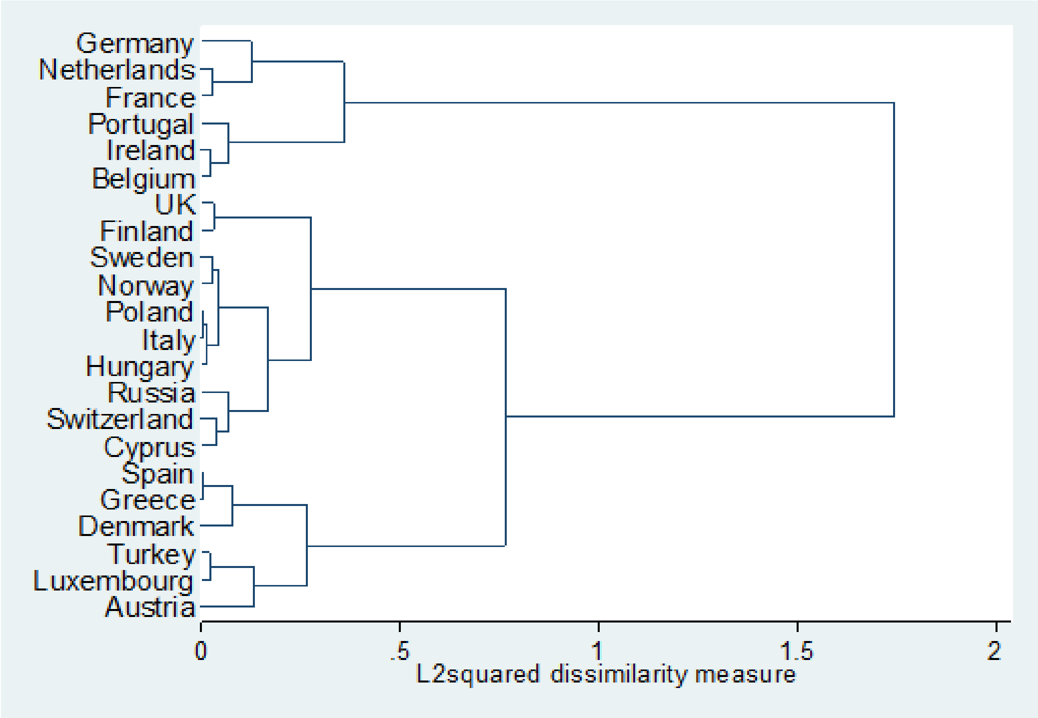

Figure 3. Dendrogram for the cluster analysis of systemic risk patterns in European economies.

We apply three criteria to determine an optimal number of clusters: Calinski-Harabasz pseudo-F statistic, the Duda-Hart stopping rule and the V-fold cross validation procedure. All the techniques suggest that two clusters need to be considered[9]. Cluster 1 comprises Belgium, France, Germany, Ireland, the Netherlands and Portugal. The rest of the countries constitute cluster 2.

We compare systemic risk patterns in both clusters by assessing means of the coefficients of determination from Table 7. We also focus on the significance of their difference estimated via the Mann-Whitney test (Table 8). The test is nonparametric and is valid for small samples. Its null in our case is that the means of the coefficients of determination are identical in both clusters.

Table 8. Comparison of systemic risk patterns by clusters

Mean of	**Cluster 1**	**Cluster 2**	**Mann-Whitney Z-ratio**	**p-value**
VIX	0.23	0.19	-0.81	0.42
TED	0.12	0.16	0.59	0.56
CISS	0.43	0.20	–3.10	0.00
LTRATE	0.51	0.12	–3.17	0.00

[9] The detailed output of these tests is available from the authors upon request.

The difference in systemic risk patterns between the clusters lies in the CISS indicator and long-term interest rates. Their relative importance as systemic risk determinants is significantly higher for cluster 1. We strongly reject the null that their means are the same in the two clusters. The impact of global determinants (the VIX index and TED spread) appears to be equally moderate. Hence, the countries pertaining to cluster 1 are particularly sensitive to deteriorating financial conditions domestically and in the EU as a whole. The countries from cluster 2 exhibit a more mixed pattern of systemic risk as the role of global, regional and country-specific factors is commensurate. Interestingly, the PIIGS countries are split between the clusters, suggesting that they do not follow a uniform pattern of systemic risk. Long-term interest rates is the most salient factor underlying systemic risk in Ireland and Portugal. In Greece and Spain its significance is less pronounced though the respective coefficient of determination is still the biggest among other determinants. However, in Italy the VIX index, TED spread and CISS are by far more important than long-term interest rates.

5 Real effects of systemic risk

Systemic risk becomes particularly hazardous when it spills over to the real economy. Hence, it appears important to examine real effects which the revealed leading systemic risk measures can bring about. We first do it in a bivariate VAR framework, linking the respective measures and industrial production indices (IP). Similar to the horse race described in Section 3, the Toda-Yamamoto procedure applies to estimate the VAR models and conduct Granger (no) causality tests for each country.

At the initial step, we look into the orders of integration of industrial production indices. As shown in Table 9, the IP series are I(0) and I(1). We combine this information with that on the integration properties of systemic risk measures from Table 2 to determine cases for which the Toda-Yamamoto correction for exogenous lags is required.

Table 9. Orders of integration of industrial production indices

Country	Order of integration for IP
Austria	I(0)
Belgium	I(0)
Cyprus	I(0)
Denmark	I(0)
Finland	I(0)

France	I(0)
Germany	I(0)
Greece	I(1)
Hungary	I(1)
Ireland	I(1)
Italy	I(1)
Luxembourg	I(1)
Netherlands	I(0)
Norway	I(0)
Poland	I(0)
Portugal	I(1)
Russia	I(0)
Spain	I(1)
Sweden	I(1)
Switzerland	I(1)
Turkey	I(0)
UK	I(1)

Based on the linear causality tests, we find scarce evidence for causality running from the systemic risk measures to industrial production. Such unidirectional causality holds only for Sweden and Italy. For Cyprus, Denmark, Hungary, Ireland, Norway, and Turkey industrial production Granger causes systemic risk. However, in none of these countries the statistical significance of causal relationships exceeds five percent. Spain is the only economy to exhibit bidirectional causal linkages significant at the one percent level (Table 10).

Table 10. Results of Granger (no) causality tests between leading systemic risk measures and industrial production

Country	**Optimal lag length of the VAR model**	**Toda–Yamamoto correction for exogenous lags**	**VAR Granger (no) causality/Block Exogeneity Wald test**			
			SYSRISK does not cause IP (χ^2)	p-value	IP does not cause SYSRISK (χ^2)	p-value
Austria	VAR(3)	–	3.68	0.30	2.78	0.43
Belgium	VAR(1)	VAR(2)	0.62	0.43	1.34	0.25
Cyprus	VAR(2)	–	0.83	0.66	5.14	0.08
Denmark	VAR(1)	–	2.20	0.14	2.90	0.09
Finland	VAR(2)	–	1.38	0.50	0.54	0.76
France	VAR(2)	VAR(3)	0.29	0.86	0.30	0.86
Germany	VAR(2)	VAR(3)	1.09	0.58	0.07	0.97
Greece	VAR(2)	VAR(3)	1.77	0.41	1.83	0.40
Hungary	VAR(1)	VAR(2)	0.92	0.34	3.44	0.06
Ireland	VAR(1)	VAR(2)	0.10	0.75	2.71	0.09
Italy	VAR(2)	VAR(3)	5.48	0.06	0.14	0.93
Luxembourg	VAR(2)	VAR(3)	0.40	0.82	0.79	0.68
Netherlands	VAR(1)	VAR(2)	0.06	0.81	2.47	0.12
Norway	VAR(1)	–	0.07	0.79	4.63	0.03
Poland	VAR(1)	VAR(2)	0.02	0.90	0.75	0.39
Portugal	VAR(2)	VAR(3)	0.50	0.47	2.30	0.32
Russia	VAR(3)	VAR(4)	2.73	0.43	1.85	0.60
Spain	VAR(4)	VAR(5)	16.64	0.00	18.92	0.00
Sweden	VAR(2)	VAR(3)	7.77	0.02	1.06	0.59
Switzerland	VAR(4)	VAR(5)	2.49	0.65	4.26	0.37
Turkey	VAR(2)	VAR(3)	0.49	0.78	6.43	0.04
UK	VAR(1)	VAR(2)	0.03	0.87	0.80	0.37

Since we first identify leading systemic risk measures and then investigate if they have real effects, our findings cannot be directly compared with those obtained by Engle et al. (2015) who carry out a comprehensive study of systemic risk in Europe. They use

VAR models to assess the relationship between systemic risk and a set of macroeconomic variables, including industrial production indices, for eight countries ranked by the magnitude of a single measure – SRISK. Despite these methodological differences, it is interesting to note that our results partly overlap. For example, Engle et al. (2015) underscore unidirectional causality running from systemic risk to industrial production for Italy and Sweden. Similarly, they find no causality for Germany and the Netherlands. Our findings are also consistent with De Nicoló and Lucchetta (2010, 2012) who employ the VAR models and report feedback effects from macroeconomic variables to systemic financial risk for G–7 economies.

In addition to testing for causality in a linear framework, we run the Diks-Panchenko nonparametric test, accounting for potential nonlinear dependence between the leading systemic risk measures and industrial production[10]. Overall, this empirical strategy identifies a higher number of causal linkages compared with the VAR framework (Table 11).

Table 11. Results of Diks-Panchenko (no) causality tests between leading systemic risk measures and industrial production

Lag	Nonparametric Granger (no) causality **SYSRISK does not cause IP (T-statistic)**	**p-value**	**IP does not cause SYSRISK (T-statistic)**	**p-value**
	Austria			
1	1.11	0.13	1.58	0.06
2	1.65	0.05	1.56	0.06
3	1.39	0.08	1.72	0.04
4	1.24	0.11	1.26	0.10
5	0.96	0.17	1.43	0.08
	Belgium			
1	1.92	0.03	1.40	0.08
2	1.55	0.06	1.56	0.06
3	1.54	0.06	1.38	0.08
4	1.42	0.08	1.58	0.06
5	1.42	0.08	1.07	0.14
	Cyprus			
1	1.46	0.07	1.93	0.03
2	0.62	0.27	1.70	0.04
3	0.22	0.41	1.65	0.05
4	-0.70	0.76	1.33	0.09
5	-0.71	0.76	0.80	0.21
	Denmark			
1	0.28	0.39	0.73	0.23
2	0.58	0.28	0.02	0.49
3	0.66	0.25	0.17	0.43
4	0.75	0.23	-0.58	0.72
5	0.70	0.24	-0.09	0.53
	Finland			
1	0.94	0.17	-0.09	0.54
2	0.49	0.31	-0.14	0.55

[10] We are led to this approach by Freixas et al. (2015) and Giglio et al. (2015) who argue that systemic risk measures are more informative about industrial production or other real activity indicators' lower tails than about their central tendency. Unfortunately, due to the limited length of the time series, we are unable to exploit quantile regressions to assess an impact of the leading systemic risk measures on some lower percentile of industrial production in the sample countries.

3	0.60	0.28	-0.50	0.69
4	0.69	0.24	-0.12	0.55
5	1.07	0.14	0.63	0.27
		France		
1	0.07	0.47	-0.05	0.52
2	0.23	0.41	-0.89	0.81
3	-0.48	0.68	0.62	0.27
4	-0.76	0.77	1.48	0.07
5	0.28	0.39	1.72	0.04
		Germany		
1	0.78	0.22	1.29	0.09
2	1.04	0.15	-0.18	0.57
3	1.18	0.12	-0.66	0.74
4	1.17	0.12	-1.08	0.86
5	1.14	0.13	-0.74	0.77
		Greece		
1	0.87	0.19	0.47	0.32
2	0.48	0.32	0.45	0.33
3	-0.10	0.54	0.49	0.31
4	0.47	0.32	0.60	0.27
5	0.73	0.23	0.13	0.45
		Hungary		
1	0.84	0.20	1.56	0.06
2	0.47	0.32	1.30	0.09
3	0.10	0.46	1.30	0.09
4	0.35	0.36	1.03	0.15
5	1.20	0.11	0.78	0.22
		Ireland		
1	0.97	0.17	-2.23	0.99
2	0.81	0.21	-1.45	0.93
3	0.88	0.19	-1.27	0.90
4	0.85	0.20	-1.11	0.87
5	1.17	0.12	-1.12	0.87
		Italy		
1	0.20	0.42	0.19	0.43
2	0.18	0.43	-0.18	0.57
3	0.05	0.48	-0.02	0.51
4	0.33	0.37	0.83	0.20
5	0.55	0.29	0.34	0.37
		Luxembourg		
1	-0.40	0.65	-1.01	0.84
2	-1.16	0.87	-1.01	0.84
3	-0.73	0.77	-1.00	0.84
4	-0.15	0.56	-0.98	0.84
5	0.10	0.46	-0.97	0.83
		Netherlands		
1	1.76	0.04	0.12	0.45
2	1.87	0.03	0.49	0.31
3	1.53	0.06	0.04	0.48
4	1.61	0.05	0.30	0.38
5	1.66	0.04	0.57	0.28
		Norway		
1	-2.14	0.98	-0.04	0.51
2	0.18	0.43	-0.40	0.65
3	-0.78	0.78	0.86	0.19
4	-1.17	0.88	0.84	0.20
5	-1.26	0.90	0.71	0.24
		Poland		
1	-0.33	0.63	0.41	0.34
2	0.19	0.43	0.44	0.33
3	0.51	0.31	0.37	0.36
4	0.66	0.26	0.24	0.41
5	0.73	0.23	0.13	0.45
		Portugal		
1	-0.10	0.54	-1.35	0.91
2	-0.23	0.59	-1.13	0.87
3	-0.16	0.56	-0.81	0.79
4	-0.10	0.54	-0.21	0.58
5	0.39	0.35	0.54	0.29
		Russia		
1	0.29	0.39	1.54	0.06
2	-1.02	0.85	1.47	0.07

3	-0.94	0.83	0.96	0.17
4	-0.80	0.79	0.97	0.17
5	-0.70	0.76	0.91	0.18
		Spain		
1	-0.54	0.70	-0.12	0.55
2	0.76	0.23	0.21	0.42
3	1.52	0.06	0.75	0.23
4	1.68	0.04	0.92	0.12
5	2.01	0.02	0.73	0.23
		Sweden		
1	1.16	0.12	-2.28	0.99
2	1.36	0.09	-1.96	0.97
3	1.56	0.06	-0.67	0.75
4	1.85	0.03	-0.45	0.67
5	1.65	0.04	-1.04	0.85
		Switzerland		
1	0.44	0.33	0.26	0.40
2	0.47	0.32	0.97	0.17
3	0.19	0.43	1.43	0.08
4	0.11	0.46	1.38	0.08
5	0.32	0.37	1.31	0.09
		Turkey		
1	1.70	0.04	2.65	0.00
2	1.76	0.04	2.67	0.00
3	1.72	0.04	2.26	0.01
4	1.79	0.03	1.71	0.04
5	1.89	0.02	1.48	0.07
		UK		
1	-0.84	0.80	-0.86	0.80
2	0.22	0.41	0.41	0.34
3	1.30	0.09	1.31	0.09
4	0.93	0.18	0.95	0.17
5	1.61	0.06	0.25	0.40

The nonparametric test confirms the causality running from systemic risk to industrial production for Sweden and in the opposite way – for Hungary. In contrast to the linear causality tests, it shows that systemic risk drives industrial production in the Netherlands and Spain. Austria, Belgium, Cyprus, Turkey and the UK are characterized by bidirectional linkages whereas in France, Germany, Russia and Switzerland industrial production Granger causes systemic risk.

In a nutshell, there is coincident evidence that systemic risk Granger causes industrial production in Sweden while in Hungary and Turkey industrial production is sure to drive systemic risk. The two tests concur as regards causality running from systemic risk to industrial production for Spain and vice versa – for Cyprus, but do not rule out bidirectional linkages for these countries either. Both tests don’t unveil any causality for Finland, Greece, Luxembourg, Poland and Portugal. All in all, it is premature to formulate any clear-cut and policy-oriented conclusions based on the two tests. Further research shedding more light on presumably non-monotonic dependence between systemic risk and industrial production is needed. Our view comports with the burgeoning literature, showing that such dependence is sensitive not only to the presence/absence of systemic stress regime but also to its magnitude and the observation period, e.g. Mittnik and Semmler (2013), van Roye (2014) as well as Schleer and Semmler (2015).

6 Conclusions

The paper empirically studies systemic risk in Europe. Our sample includes 22 countries (both EU and non-EU) and covers the period from January 2010 to March 2016. The research is based on the Lausanne systemic risk dataset, comprising return-based and balance sheet metrics. We have investigated three aspects of systemic risk by identifying the most informative metrics, their global, regional and domestic determinants which enable to figure out common patterns in systemic risk across the sample, and the impact on industrial production.

SRISK and volatility appear the most salient measures in six countries, followed by leverage (four countries) and the inverted value of stock market capitalization (two countries). The measures based on the sum of the first three principal and independent components perform worse, thereby challenging the conventional wisdom that aggregation across individual systemic risk measures results in more informative metrics. LRMES, another popular measure, also fares modestly in our comparative analysis. The dynamics of these normalized leading measures captures all major surges in financial stress during the observation period, ranging from the outbreak of the EU financial crisis to purely country-specific episodes. The identification of the leading measures can contribute to the conduct of macroprudential policy. For example, it appears particularly feasible to adopt limits on leverage ratios for the countries where leverage has been found the key systemic risk measure.

The VIX index, TED spread, CISS indicator and long-run interest rates underpin the revealed leading systemic risk measures. We have singled out two clusters in the sample, based on their relative significance as explanatory variables for the systemic risk measures. The distinction between these clusters hinges around the role of regional and domestic determinants of systemic risk. CISS and long-run interest rates are significantly more influential in explaining systemic risk for Belgium, France, Germany, Ireland, the Netherlands and Portugal than for the rest of the countries. Global market conditions embedded in the VIX index and TED spread play a more modest and commensurate role for both country groups.

We have found consistent evidence of causality running from systemic risk to industrial production for Sweden and in the opposite direction – for Hungary and

Turkey. Systemic risk Granger causes real economic activity in Spain though a feedback effect cannot be ruled out. Similarly, industrial production leads systemic risk in Cyprus with a possibility of bidirectional causality. No causal linkages have been found for Finland, Greece, Luxembourg, Poland and Portugal. We have obtained mixed evidence for causality regarding other countries in the sample.

References

Abrigo, M., and I. Love (2015) "Estimation of Panel Vector Autoregression in STATA: A Package of Programs". Mimeo.

Adrian, T., and M.K. Brunnermeier (2016) "CoVaR", *American Economic Review* 106(7), 1705–1741.

Alter, A., and Y. Schuler (2012) "Credit Spread Interdependencies of European States and Banks during the Financial Crisis" *Journal of Banking & Finance* 36, 3444–3468.

Benoit, S., J.-E. Colliard, C. Hurlin, C. Pérignon (2016) "Where the Risks Lie: A Survey on Systemic Risk", *Review of Finance*, forthcoming, doi: 10.1093/rof/rfw026.

Billio, M., A.W. Lo, M. Getmansky, L. Pelizzon (2012) "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors", *Journal of Financial Economics* 104, 535–539.

Bisias, D., M. Flood, A.W. Lo, S. Valavanis (2012) "A Survey of Systemic Risk Analytics", *Annual Review of Financial Economics* 4, 255–296.

Brei, M., and L. Gambacorta (2016) "Are Bank Capital Ratios Pro-cyclical? New Evidence and Perspectives", *Economic Policy* 31(86), 357–453.

Brownlees, C., and R. Engle (2016) "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk", *Review of Financial Studies*, forthcoming, doi: 10.1093/rfs/hhw060.

Byström, H. (2015) "Credit-Implied Equity Volatility – Long-Term Forecasts and Alternative Fear Gauges", *Journal of Futures Markets* 35(8), 753–775.

Corzo Santamaría, M.T., J. Gómez Biscarri, L. Lazcano Benito (2014) "Financial Crises and the Transfer of Risks between the Private and Public Sectors: Evidence from European Financial Markets" *The Spanish Review of Financial Economics* 12(1), 1–14.

De Nicoló, G., and M. Lucchetta (2010) "Systemic Risks and the Macroeconomy", IMF Working Paper № WP/10/29 and in: J. Haubrich and A. Lo (eds.), NBER Volume *Quantifying Systemic Risk*, National Bureau of Economic Research, Cambridge, MA.

De Nicoló, G. and M. Lucchetta (2012) "Systemic Real and Financial Risks: Measurement, Forecasting and Stress Tests", IMF Working Paper № WP/12/58.

Dermine, J. (2015) “Basel III Leverage Ratio Requirement and the Probability of Bank Runs”, *Journal of Banking and Finance* 53, 266–277.

Diks, C., and V. Panchenko (2006) “A New Statistic and Practical Guidelines for Nonparametric Granger Causality Testing”, *Journal of Economic Dynamics and Control* 30(9-10), 1647–1669.

Doornik, J., and H. Hansen (2008) “An Omnibus Test for Univariate and Multivariate Normality”, *Oxford Bulletin of Economics and Statistics* 70 s1, 927–939.

Engle, R., E. Jondeau, M. Rockinger (2015) “Systemic Risk in Europe”, *Review of Finance* 19, 145–190.

Fabozzi, F.J., R. Giacometti, N.Tsuchida (2016) “Factor Decomposition of the Eurozone CDS Spreads”, *Journal of International Money and Finance* 65, 1–23.

Freixas, X., L. Laeven, J.-L. Peydró (2015) “Systemic Risk, Crises, and Macroprudential Regulation”, Massachusetts: MIT Press, 472 p.

Giglio S., B. Kelly, S. Pruit (2016) “Systemic Risk and the Macroeconomy: An Empirical Evaluation”, *Journal of Financial Economics* 119, 457–471.

González-Hermosillo, B., and H. Hesse (2011) “Global Market Conditions and Systemic Risk”, *Journal of Emerging Market Finance* 10(2), 227–252.

Gonzalo, J., and C. Granger (1995) “Estimation of Common Long-memory Components in Cointegrated Systems”, *Journal of Business and Economic Statistics* 13, 27–35.

Holló, D., M. Kremer, M. Lo Duca (2012) “CISS – A Composite Indicator of Systemic Stress in the Financial System”, ECB Working Paper № 1426.

Hyvärinen, A., J. Karhunen, E. Oja (2001) “Independent Component Analysis”, John Wiley&Sons.

Idier, J., G. Lamé, J.-S. Mésonnier (2014) “How Useful is the Marginal Expected Shortfall for the Measurement of Systemic Exposure? A Practical Assessment”, *Journal of Banking & Finance* 47(C), 134–146.

Kinateder, H. (2015) “What Drives Tail Risk in Aggregate European Equity Markets?”, *Journal of Risk Finance* 16(4), 395–406.

Kinda, T., M. Mlachila, R. Quedraogo (2016) “Commodity Price Shocks and Financial Sector Fragility”, IMF Working Paper № WP/16/12, International Monetary Fund, Washington, D.C.

Kremer, M. (2016) "Macroeconomic Effects of Financial Stress and the Role of Monetary Policy: a VAR Analysis of the Euro Area", *International Economics and Economic Policy* 13(1), 105–138.

Kritzman, M., Y.Li, S. Page, R. Rigobon (2011) "Principal Components as a Measure of Systemic Risk", *Journal of Portfolio Management* 37, 112–126.

Mardia, K.V., J. Bibby, J. Kent (1979) "Multivariate Analysis", London: Academic Press, 521 p.

Mittnik, S., and W. Semmler (2013) "The Real Consequences of Financial Stress", *Journal of Economic Dynamics and Control* 37(8), 1479–1499.

Pankoke, D. (2014) "Sophisticated vs. Simple Systemic Risk Measures", University of St. Gallen Working Paper on Finance № 2014/22.

Park, C.-Y., and R. Mercado (2014) "Determinants of Financial Stress in Emerging Market Economies", *Journal of Banking & Finance* 45, 199–224.

Rodríguez-Moreno, M., and I. Peña (2013) "Systemic Risk Measures: the Simpler the Better?" *Journal of Banking & Finance* 37, 1817–1831.

Schleer, F., and W. Semmler (2015) "Financial Sector and Output Dynamics in the Euro Area: Non-Linearities Reconsidered", *Journal of Macroeconomics* 46, 235–263.

Toda, H.Y., and T. Yamamoto (1995) "Statistical Inference in Vector Autoregressions with Possibly Integrated Processes", *Journal of Econometrics* 66(1–2), 225–250.

Van Roye, B. (2014) "Financial Stress and Economic Activity in Germany", *Empirica* 41(1), 101–126.

Appendix

Table A1. Results of bivariate Granger (no) causality tests

Country	SRISK	LRMES	LEVERAGE	MCAP	VOLAT	WMCor	PC	IC
AUSTRIA	LRMES	LEVERAGE			LRMES MCAP		LRMES MCAP	LRMES LEVERAGE MCAP
Score	1	-3	-2	-3	2	0	2	3
BELGIUM	-	-	-	-	-	-	-	-
Score	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
CYPRUS	-	SRISK IC	IC	-	-	-	SRISK IC	-
Score	**-2**	**2**	**1**	**0**	**0**	**0**	**2**	**-3**
DENMARK	MCAP	LEVERAGE MCAP	MCAP	LEVERAGE	WMCor			MCAP
Score	**1**	**2**	**-1**	**-3**	**1**	**-1**	**0**	**1**
FINLAND	-	IC	-	-	SRISK LRMES IC	-	SRISK LRMES	LRMES
Score	**-2**	**-2**	**0**	**0**	**3**	**0**	**2**	**-1**
FRANCE	LRMES	_	SRISK LRMES	SRISK LRMES LEVERAGE PC	LRMES PC	_	SRISK LRMES	LRMES PC
Score	**-2**	**-6**	**1**	**4**	**2**	**0**	**-1**	**2**
GERMANY	LRMES	_	SRISK LRMES MCAP	SRISK LRMES LEVERAGE	LRMES LEVERAGE WMCor PC	PC	SRISK	SRISK LRMES WMCor
Score	**-3**	**-5**	**1**	**2**	**4**	**0**	**-1**	**3**
GREECE	LEVERAGE MCAP	SRISK LEVERAGE MCAP	MCAP	_	_	_	MCAP IC	_
Score	**1**	**3**	**-1**	**-4**	**0**	**0**	**2**	**-1**
HUNGARY	-	LEVERAGE IC	IC	LRMES IC	LEVERAGE MCAP IC	LRMES	LRMES LEVERAGE MCAP IC	LEVERAGE MCAP WMCor
Score	**0**	**-1**	**-3**	**-1**	**3**	**0**	**4**	**-2**
IRELAND	WMCor PC	_	MCAP PC	LEVERAGE WMCor PC	PC IC	LRMES PC	-	-
Score	**2**	**-1**	**1**	**2**	**2**	**1**	**-5**	**-1**
ITALY	IC	_	MCAP VOLAT IC	LEVERAGE IC	SRISK IC LEVERAGE MCAP	_	IC LEVERAGE MCAP	_
Score	**0**	**0**	**0**	**-1**	**3**	**0**	**3**	**-5**
LUXEMBOURG	-	-	-	VOLAT PC IC	MCAP	-	WMCor	-
Score	**0**	**0**	**0**	**2**	**0**	**-1**	**0**	**-1**
NETHERLANDS	-	-	-	SRISK LRMES	-	SRISK	SRISK LRMES	LRMES
Score	**-3**	**-3**	**0**	**2**	**0**	**1**	**2**	**1**
NORWAY	LEVERAGE	_	_	_	LRMES WMCOR IC	PC	LRMES MCAP	WMCOR
Score	**1**	**-2**	**-1**	**-1**	**3**	**-1**	**1**	**0**
POLAND	LEVERAGE IC	_	_	_	WMCOR	_	WMCOR	VOLAT
Score	**2**	**0**	**-1**	**0**	**0**	**-2**	**1**	**0**
PORTUGAL	PC	_	LRMES	LRMES WMCOR	WMCOR	_	_	MCAP WMCOR
Score	**1**	**-2**	**1**	**1**	**1**	**-3**	**-1**	**2**
RUSSIA	LEVERAGE VOLAT PC	_	SRISK	_	_	PC	_	_
Score	**2**	**0**	**0**	**0**	**-1**	**1**	**-2**	**0**
SPAIN	IC	SRISK MCAP	IC	IC	_	_	IC	SRISK MCAP
Score	**-1**	**2**	**1**	**-1**	**0**	**0**	**1**	**-2**
SWEDEN	IC	_	MCAP	SRISK LEVERAGE	LRMES WMCOR PC IC	PC	IC	SRISK WMCOR
Score	**-1**	**-1**	**0**	**1**	**4**	**-1**	**-1**	**-1**
SWITZERLAND	LEVERAGE	LEVERAGE	LRMES	LRMES	PC	_	LRMES	VOLAT

	MCAP	IC	MCAP	LEVERAGE VOLAT PC	IC		LEVERAGE IC	
Score	**2**	**-1**	**-2**	**2**	**0**	**0**	**1**	**-2**
TURKEY	_	_	SRISK PC	SRISK PC	PC	_	_	_
Score	**-2**	**0**	**2**	**2**	**1**	**0**	**-3**	**0**
UK	LRMES	PC	LRMES MCAP	LRMES	_	_	LRMES	LRMES VOLAT
Score	**1**	**-4**	**2**	**0**	**-1**	**0**	**0**	**2**

Table A2. Results of nonparametric Granger (no) causality tests

Country	**SRISK**	**LRMES**	**LEVERAGE**	**MCAP**	**VOLAT**	**WMCor**	**PC**	**IC**
AUSTRIA	LEVERAGE MCAP WMCor PC	SRISK PC IC	SRISK MCAP	LRMES	WMCor	-	SRISK LRMES MCAP WMCor	SRISK LRMES MCAP WMCor PC
Score	**0**	**0**	**1**	**-3**	**1**	**-3**	**2**	**4**
BELGIUM	MCAP PC	MCAP IC	MCAP PC IC	WMCor	MCAP	-	LEVERAGE LRMES MCAP WMCor	MCAP WMCor
Score	**2**	**1**	**2**	**-5**	**1**	**-3**	**2**	**0**
CYPRUS	LRMES LEVERAGE PC	SRISK LEVERAGE PC	PC	-	SRISK LRMES WMCor	-	LRMES LEVERAGE IC	-
Score	**1**	**0**	**-2**	**0**	**3**	**-1**	**0**	**-1**
DENMARK	WMCor	LEVERAGE MCAP IC	SRISK MCAP WMCor PC	SRISK LEVERAGE	-	-	SRISK WMCor	SRISK LRMES LEVERAGE
Score	**-3**	**2**	**1**	**0**	**0**	**-3**	**1**	**2**
FINLAND	WMCor	IC MCAP	WMCor IC	SRISK LEVERAGE	LEVERAGE IC	PC	WMCor	MCAP WMCor
Score	**0**	**2**	**0**	**0**	**2**	**-3**	**0**	**-1**
FRANCE	LRMES	SRISK	SRISK LRMES MCAP	SRISK LRMES LEVERAGE WMCOR	WMCOR	SRISK	SRISK LRMES WMCOR	LRMES LEVERAGE MCAP WMCOR
Score	**-4**	**-4**	**0**	**2**	**1**	**-2**	**3**	**4**
GERMANY	WMCOR	WMCOR	SRISK WMCOR	SRISK LEVERAGE WMCOR PC	LEVERAGE WMCOR	-	SRISK LEVERAGE WMCOR	LRMES WMCOR
Score	**-2**	**0**	**-1**	**4**	**2**	**-7**	**3**	**2**
GREECE	LEVERAGE MCAP	-	SRISK WMCOR	SRISK LEVERAGE WMCOR	MCAP	-	SRISK LRMES LEVERAGE MCAP	LRMES LEVERAGE MCAP
Score	**-1**	**-2**	**-2**	**-1**	**1**	**-2**	**4**	**3**
HUNGARY	-	MCAP	LRMES WMCOR PC IC	LRMES LEVERAGE PC IC	LEVERAGE MCAP PC	MCAP	LRMES MCAP	LRMES PC
Score	**0**	**-3**	**2**	**0**	**3**	**0**	**-1**	**0**
IRELAND	PC IC	SRISK VOLAT WMCOR PC IC	SRISK LRMES PC IC	SRISK LRMES PC IC	LRMES	PC	LRMES IC	LRMES VOLAT
Score	**-1**	**0**	**4**	**4**	**0**	**0**	**-3**	**-2**
ITALY	LEVERAGE MCAP WMCOR IC	SRISK WMCOR	WMCOR IC	LEVERAGE WMCOR IC	SRISK LRMES LEVERAGE IC	LRMES	SRISK LEVERAGE MCAP IC	WMCOR
Score	**1**	**0**	**-2**	**1**	**4**	**-3**	**4**	**-4**
LUXEMBOURG	MCAP WMCOR PC IC	MCAP VOLAT	MCAP WMCOR PC IC	VOLAT WMCOR PC IC	WMCOR	MCAP	MCAP WMCOR IC	MCAP WMCOR PC
Score	**4**	**2**	**4**	**-2**	**-1**	**-5**	**-1**	**-1**
NETHERLANDS	LRMES LEVERAGE MCAP PC	WMCOR	SRISK MCAP VOLAT PC	SRISK VOLAT PC	WMCOR	-	MCAP	WMCOR
Score	**2**	**0**	**3**	**0**	**-1**	**-3**	**-2**	**1**
NORWAY	WMCOR	-	-	LEVERAGE IC	LRMES	-	IC	-

Score	**1**	**-1**	**-1**	**2**	**1**	**-1**	**1**	**-2**
POLAND	IC	LEVERAGE VOLAT	IC	WMCOR	WMCOR	-	LEVERAGE WMCOR	-
Score	**1**	**2**	**-1**	**1**	**0**	**-3**	**2**	**-2**
PORTUGAL	LRMES IC	-	SRISK	LRMES WMCOR	MCAP WMCOR	-	MCAP WMCOR	LRMES
Score	**1**	**-3**	**1**	**0**	**2**	**-3**	**2**	**0**
RUSSIA	LEVERAGE	WMCOR	SRISK MCAP VOLAT IC	VOLAT IC	-	-	VOLAT IC	-
Score	**0**	**1**	**3**	**1**	**-3**	**-1**	**2**	**-3**
SPAIN	LRMES LEVERAGE IC	-	SRISK LRMES IC	LRMES IC	-	PC	-	LRMES
Score	**2**	**-4**	**2**	**2**	**0**	**1**	**-1**	**-2**
SWEDEN	LEVERAGE WMCOR IC	IC	LRMES	LRMES LEVERAGE	LRMES WMCOR	-	WMCOR	-
Score	**3**	**-2**	**-1**	**2**	**2**	**-3**	**1**	**-2**
SWITZERLAND	LRMES LEVERAGE MCAP WMCOR IC	VOLAT IC	LRMES PC IC	LRMES LEVERAGE VOLAT PC IC	LRMES	-	SRISK LRMES LEVERAGE VOLAT	MCAP
Score	**4**	**-3**	**0**	**3**	**-2**	**-1**	**2**	**-3**
TURKEY	-	VOLAT IC	SRISK MCAP PC	PC	-	-	-	-
Score	**-1**	**2**	**3**	**0**	**-1**	**0**	**-2**	**-1**
UK	LRMES PC IC	-	LRMES	LRMES LEVERAGE	LRMES	VOLAT	SRISK LRMES IC	SRISK LRMES PC
Score	1	-6	0	2	0	1	1	1

Table A3. Results of Granger (no) causality tests based on BVAR models

Country	**SRISK**	**LRMES**	**LEVERAGE**	**MCAP**	**VOLAT**	**WMCor**	**PC**	**IC**
AUSTRIA	LEVERAGE	SRISK IC	SRISK MCAP	LEVERAGE	-	PC	WMCor	-
Score	**-1**	**2**	**0**	**0**	**0**	**0**	**0**	**-1**
BELGIUM	LRMES LEVERAGE	IC	SRISK MCAP	LEVERAGE PC	-	-	MCAP	-
Score	**1**	**0**	**0**	**0**	**0**	**0**	**0**	**-1**
CYPRUS	LRMES LEVERAGE MCAP PC	PC IC	SRISK PC IC	SRISK PC	-	-	SRISK LRMES LEVERAGE	LRMES
Score	**1**	**-1**	**1**	**1**	**0**	**0**	**0**	**-1**
DENMARK	LEVERAGE	IC	SRISK MCAP	SRISK LEVERAGE PC IC	–	–	–	LRMES
Score	**-1**	**0**	**0**	**3**	**0**	**0**	**-1**	**-1**
FINLAND	PC	MCAP	MCAP PC	LRMES LEVERAGE	WMCor PC IC	LEVERAGE	SRISK	LRMES PC
Score	**0**	**-1**	**0**	**0**	**3**	**0**	**-2**	**1**
FRANCE	–	–	MCAP	LEVERAGE IC	PC			
Score	**0**	**0**	**0**	**1**	**1**	**0**	**-1**	**-1**
GERMANY	LEVERAGE	SRISK	SRISK MCAP	SRISK LEVERAGE PC	–	–	–	–
Score	**-2**	**1**	**0**	**2**	**0**	**0**	**-1**	**0**
GREECE	LEVERAGE MCAP	–	SRISK MCAP	LEVERAGE	–	–	–	–
Score	**1**	**0**	**0**	**-1**	**0**	**0**	**0**	**0**
HUNGARY	–	MCAP	MCAP IC	LRMES LEVERAGE PC IC	–	–	–	–
Score	**0**	**0**	**1**	**2**	**0**	**0**	**-1**	**-2**
IRELAND	LRMES LEVERAGE MCAP PC IC	LEVERAGE MCAP	LRMES MCAP	LRMES LEVERAGE	–	–	–	–
Score	**5**	**-1**	**-1**	**-1**	**0**	**0**	**-1**	**-1**
ITALY	MCAP	IC	MCAP	SRISK LEVERAGE	PC			LRMES
Score	**0**	**0**	**0**	**0**	**1**	**0**	**-1**	**0**

LUXEMBOURG	LEVERAGE IC	LEVERAGE PC	SRISK PC IC	PC	-	LRMES	LEVERAGE MCAP	LEVERAGE VOLAT
Score	**1**	**1**	**-1**	**0**	**-1**	**1**	**-1**	**0**
NETHERLANDS	LEVERAGE MCAP	-	SRISK MCAP	SRISK LEVERAGE	-	-	-	-
Score	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
NORWAY	LEVERAGE	IC	-	LEVERAGE IC	LRMES PC	-	LRMES	-
Score	**1**	**-1**	**-2**	**2**	**2**	**0**	**0**	**-2**
POLAND	LEVERAGE MCAP IC	-	SRISK IC	PC	-	-	-	LEVERAGE
Score	**2**	**0**	**0**	**0**	**0**	**0**	**-1**	**-1**
PORTUGAL	LEVERAGE WMCor IC	-	SRISK MCAP	LRMES LEVERAGE PC	-	-	-	-
Score	**2**	**-1**	**0**	**2**	**0**	**0**	**-1**	**-1**
RUSSIA	LEVERAGE VOLAT	LEVERAGE WMCor IC	SRISK LRMES MCAP PC	LEVERAGE	-	-	-	-
Score	**1**	**2**	**1**	**0**	**-1**	**-1**	**-1**	**-1**
SPAIN	LEVERAGE MCAP	-	SRISK MCAP	SRISK LEVERAGE	-	-	-	-
Score	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
SWEDEN	IC	-	MCAP	SRISK	SRISK PC	-	-	-
Score	**-1**	**0**	**1**	**0**	**2**	**0**	**-1**	**-1**
SWITZERLAND	LRMES LEVERAGE	-	SRISK MCAP	LRMES LEVERAGE PC IC	-	-	MCAP	-
Score	**1**	**-2**	**0**	**2**	**0**	**0**	**0**	**-1**
TURKEY	LEVERAGE	IC	SRISK MCAP PC	LEVERAGE	-	-	-	LRMES
Score	**0**	**0**	**1**	**0**	**0**	**0**	**-1**	**0**
UK	PC	-	MCAP	-	-	VOLAT	SRISK	SRISK PC
Score	**-1**	**0**	**1**	**-1**	**-1**	**1**	**0**	**2**