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Regime-Dependent Effects of Uncertainty Shocks. A Markov-Switching Approach for Central Eastern European Countries

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Abstract

Over the past decades, the Central Eastern European (CEE) economies have experienced events characterized by a high degree of uncertainty that have had adverse and persistent effects at the macroeconomic level. This paper analyzes the asymmetric effects of uncertainty shocks (alternately defined by a financial stress index and implied volatility) in two distinct regimes. Structural sudden regime shifts from a high-volatility regime to a low-volatility one are modeled using Markov-switching vector autoregressive models with sign restrictions, given that the probability transition matrix is either time-invariant or time-variant. Our results on key macroeconomic monthly indicators (industrial production, inflation, interest rate) suggest that uncertainty shocks produce significant short-term effects on industrial production and inflation, slightly different in these two regimes, along with a persistent effect on the interest rate.

1. Introduction

Uncertainty is a widely accepted concept in many fields, including economics, but the existing literature has yet to find a consensus on its meaning and numerically quantified measures. A famous approach in macroeconomics and finance theory is *Knightian uncertainty* addressed by Frank Knight (1921) in his seminal work, where the economist formalized an essential distinction between risk and uncertainty. According to him, uncertainty is defined by the inability of forecasters to predict the likelihood of an event occurring. Following this definition, it is impossible to make a perfect measurement for this concept, but instead, a broad range of proxies could be used to approximate it (Bloom, 2014).

This surge of interest in this research topic for the past decade has been driven mainly by the bankruptcy of Lehman Brothers in September 2008, with spillover effects on the global economy (Clayes and Vasicek, 2014; Bernal et al., 2016). Financial disruptions and heightened uncertainty are commonly the primary sources of prolonged recession after the outbreak of the international financial crisis in 2008. Most recent literature based on VAR models indicates that the impact of uncertainty shocks on the real economy is equivalent to an aggregate demand shock.

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Consequently, it significantly decreases economic activity and lowers inflation (Leduc and Liu, 2016).

In macroeconomics, research studies frequently use linear models to analyze the dynamic behavior of time series. Although these models are reasonably successful in applications, they lack the ability to capture nonlinear dynamics such as asymmetry, persistence, or volatility clustering of the data. In times marked by high levels of economic distress (e.g., crises), it might not be reasonable to expect the data to behave the same as in normal times.

Therefore, to study the potential existence of asymmetries in the transmission mechanism of uncertainty shocks, we include the following group of CEE countries: Czech Republic, Hungary, Poland, and Romania. These countries are small open economies with a comparable economic model given their characteristics (including inflation targeting and floating exchange rate regime). Furthermore, a key aspect is that these states are European Union member countries that aim to join the euro area once they have met the necessary conditions (i.e., convergence criteria). It might be difficult to attain these requirements once the economies are significantly affected by increased uncertainty. Given the interconnection of real economic activity and financial markets dynamics, the relevance of the financial markets as a trigger for a recession, to which add the limited techniques to measure uncertainty, we use two measures of uncertainty as proxies: the Euro Stoxx Volatility Price Index (VSTOXX) and a Country Level Index of Financial Stress (CLIFS). In this way, we test the hypothesis of asymmetric effects of uncertainty shocks (namely financial stress and stock market implied volatility) on three key macroeconomic indicators: industrial production, inflation, and interest rates. This study contributes to the existing literature by considering the regime-dependent perspective of analyzing the uncertainty shocks by the two approaches mentioned above, particularly at the level of this group of four CEE countries.

We motivate why we favor models with abrupt switching processes by the fact that the events of recent years demonstrated that a crisis hit the economy almost instantaneously (e.g., a pandemic crisis). The class of nonlinear Markov-switching models represents one of the most widely applied econometric methods to study structural breaks and sudden changes among various regimes over time. Thus, we adopt a Markov-switching vector autoregressive approach pioneered by Hamilton (1989) with two distinct regimes characterized by low and high volatility in the data set. From an economic perspective, this could be equivalent to a "tranquil" versus an economic "distress" period. This model allows switching between two states of the economy while each state has a distinct set of parameters controlling the data-generating process, and the transition between states is governed by a Markov chain. In this paper, for identification of the model, we impose sign restrictions[1] for the first two periods after the shock to underline those findings that are consistent with a negative impact on economic activity after an increase in uncertainty.

Moreover, the motivation for this regime-dependent analysis of uncertainty shocks in these CEE countries is supported by the fact that the impact of an increase

[1] This particular non-structural identification, proposed by Faust (1998) and Uhlig (2005), comes from the critique that conventional recursive identification strategies are inconsistent with economic theory and monetary policy responses to shocks.

in uncertainty on the real economy may vary through the business cycle[2] and across emerging and developed countries (Bloom, 2014). Some evidence of different adverse effects of uncertainty shocks on the economy points out from the comparison between the global financial crisis (the longest in the postwar history crisis) and the pandemic crisis, both marked by high levels of volatility in the data set. While for the first one, the global economy experienced a more than four-year delay in recovery caused by the fragility of the financial systems, during the COVID-19 crisis, the measures implemented to prevent infections efficiently speed up the recovery (Brada et al., 2021). The global economy recovered fast and firmly at the end of 2020 and the beginning of 2021 from its low levels during pandemic, with an almost V-shaped rebound confirmed by macroeconomic data releases. Nowadays, we have to face the impacts and challenges of the COVID-19 pandemic and the consequences of the prolonged war in Ukraine over energy prices and supply chain disruptions. Following all the recent adverse events mentioned above, models with regime-switching are appropriate to assess the impact of uncertainty shocks.

The rest of the paper is organized as follows. The next section reviews some measures of uncertainty and potential mechanisms for the transmission of shocks identified in the existing literature. The third to fifth sections present the data, the model and empirical results from the economic framework following a Markov-switching approach. The last section summarizes the key ideas that arose from this study.

2. Literature Review

This paper relates to increasing research that seeks to use the indicators that approximate measures for uncertainty and risk and their economic implications on macroeconomic fluctuations. Among others, Bloom (2009) and Cascaldi-Garcia et al. (2020) document comprehensively different measures for uncertainty established in studies. Defining the nature of the risk is crucial, especially when we confront new sources of risk, including trade and global tensions, natural disasters, or health crises such as the outbreak of the COVID-19 pandemic. In economics, the differences between real-time measures and those that are constructed ex-post influence the forecasting performance of the econometric models. A selective list with economic uncertainty measures gathers indicators estimated from news-based metrics, including the frequency of occurrence of policy-related words[3], measured by the monthly Economic Policy Index[4] or World Uncertainty Index[5] based on the quite same standpoint. Other indicators of risks are related to market volatility, such as option-implied stock market volatility (e.g., the Euro Stoxx 50 Volatility Index, VSTOXX) or a relatively new measure of financial stress, represented by the Country-Level Index of Financial Stress (CLIFS index). In this paper, we focus on the last two abovementioned measures.

[2] In particular, uncertainty rises sharply in recessions and falls rapidly in booms.
[3] There were collected news articles containing specific terms such as: "uncertain" or "uncertainty", "economic" or "economy" and also "congress", "deficit", and "regulation".
[4] Developed by Baker et al. (2018).
[5] Developed by Ahir et al. (2018) at a quarterly frequency.

Before the seminal work of Bloom (2009), there was little concern about the transmission mechanism of uncertainty shocks. The effects of uncertainty on macroeconomic and financial activity have become a prevalent topic in economics. Most academic research on this topic concurs that uncertainty shocks adversely affect the economy (Bloom, 2009; Caggiano et al., 2014). Moreover, uncertainty shock propagates in the economy as an aggregate-type demand shock that decreases economic growth and inflation. While literature attempts to provide that uncertainty shocks produce specific recessionary effects, primarily through consumption and precautionary saving channels, empirical evidence on the relationship between uncertainty and inflation is mixed or indeterminate, as in Meinen and Roehe (2018). On one side, Christiano et al. (2014), Leduc and Liu (2016), and Haque and Magnusson (2021) conclude that uncertainty shocks are deflationary, while Caggiano et al. (2022) find that uncertainty triggers only a temporary decrease in prices in recessions while in normal times the response is not statistically significant. On the other side, Mumtaz and Theodoridis (2018) found inflationary effects for the entire period after the WWII period, and Alessandri and Mumtaz (2019) found evidence of inflationary responses in normal times when they have a limited impact on the output. The effects of the uncertainty shocks over the interest rates are negative, according to Haque and Magnussun (2021). They brought evidence from a time-varying parameter vector autoregressive with stochastic volatility. The global uncertainty eases the low-rate environment, which significantly reduces the effectiveness of monetary policy (Ulate, 2021).

Moreover, after the outbreak of the COVID-19 pandemic, recent literature gained interest in this topic. Dietrich et al. (2022) show that consumers' perceptions regarding output and inflation react rapidly to uncertainty shocks, and effective policy communication with the household sector may dampen the rise in uncertainty and limit the effects. Using a threshold vector autoregressive model, Balcilar et al. (2022) prove that the contraction of industrial production due to uncertainty shocks is significantly larger than during normal times. The response of monetary authorities against financial uncertainty shocks is cautious, and the central bank adopts a more hawkish monetary policy in times of financial stress.

The methodology frequently used to assess the effects of the uncertainty shocks divides models into vector autoregressive models (VAR) and Dynamic Stochastic General Equilibrium models (DSGE). The negative impact of aggregate uncertainty and financial conditions shocks through a VAR perspective is studied in papers such as Balcilar et al. (2022), Caggiano et al. (2014), Choi (2017), Meinen and Roehe (2018), and Houari (2022). The other approach of equilibrium models is widely used to study the impact over the business cycle with nominal, real, or financial frictions (see, for example, Leduc and Liu, 2016; Bonciani and van Rye, 2016; Basu and Bundick, 2017; Ascari et al., 2023). In this sense, results point out that uncertainty can be a source of economic fluctuations. These are in line with the seminal work of Bernanke et al. (1998) that following a DSGE model under financial frictions and incorporating the financial accelerator mechanism, the authors find that risk shocks (i.e., fluctuations in the volatility of cross-sectional idiosyncratic uncertainty) are the most critical drivers of the business cycle. Additionally, a few papers attain the impact of uncertainty shocks by using the Dynamic Factor Model (see, for example, Mumtaz and Theodoridis (2017)) or a Factor-Augumented VAR model (see Hankins et al. (2022).

From a regime-switching model with smooth drifting coefficients (i.e., smoothed transition regression model), Caggiano et al. (2014) conclude that uncertainty shocks produce asymmetric effects over the business cycle. Thus, inflation reacts more strongly to uncertainty shocks during recessions than expansions. The work of Jurado et al. (2015) and Scotti (2013) provides similar evidence.

Regarding the case of Markov-switching VAR models, we found evidence in the recent literature about the adverse impact of uncertainty shocks over the exchange rate and oil price (Aimer and Lusta, 2021) or the role of oil price uncertainty in driving inflation expectations or inflation anchoring as in Chang et al. (2023). The last mentioned paper also proves that uncertainty shocks, particularly for oil prices, act as an aggregate demand shock, resulting in lower expected inflation and increased disagreement about the expected inflation of professional forecasters and households.

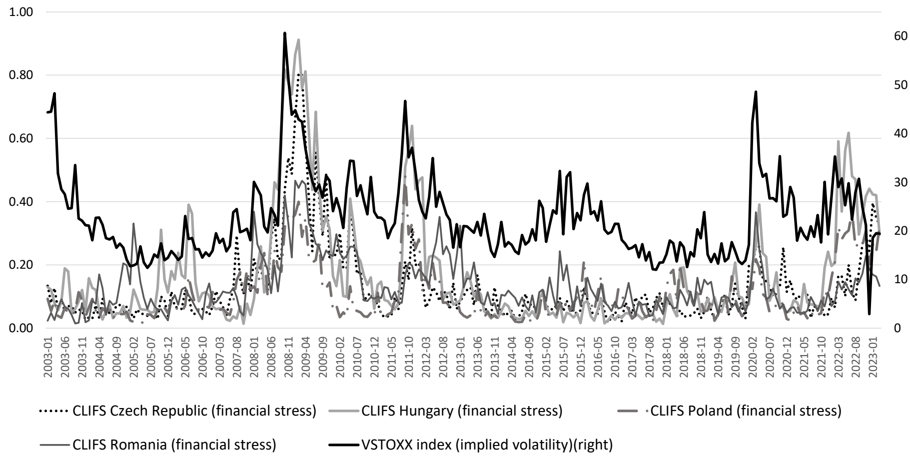
Diebold et al. (1994) and Filardo and Gordon (1998), among others, suggest that movements across regimes are recurrent. Consequently, the two-regime Markov-switching model is adequate to capture the behavior of macroeconomic data. In addition, we can consider that the two regimes are equivalent to low-high volatility regimes or recession-expansion periods. We assume symmetry across regimes and that the probabilities of jumping from one regime to another are identical, a procedure similar to Sims and Zhao's (2006) or Lhuissier and Tripier's (2016) approach to parsimonious parametrization. To the extent of Filardo and Gordon (1998) that the economy's internal propagation mechanism may affect the expectation of the duration of a business cycle phase, we extend our analysis to a time-varying Markov-switching model with a probit form for the latent variable to specify the transition probability process. We use the Economic Sentiment Indicator (ESI) as a leading indicator, given that a low index value could be positively associated with the probability of a recession.

According to Bloom (2014), uncertainty shocks generate large and persistent drops, followed by rebound and an overshoot in economic activity. The size and the persistence of spillover effects across regimes and countries depend on the sources of uncertainty. Due to the strong correlation between volatility shocks and other uncertainty measures, Bloom (2009) suggests that the implied share-returns volatility VIX index is a canonical measure of uncertainty in financial markets. Furthermore, this index could be a broad measure of uncertainty as it captures uncertainty directly related to financial markets and the macroeconomic framework. In this paper, the VSTOXX index based on Euro Stoxx real-time option prices was preferable at the expense of the broadly used VIX index because of the increased integration and co-movements across European and US markets (Morana and Beltratti, 2008). Ferrera and Guerin (2016) state that there could be a mismatch between the frequency of data from the estimated model and the frequency at which economic agents form their decisions, which results in a temporal aggregate bias. According to their recommendation, we perform the models with monthly data to identify uncertainty shocks at a high frequency and evaluate the macroeconomic effects in the context of the limited availability of macroeconomic data for the analyzed economies.

3. Data

In this paper, as we mentioned before, we identify uncertainty shocks from two different viewpoints. One of these is the most-watched European volatility index, the Euro Stoxx 50 Volatility Index (VSTOXX), which is the equivalent of VIX, the "investor fear gauge" market index and which measures the implied volatility of near-term EuroStoxx 50 options, a benchmark to quantify market expectations. Data series are available at Thomson Reuters Datastream, and these have been aggregated at monthly frequency as the average of daily data. The second proxy for uncertainty is the country-level financial stress index (CLIFS), which measures the current state of stress in the financial system. This indicator at the country level is from Duprey and Klaus (2017), and it is available on the European Central Bank (ECB) statistical database[6]. Given the different estimations for each of the two indicators above, we find a moderate linear association for each country, described by a correlation coefficient between VSTOXX and CLIFS of 0.6 (Czech Republic), 0.6 (Hungary), 0.5 (Poland) and 0.5 (Romania), respectively.

Figure 1 Evolution of CLIFS Index and VSTOXX in the Period January 2003 – March 2023



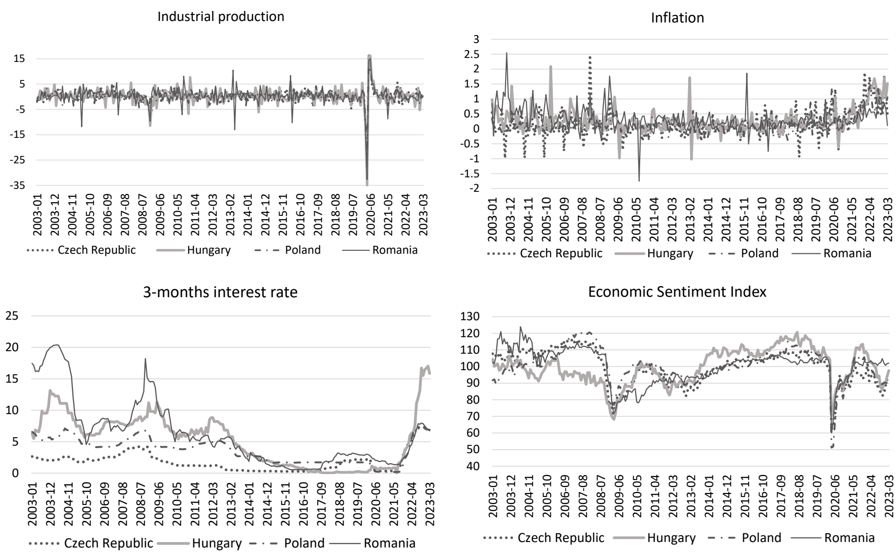
Source: ECB, authors' calculations

The evolution of these two types of uncertainty measures from January 2003 to March 2023 is represented in Figure 1. The outbreaks of the global financial crisis and the COVID-19 pandemic have been mirrored by a sudden and sharp increase in market volatility and financial stress for all CEE countries considered in this analysis. The dataset is completed by three monthly observable variables for each country: industrial production, inflation and interest rate. The first two indicators are representative of the real economy, available on the Eurostat database, to which we applied relative change. Therefore, we define the output as industrial production growth while inflation is calculated as a percentage change from the harmonized

[6] Available at https://sdw.ecb.europa.eu/browse.do?node=9693347.

index of consumer prices. For the third indicator, we include the level of the short-term interest rate on the interbank money market (at three months) due to its importance for monetary policy effectiveness, which is also available on the Eurostat database. Besides these, we include the Economic Sentiment Indicator (ESI) as a leading indicator in the probability matrix for the extension of Markov-switching. The Directorate General for Economic and Financial Affairs (DG ECFIN) produces this indicator. We plot the evolution of the dataset in Figure 2. A table with descriptive statistics is in Appendix 1. The maximum and minimum values are recorded at the pandemic outbreak and the subsequent recovery.

Figure 2 The Evolution of the Dataset in the Period January 2003 – March 2023



Source: Thomson Reuters Datastream, DG ECFIN, authors' calculations

4. Gibbs Sampling for Markov – Switching Bayesian models

A Gibbs sampling algorithm represents a well-suited approach to estimate Markov-switching models by carrying out the abrupt structural change of macroeconomic variables. Both extensions developed in this paper are based on Hamilton (1989), Hamilton (1994) and Kim and Nelson (1999).

4.1 Markov – Switching VAR

Before considering the case of the Markov-switching vector autoregressive model with two distinct regimes, we need to define the Markov-switching regression as follows:

$$y_t = x_t b_{S_t} + v_t, v_t \sim N(0, \sigma_{S_t}^2)$$
$$b_{S_t} = b_0(1 - S_t) + b_1 S_t,$$
$$\sigma_{S_t}^2 = \sigma_0^2 (1 - S_t) + \sigma_1^2 S_t$$

where S_t for $t = 1, \dots T$ is an unobserved dummy variable that indicates when a sudden regime shift takes place and follows a first-order Markov chain. Hence, the economic fluctuations are modeled as a state-dependent autoregressive process, where S_t depend on S_{t-1}. As we mentioned before, we consider the simplified model with two regimes where the transition probabilities are time-invariant given by

$$Pr[S_t = 0|S_{t-1} = 0] = p_{00}$$
$$Pr[S_t = 1|S_{t-1} = 0] = p_{01} = 1 - p_{00}$$
$$Pr[S_t = 1|S_{t-1} = 1] = p_{11}$$
$$Pr[S_t = 0|S_{t-1} = 1] = p_{10} = 1 - p_{11}$$

If we note $i, j = \{0,1\}$, then p_{ij} denotes the probability that the current regime j is conditioned by the fact that the regime from the previous period was i. Thus p_{ii} refers to the probability of the process remaining in the same regime. A value for p_{00} and p_{11} close to 1 indicates persistence in the respective regime. The transition probability matrix is

$$P = \begin{pmatrix} p_{00} & p_{10} \\ p_{01} & p_{11} \end{pmatrix}$$

The filtering algorithm to estimate the probability terms $Pr[S_t = i|I_t]$ proceeds in two steps (prediction step and update step, respectively) computed at each point in time[7]. We define the multivariate representation of a Markov-switching VAR as in Blake and Mumtaz (2017)

$$Y_t = c_{S_t} + \sum_{p=1}^{P} B_{S_t} Y_{t-p} + v_t,\ v_t \sim N(0, \Omega_{S_t})$$

A Gibbs algorithm to estimate the four sets of unknown parameters (latent variable $\tilde{S}_t = [S_1, \dots S_T]$, the elements of P matrix, coefficients b_{S_t} and variances $\sigma^2_{S_t}$ from Ω_{S_t}) sample from the following posteriors distributions

Conditional on P, $\sigma^2_{S_t}$ and $\tilde{S}_t$ draw b_{S_t} from its conditional posterior distribution.
Conditional on P, b_{S_t} and $\tilde{S}_t$ draw $\sigma^2_{S_t}$ from its conditional posterior distribution.
Conditional on $\sigma^2_{S_t}$, b_{S_t} and $\tilde{S}_t$ draw P from its conditional posterior distribution.
Conditional on $\sigma^2_{S_t}$, b_{S_t} and P draw $\tilde{S}_t$ from its conditional posterior distribution.

Conditional posterior for the transition matrix is sampled from a Dirichlet prior distribution widely used in probability theory and Bayesian statistics to model categorical variables. Thus, for each column of P matrix, it is defined the Dirichlet prior $p(p_{00}) \sim D(\alpha_{00}, \alpha_{01})$ and $p(p_{11}) \sim D(\alpha_{11}, \alpha_{10})$.

[7] For additional technical details regarding the algorithm, see Hamilton (1994).

By using Bayes' theorem and combining the prior defined above with the likelihood of the parameters given the data, it will result a conditional posterior distribution which is also Dirichlet: $H(p_{00}|S) \sim D(\alpha_{00} + \eta_{00}, \alpha_{01} + \eta_{01})$ and $H(p_{11}|S) \sim D(\alpha_{11} + \eta_{11}, \alpha_{10} + \eta_{10})$, where the parameters η_{ij} counts for the number of times that regime j is followed by regime i. This can be done using the draws of the state variable $\tilde{S}_t$, and therefore, the conditional posterior is independent of the data or other parameters from the model.

The conditional posterior of $\tilde{S}_t$ defined as $H(\tilde{S}_t|\sigma^2_{S_t}, b_{S_t}, P, Y_t)$ is drawn by using the same method as the one used by Kim and Nelson (1999) to derive Carter and Kohn's recursion algorithm for state-space models. Using the Markov property of S_t, the state variable is from the following density

$$H\left(\tilde{S}_t \middle| \sigma^2_{S_t}, b_{S_t}, P, Y_t\right) = H(S_T|\tilde{Y}_T) \prod_{t=1}^{T-1} H(S_t|S_{t+1}, \tilde{Y}_t)$$

During the estimation through Hamilton filter to obtain the probability $f(S_t|I_{t-1}, y_t)$, for $t = 1,2, \dots T$, the conditional likelihood is defined as

$$f(y_t|S_t = i, I_{t-1}) = 2\pi^{-0.5} det\left(\Omega^{-1}_{S_t}\right)^{0.5} exp\left(-0.5\left(Y_t - X_t b_{S_t}\right)' \Omega^{-1}_{S_t}\left(Y_t - X_t b_{S_t}\right)\right)$$

Where X stands for the lags and the intercept, while b is the $(np + 1)\ x\ n$ matrix (n variables and p lags) of coefficients B and the intercept term c.

The vector autoregressive parameters are sampled in each regime by using a Normal prior for coefficients $p\left(b_{S_t}\right) \sim N\left(\tilde{b}_0,\ H\right)$ and an inverse Wishart prior for the error covariance matrix $p\left(\Omega_{S_t}\right) \sim IW(\bar{S}, \alpha)$, the conditional posterior will follow the same distributions.

$$H\left(b_{S_t}|\Omega_{S_t}, P, S_t, Y_t\right) \sim N\left(M^*_{S_t}, V^*_{S_t}\right)$$
$$H\left(\Omega_{S_t}|b_{S_t}, P, S_t, Y_t\right) \sim IW\left(\bar{\Omega}_{S_t}, T + \alpha\right)$$

Where

$$M^*_{S_t} = \left(H^{-1} + \Omega^{-1}_{S_t} \otimes X'_{S_t} X_{S_t}\right)^{-1} \left(H^{-1}\tilde{b}_0 + \Omega^{-1}_{S_t} \otimes X'_{S_t} X_{S_t}\ \hat{b}_{S_t}\right)$$
$$V^*_{S_t} = \left(H^{-1} + \Omega^{-1}_{S_t} \otimes X'_{S_t} X_{S_t}\right)^{-1},$$
$$\bar{\Omega}_{S_t} = \left(Y_{S_t} - X_{S_t}\hat{b}_{S_t}\right)' \left(Y_{S_t} - X_{S_t}\hat{b}_{S_t}\right) + \bar{S}$$

where $\hat{b}_{S_t}$ is the OLS estimate in the regime $S_i = i$.

The value of the likelihood is not influenced by switching the labels attached to each regime (e.g. regime 0 and 1) and consequently, we need to impose some additional identifying restrictions to avoid a multi-modal marginal posterior. Thus we use rejection sampling, as in Blake and Mumtaz (2017), by assuming $\sigma^2_0 > \sigma^2_1$, that the first regime have higher volatility than the second one.

4.2 Markov – Switching VAR with Time-Varying Transition Probabilities

The Markov-switching models represent a useful approach to studying business cycle dynamics since volatility switches might detect turning points. The weakness of those models comes from the difficulty of establishing maximum-likelihood estimates for the unobserved variables in state space. Moreover, if we assume a time-invariant probability transition matrix, the conditionally expected duration of a regime is constant. Following Filardo and Gordon (1998) we extend the regime-switching framework to the time-varying transition probability Markov-switching model by incorporating a probit model so that the information contained in the leading indicator, defined by the Economic Sentiment Indicator improves the Bayesian estimation of transition probabilities, which are given by

$$P(S_t = s_t | S_{t-1} = s_{t-1}, z_t) = \begin{pmatrix} p_{00}(z_t) & p_{10}(z_t) \\ p_{01}(z_t) & p_{11}(z_t) \end{pmatrix}$$

Where the evolution of the latent variable is driven by its lag S_{t-1} and the lag of the consumer sentiment indicator z_{t-1}

$$P(S_t = 0) = P(S_t^* < 0)$$
$$S_t^* = \gamma_0 + \lambda z_{t-1} + \gamma_1 S_{t-1} + u_{t,}\ u \sim N(0,1)$$

We sample the transition probabilities from the normal cumulative distribution function (CDF) $\Phi(.)$.

$$Pr[S_t = 0 \mid S_{t-1} = 0\,] = \Pr[u_t < -\gamma_0 - \lambda z_{t-1} - \gamma_1 S_{t-1}\,] = \Phi(-\gamma_0 - \lambda z_{t-1})$$
$$Pr[S_t = 1 \mid S_{t-1} = 1\,] = \Pr[u_t \geq -\gamma_0 - \lambda z_{t-1} - \gamma_1 S_{t-1}\,] = \Phi(-\gamma_0 - \lambda z_{t-1} - \gamma_1 S_{t-1})$$

The Gibbs sampling algorithm for time-variant models involves additional steps to draw S_t^* and the coefficient from the vector $\Gamma = [\gamma_0, \lambda, \gamma_1]$. The algorithm is as follows

a) Sample the latent variable from $H(S_t | b_{S_t}, \sigma_{S_t}^2, \Gamma, S_t^*)$ by using the Hamilton filter where there is a different transition probability at each point in time.
b) Sample from $H(S_t^* | b_{S_t}, \sigma_{S_t}^2, \Gamma, S_t)$. S_t^* can be sampled from the left and right truncated at zero normal distribution for $t = 1,2, \ldots T$ as following

$$S_t^* \sim N_{LT}(m, 1)\ if\ S_t = 1$$
$$S_t^* \sim N_{RT}(m, 1)\ if\ S_t = 0$$

Where we noted $m = \gamma_0 + \lambda z_{t-1} + \gamma_1 S_{t-1}$.

c) Sample from $H(\Gamma\ | S_t^*, b_{S_t}, \sigma_{S_t}^2, S_t)$ where the probability equation of S_t^* is a simple linear regression with a known error variance. Assuming the prior probability distribution is $N(\Gamma_0, \Sigma_\Gamma)$, the conditional posterior is also given by a normal distribution $N(M, V)$, having

$$V = \left(\Sigma_\Gamma{}^{-1} + \tilde{z}_t' \, \tilde{z}_t\right)^{-1}$$
$$M = \left(\Sigma_\Gamma{}^{-1} + \tilde{z}_t' \, \tilde{z}_t\right)^{-1}\left(\Sigma_\Gamma{}^{-1}\Gamma_0 + \tilde{z}_t' S_t^*\right)$$

And the vector $\tilde{z}_t = [1, z_{t-1}, S_{t-1}]$.

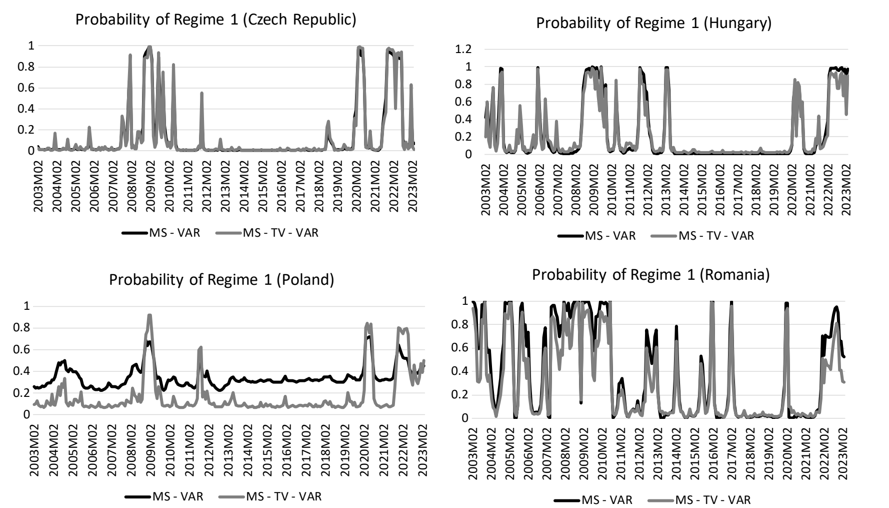
d) Sample from $H\left(b_{S_t} \middle| S_t, \sigma_{S_t}^2, \Gamma, S_t^*\right)$.

e) Sample from $H\left(\sigma_{S_t}^2 \middle| b_{S_t}, S_t, \Gamma, S_t^*\right)$.

5. Empirical Results

This section presents the estimated results associated with our identification scheme. We estimate two different vector autoregressive models by sequentially one of these two uncertainty above measures. To model the relationship between variables following a regime-switching approach, we use two Markov-switching versions with time-invariant (MS-VAR) and time-variant probabilities (MS-TV-VAR), respectively. In addition to using monthly data, particularly for the second approach, this paper applies Filardo and Gordon's (1998) method. Consequently, the transition probability matrix is governed at each moment by a probit model that incorporates the information available in a latent variable described by the ESI, deemed a leading indicator to provide signals about the state of the economy[8]. We fit our models to the key economic indicators listed in the previous section.

Figure 3 Probability of a High-Volatility Regime Using CLIFS Index (Financial Stress) as a Proxy for Uncertainty

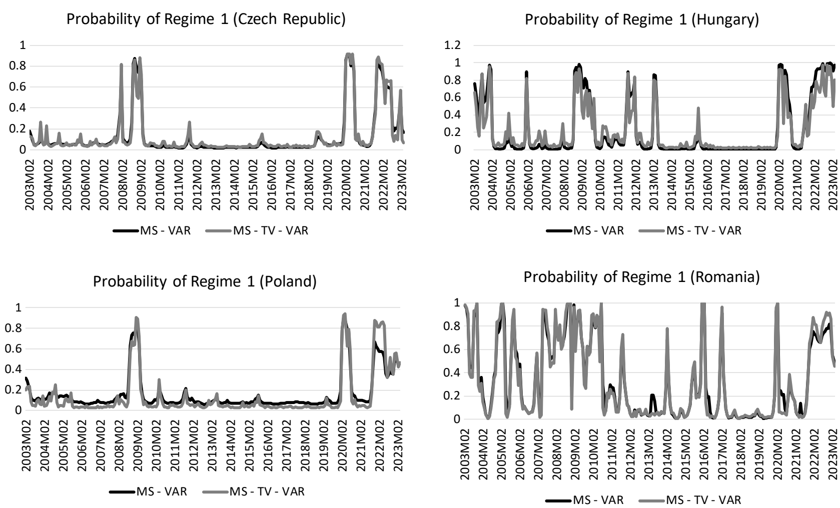


Source: Authors' calculations

[8] The assumption of the existence of two states of the economy is the most exploited in economics by aiming at "tranquil" versus "turbulent" periods.

The non-recursive identification scheme that we propose is under literature and economic theory based on sign restrictions. Hence, following Leduc and Liu (2016) and assuming that uncertainty shocks act as aggregate demand shocks, we impose negative responses in output and inflation. To stimulate economic activity, the central bank should reduce the interest rate. For robustness check and sensitivity analysis, we propose two schemes for ordering variables similar to Caggiano et al. (2014). We order the fast-moving indicator (uncertainty measure) last in the VAR model and slow-moving (macroeconomic) variables first, respectively (as in Bernanke et al., 2005). Conversely, recent studies (Caggiano et al., 2014; Ferrara and Guérin, 2018) order financial variables such as uncertainty measures first in VAR – an extension of this approach is in Appendix 4 and Appendix 5 of the paper as an exercise for robustness check.

Figure 4 Probability of a High-Volatility Regime Using VSTOXX Index (Implied Volatility) as a Proxy for Uncertainty

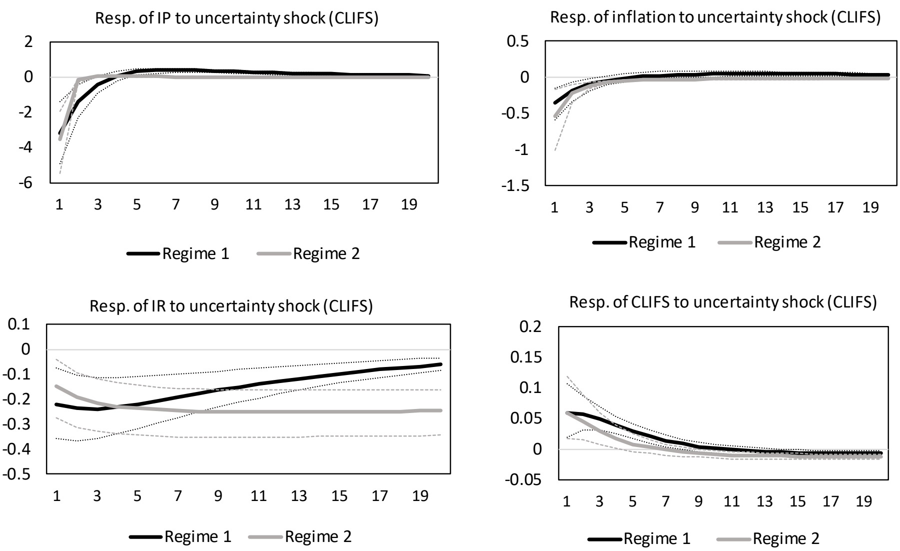


Source: Authors' calculations

In Figure 3 and Figure 4, we display the filtered probabilities of regime 1, which are representative of a period characterized by a high degree of volatility. These probabilities result from the Hamilton filter through estimating both Markov-switching VAR models consecutively using the financial stress index and implied volatility of Euro Stoxx 50 options as measures of uncertainty. We can identify the moments when the system switches from a tranquil period to times marked by economic distress. These are related to some key economic events, such as the adoption of the inflation targeting regime, the international financial crisis that started in 2008, the global trade tensions in 2016, and the COVID-19 pandemic. Among these countries, the estimated probability of the first regime from Romanian and Hungarian data provides a significant number of moments when the economy switches to the second regime. This feature could result from some particularities of the economies (such as vulnerabilities in financial markets) or volatile data. In all cases, we can observe a relatively similar estimation pattern for both measures of uncertainty.

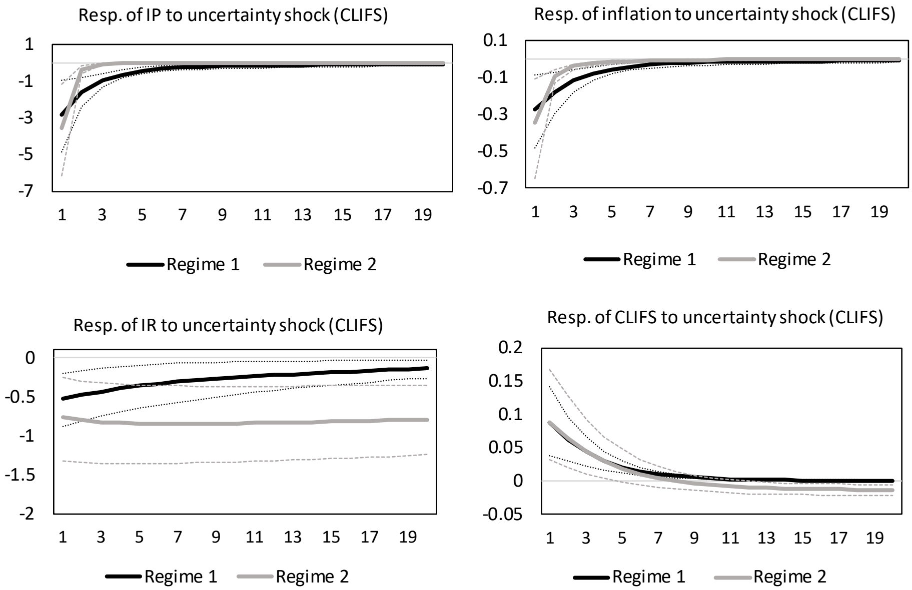
In the following figures (Figure 5 to Figure 8), we represent the impulse response functions to an uncertainty shock measured by a one standard deviation increase in financial stress CLIFS index in the Markov-switching model with time-invariant probabilities (MS-VAR). We include the results obtained with the second approach, a Markov-switching with time-varying probabilities (MS-TV-VAR), in Appendix 2. In order to make the results comparable across the two distinct regimes considered in this analysis, we scaled the estimates at regime 1 (distinguished by higher volatility than regime 2) for each of those two models (MS-VAR and MS-TV-VAR) and each country. All scenarios confirm the remarkable decreases in output and inflation (with a lower magnitude in this case) as a response to the uncertainty shocks. If we approximate an uncertainty shock as a sudden increase in the level of financial stress measured by the CLIFS index, slowly different results in these two regimes reflect the asymmetry of the transmission mechanism of shocks. Moreover, there is a persistent effect on the interest rate; the indicator does not return over the medium term to the level before the shock.

Figure 5 Impulse Response Functions to a CLIFS Uncertainty Shock for Czech Republic in MS-VAR Model



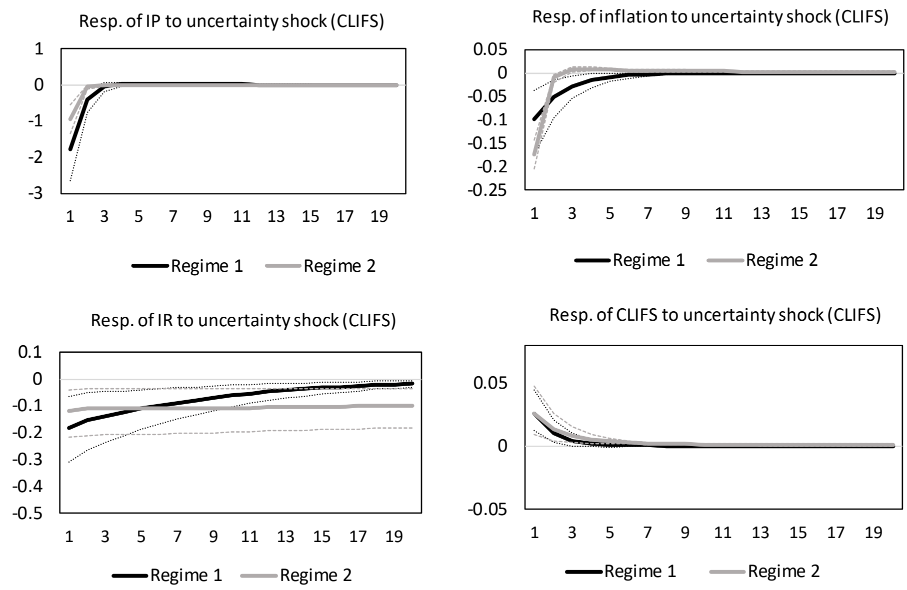
Source: Authors' calculations

Figure 6 Impulse Response Functions to a CLIFS Uncertainty Shock for Hungary in MS-VAR Model



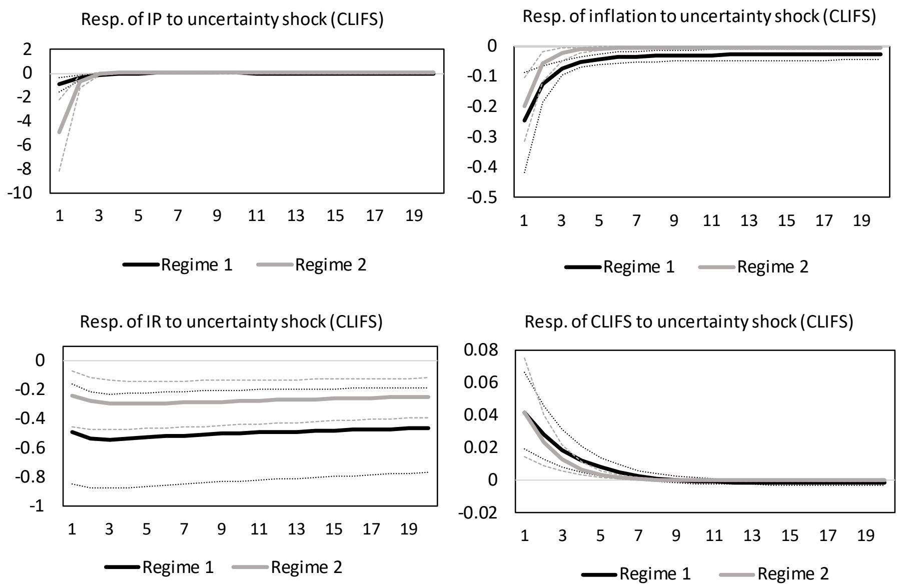
Source: Authors' calculations

Figure 7. Impulse Response Functions to a CLIFS Uncertainty Shock for Poland in MS-VAR Model



Source: Authors' calculations

Figure 8 Impulse Response Functions to a CLIFS Uncertainty Shock for Romania in MS-VAR Model



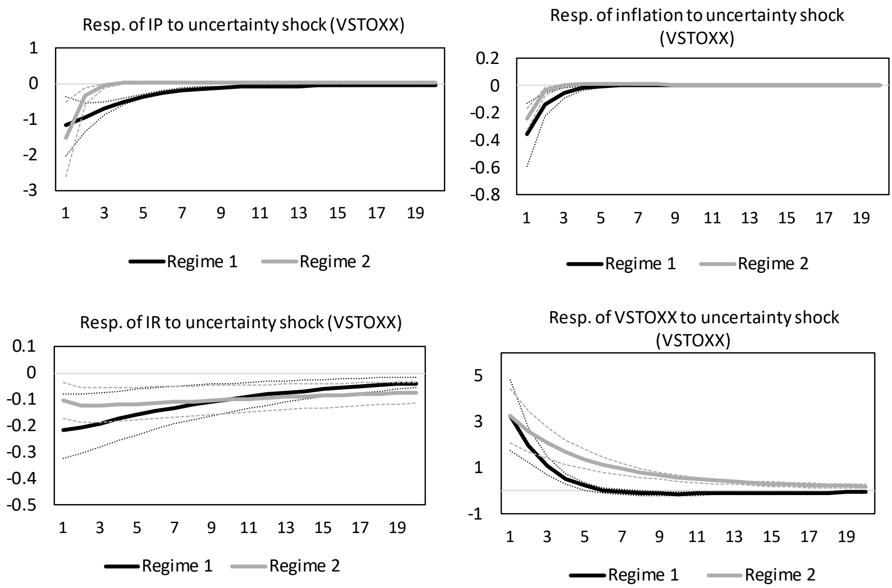
Source: Authors' calculations

In both regimes, the different magnitude of the estimates for each country results from the standard deviation of uncertainty shock. The lowest standard deviations of shocks in both MS-VAR and MS-TV-VAR (see Appendix 2) are estimated for Romania's and Poland's cases. Quantitatively, for example, in the Romania case in Regime 1, after an increase of 0.04 points for CLIFS, we expect a decrease in industrial production of almost one percentage point and a deflationary effect by 0.25 points in inflation, along with a reduction of almost 0.5 percentage points in the interest rate (Figure 8). For this case, we observe differences between Regime 1 and Regime 2; the effects are slower in Regime 1 for industrial production but slowly higher for inflation and interest rate. In the real economy, the effects are dissipated in almost five months, while monetary policy reaction exhibits persistence over the medium term. In Figure 7, the response of inflation urges a clear and abrupt fall in the short run, followed by a relatively quick rebound.

Moreover, the inflation path indicates a possible "overshoot" as Bloom (2014) suggested, such as in the case of Poland, which was after almost three months. The response to policy interest rates is robust as well. Hence, we can observe a few more discrepancies between those two methodologies, especially concerning the magnitude of the effects on the real economy. For example, in the case of Hungry, even if we have the same shock, an increase of 0.1 percentage points, the results provided by a model with time-variant probabilities (MS-TV-VAR) are higher than those from the other one (-1 percentage point relative to -0.5 percentage points).

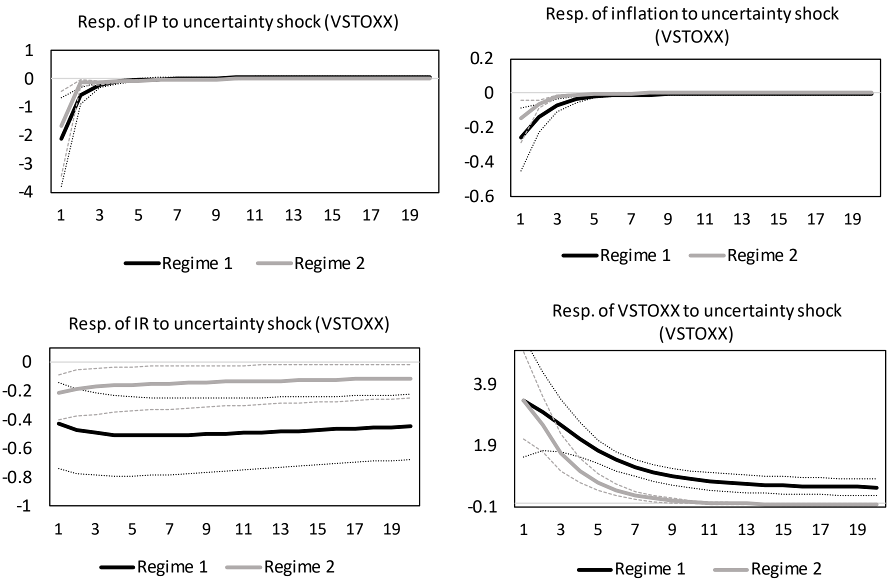
Regarding the second measure used to approximate uncertainty, we include the same indicator in each vector autoregressive model for all countries analyzed, the VSTOXX index, because this index represents all European markets (see impulse response functions in Figure 9 to 12).

Figure 9 Impulse Response Functions to a VSTOXX Uncertainty Shock for Czech Republic in MS-VAR Model



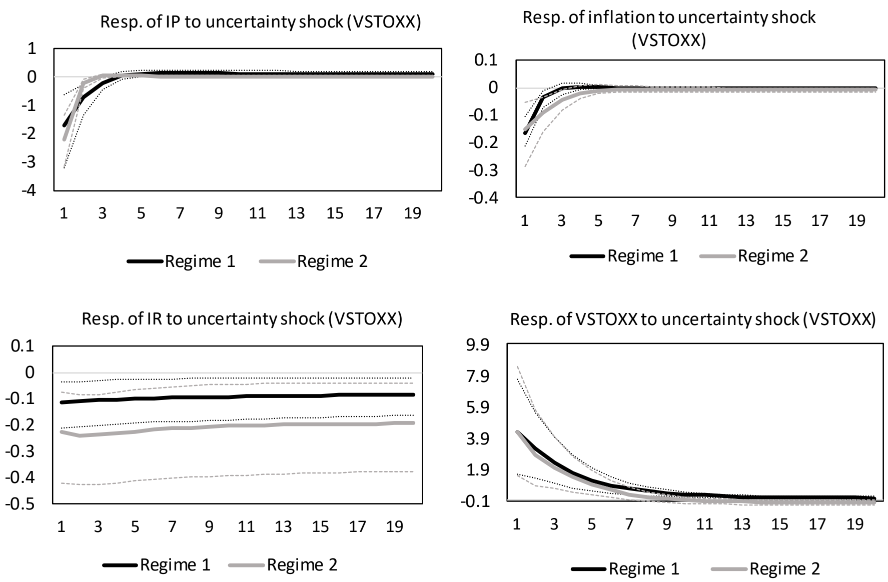
Source: Authors' calculations

Figure 10 Impulse Response Functions to a VSTOXX Uncertainty Shock for Hungary in MS-VAR Model



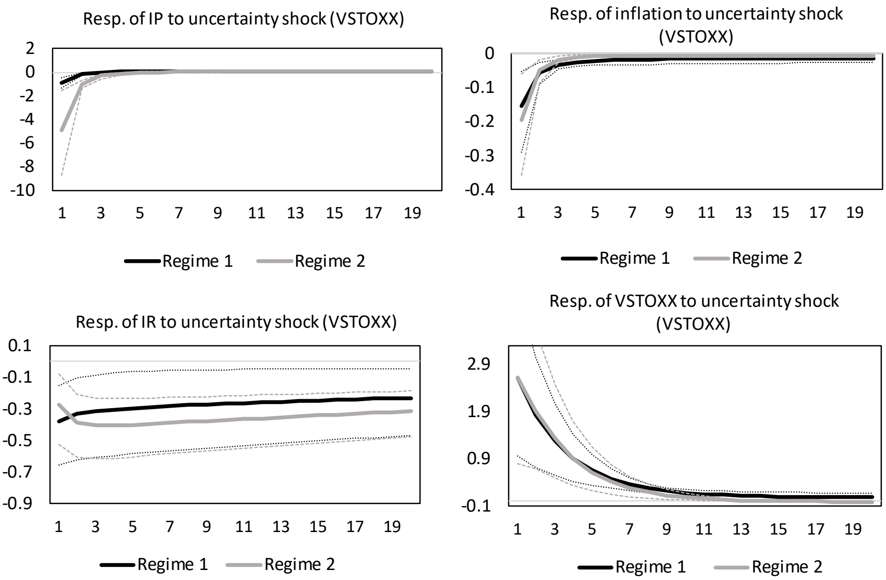
Source: Authors' calculations

Figure 11 Impulse Response Functions to a VSTOXX Uncertainty Shock for Poland in MS-VAR Model



Source: Authors' calculations

Figure 12 Impulse Response Functions to a VSTOXX Uncertainty Shock for Romania in MS-VAR Model



Source: Authors' calculations

On the one side, the magnitude of estimated impulses for uncertainty shocks is more extensive than for the other measure, which might have explanations in different units of measurement. On the other side, the effects of shocks estimated by the Markov-switching models with time-invariant transition probability matrix (MS-VAR) turn out to have a similar path of the recovery in "distress" (i.e., high-volatility regime) and "tranquil" (i.e., low-volatility regime) times for the group of CEE analyzed countries.

However, we can also observe a persistent response of interest rate, except for the case of the Czech Republic, where the impulse response functions suggest a return to the steady state for the indicator in a high-volatility regime. This persistence is evidence providing that the decision of the central bank to lower interest rates to stimulate the real economy could be permanent (i.e., the interest rate does not return to the level previous to the shock). The responses to the same shock in two different regimes are relatively similar. However, we observe slightly higher responses on industrial production and inflation in the second regime (e.g., Romania). Moreover, similar to Caggiano et al. (2014), the estimates on the macroeconomic effects of uncertainty shocks and the recovery path, especially in turbulent periods (such as recessions), turn out to be robust in these two alternatives ordering (i.e., uncertainty measure being ordered last and first, respectively). For details, see Appendix 4 and Appendix 5.

6. Concluding Remarks

This paper focuses on the impact of uncertainty shocks on some CEE economies, particularly on monthly macroeconomic key variables. Within this scope, we use two proxy approximations for uncertainty, a country financial stress index (CLIFS indicator) and the stock market volatility quantified by the Euro Stoxx 50 Volatility Index (VSTOXX), to reflect the market investors' expectations. We use industrial production growth, inflation rate, and interbank 3-month short-term interest rates to determine the effects on the macroeconomic framework.

To perform this analysis, we apply the class of two states Markov-switching models in sign restrictions vector autoregressive (VAR) models from two perspectives. First, we assume the probability transition matrix is time-invariant, so the probability of switching in the Markov chain from one state to another is constant in time. Second, we extend this model as in Filardo and Gordon (1998) to a time-varying probability matrix, where the latent variable is related to the evolution Economic of Sentiment Indicator as a leading indicator that could provide signals about the current state of the economy and the potential risk of recession. We perform a robustness analysis from two alternative ordering of uncertainty measures in the VAR model (first and last).

Our main results suggest that there are some pieces of evidence of regime-dependent responses to uncertainty shocks, which are in just a few cases slightly more pronounced in the high-volatility regime or financial distress periods, or they are similar in both states. Despite the magnitude of the effects being related to the estimation method of parameters, in both Markov-switching models, the recovery paths after the shock are similar. While output and inflation have an abrupt decrease in the short-run followed by a quick rebound, the monetary policy response exhibits persistence, being more resilient in the medium term.

APPENDIX

Appendix 1

Table 1a Descriptive Statistics for Czech Republic and Hungary Data Set

	Czech Republic				*Hungary*			
	Industrial production (%)	Inflation (%)	Interest rate	Clifs index	Industrial production (%)	Inflation (%)	Interest rate	Clifs index
Mean	0.13	0.20	0.18	1.83	0.17	0.26	0.30	5.26
Median	0.09	0.25	0.10	1.54	0.09	0.24	0.21	6.13
Maximum	0.81	16.73	2.47	7.30	0.91	16.24	2.09	17.03
Minimum	0.02	-27.61	-0.99	0.28	0.01	-35.04	-1.02	0.00
Standard deviation	0.12	2.98	0.47	1.61	0.18	3.68	0.41	4.11
Skewness	2.79	-2.75	1.10	1.63	2.02	-3.16	1.25	0.42
Kurtosis	12.44	38.76	6.55	5.97	6.77	39.14	6.55	2.55
Jarque-Bera test	1219.09	13255.42	176.75	197.32	310.26	13625.70	191.06	9.08
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01

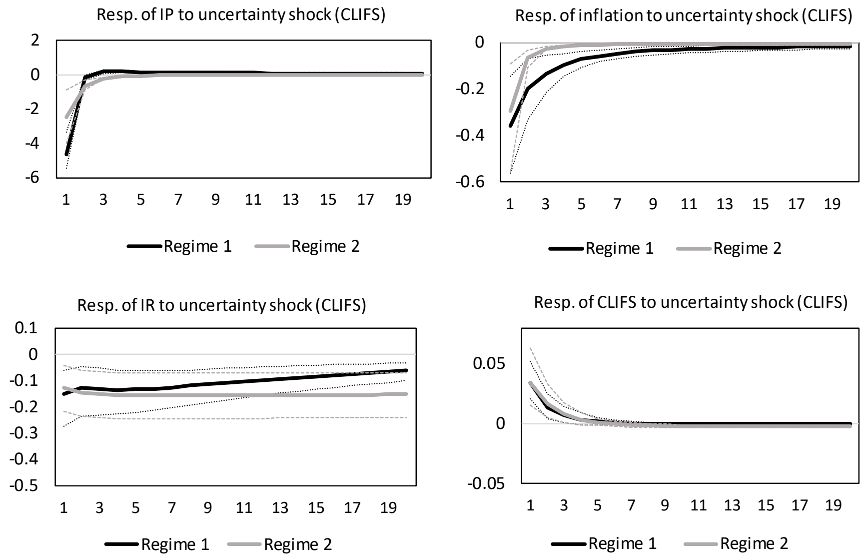
Table 1b Descriptive Statistics for Poland and Romania Data Set

	Poland				*Romania*			
	Industrial production (%)	Inflation (%)	Interest rate	Clifs index	Industrial production (%)	Inflation (%)	Interest rate	Clifs index
Mean	0.11	0.45	0.18	3.62	0.13	0.22	0.33	6.30
Median	0.07	0.61	0.11	4.12	0.10	0.31	0.25	5.25
Maximum	0.48	12.10	1.43	7.43	0.47	15.06	2.55	20.39
Minimum	0.02	-22.90	-0.42	0.21	0.01	-32.70	-1.75	0.51
Standard deviation	0.09	2.50	0.31	1.96	0.09	3.74	0.40	5.32
Skewness	1.61	-2.97	1.46	0.03	1.59	-2.87	0.82	1.17
Kurtosis	5.10	35.82	5.92	1.91	5.83	29.83	9.99	3.54
Jarque-Bera test	149.83	11265.76	172.04	12.11	183.38	7622.82	521.17	58.36
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors'calculations
Notes: All time series include 243 observations, equal to the period between fourth month of 2003 and third month of 2023

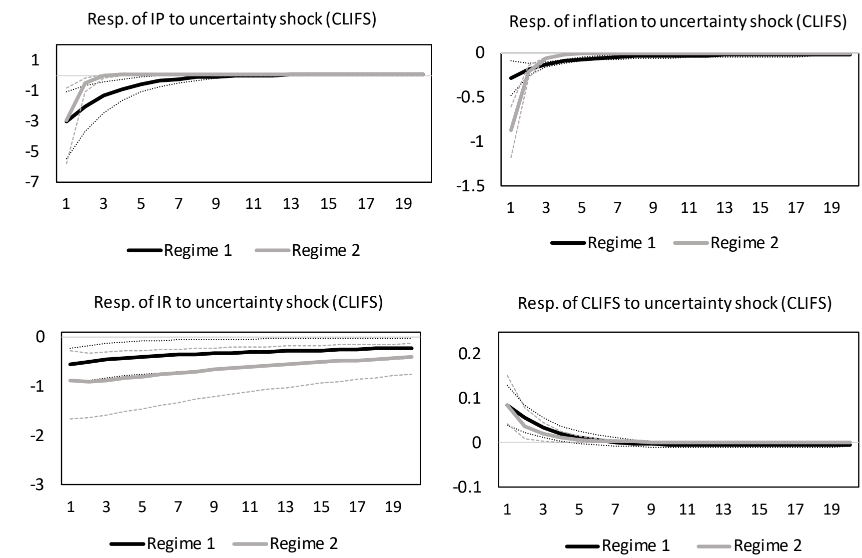
Appendix 2

Figure 2a Impulse Response Functions to a CLIFS Uncertainty Shock for Czech Republic in MS-TV-VAR Model



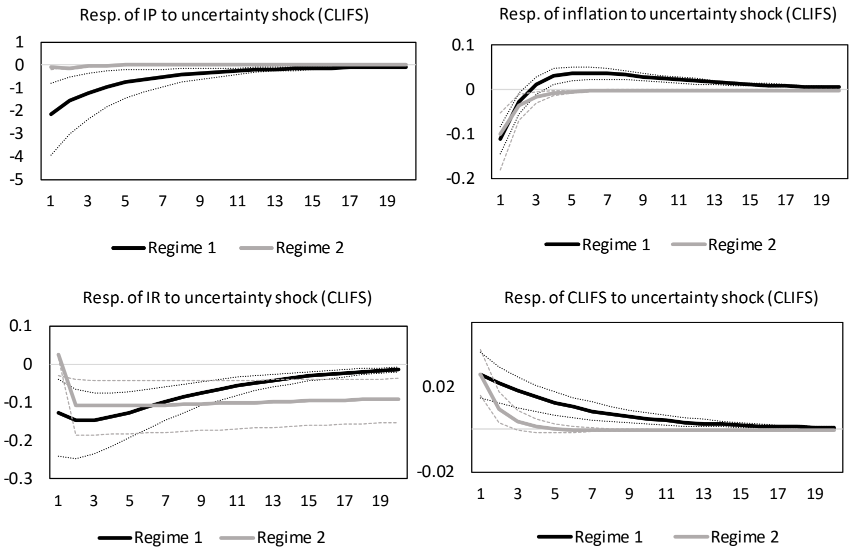
Source: Authors' calculations

Figure 2b Impulse Response Functions to a CLIFS Uncertainty Shock for Hungary in MS-TV-VAR Model



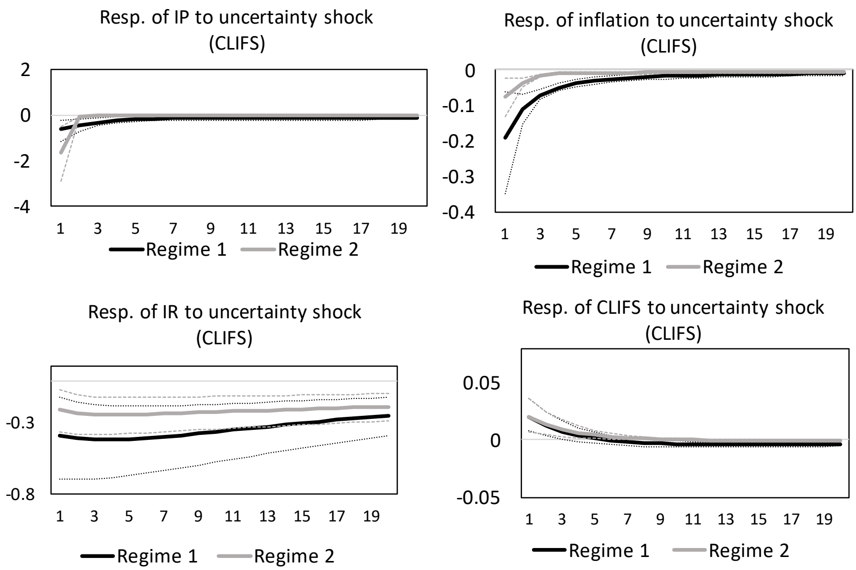
Source: Authors' calculations

Figure 2c Impulse Response Functions to a CLIFS Uncertainty Shock for Poland in MS-TV-VAR Model



Source: Authors' calculations

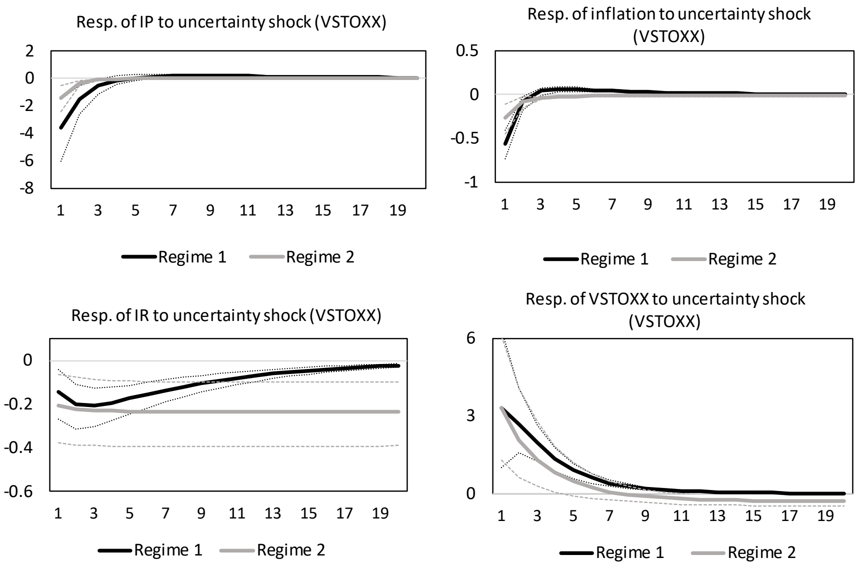
Figure 2d Impulse Response Functions to a CLIFS Uncertainty Shock for Romania in MS-TV-VAR Model



Source: Authors' calculations

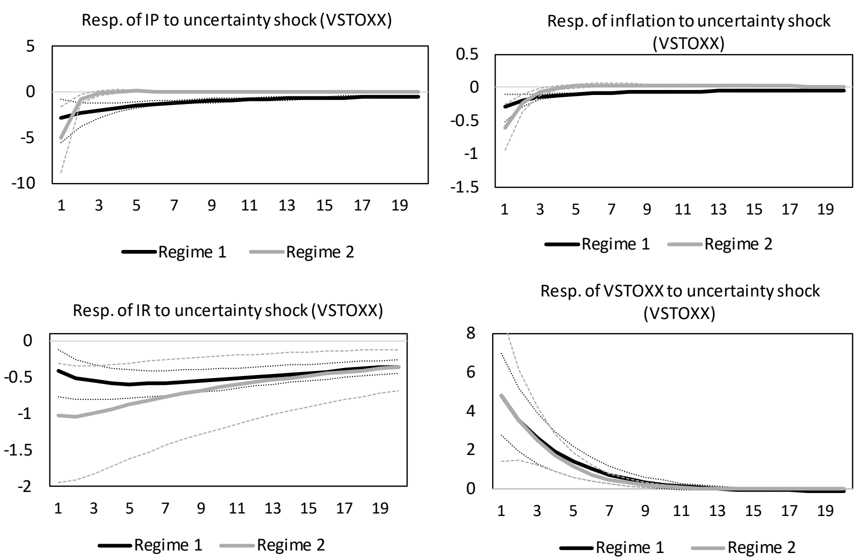
Appendix 3

Figure 3a Impulse Response Functions to a VSTOXX Uncertainty Shock for Czech Republic in MS-TV-VAR Model



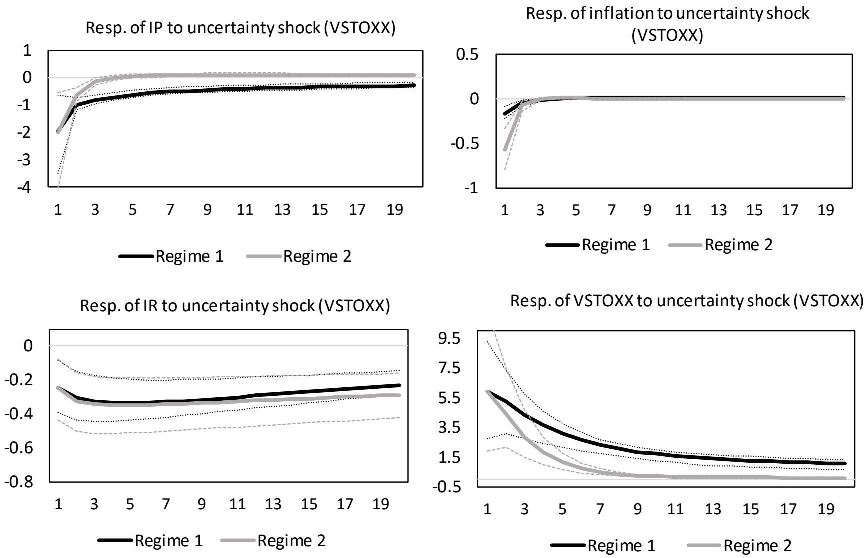
Source: Authors' calculations

Figure 3b Impulse Response Functions to a VSTOXX Uncertainty Shock for Hungary in MS-TV-VAR Model



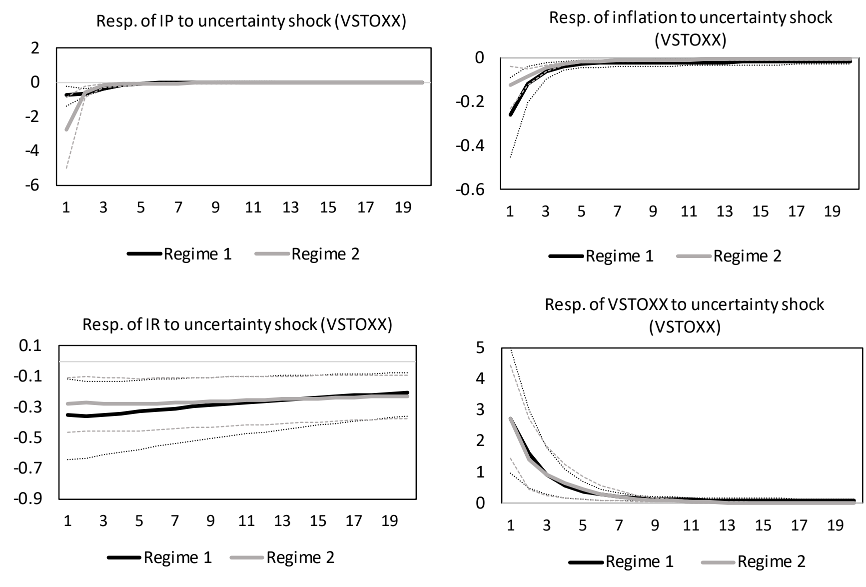
Source: Authors' calculations

Figure 3c Impulse Response Functions to a VSTOXX Uncertainty Shock for Poland in MS-TV-VAR Model



Source: Authors' calculations

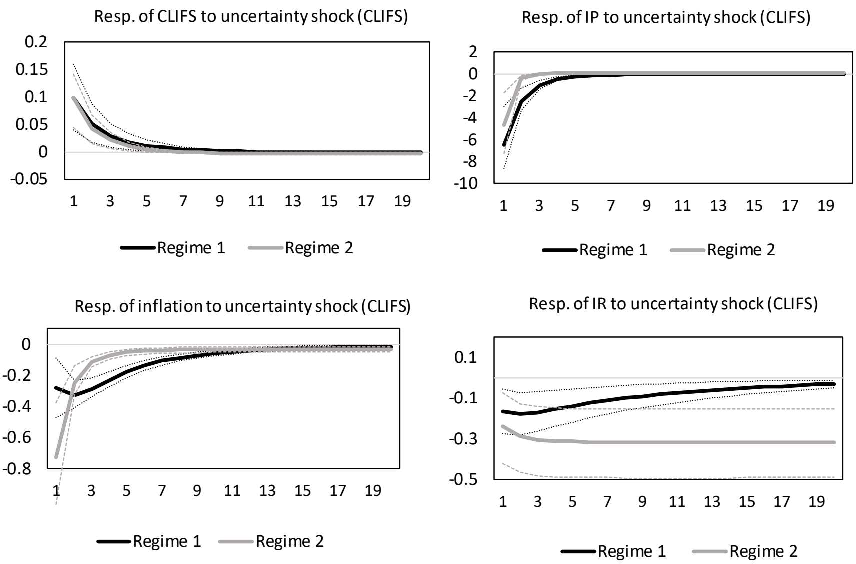
Figure 3d Impulse Response Functions to a VSTOXX Uncertainty Shock for Romania in MS-TV-VAR Model



Source: Authors' calculations

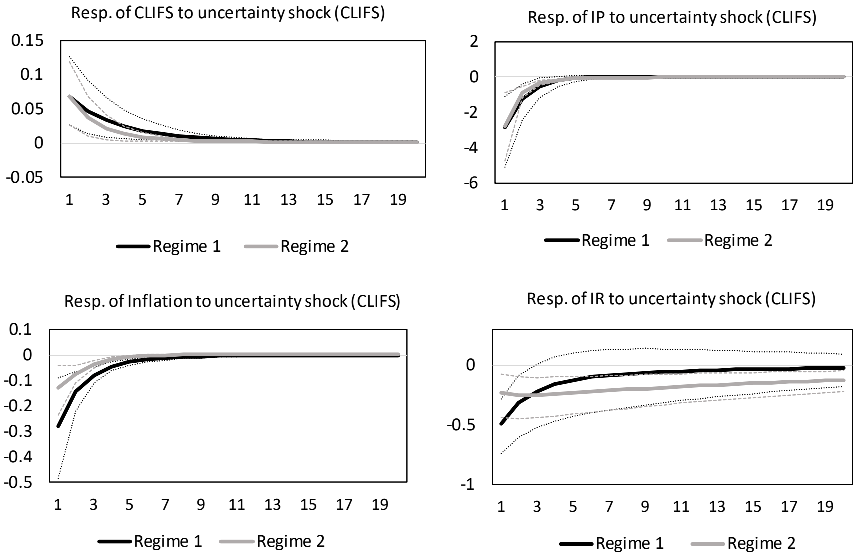
Appendix 4 - Robustness Check - Uncertainty CLIFX Index is Ordered First in the VAR Model

Figure 4a Impulse Response Functions to a CLIFS Uncertainty Shock for Czech Republic in MS-VAR Model



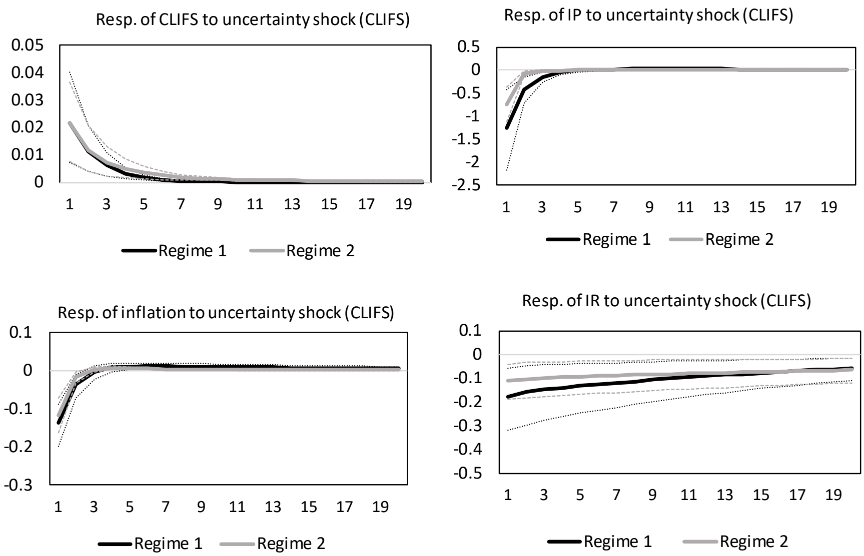
Source: Authors' calculations

Figure 4b Impulse Response Functions to a CLIFS Uncertainty Shock for Hungary in MS-VAR Model



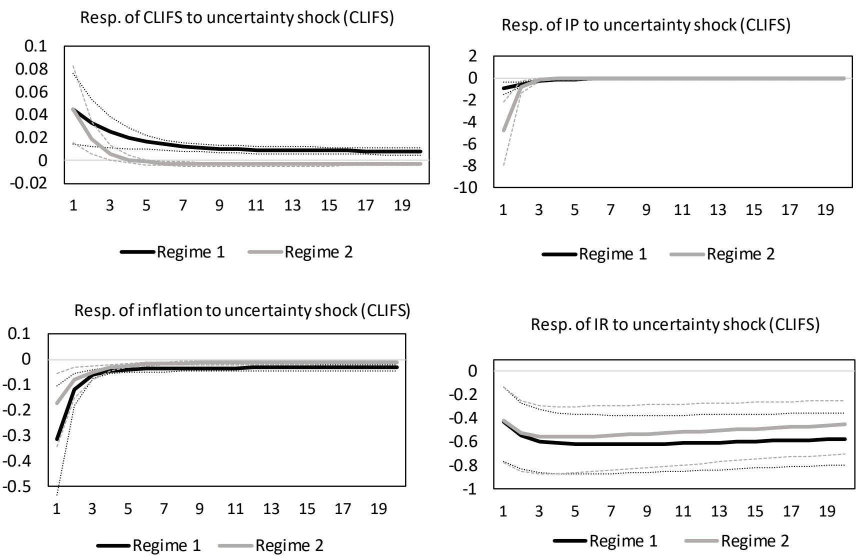
Source: Authors' calculations

Figure 4c Impulse Response Functions to a CLIFS Uncertainty Shock for Poland in MS-VAR Model



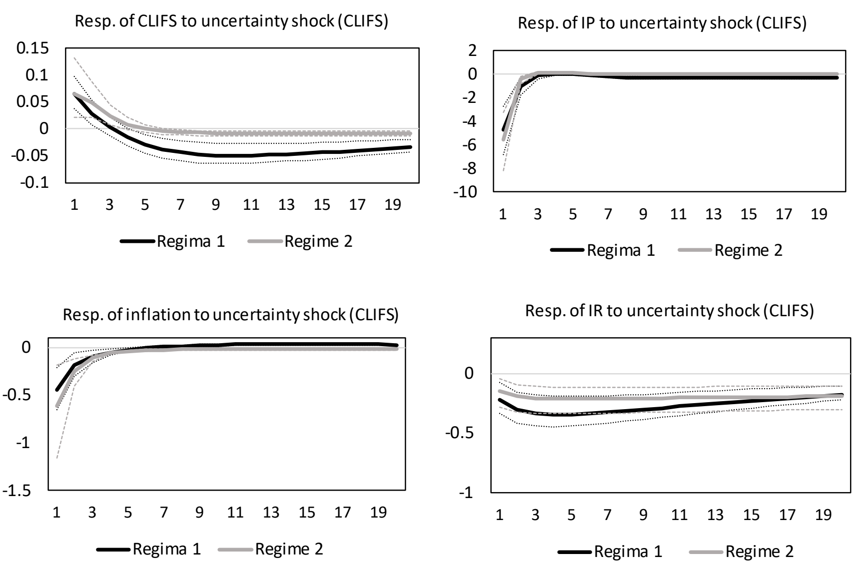
Source: Authors' calculations

Figure 4d Impulse Response Functions to a CLIFS Uncertainty Shock for Romania in MS-VAR Model



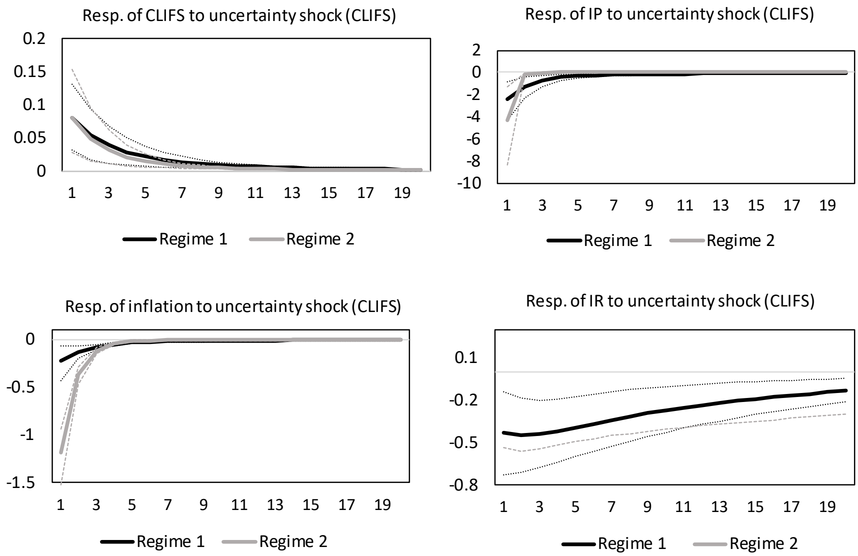
Source: Authors' calculations

Figure 4e Impulse Response Functions to a CLIFS Uncertainty Shock for Czech Republic in MS-TV-VAR Model



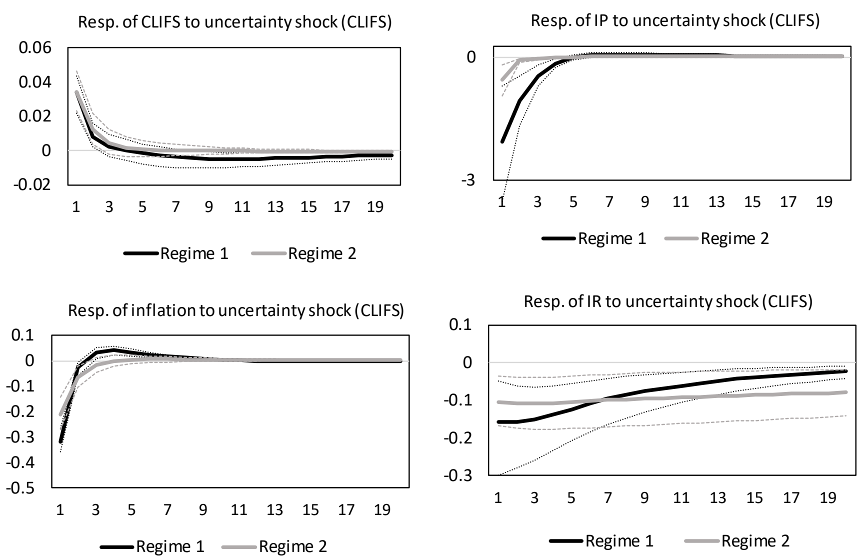
Source: Authors' calculations

Figure 4f Impulse Response Functions to a CLIFS Uncertainty Shock for Hungary in MS-TV-VAR Model



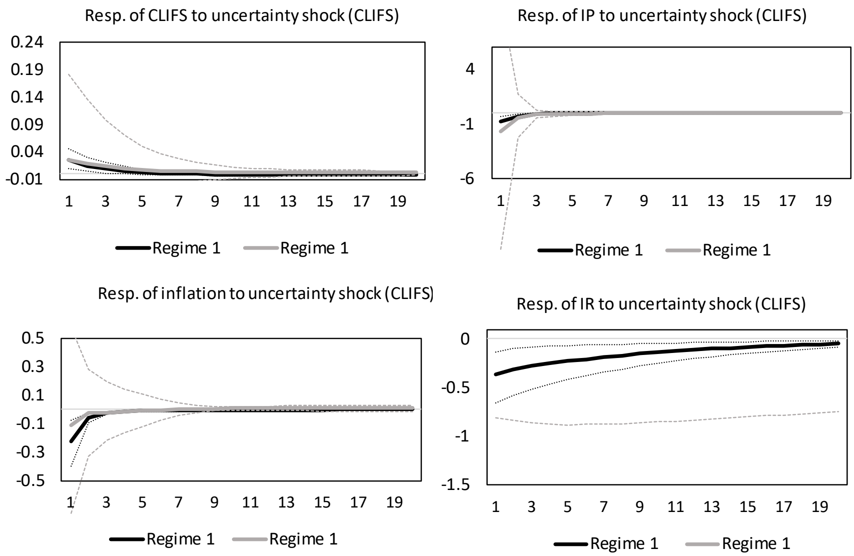
Source: Authors' calculations

Figure 4g Impulse Response Functions to a CLIFS Uncertainty Shock for Poland in MS-TV-VAR Model



Source: Authors' calculations

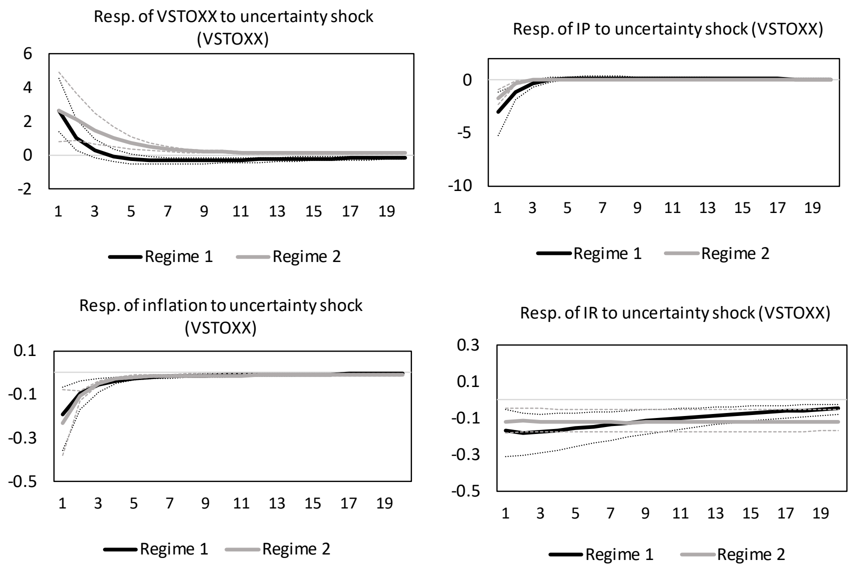
Figure 4h Impulse Response Functions to a CLIFS Uncertainty Shock for Romania in MS-TV-VAR Model



Source: Authors' calculations

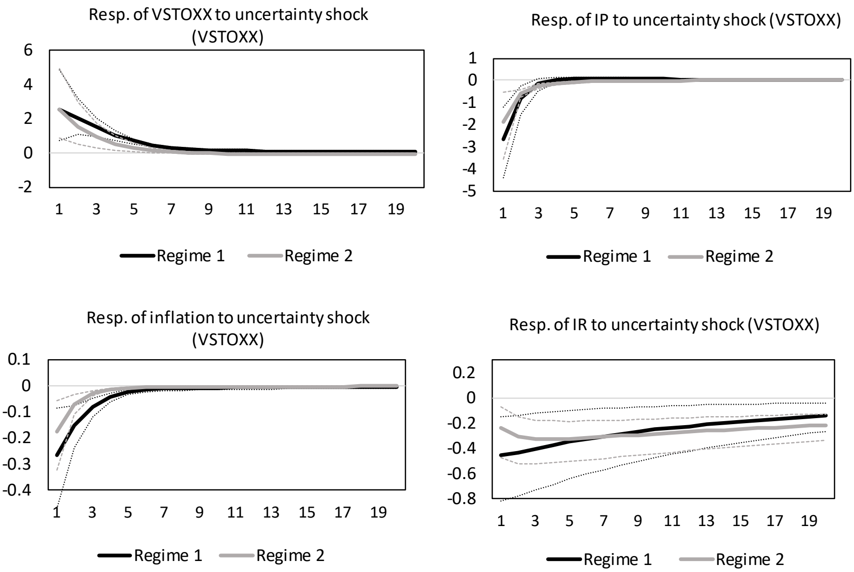
Appendix 5 - Robustness Check - Uncertainty VSTOXX Index Is Ordered First in the VAR Model

Figure 5a Impulse Response Functions to a VSTOXX Uncertainty Shock for Czech Republic in MS-VAR Model



Source: Authors' calculations

Figure 5b Impulse Response Functions to a VSTOXX Uncertainty Shock for Hungary in MS-VAR Model



Source: Authors' calculations

Figure 5c Impulse Response Functions to a VSTOXX Uncertainty Shock for Poland in MS-VAR Model

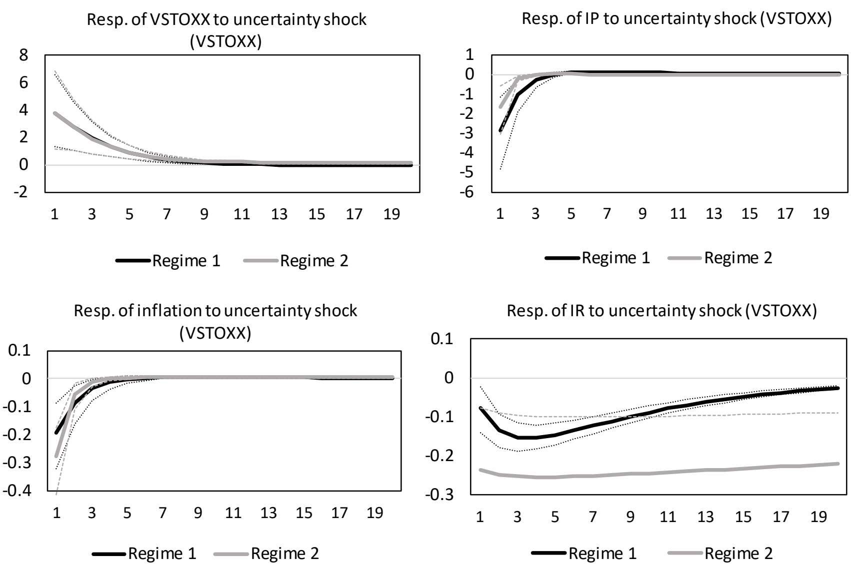


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Figure 5d Impulse Response Functions to a VSTOXX Uncertainty Shock for Romania in MS-VAR Model

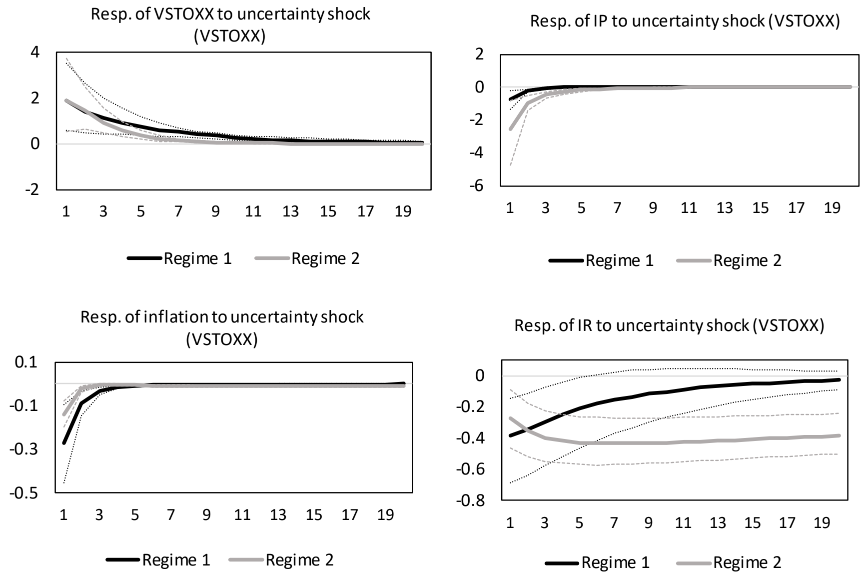

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Figure 5e Impulse Response Functions to a VSTOXX Uncertainty Shock for Czech Republic in MS-TV-VAR Model

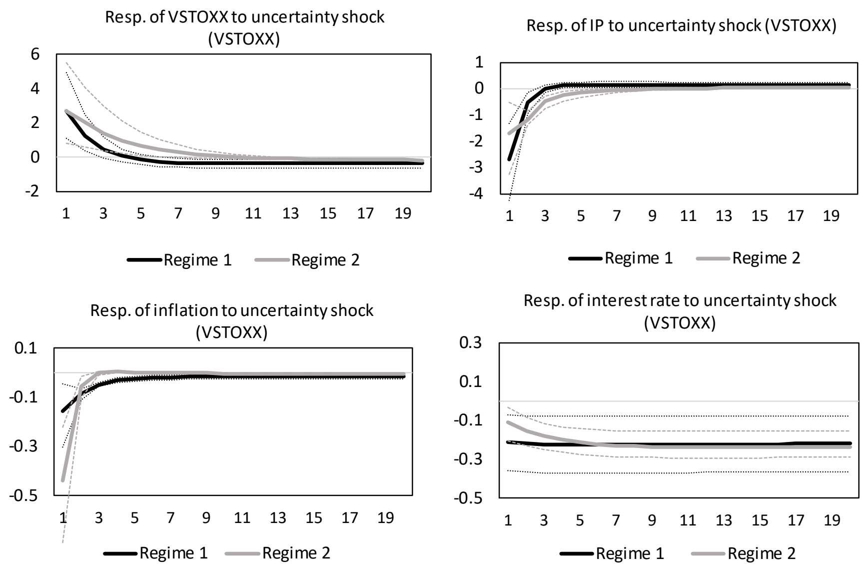

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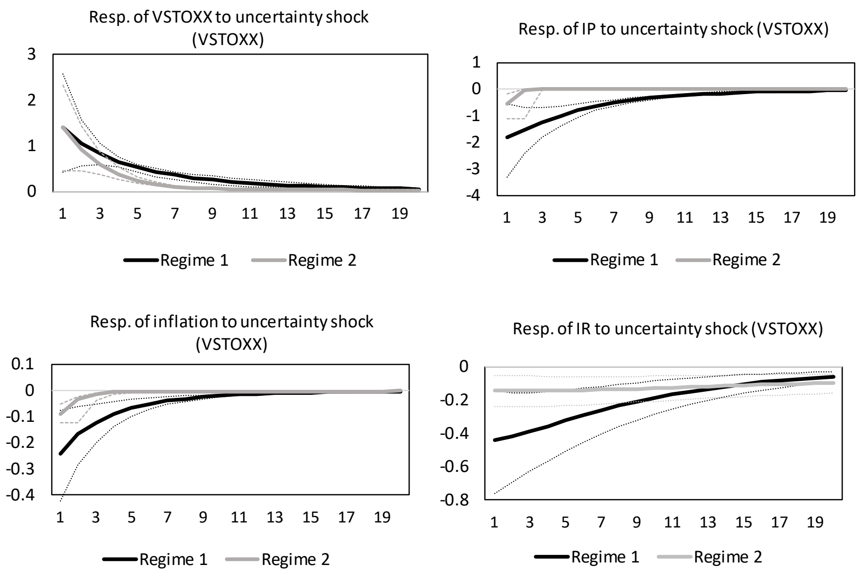
Figure 5f Impulse Response Functions to a VSTOXX Uncertainty Shock for Hungary in MS-TV-VAR Model



Source: Authors' calculations

Figure 5g Impulse Response Functions to a VSTOXX Uncertainty Shock for Poland in MS-TV-VAR Model

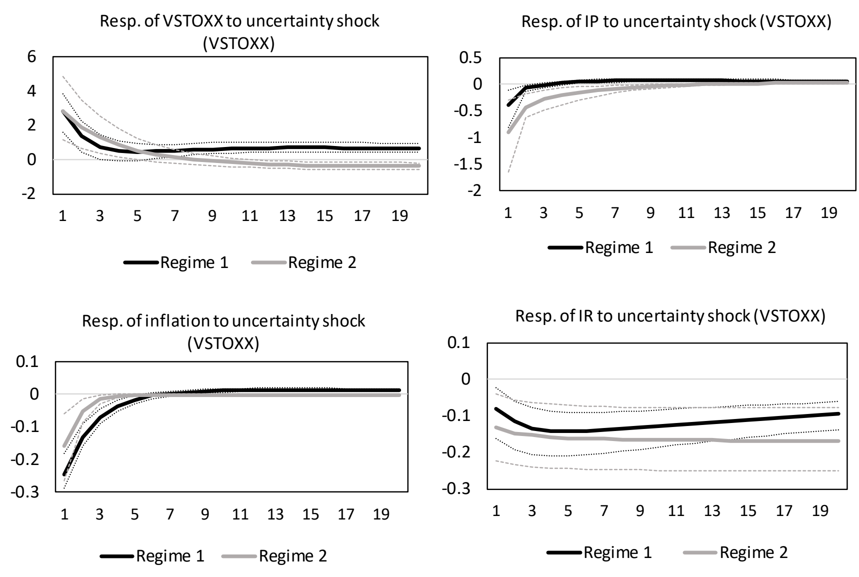


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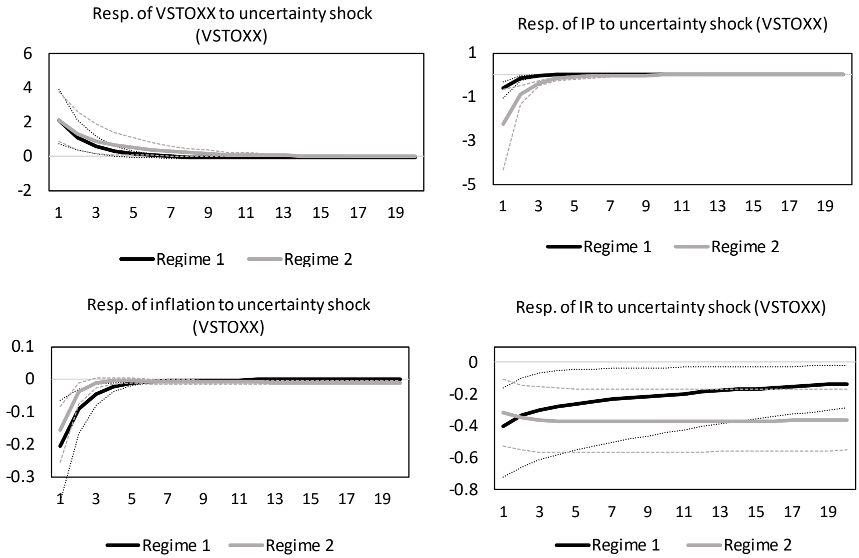
Figure 5h Impulse Response Functions to a VSTOXX Uncertainty Shock for Romania in MS-TV-VAR Model



Source: Authors' calculations

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