5. SYSTEMIC RISK IMPACT ON ECONOMIC GROWTH - THE CASE OF THE CEE COUNTRIES[1]

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Abstract

The present paper analyses the systemic financial shock transmission mechanism in an empirical macro-financial model, estimated using a Time-Varying Parameter Vector Autoregression (TVP-VAR) with stochastic volatility. By introducing a robust measure that captures systemic risk stemming from the Eurozone financial markets, namely the Composite Indicator of Systemic Stress (CISS), along with the most relevant macroeconomic variables in a richly specified Bayesian framework, we study the time-varying impulse response functions in order to assess the structural changes that have appeared over the analyzed period. Our results suggest that, even though economies became less susceptible to systemic risk shocks after the outbreak of the financial crisis, recent years have brought a common development among analyzed countries, their main macroeconomic indicators seemingly growing more vulnerable to such shocks. We ascertain that, as a natural consequence of financial innovation, the financial system has become more robust by allowing a higher degree of connectivity and, subsequently, lowering the probability of systemic crisis episodes. Nevertheless, we also conclude that interconnectivity between financial institutions can lead to significant second-round effects, practically transforming the risk-sharing mechanism into a contagion transmission network, leading to potentially systemic events.

Keywords: systemic risk, financial stability, macro-financial linkages, TVP-VAR, stochastic volatility

JEL Classification: E44, C11, C32

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I. Introduction

The recent global financial crisis has highlighted the fact that the strong interlinkages and relationships established through the globalization process between market segments and participants have significantly altered the financial shock transmission mechanism, paving the way towards a new policy analysis paradigm, in which the financial stability of the system is a prerequisite condition for achieving sustainable growth. Furthermore, the crisis revealed how increasing financial innovation, in the context of prolonged financial stability, has created a complex financial system with a low degree of regulatory oversight. In consequence, monetary policy authorities from around the world have adopted unparalleled policy measures in order to achieve financial market stability, acknowledging the significant role that market stress episodes play in the financial system, as well as their substantial negative impact on the real economy via contagion or spillover effects, in periods of high uncertainty. The inherent lack of financial stability analysis tools was emphasized by the fact that existing macroeconomic models were incapable of quantifying abrupt non-linear adjustments as well as systemic spillover and contagion dynamics between the financial system and the real economy.

Before embarking on the daunting task of quantifying systemic risk and analyzing its impact on the real economy, we must first define the concept in a rigorous manner. The European Systemic Risk Board (ESRB), established in January 2011 as the designated authority responsible for the macroprudential oversight of the EU financial system, defines this broad concept as "a risk of disruption in the financial system with the potential to have negative consequences for the internal market and the real economy". According to the International Monetary Fund, the crucial lesson to be learned from the financial crisis is that the only way to safeguard financial stability is to treat the financial system both as an interdependent system and in the context of its interaction with the real economy. In accordance, the mandate of the ESRB[4] involves the timely identification and assessment of potential financial system vulnerabilities and their estimated impact, which allows for a proper prioritization of mitigating actions that can be taken in order to address these issues. In the aftermath of the financial crisis, the creation of the ESRB confirmed the growing importance and recognition of macroprudential oversight of the financial system as one of the main policy tools used by central banks. By applying a system-wide perspective, maintaining financial stability implies monitoring, assessing and addressing potential vulnerabilities that arise from the interconnectivity between market participants and institutions, as well as form adverse macroeconomic developments.

In an ever-changing macroeconomic environment, the benefits and vulnerabilities of financial innovation still represents a debated subject among policy-makers and market participants. From a financial stability point of view, some argue that innovation enables diversification, contributing to the resilience of the financial system while others argue the contrary by appealing to the same underlying forces.

[4] *"The ESRB's task should be to monitor and assess systemic risk in normal times for the purpose of mitigating the exposure of the system to the risk of failure of systemic components and enhancing the financial system's resilience to shocks", Regulation (EU) No. 1092/2010.*

In conclusion, systemic risk analysis implies a broad perspective of the financial system, taking into account individual developments as well as interactions between market players and institutions and, at the same time, requires identifying the main transmission channels of financial shocks to the real economy.

II. Literature Review

Systemic risk measures have become increasingly popular in recent academic literature, following the significant macroeconomic consequences of the recent financial crisis. Taking into consideration the multiple facets and definitions of the concept, several strands of empirical research have arisen, spanning from the risk contribution of large and complex financial institutions to contagion and spillover effects between counterparties and market segments and, more recently, to macro-financial linkages and stress-tests.

Estimating systemic risk contribution implies deriving methods to identify systemically important financial institutions, mainly based on equity return data. The most important studies in this field include Brownlees and Engle (2010), who introduce the concept of *Mean Expected Shorfall* (MES), Acharya, Pedersen, Philippon, and Richardson (2010), who propose a *Systemic Expected Shortfall* measure (SES) that quantifies an individual institution's contribution to overall systemic risk and Huang, Zhou, and Zhu (2009, 2010), who formulate a systemic risk measure called the *Distress Insurance Premium* (DIP), as a hypothetical insurance premium against systemic financial distress. Adrian and Brunnermeier (2009) formulate the *CoVaR* measure, i.e. the Value at Risk of the financial system conditional on an individual institution being under stress and Brownlees and Engle (2011, 2015) introduces the *SRISK* index to measure the systemic risk contribution of a financial firm.

A second direction taken by several authors in modeling and estimating systemic risk refers to quantifying contagion and spillover effects, as financial vulnerabilities from an isolated market segment can be transmitted to other parts of the financial system, leading to systemically significant episodes of turmoil. In this field of research, Diebold and Yilmaz (2009, 2012) develop a spillover index measure in order to quantify return and volatility spillovers between international capital markets, Segoviano and Goodhart (2009) define banking stability measures based on an entropy-based copula methodology that matches marginal default probability constraints from CDS markets or other sources and, similarly, Hartmann, Straetmans, and de Vries (2005) construct indicators of the severity of banking system risk by applying multivariate extreme value theory.

Hartmann, Hubrich and Kremer (2013) highlight the fact that although financial crises are a regular and infrequent occurrence across long periods of time, until recently the vast majority of macroeconomic models did not account for financial interactions and markets, in a robust manner. In order to support economic research in this relatively unexplored field, the European System of Central Banks (ESCB) has created a work stream within its Macroprudential Research Network (MaRs). According to ESCB Report on the Macroprodential Research Network published in June 2014, several

MaRs papers[5] use standard vector autoregression (VAR) or structural factor approaches to investigate the impact of various financial variables and shocks on growth and inflation in different countries (Abildgren, 2010; Fornari and Stracca, 2012; Franta *et al*., 2011; Guarda and Jeanfils, 2012; and Tamási and Világi, 2011), drawing the main conclusion that financial factors play an important role in the macroeconomic environment.

One of the fundamental challenges in assessing systemic risk and its impact on aggregate economic variables is incorporating a robust measure for systemic financial stress in macroeconomic models. An important contribution was brought by Hartmann *et al*. (2014) on the matter of incorporating systemic risk in empirical macroeconomic models using an European dataset. The authors integrated the Composite Indicator of Systemic Stress (CISS), which was developed by Holló, Kremer and Lo Duca (2012) as a measure of systemic financial instability, in a Bayesian Markov-Switching Vector Autoregression (MS-BVAR) model, following a methodology formulated in Sims and Zha (2006). The authors conclude that the most significant regime changes have an inclination to overlap with the most severe financial turmoil episodes, implying the fact that the economy functions in a profoundly different way in times of systemic instability compared to tranquil periods.

III. The Model

The present econometric approach is conceived starting from the seminal work of Hartmann *et al*. (2012), but instead uses a TVP-VAR (time-varying parameter VAR) framework in order to capture structural shifts that occurred in the estimated model parameters, implying significant changes in the systemic risk shock transmission mechanism. The main difference between, say, TVP-VAR and MS-VAR classes resides in the fact that, while the former assume that the parameters display a smooth dynamic, the coefficients of the latter are defined as discrete and sudden shifts from one state to another. In general, vector autoregressive models offer a credible approach in describing the idiosyncratic shock transmission mechanism, yet they cannot be used successfully in assessing its conduit in time, because through their conception they fall under the shortcomings described by the well-known Lucas Critique[6]. In order to address the issues identified in empirical literature, the VAR methodology was extended by incorporating concepts such as parameter time-variation or stochastic volatility inserted in the variance of the model's shocks. A decisive contribution in this line of research was brought by Primiceri (2005), who formulated a flexible model for estimating and interpreting the dynamics of monetary policy systematic and nonsystematic components and their effects on the economy. The novel technique employed in Primiceri's model involves introducing time-variation in the model parameters, as well as in the covariance matrix of the innovations, a crucial element in

[5] *Papers from Work Stream 1 (WS1) - "Macro-financial models linking financial stability and the performance of the economy".*

[6] *Lucas (1976) showed that, following a shift in economic policy, individual agents change their behavior in order to optimally adapt to the new conditions. It follows naturally that evaluating changes in policy based on estimated coefficients from historical data is infeasible, due to the fact that these coefficients will be in turn influenced by changes in the agents' behavior.*

distinguishing changes that appear in the size of the exogenous shocks from shifts in the transmission mechanism.

The estimation was performed under a Bayesian framework: the system was partitioned into three distinct blocks: a state-space representation for the VAR coefficients, one for the elements of the matrix containing the contemporaneous interactions among variables and another for the stochastic volatilities. While the first two blocks allowed for an estimation methodology using a multi-move Gibbs sampler, in the latter case the use of the Metropolis-Hastings algorithm was necessary to obtain draws from the posterior conditional distributions of the time-varying standard deviations of the shocks.

Defining a TVP-VAR model requires two main components that address the time-varying characteristics of systemic risk shock transmission: the variable parameters that measure the changes that appear in the transmission mechanism and the multiple equation model which describes the economy:

$$Y_t = c_t + \sum_{j=1}^{P} B_{j,t} Y_{t-j} + v_t \tag{1}$$

$$\beta_t = \{c_t, B_{1,t}, B_{2,t}, \dots, B_{P,t}\} \tag{2}$$

$$\beta_t = \mu + F\beta_{t-1} + e_t, \quad VAR(e_t) = Q \tag{3}$$

where: Y_t is the vector of endogenous variables of size *(M* x *1)*, c_t represents the time-varying free-term vector of equal size, $B_{i,t}$ denote the time-varying coefficients included in a *(M* x *M)* matrix and v_t are the normally distributed innovations with covariance matrix t, decomposed as follows:

$$A_t \Omega_t A_t' = \Sigma_t \Sigma_t' \tag{4}$$

The approach adopted follows Primiceri (2005), in allowing for time variation in both the additive innovations and the simultaneous interactions among variables. The simultaneous interaction is captured through the coefficients of the lower triangular matrix A_t. This specification is important in the recursive identification of the VAR system later on, as well as in the specification of the state-space system used to estimate the time-varying covariances.

$$A_t = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ a_{M1,t} & \cdots & a_{MM-1,t} & 1 \end{pmatrix} \tag{5}$$

where: M is the number of variables. The elements of A_t follow a random walk process:

$$a_{ij,t} = a_{ij,t-1} + u_t \qquad VAR(u_t) = R \tag{6}$$

Considering the decomposition of Ω_t, the above equation becomes:

$$Y_t = c_t + \sum_{j=1}^{P} B_{j,t} Y_{t-j} + A_t^{-1} \Sigma_t \varepsilon_t, \quad \varepsilon \sim N(0, I_n) \tag{7}$$

The final missing element is the equation describing the dynamics of the residuals, i.e. the elements of the matrix Σ_t.

$$\Sigma_t = \begin{pmatrix} h_{1,t} & 0 & \cdots & 0 \\ 0 & h_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & h_{M,t} \end{pmatrix} \quad (8)$$

These have been modeled as geometric random walks for two reasons: the first was to reduce the problem dimensionality, since the number of the parameters to estimate was already large, and the second was the intention to focus on permanent shifts, rather than of transitory moves:

$$\ln(h_{i,t}) = \ln(h_{i,t-1}) + \eta_{i,t} \qquad VAR(\eta_{i,t}) = z_i \quad (9)$$

IV. Estimation Methodology

Considering the fact that TVP-VAR models have a non-linear specification and contain a high number of parameters, classical approaches such as maximum likelihood are unfeasible. In this case, Bayesian inference can be applied in order to extract values from the posterior distribution of the time-varying parameters. Some of the main advantages brought by this type of estimation can be summarized by the following arguments:

- In the case of unobservable components models, for which the distinction between parameters and shocks is less clear, Bayesian Inference methods are recommended;
- Maximizing the likelihood function can prove to be a daunting task for models which contain a high number of parameters, thus implying the need for numerical approximation methods;
- Applying approaches such as the Gibbs Sampler, the general optimization problem can be segmented into simplified local optimization problems, without losing any significant information;
- The nonlinearity of the optimization problem can generate spurious solutions, some implausible for the analyzed model. Specifying a non-informative prior distribution on a plausible region can lead to better results, eliminating the issues that can arise following the classical methodology.

The estimation procedure involves combining the Carter-Kohn (1994) algorithm, used to draw β_t and $a_{ij,t}$, with the independence Metropolis-Hastings algorithm to obtain the stochastic volatility parameters[7]. The Gibbs Sampler can be defined by postulating that the state variable β_t is known and observed. In this case, the system of equations defined above can be treated as a series of linear regressions with known conditional posterior distribution of the parameters and variances. Since the state-space model for the stochastic volatility has a non-linear transition equation, the Carter and Kohn algorithm cannot be applied. Instead, Metropolis-Hastings is used to draw from its

[7] *For a comprehensive review of the main Bayesian estimation algorithms employed in this paper, please refer to Blake and Mumtaz (2012), "Applied Bayesian econometrics for central bankers", CCBS Technical Handbook No. 4, Bank of England. The present paper applies a modified version of the authors' TVP-VAR code.*

conditional distribution, and then this draw is used in the conditioning set for the posterior distribution of Z (its covariance matrix).

We have chosen the following prior distributions, based on Blake and Mumtaz (2012):

$$p(Q)\sim IW(Q_0,T_0)$$
$$p(R)\sim IW(R_0,T_0) \quad (10)$$
$$p(z_i)\sim IG(z_0,v_0)$$

As Blake and Mumtaz argue, the prior for Q is quite crucial as it influences the amount of time-variation allowed for in the VAR model. In other words, a large value for the scale matrix Q_0 induces a higher degree of variation in the model parameters. Additionally, we set $z_0 = 0.001$ and the elements of the diagonal matrix R_0 also equal to 0.001. Typically, this priors are set using a training sample, however, in order to overcome sample length issues, we chose to use the entire sample in prior selection, a strategy proposed in academic literature by Canova (2007) for limited availability of statistical information, in which choosing a small training sample can lead to significant changes in the model's output.

V. The Dataset

Estimating a TVP-VAR with stochastic volatility for the CEE countries requires selecting representative macroeconomic variables that sufficiently capture the underlying dynamics and, at the same time, formulate a robust model, as a potential over specification can lead to infeasible computational requirements. Consequently, we have chosen to study the behavior of four representative economies from the CEE region, namely Romania, Hungary, the Czech Republic and Poland, using a dataset that covers the period spanning between 2003 and 2014. The macroeconomic variables chosen are real GDP growth, a CORE measure of inflation because of its strong relationship with monetary policy dynamics and a short-term interest rate (ROBOR 3M, BUBOR 3M, PRIBOR 3M and WIBOR 3M), with quarterly frequency and totaling 48 observations per series.

Table 1

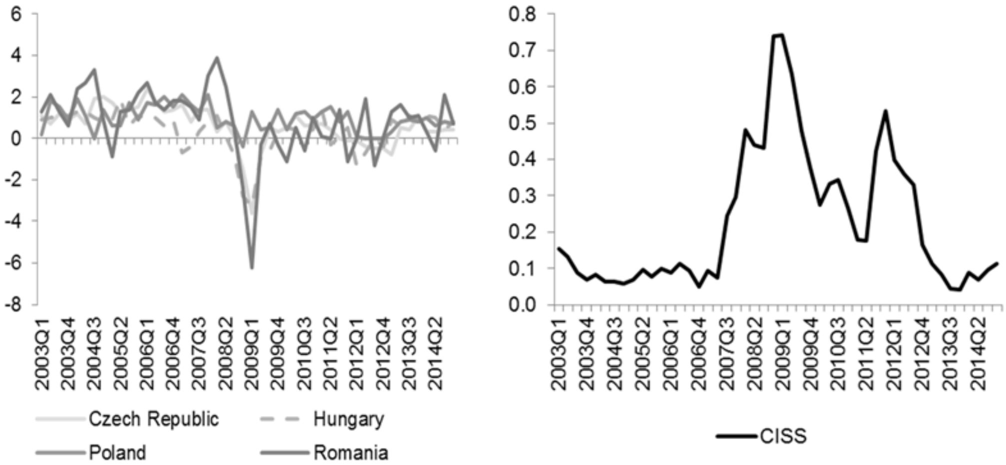
Descriptive Statistics for the CISS Indicator and Its Components (1999-2016)

	MM	FX Mkt.	Fin. Interm.	Equity Mkt.	Bonds Mkt.	Correlation contrib.	CISS
Mean	0.044	0.047	0.114	0.090	0.051	-0.149	0.197
Median	0.038	0.043	0.099	0.083	0.045	-0.142	0.131
Maximum	0.144	0.143	0.289	0.226	0.143	-0.011	0.839
Minimum	0.005	0.001	0.017	0.008	0.004	-0.396	0.021
Std. Dev.	0.026	0.029	0.064	0.051	0.029	0.079	0.171
Skewness	1.285	0.765	0.606	0.283	0.741	-0.389	1.597
Kurtosis	4.655	3.237	2.506	2.048	3.079	2.524	5.096
Jarque-Bera	351.91	90.312	64.507	46.144	83.091	31.355	549.61
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Sum	40.118	42.65	102.989	82.163	45.354	-134.711	178.561
Sum Sq. Dev.	0.635	0.805	3.755	2.417	0.799	5.755	26.352

The key missing element is a robust measure for systemic stress which, we will use as a basis to construct systemic risk shocks and study the transmission mechanism to the real economy. Although, as we have shown in the second section of the present paper, many formulations exist in recent economic literature, we have chosen to follow Hartmann, Hubrich, Kremer and Tetlow (2014), by introducing the Composite Indicator of Systemic Stress (CISS) developed by Holló, Kremer and Lo Duca (2012) in our macroeconomic model. The main descriptive statistics of the CISS indicator and its components can be found in Table 1.

Figure 1

Real GDP Growth Rate (%) and CISS Indicator (Index)



According to the aforementioned authors, this approach has several advantages:

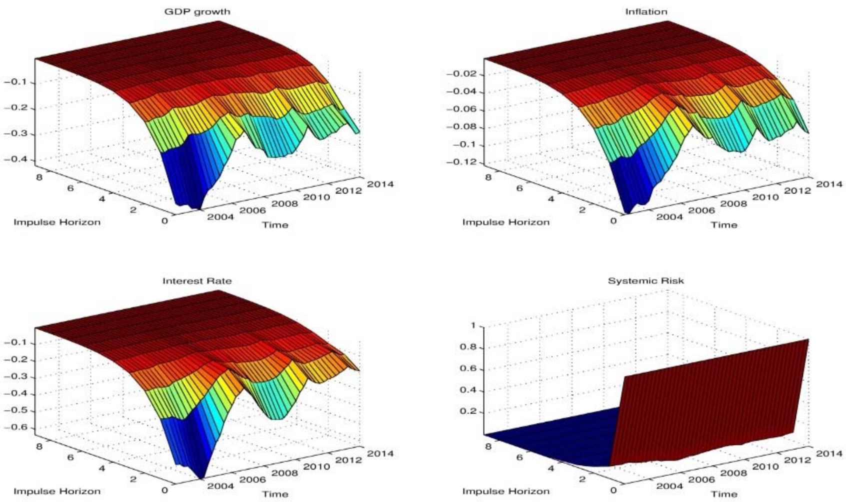
- The CISS indicator has a broad formulation as it includes representative stress measures, widely accepted as robust proxies of fundamental risks and market turmoil, such as spreads, volatilities and return correlations.
- By including 5 representative market segments (financial intermediaries, money markets, bond markets, equity markets and foreign exchange markets), it covers the main channels through which funds are reallocated, practically linking financial markets to the financing of the real economy.
- The key innovation of this approach is brought in the aggregation methodology of individual market sub-indices, by taking into account the time-varying correlations and assigning weights based on these dynamic correlations. Intuitively speaking, the CISS indicator is able to put more weight on situations in which stress prevails on several market segments at the same time.

The Bayesian estimation methodology consisted of extracting 120000 draws from the conditional posterior distribution of the parameters, using MCMC (Markov Chain Monte Carlo) methods. The first 115000 were discarded and the remaining 5000 were used for analysis in the estimated model. One lag was included in the estimation based on lag length criteria test while taking into account the relatively limited data availability for the CEE countries.

VI. Estimation Results

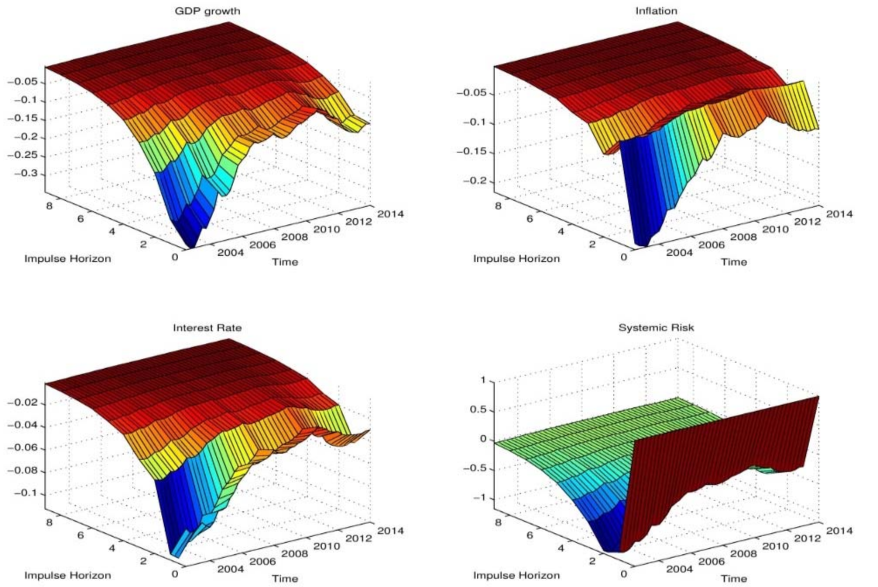
After applying the estimation procedure, we construct the time-varying impulse response functions to a unitary shock in the systemic risk indicator, in order to evaluate the changes that have affected the transmission mechanism over time. Statistical significance can be verified by analyzing Markov chain convergence (provided in the Appendix). Our results, in line with Hartmann *et al*. (2014), show that an external systemic risk shock stemming from the euro area has a negative impact on GDP growth, all the while pushing inflation and interest rates lower.

Figure 2
Time-varying Impulse Responses of Macro Variables to a Unitary Systemic Risk Shock (%) - Romania



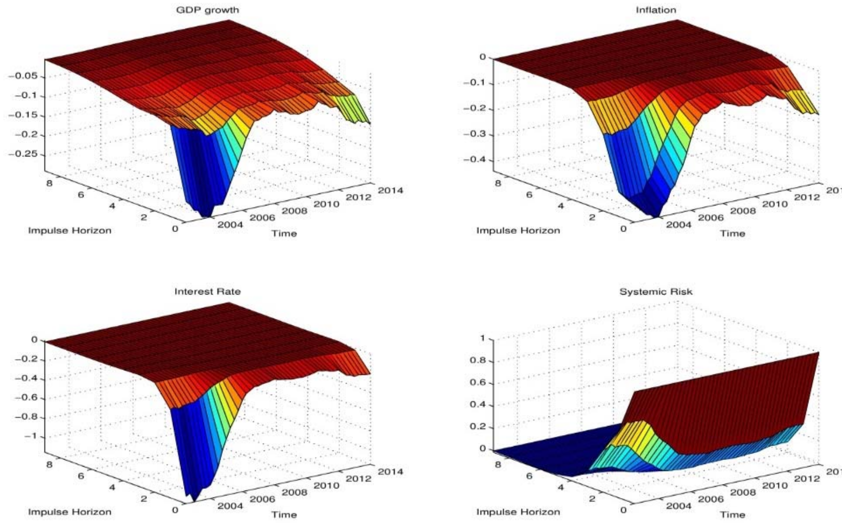
Economic growth, as well as the other variables, was more susceptible to systemic risk shocks in the pre-crisis period, as the financial systems had many weaknesses, the economic policies pursued were oftentimes inadequate and regulation was inefficient and insufficient. This confirms our previous statement regarding the consequences of the globalization process, which has significantly altered the financial shock transmission mechanism, paving the way to a new policy analysis paradigm, in which the financial stability of the system is a prerequisite condition for achieving sustainable growth. Time variation allows us to ascertain that external systemic risk shocks had a diminishing impact up to the outbreak of the financial crisis as the synchronization between the CEE countries' business cycles and the Eurozone became more obvious.

Figure 3
Time-varying Impulse Responses of Macro Variables to a Unitary Systemic Risk Shock (%) – The Czech Republic



During 2007 - 2012, the sensitivity of these variables to systemic shocks has decreased, as the crisis determined corrections to a large part of the economy, raised investor risk awareness and aversion, introduced new and stricter regulation and generally brought economic activity closer to a more sustainable level and to the long-term equilibrium.

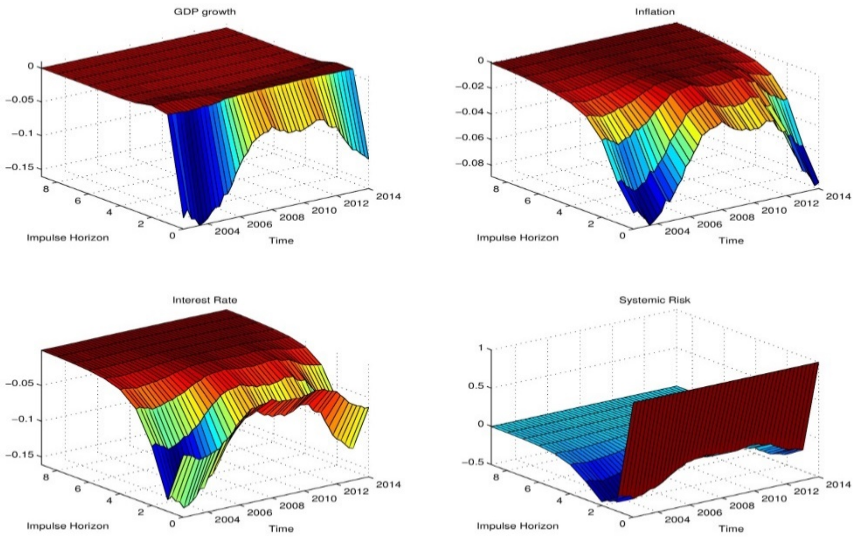
Figure 4
Time-varying Impulse Responses of Macro Variables to a Unitary Systemic Risk Shock (%) – Hungary



Although this would normally seem like an encouraging development, our results show that, with the rebound of economic activity, the main macroeconomic variables appear to have again become more likely to be affected by systemic risk shocks after 2012, in some cases nearing the pre-crisis levels. For all countries, systemic risk shocks on economic growth rate as well as on interest and inflation rates are completely dissipated after about 5 quarters of negative impact. Inflation rates and interest are only affected in the short run, the impact of systemic risk shocks being absorbed after 2-3 quarters. A slow-down in inflation, following a demand shock, is caused by a lack of spending in the economy. Following these developments, the monetary policy authority will try to drive interest rates down in order to stimulate the economy, confirmed by our time-varying impulse response analysis. In this respect, our results validate the conclusions other similar studies such as Hartman (2014) and Kremer (2015).

Even though the shapes of the impulse response functions are rather similar across countries, their magnitude is not. In the case of Poland, this difference stems from the joint influence of slow private credit growth, the effects of the Vienna Initiative and the counter-cyclical fiscal policies which, coalesced, reduced the country's exposure to external shocks. The Czech economy has historically operated at lower inflation and interest rates, so it is hard for such variables to fluctuate as drastically when affected by a shock. For illustration, the average interest rates taken into consideration for the 2002 - 2014 period were 1.87% for the Czech Republic, 4.64% in Poland, 7.31% for Hungary and 9.04% in the case of Romania. Taking all this into consideration, it is unsurprising that external systemic risk shocks have a bigger impact in on the Romanian and Hungarian economies.

Figure 5
Time-varying Impulse Responses of Macro Variables to a Unitary Systemic Risk Shock (%) – Poland



The impact on the growth rate of the GDP is greatest in Romania, which indeed had a vulnerable economy at the time, and a volatile GDP growth, falling from +8.5% in 2008 to -7.1% in 2009, while having close to no impact and being absorbed immediately in Poland. This is generally the case for all variables, meaning that Romania and Hungary have generally been more exposed to external shocks as compared to Poland and the Czech Republic. Indeed, this was apparent in 2009, when economic growth turned negative for Romania (-7.1%) and Hungary (-6.6%), while the Czech Republic's GDP dropped by only 4.8% and Poland managed to maintain positive growth.

Conclusions

Starting from the works of Primiceri (2005) and Hartmann et al. (2012), we have employed a VAR framework with time-varying parameters and stochastic volatility in order to capture the transmission mechanism of a systemic risk shock from the Eurozone to some Eastern European countries. We used Bayesian inference and a Gibbs sampling approach to measure the impact of an increase in the Composite Indicator of Systemic Risk (CISS) on GDP growth rates, inflation rates and interest rates in Romania, Hungary, the Czech Republic and Poland.

We found that, during the pre-crisis period, the economies were more vulnerable to such shocks and the impact of the abrupt rise in the CISS during 2008 brought a decline in growth rate, as well as in inflation and interest rates. This correlation became less evident during 2008 - 2012, as agents became more risk-aware and regulated and the economy was functioning closer to its potential, leaving less room for additional adjustments. A disquieting trend has been set in the most recent years however, sensitivity to systemic risk having increased, in some cases reaching levels close to those of 2007 and before. Even though, out of the 4 countries, Poland has been the least susceptible to external shocks, our analysis shows that this latter development has taken place there as well, with the economy becoming more likely to be affected by external systemic risk. While action undertaken in order to minimize and prevent further effects of the financial crisis was substantial and managed to reduce transmission of systemic risk across countries effectively, our study concludes that systemic shocks again have the potential to damage economic activity and reduce potential growth. Despite such a shock affecting macroeconomic variables for the same time horizon, the initial shock would be higher now than, say, 5 years ago.

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Appendix

Figure 6

Recursive Means for TVP-VAR Model Variables - Romania

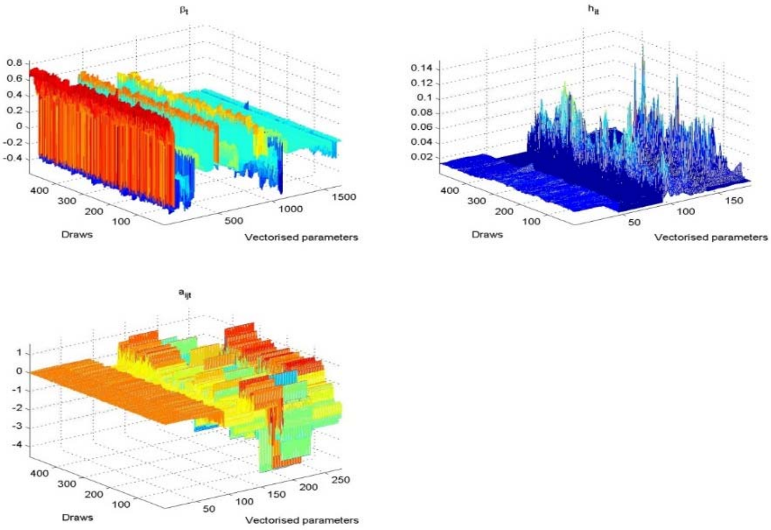


Figure 7

Recursive Means for TVP-VAR Model Variables – The Czech Republic

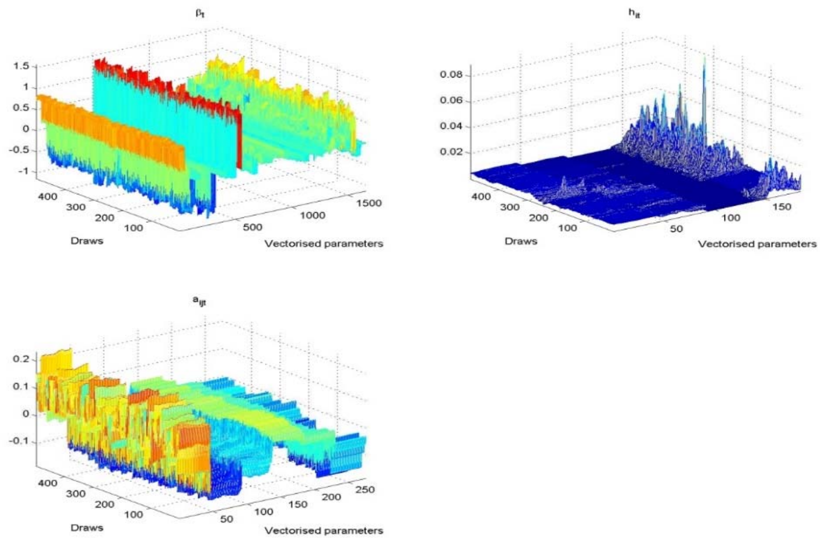


Figure 8

Recursive Means for TVP-VAR Model Variables – Hungary

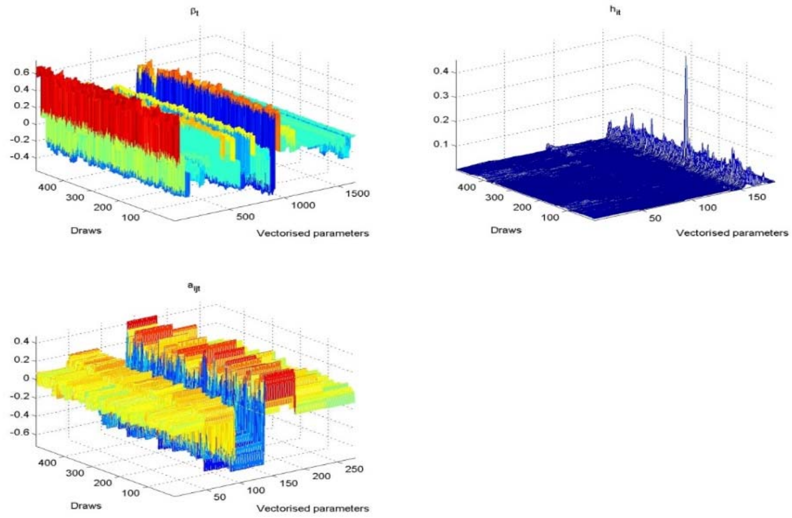
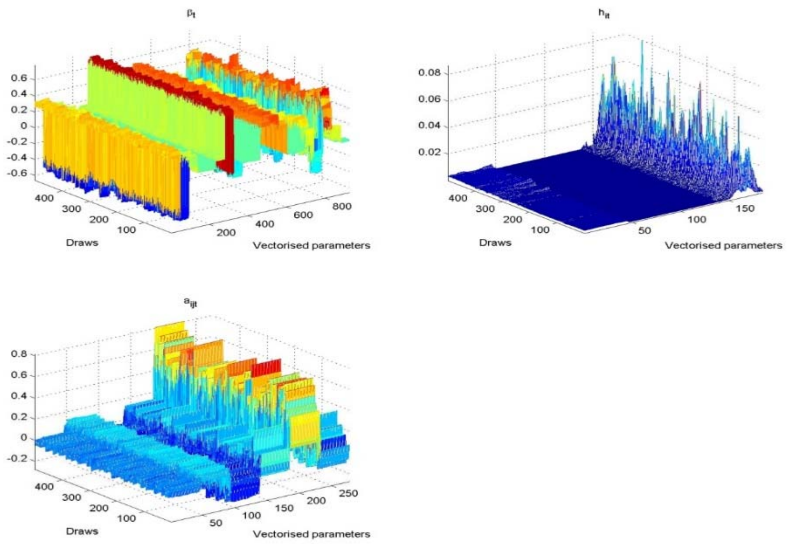


Figure 9

Recursive Means for TVP-VAR Model Variables – Poland



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