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Does global financial cycle drive systemic risk?

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Abstract

The paper studies the relationship between a financial cycle proxy and conditional capital shortfall (SRISK), a popular systemic risk measure, at the global level. Based on causal and directional dependence analyses in the time and time-frequency domains, we find that global financial cycle (GFC) drives SRISK. Besides, the GFC variable appears more useful in forecasting world industrial production. The results emphasize the GFC relevance for monitoring financial stability and forecasting crises relative to narrow systemic risk measures.

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1. Introduction

Numerous systemic risk measures have been developed to monitor and forecast financial instability at the national and global levels. Most of them are sophisticated indicators based on balance-sheet data and/or asset prices processed with advanced quantitative methods, e.g. quantile regressions, extreme value theory, networks, etc. (Bisias et al., 2012; Silva et al., 2017; Neveu, 2018). One of the most popular systemic risk measures is conditional capital shortfall (SRISK) proposed by Brownlees and Engle (2017), which assesses the capital shortfall of a financial institution conditional on a severe market decline. It is found to be the most consistent and informative measure relative to its contenders in various horse races among systemic risk indicators, e.g. Stolbov and Shchepeleva (2018), Grundke and Tuchsherer (2019), Dissem and Lobez (2020). However, such superior performance of SRISK need not to be taken for granted once it compares with a measure, which does not formally belong in the class of systemic risk indicators, while containing useful information about the buildup of financial risks. A plausible candidate is the Global Financial Cycle (GFC) variable, which captures global dynamics in risky asset prices and also reflects aggregate risk aversion in global markets as well as US monetary policy stance. (Miranda-Agrippino et al., 2020; Miranda-Agrippino and Rey, 2020).

Against this backdrop, we examine the relationship between global SRISK and the Global Financial Cycle (GFC) variable. To our knowledge, this is the first study investigating the dynamic interaction between a proxy of the global financial cycle and systemic risk. By conducting such research, we seek to figure out whether the GFC variable leads global SRISK, thereby bearing more usefulness than the latter in terms of financial stability monitoring and crisis forecasting. To make our comparison of the two indicators more comprehensive, our empirical analysis consists of two complementary steps. First, we test for the relationship between the GFC proxy and global SRISK in a bivariate setting. Second, we compare their relative contribution to forecasting world industrial production. This step is equally important, since the materialization of financial risks worldwide may eventually dampen global output growth.

Regarding the first step, by running a number of causality and directional dependence tests, we find that the GFC variable indeed leads global SRISK for the period July 2000-April 2019. The effect is persistent and primarily observed over longer time horizons (3 years and more), manifesting itself in the short run only during the acute phase of the global financial crisis and its aftermath (2007-2011). We also conjecture that there are two channels through which the impact of GFC on global SRISK is propagated: (i) changes in the market value of equity and (ii) the sensitivity of equity to a sharp market decline. As for the second step, we document that the GFC variable contributes more significantly than global SRISK to forecasting world industrial production.

Overall, our results indicate that policymakers involved in financial regulation and macroprudential policy design should assess the impact of the GFC variable on national SRISK, other systemic risk measures and macroeconomic fundamentals, thereby incorporating the proxy of the global financial cycle into stress-testing exercises as a salient risk factor.

The rest of the paper is organized as follows. In Section 2 we describe the data. Section 3 explains the methodology. Section 4 discusses the results, while Section 5 concludes.

2. Data

SRISK is an increasing function of the financial entity's size, leverage and expected equity loss arising from the market decline (Brownlees and Engle, 2017). SRISK can be represented as follows:

$$SRISK_{it} = kD_{it} - (1-k)W_{it}(1 - LRMES_{it}), \quad (1)$$

where W_{it} is the market value of equity, D_{it} - the book value of debt, k - the prudential capital adequacy ratio. $LRMES_{it}$, long-run marginal expected shortfall, measures the sensitivity of the financial institution's equity value to the severe market decline[1]. Positive SRISK values can be aggregated across financial institutions to make a nationwide measure. Similarly, summing up such national indicators yields a global SRISK measure.

The GFC variable is a factor extracted from over 1000 asset prices, which captures a significant fraction of common variation in global markets. Miranda-Agrippino et al. (2020) show that this factor is inversely related to realized market variance and aggregate risk-aversion in global markets.

World industrial production (WIP) index is a weighted index based on industrial production in 85 countries, which account for about 97% of global industrial output. The series is seasonally adjusted. The base year is 2010.

SRISK, the GFC variable and the WIP index are monthly series available for July 2000 – April 2019[2]. SRISK is retrieved from the Volatility Laboratory at New York University (https://vlab.stern.nyu.edu/), the GFC series comes from Silvia Miranda-Agrippino's website (http://silviamirandaagrippino.com/code-data), while the WIP index is borrowed from the CPB Netherlands Bureau for Economic Policy Analysis (https://www.cpb.nl/en/worldtrademonitor). The data series are described in Table 1.

Table 1. Descriptive statistics of the GFC variable, SRISK and the WIP index.

	GFC	SRISK	WIP index
Mean	0.39	2.20	100.90
Median	0.30	2.69	101.96
Maximum	2.85	4.37	122.32
Minimum	-2.69	0.23	81.70
Std. Dev.	1.01	1.21	11.69
Skewness	0.31	-0.27	0.04
Kurtosis	3.22	1.52	1.93
Jarque-Bera	4.05	23.26	10.80
Probability	0.13	0.00	0.00
Obs.	226	226	226

3. Methodology

Our empirical exercise is divided into two steps. First, by applying a battery of causal and directional dependence tests, we study the interaction between SRISK and the GFC variable during the whole observation period. Second, we compare the contribution of these variables to forecasting the WIP index, both during July 2000 – April 2019 and July 2000 – December 2019, i.e. encompassing the out-of-sample period from May 2019 to December 2019[3].

[1] In line with Brownlees and Engle (2017), k is set to 8%, while the severe market decline implies a 40-percent semiannual shrinkage in global stock market indices, e.g. the MSCI world index.

[2] The GFC variable determines the length of our observation period, as it is available only till April 2019. The starting point (July 2000) is determined by the availability of the SRISK measure.

[3] We do not include the period after the COVID-19 outbreak, i.e. from January 2020 onwards, due to notable downward outliers in world industrial production.

In step 1, we first specify a standard bivariate VAR model to run Granger (no) causality tests and obtain impulse-response functions. Since both variables are I(1)[4], the Toda-Yamamoto (1995) approach applies to estimate the VAR model 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 determined on the basis of the Akaike information criteria. 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 as exogenous parameters. 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). However, the linear (no) causality 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.

To account for possible nonlinear causality, we next extract residuals from the VAR model and apply the Diks-Panchenko (2006) nonparametric (no) causality test to them. It runs in both directions for lags from 1 to 10 and for the bandwidth equal to 1.5, taking into account the time series length.

In addition to the causal analysis in the time scale, we test for dynamic dependence between SRISK and the GFC variable in the time-frequency domain by means of the continuous wavelet transform (CWT) and a specific tool pertaining to this approach – the wavelet coherence. It is analogous to localized correlation coefficients between two data series decomposed in the time-frequency space. There are different wavelet functions available for such decomposition. In this study, we adopt the Morlet wavelet:

$$\psi(t) = \pi^{-\frac{1}{4}} \exp(i\omega_0 t) \exp(-\frac{1}{2} t^2), \tag{2}$$

which is a complex valued wavelet with an optimal joint time-frequency concentration. In most cases, the frequency parameter ω_0 is set to 6, making the so-called wavelet scale (the parameter accounting for the wavelet length) inversely related to the frequency. The wavelet coherence is a convenient tool to analyze lead-lag relationships because it enables to test if two series move in-phase or anti-phase. Moving in-phase suggests that both series change in the same direction.

In step 2, we estimate two bivariate VAR models for the WIP index interacting with SRISK and the GFC variable, respectively. The models are then used to build forecasts of the WIP index during July 2000 – April 2019 and July 2000 – December 2019, thereby comparing the relevance of SRISK and the GFC variable for such prediction, based on root mean square errors (RMSE) and the Diebold-Mariano (1995) forecast evaluation test. In this exercise, a naïve ARIMA forecast of the WIP index constitutes a benchmark for comparison.

4. Results

We run Granger (no) causality tests and derive impulse response functions from the bivariate VAR(5) model linking the GFC variable and global SRISK. The tests indicate that the GFC variable Granger causes global SRISK at the one percent level without experiencing any feedback (Table 2).

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[4] The results of the ADF unit root tests are available from the authors upon request.

Table 2. Results of standard Granger (no) causality test

Null hypothesis	χ^2	**p-value**
GFC does not Granger cause	23.95	0.00
SRISK does not Granger cause GFC	6.29	0.18

The impulse response functions reveal that the impact is negative, i.e. an increase in the GFC variable by one standard deviation (S.D.) leads to a decline in global SRISK by approximately 0.1 S.D. (Figure 1). In absolute terms, it totals 120 bln US dollars. Given the average global SRISK for July 2000 – April 2019 equal to 2200 bln US dollars, such reduction appears economically significant, i.e. 5.5% of the average SRISK volume.

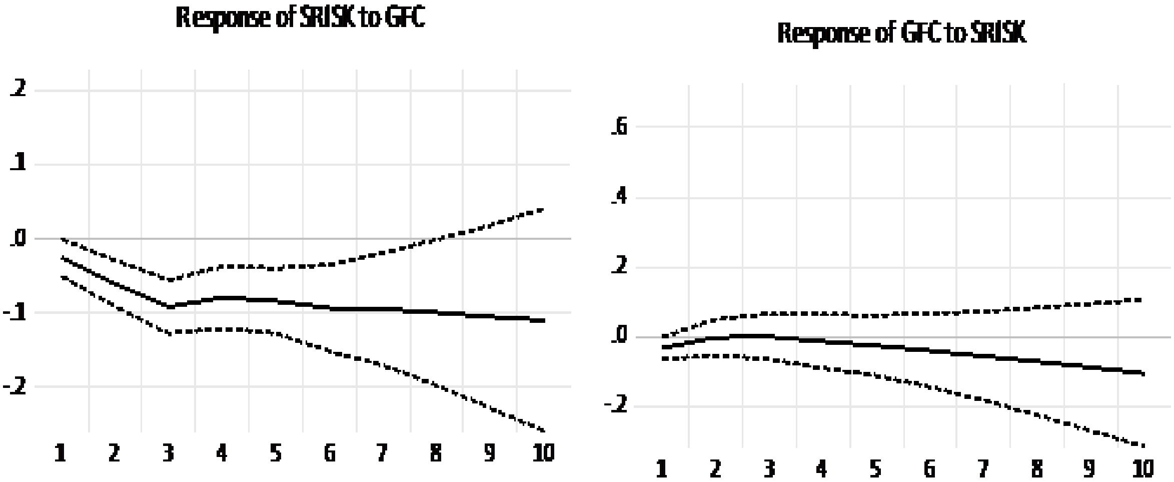

Figure 1. Generalized impulse-response functions based on the VAR(5) model for the GFC variable and SRISK.

The causality between the GFC variable and global SRISK is only found in the linear setting, as the Diks-Panchenko nonparametric (no) causality test applied to the residuals from the VAR(5) model does not detect any linkages at the conventional significance level for up to 10 lags (Table 3).

Table 3. Results of Diks-Panchenko nonparametric (no) causality test

Lag	GFC does not cause SRISK (T-statistic)	p-value	SRISK does not cause GFC (T-statistic)	p-value
1	1.22	0.11	0.32	0.37
2	1.04	0.15	-0.08	0.53
3	1.34	0.09	-0.56	0.71
4	0.35	0.36	-0.05	0.52
5	1.08	0.14	0.10	0.46
6	1.01	0.16	-0.11	0.54
7	0.07	0.47	-0.18	0.57
8	0.39	0.35	-0.35	0.64
9	0.80	0.21	0.05	0.48
10	1.31	0.09	-0.28	0.61

Then, the continuous wavelet transform analysis is conducted, and a corresponding wavelet coherence plot is obtained. The leftward direction of arrows in the plot indicates that the GFC variable and global SRISK move anti-phase, with the former leading the latter (Figure 2). This finding in the time-frequency domain is consistent with the results from the bivariate VAR analysis. The statistically significant wavelet coherences are concentrated in the upper part of the plot, in a delineated, dark grey area. Except for the period 2007-2011, these coherences are observed over long time horizons (32 months and longer) and almost across the entire sample period[5]. Thus, the impact of the GFC variable on global SRISK is persistent and mostly pronounced in the long run. This finding is likely to capture the slow-moving nature of the GFC effect on the systemic risk buildup. That is, over short time spans it may be reasonably hard to detect such effect, except for evident crisis episodes. However, as a contractionary (expansionary) phase of the GFC lasts a sufficiently long period, its effect on the systemic risk buildup (decline) gradually strengthens.

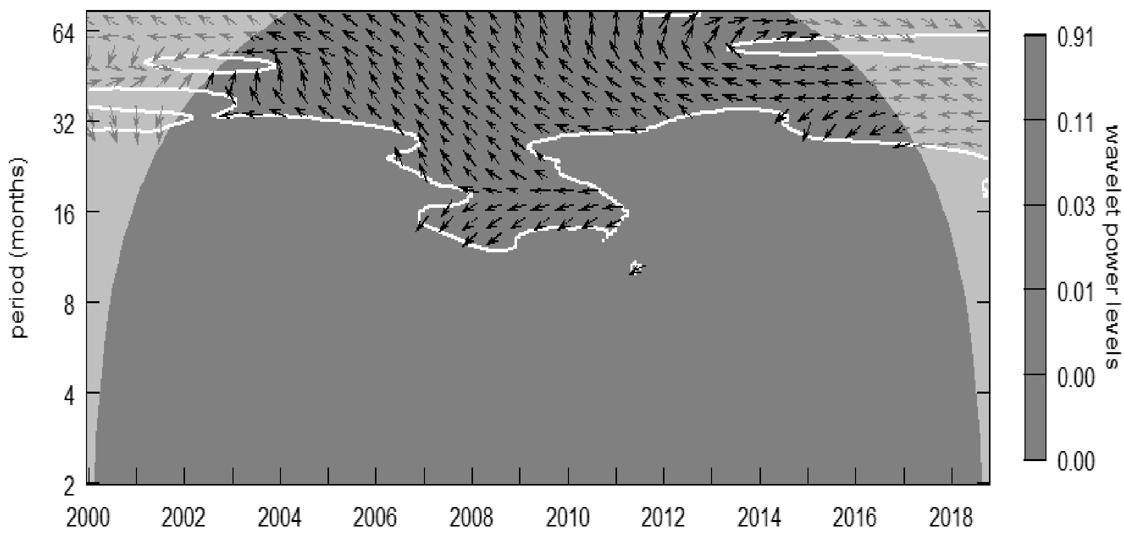

Figure 2. Results of the wavelet coherence analysis for the GFC variable and global SRISK.

Finally, we estimate bivariate VAR models linking the WIP index to the GFC variable and global SRISK, respectively. The preferred specifications in both cases are also VAR(5). Based on them, the forecasts of the WIP index are built for two periods, July 2000 – April 2019 and July 2000 – December 2019. We also do a naïve ARIMA forecast of the WIP index which serves a benchmark for forecast accuracy comparison. The best ARIMA specification is ARIMA(4,1,2). Actual and fitted dynamics of the WIP index are represented in Figure 3.

[5] The hatched cone-type area, called the cone of influence, is an approximation to the boundaries of statistically significant wavelet coherences.

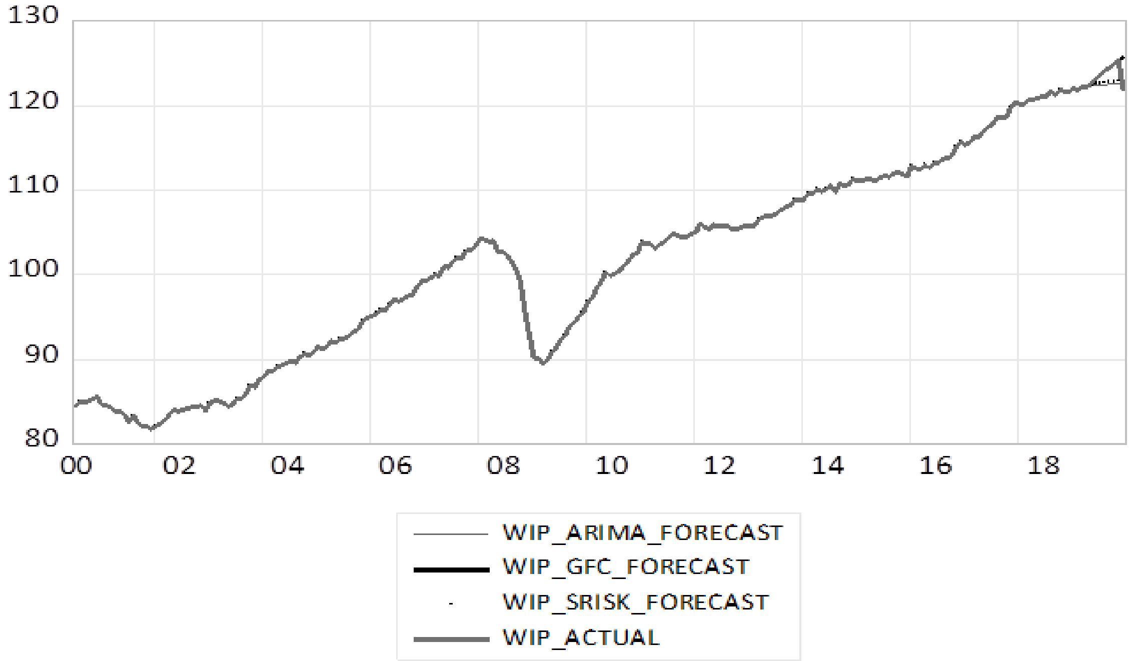

Figure 3. Actual dynamics of the WIP index and its forecasts from the predictive models.

Table 4 reports root mean square errors (RMSE) for each of the forecasts. For both periods we consider, RMSE appear the lowest in case of the bivariate VAR (5) for the GFC variable and the WIP index.

Table 3. RMSE values for the constructed forecasts

	July 2000-April 2019	**July 2000-December 2019**
VAR(5) for GFC and WIP	3.49	3.48
VAR(5) for SRISK and WIP	3.93	3.90
ARIMA(4,1,2)	4.22	4.15

We next run the Diebold-Mariano (DM) forecast evaluation test to check if the differences in the forecast accuracy are statistically significant. The null hypothesis of the DM test is that two forecasts to be compared have the same accuracy, based on the DM test statistic. Table 4 conveys the results of the DM test.

Table 4. Results of the DM test for forecast accuracy of the WIP index

	July 2000-April 2019		**July 2000-December 2019**	
	DM test statistic	p value	DM test statistic	p value
VAR(5) for GFC and WIP **vs.** VAR(5) for SRISK and WIP	-3.50	0.00	-3.39	0.00
VAR(5) for GFC and WIP **vs.** ARIMA(4,1,2)	-5.64	0.00	-5.25	0.00
VAR(5) for SRISK and WIP **vs.** ARIMA(4,1,2)	-9.43	0.00	-7.36	0.00

The null is strongly rejected in all the cases, suggesting that the best forecast is based on the bivariate VAR (5) model including the GFC variable. Thus, we provide evidence that the proxy of the global financial cycle not only leads global SRISK, but also yields more accurate forecasts of global real economic activity.

What explains the pivotal role of the GFC variable from the conceptual standpoint? We argue that there are at least two channels through which the impact of the GFC variable on global SRISK can be transmitted. The straightforward one is via the market value of equity, W. In the contractionary (expansionary) phase of the global financial cycle when asset prices shrink (rise), it also diminishes (increases). Given equation (1), SRISK increases (decreases) in this case. The other plausible channel is via long-run marginal expected shortfall, $LRMES$. Benoit et al. (2017) show that $LRMES$ is proportional to market beta, being the product of the latter and market tail risk. In the contractionary phase of the global financial cycle asset prices become tightly correlated. As a result, correlations of most asset prices with market indices increase, so do market betas and, consequently, $LRMES$. Given the additivity of positive SRISK values at the national and international levels, both channels are likely to be valid for global SRISK.

In this short paper, we report preliminary evidence which largely supports our conjecture about the two channels propagating the impact of the GFC variable on SRISK. First, using data on the global market value of equity (GLEQ)[6] along with the GFC variable and global SRISK, we specify a VAR(3) model for the period July 2000-April 2019, which, based on Granger causality tests and impulse response functions, suggests that GFC leads GLEQ while the latter drives SRISK (Table A1, Figure A1 in the Appendix). Although these causalities are not so strong, holding at the ten percent level, they provide tentative evidence for the first channel. Since data on $LRMES$ is unavailable at the global level and for most countries except European ones[7], we examine the existence of the second channel, using two notable constituents of global SRISK on the corporate and national levels, Citigroup, Inc. and the UK, respectively[8]. By applying our standard methodology, we document in both exercises that the GFC variable leads $LRMES$ at the one percent level, while the latter Granger causes SRISK at least at the five percent level (Tables A2-A3, Figures A2-A3 in the Appendix)[9].

Overall, our results inform the debate on the consistency and informativeness of SRISK, corroborating concerns about its universal usefulness and superiority over other metrics, for example, expressed by Tavolaro and Visnovsky (2014) as well as Bancel et al. (2014). Besides, our findings mesh well with most recent contributions by Hartwig et al. (2020) and Schüler et al. (2020) who demonstrate that composite financial cycle indicators embedding price fluctuations in multiple assets predict financial crises better than narrow systemic risk measures, including such popular ones as credit-to-GDP gap. In this light, our empirical results call for the use of the GFC variable as a major risk factor in stress tests conducted by financial regulators.

5. Conclusion

We examine the relationship between the global financial cycle (GFC) variable and global systemic risk proxied with the conditional capital shortfall (SRISK) measure. Using a battery of causality and directional dependence tests in the time and time-frequency domains

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[6] The data comes from the statistical portal of the World Federation of Exchanges. See https://statistics.world-exchanges.org/.

[7] We exploit country-level data on $LRMES$ for the UK from the Centre for Risk Management at HEC Lausanne. See http://www.crml.ch/index.php/european-measures/.

[8] As of April 2019, Citigroup, Inc. accounts for 16% of the aggregate US SRISK and totals 1.9% of the global measure, while the share of the UK, the most important European contributor to systemic risk during most of the observation period, in the global SRISK is about 7%.

[9] The causal effect of $LRMES$ on SRISK for Citigroup, Inc. and the UK does not rule out a direct impact of the GFC variable on SRISK. It is due to the fact that the GFC variable accounts for the dynamics of many other assets besides equity, e.g. commodities, which may influence systemic risk without being captured by $LRMES$.

as well as assessing the relative contribution of the two indicators to world industrial production forecasts, we find that the GFC variable drives SRISK and also outperforms the latter as a predictor of world industrial production. We provide preliminary evidence that this impact of the GFC variable on SRISK is channeled through the market value of equity and long run marginal expected shortfall which are used to compute SRISK. From the policymaking perspective, our results emphasize potential merits of the GFC variable as a major risk factor in macrofinancial stress tests. Regulators should assess its impact on different systemic risk measures and macroeconomic fundamentals at the national level.

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Appendix

Table A1. Results of standard Granger (no) causality tests based on the VAR(3) model for GFC, GLEQ and global SRISK

Null hypothesis	χ^2	**p-value**
GFC does not Granger cause GLEQ	5.18	0.07
GLEQ does not Granger cause GFC	1.42	0.49
Null hypothesis	χ^2	**p-value**
SRISK does not Granger cause GLEQ	1.75	0.42
GLEQ does not Granger cause SRISK	5.65	0.06
Null hypothesis	χ^2	**p-value**
SRISK does not Granger cause GFC	3.49	0.17
GFC does not Granger cause SRISK	0.47	0.79

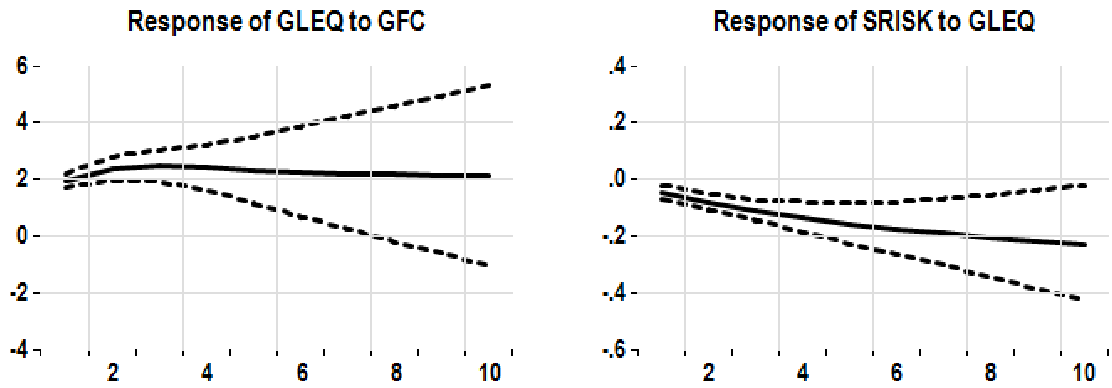

Figure A1. Generalized impulse-response functions based on the VAR(3) model for GFC, GLEQ and global SRISK.

Table A2. Results of standard Granger (no) causality tests based on the VAR(4) model for GFC, LRMES and SRISK for Citigroup, Inc.

Null hypothesis	χ^2	**p-value**
CITI_LRMES does not Granger cause GFC	7.16	0.07
GFC does not Granger cause CITI_LRMES	48.02	0.00
Null hypothesis	χ^2	**p-value**
CITI_SRISK does not Granger cause CITI_LRMES	7.37	0.06
CITI_LRMES does not Granger cause CITI_SRISK	17.49	0.00
Null hypothesis	χ^2	**p-value**
CITI_SRISK does not Granger cause GFC	4.90	0.18
GFC does not Granger cause CITI_SRISK	13.70	0.00

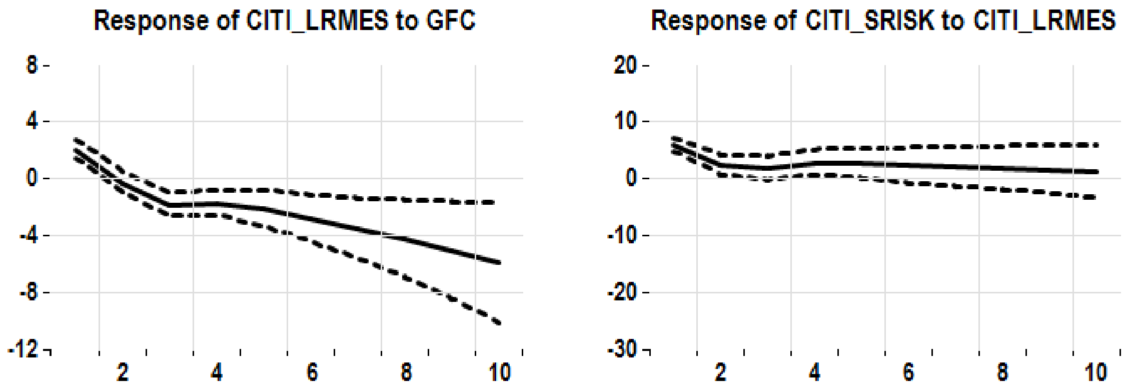

Figure A2. Generalized impulse-response functions based on the VAR(4) model for GFC, LRMES and SRISK for Citigroup, Inc.

Table A3. Results of standard Granger (no) causality tests based on the VAR(2) model for GFC, LRMES and SRISK for the UK.

Null hypothesis	χ^2	**p-value**
UK_LRMES does not Granger cause GFC	0.12	0.73
GFC does not Granger cause UK _LRMES	19.14	0.00
Null hypothesis	χ^2	**p-value**
UK_SRISK does not Granger cause UK_LRMES	1.40	0.24
UK_LRMES does not Granger cause UK_SRISK	4.00	0.05
Null hypothesis	χ^2	**p-value**
UK_SRISK does not Granger cause GFC	0.03	0.87
GFC does not Granger cause UK_SRISK	22.42	0.00

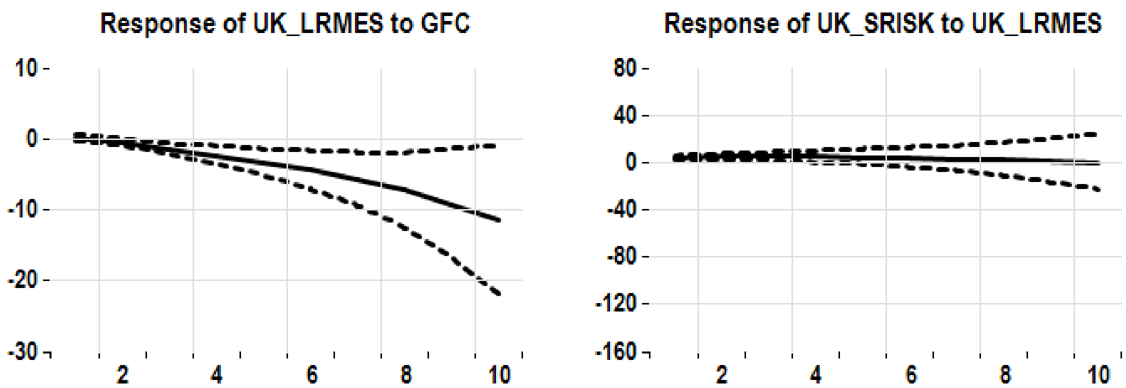

Figure A3. Generalized impulse-response functions based on the VAR(2) model for GFC, LRMES and SRISK for the UK.