How does oil price uncertainty affect output in the Central and Eastern European economies? – the Bayesian-based approaches

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Abstract

Purpose – This paper aims to investigate how oil price uncertainty affects real gross domestic product (GDP) and industrial production in eight Central and Eastern European countries (CEEC).

Design/methodology/approach – In the research process, the authors use the Bayesian method of inference for the two applied methodologies – Markov switching generalized autoregressive conditional heteroscedasticity (GARCH) model and quantile regression.

Findings – The results clearly indicate that oil price uncertainty has a low effect on output in moderate market conditions in the selected countries. On the other hand, in the phases of contraction and expansion, which are portrayed by the tail quantiles, the authors find negative and positive Bayesian quantile parameters, which are relatively high in magnitude. This implies that in periods of deep economic crises, an increase in the oil price uncertainty reduces output, amplifying in this way recession pressures in the economy. Contrary, when the economy is in expansion, oil price uncertainty has no influence on the output. The probable reason lies in the fact that the negative effect of oil volatility is not strong enough in the expansion phase to overpower all other positive developments which characterize a growing economy. Also, evidence suggests that increased oil uncertainty has a more negative effect on industrial production than on real GDP, whereas industrial share in GDP plays an important role in how strong some CEECs are impacted by oil uncertainty.

Originality/value – This paper is the first one that investigates the spillover effect from oil uncertainty to output in CEEC.

Keywords Output, Bayesian quantile regression, Bayesian MS-GARCH, Central and Easter European countries, Oil uncertainty

Paper type Research paper

1. Introduction

Oil stands as one of the most strategic commodities for the global economy, but it has become more volatile in recent decades due to a number of geopolitical issues, such as

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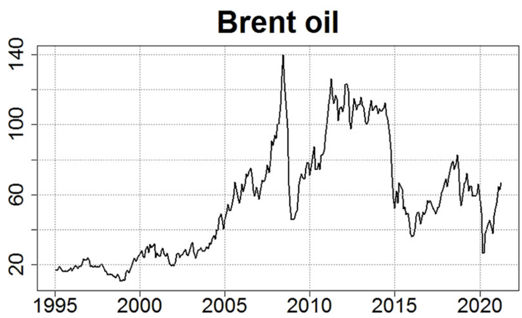
different conflicts in the Middle East, the global financial crisis of 2008–2010, the Russia–Ukraine dispute and frequent changes in global demand and supply of oil. (Arouri and Rault, 2011; Mohaddes and Raissi, 2019; Ozcelebi, 2021). The importance of oil for the world economy is further corroborated by the fact that the global oil market is worths over US $1.7tn (Nasir *et al.*, 2018). It is well known that the price of oil has experienced a number of heavy oscillations in the past few decades (Figure 1), whereby each cyclical swing produces huge concerns for countries because it has important implications for their economic activities. According to Cheng *et al.* (2019), oil price fluctuations affect economic activities through several channels. On the one side, increasing oil prices have a direct negative impact on the output via higher production costs. However, these authors argue that even more important is the second-moment measure of oil price changes, because it influences firms' expectations about current production and investment behaviour in future projects. In particular, oil price uncertainty discerns the periods of high and low volatility, which may be caused by either rising or falling oil prices. Rahman and Serletis (2012) and Aye *et al.* (2014) contended that falling oil prices may not necessarily increase manufacturing production, because the sharp rise in the volatility of oil prices may wipe out the positive effects of a significant oil price drop in the price of oil.

Bergmann (2019) claimed that the first- and second-moment oil price changes are not necessarily synchronized because volatility can increase in both boom and bust periods. This implies that increases in the oil price volatility can inhibit real gross domestic product (GDP) growth and investments even in periods when oil prices are declining. Therefore, it is crucial for countries to properly recognize the difference between these two types of changes and their influence on the economy. Federer (1996) explained that oil price uncertainty shock means more external risk, which can induce a delay in corporate investments due to uncertain conditions about the future cost of inputs. In that regards, firms prefer to delay irreversible investment to keep total risk at a manageable level, whereas households delay their present consumption for precautionary savings reasons. Besides, it should not be forgotten that the impact of oil uncertainty shocks on the economy could depend on a number of different factors, such as the size of the shock, its persistence, macroeconomic policy responses and the structure of the economy. Cheng *et al.* (2019) asserted that the first-moment transmission channel is well explored in the literature, but fundamental mechanisms of the second-moment conduit remain unclear, which leaves room for further investigation.

Having in mind the aforementioned, this paper investigates thoroughly the issue of how oil price uncertainty affects output in eight Central and Eastern European countries (CEEC), which became the EU members in 2004 – the Czech Republic, Poland, Hungary, Slovakia,



Note: Y axis denotes USD per barrel

Figure 1.
Empirical dynamics of Brent oil

Lithuania, Latvia, Estonia and Slovenia. These countries are dependent on oil import, and Table 1 contains the level of oil consumption per capita. It can be seen that the overall oil consumption of CEECs is relatively high, which puts these countries in the first half of all countries in the world.

In the research process, we choose oil futures rather than oil spot prices, because futures prices by definition incorporate all available information as well as expectations and predictions, which provides a more realistic measurement of oil prices in comparison with the spot prices (Natanelov *et al.*, 2011). In addition, to be more informative, we observe the output of these countries in two ways – as real GDP growth (quarterly data) and as seasonally adjusted industrial production (monthly data). The intention is to see what is the difference in the transmission effect from oil uncertainty to output when we observe two different aggregate macroeconomic levels – industrial production, which represents only a fraction of the total output generated and real GDP, which encompasses all productive and non-productive activities in one economy.

We strive to recognize oil price uncertainty as accurate as possible, and in this process, we consider markov switching generalized autoregressive conditional heteroscedasticity (GARCH) (MS-GARCH) model. This particular model is used to estimate regime-switching conditional volatility, which serves as a proxy for oil price uncertainty. We opt for MS-GARCH model, because there is a reasonable concern that oil time series are permeated with structural breaks, and it is well known in the literature that estimates of GARCH type models can be biased due to the presence of structural breaks in the volatility dynamics (Bauwens *et al.*, 2010). If this is the case, the sum of estimated GARCH coefficients is close to or even exceeds one, as Klaassen (2002) explained, which yields an estimation of non-stationary volatility in single-regime GARCH models, biased conclusions and poor-risk predictions. Frommel (2010) contended that this leads to the overestimation of volatility persistence and misspecification of the GARCH model. An efficient way to deal with this issue is to estimate Markov switching GARCH model, in which parameters can change over time according to a discrete latent (unobservable) variable. In addition, we estimate the MS-GARCH model using the Bayesian procedure instead of the maximum likelihood (ML) method because Bayesian estimation provides reliable results even for finite samples (Bauwens *et al.*, 2014; Ardia, 2008). Besides, Virbickaite *et al.* (2015) asserted that ML approach has some limitations when the errors are heavy-tailed, when the convergence rate is slow or when the estimators are not asymptotically Gaussian.

After the construction of regime-switching conditional volatility, we insert estimated oil price uncertainty in the Bayesian quantile regression (BQR) framework to assess how it affects the output of the selected countries. An intrinsic characteristic of quantile regression is the fact that it can provide an insight into the transmission effect from oil price uncertainty to output in different market conditions – downturn (lower quantiles), normality (intermediate quantiles) and upturn (upper quantiles). More specifically, QR technique can recognize the underlying nonlinearities in the data, which prevents biased conclusions. Besides, like in the process of conditional volatility estimation, we also use Bayesian

Table 1. Oil consumption per capita (bbl/day per 1,000 people) of the selected CEECs

	CZE	POL	HUN	SLK	LIT	LAT	EST	SLO
Oil consumption per capita	19.23	14.69	14.72	15.29	19	13.63	24.32	31.55
World rank	77	96	95	91	79	99	71	50

Notes: CZE - The Czech Republic; POL - Poland; HUN - Hungary; SLK - Slovakia; LIT - Lithuania; LAT - Latvia; EST - Estonia; SLO - Slovenia
Source: CIA World Factbook, January 2020

inference to calculate quantile parameters. Bayesian QR uses Markov Chain Monte Carlo (MCMC) algorithm in the estimation process, which ensures efficient and exact values of the quantile parameters. In other words, Bayesian QR does not provide statistical significance to the estimated parameters, but all quantile parameters are regarded as highly statistically significant and unbiased if credible intervals are not too wide. In particular, the Bayesian QR methodology decreases the length of credible intervals and increases the accurateness of quantile estimates in comparison with the traditional quantile regression approach.

To the best of our knowledge, this paper differentiates from the existing literature along several dimensions. Generally, very few papers researched the transmission effect from oil price uncertainty to output, and none of the papers have considered CEECs. In addition, this paper uses two innovative and elaborate methodologies in the research process – Bayesian-based Markov switching GARCH model and BQR, which have never been combined before. An important trait of this paper is that we use the Bayesian inference technique, which can ensure precise measurement of oil price uncertainty, whereas in the Bayesian QR framework, it provides robustness and accurateness in the estimation of the quantile parameters. Using methodologies based on the Bayesian estimation significantly contributes to the reliability of the results, which is the primary characteristic of this paper.

Besides the introduction, the rest of the sections are structured as follows. Section 2 provides a literature review. Section 3 explains the used methodologies. Section 4 presents the data set and the construction of regime-dependent conditional volatilities of oil. Section 5 contains the finding, whereas Section 6 concludes.

2. Literature review

The existing literature differentiates two mainstream approaches when it comes to the transmission effect from oil to output, and the distinction is based on the order of moments used to characterize fluctuations in oil prices. The first approach, which is more represented in the literature, takes into account the first-moment fluctuations, while the second approach, which is much less common, focuses on the second-moment fluctuations of oil prices.

The following papers analysed the first-moment spillover effect. For instance, Bergmann (2019) investigated the effect of oil price fluctuations on GDP growth, using linear and nonlinear VAR model data from 12 countries. He found that oil-consuming countries are negatively affected by positive oil price shocks, whereas oil-exporting countries show a more variable behaviour. Lardic and Mignon (2006) tried to determine whether or not there was a link between oil prices and economic activity in 12 European countries, using asymmetric cointegration analysis. They reported that rising oil prices retard aggregate economic activity by more than falling oil prices stimulate it. The paper of Nasir *et al.* (2019) researched the influence of oil price shocks on the macroeconomy in six Gulf Cooperation Council (GCC) countries (Bahrain, Kuwait, KSA, Oman, Qatar and UAE) via an SVAR model. They found significant positive effects of oil price shocks on the GDP, inflation and trade balance of those countries, but the results, however, show substantial heterogeneities in the responses of the GCC members to oil shocks. Farzanegan and Markwardt (2009) considered the case of an oil-exporting Iran and reported that the positive oil price shocks have a larger positive impact on the Iranian GDP in comparison with the negative oil shocks, which have a negative but smaller impact on GDP.

As for the studies which considered the second-moment transmission effect, the paper of Cheng *et al.* (2019) investigated the dynamic impacts of uncertainty in international crude oil prices on the Chinese economy. They used sample standard deviation and conditional standard deviation estimated from a GARCH (1,1) model, to calculate uncertainty in oil prices. They revealed that an increase in volatility in oil prices tends to reduce the real GDP and investments. This negative impact encourages the Chinese government to stabilize the economy through expansionary fiscal and monetary policy. Punzi (2019) evaluates the macroeconomic implications of energy price volatility in 10 Asian economies, applying a dynamic stochastic general equilibrium model. She disclosed that positive energy price shocks cause an economic slowdown due to higher costs for consumers and firms. She also reported that energy price volatility shocks generate an increase in GDP in the short-run and a reversal in the long run. Phan *et al.* (2019) investigated the spillover effect from crude oil price uncertainty to investments. They considered a comprehensive data set of more than 33,000 firms from 54 countries. They showed that crude oil price uncertainty negatively influences corporate investment, whereby the effect is dependent on the market and stock characteristics of the firms. Additionally, they revealed that the effect is stronger in the cases of crude oil producers than for crude oil consumers. van Eyden *et al.* (2019) researched the impact of real oil price volatility on the growth in real GDP for 17 member countries of OECD, covering over 144 years of the time period. Their main finding is that oil price volatility has a negative and statistically significant impact on the economic growth of the OECD countries. In addition, they asserted that oil-producing countries are significantly negatively impacted by oil price uncertainty, most notably Norway and Canada.

3. Research methodologies

3.1 Bayesian Markov switching approach

The first task in our twofold procedure is to construct conditional volatility, which serves as a proxy for oil price uncertainty. Due to the fact that empirical time series can be "polluted" by the presence of structural breaks, which consequently can produce spurious estimates of conditional volatilities, we choose Markov switching GARCH model, which can recognize structural breaks in the variance endogenously. In this way, we can avoid spurious estimates of conditional volatility. To further improve the accurateness of the oil conditional volatility, we estimate the MS-GARCH model with the Bayesian procedure rather than the traditional ML technique.

In the econometric literature, it is known that ML estimation of the MS-GARCH model can generate an implementation problem. This happens because the conditional variance of the MS-GARCH model depends on all the past history of the state variable. In other words, if we take into account K-state and T-sample size, we need to consider K^T cases to get the likelihood function, which is practically infeasible to implement. Several authors tried to resolve this problem, by applying different approaches. For instance, Hamilton and Susmel (1994) use Markov switching ARCH models, while Gray (1996) and Dueker (1997) estimate Markov switching GARCH models by approximating the likelihood function which depends on only a few of the state variables. This paper deals with this problem by using a Bayesian inference procedure. According to Ardia (2009), the Bayesian statistical method efficiently obtains the posterior distribution of any non-linear function of the model parameter. On the contrary, the classical ML procedure has a problem to easy perform inferences on non-linear functions of the model parameters, whereas the convergence rate could prove slow, with the serious limitations when the residuals are heavy-tailed. Virbickaite *et al.* (2015) explained that the state variables are treated as random variables in the Bayesian context, which enables researchers to construct the likelihood function easily. In other words, a posterior distribution is constructed using priors, which integrate the posterior density function with respect to parameters and state variables.

To overcome possible autocorrelation bias, we refer to Živkov *et al.* (2016) and assume AR(1) process for the conditional mean of Brent oil, where residuals of the model follow the normal distribution $\varepsilon_t \mid I_{t-1} \sim N(0,h_{it})$, whereby I_{t-1} is the information set up to time $t-1$. Markov switching GARCH specification can be written as follows:

$$h_t = \omega_{st} + \alpha_{st}\varepsilon_{t-1}^2 + \beta_{st}h_{t-1} \tag{1}$$

where ω_{st} is state-dependent constant, whereas $\varepsilon_{t-1,\ S_t}^2$ and h_{t-1,S_t} are ARCH and GARCH effect, respectively, under regime st. The non-negativity of h_t is ensured if we set the following restrictions: $\omega_{S_t} \geq 0$, $\alpha_{S_t} \geq 0$ and $\beta_{S_t} \geq 0$. Volatility persistence in state i is measured by $\alpha_i + \beta_i$.

We estimate the Bayesian MS-GARCH model [1] with the MCMC procedure, which requires the evaluation of the likelihood function. Following Ardia (2008), we define $y_t \in \mathbb{R}$ as the (percentage) log return of oil at time t, and regroup the model parameters into the vector $\boldsymbol{\Psi}$. Accordingly, the conditional density of y_t in state $st = k$, given $\boldsymbol{\Psi}$ and I_{t-1} is presented as $(y_t \mid st = k,\ \boldsymbol{\Psi},\ I_{t-1})$. The discrete integration is subsequently obtained as follows:

$$(y_t|\ \boldsymbol{\Psi},\ I_{t-1}) = \sum_{i=1}^{K}\sum_{j=1}^{K} p_{i,j}\,\eta_{i,t-1}(y_t|st=j,\ \boldsymbol{\Psi},\ I_{t-1}) \tag{2}$$

where $\eta_{i,t-1} = \mathrm{P}\,(s_{t-1} = i \mid \boldsymbol{\Psi}, I_{t-1})$ denotes the filtered probability of state i at time $t-1$ and where $p_{i,j}$ stands for the transition probability, moving from state i to state j. The likelihood function can be obtained from equation (2) in the following way:

$$L(\boldsymbol{\Psi}\ |\mathrm{y}) = \prod_{t=1}^{T}(y_t|\ \boldsymbol{\Psi},\ I_{t-1}) \tag{3}$$

According to Ardia (2008), in the case of MCMC estimation, the likelihood function is combined with a diffuse (truncated) prior ($\boldsymbol{\Psi}$) to build the kernel of the posterior distribution ($\boldsymbol{\Psi}$ | y). Because the posterior is of an unknown form it must be approximated by simulation techniques. For our purposes, draws from the posterior are generated with the adaptive random walk Metropolis sampler of Vihola (2012).

3.2 Bayesian quantile regression

After the construction of quarterly and monthly oil regimes dependant conditional volatilities, we combine these dynamic time series with the GDP and industrial production in the BQR framework [2]. According to Dybczak and Galuščak (2013) and Maestri (2013), QR methodology extends the mean regression model to conditional quantiles of the response variable. In particular, this approach provides a more elaborate view of the interlink between the dependent variable and the covariates, because it gives an assessment of how a set of covariates affect the different parts of regressand distribution. QR methodology has been found appealing by many researchers from various theoretical disciplines (Borraz *et al.*, 2015; Vilerts, 2018).

We start the explanation of the Bayesian QR methodology with the standard linear model as in equation (4):

$$y_i = \mu(x_i) + \varepsilon_i \tag{4}$$

where y_i and x_i are both dynamic variables, whereby real GDP growth and industrial production time-series are dependent variables, whereas oil price uncertainty is an independent variable. Benoit and van den Poel (2017) explained that the regression coefficient in the case of all quantiles can be found by solving equation (5):

$$\hat{\beta}(\tau) = \operatorname{argmin} \sum_{i=1}^{n} \rho_\tau \left(y_i - x_i^{\prime} \beta \right); \quad \beta \in \Re \tag{5}$$

where $\tau \in (0,1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(\cdot)$ stands for the indicator function. The quantile $\hat{\beta}(\tau)$ is called the τth regression quantile. When $\tau = 0.5$, it corresponds to median regression. In Bayesian inference, efficient QR parameter estimates are obtained with the usage of the MCMC algorithm. An important characteristic of this process is the estimation of accurate and reliable estimates of the quantile parameters $\hat{\beta}(\tau)$. In other words, in the BQR estimation, the 95% Bayesian credible interval contains the true parameter value in 95% of the time (Sriram *et al.*, 2013).

4. Data set and the construction of regime-dependent conditional volatilities

This paper uses quarterly and monthly closing prices of Brent oil futures, quarterly real GDP growth and monthly industrial production time-series of the selected eight CEECs – the Czech Republic, Poland, Hungary, Slovakia, Lithuania, Latvia, Estonia and Slovenia. All time-series of industrial production and real GDP are seasonally adjusted, using filter-based methods of seasonal adjustment, known as the X11 style method. Both monthly and quarterly closing prices of Brent oil futures are transformed into the log-returns according to the expression: $r_{i,t} = 100 \times (P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ stands for the closing price of Brent oil futures. The length of the samples is dictated by the availability of the data. Therefore, in the case of monthly data, the sample commences from January 1995 for the Czech Republic, Poland, Hungary, Slovakia and Slovenia, for Lithuania it is February 1998, for Latvia, it is February 2000 and for Estonia, it is January 1998. As for quarterly data, all real GDP growth time series start from 1995:Q2. The end date for all time series is April 2021. We collect real GDP and industrial production data from OECD statistics, while quarterly and monthly Brent oil futures prices are obtained from the investing.com website.

Due to the very conspicuous erratic behaviour of Brent oil prices in the selected period (see Figure 1), we assume that quarterly and monthly time-series of Brent oil are probably subject to multiple structural breaks, which in turn can have serious consequences on the accuracy of the conditional volatilities, estimated in the GARCH process. To address this issue, we use MS-GARCH model with the Bayesian inference, which produces trustworthy and precise measures of conditional volatilities.

Table 2 contains conditional volatility parameters of MS-GARCH model, estimated with the Bayesian procedure and traditional single-regime GARCH model, estimated with the common ML approach, which serves as a benchmark. Table 2 suggests that none of the parameters in the ordinary GARCH model, estimated with quarterly data, is not statistically significant. On the other hand, all Bayesian MS-GARCH parameters are statistically significant by default. It is interesting to note that persistence, gauged as a sum of α and β, is higher in monthly data than the corresponding sum in quarterly data in both regimes. The most likely reason for such a finding is the presence of structural breaks in the monthly data. Therefore, a decision to use the MS-GARCH model to overcome the issue of structural breaks presence in the variance proved is justifiable.

Table 2.
Parameter estimates of the Bayesian MS-GARCH model

		Quarterly data	Monthly data
GARCH with maximum likelihood estimation	c	0.408	6.096
	α	0.000	0.180**
	β	0.999	0.781***
	$\alpha+\beta$	0.999	0.961
MS-GARCH with Bayesian estimation		Regime 1 – low volatility regime	
	c_1	89.344	8.495
	α_1	0.296	0.179
	β_1	0.302	0.706
	$\alpha_1+\beta_1$	0.598	0.885
	p-value	0.70	0.98
		Regime 2 – high volatility regime	
	c_2	83.319	9.247
	α_2	0.252	0.047
	β_2	0.591	0.904
	$\alpha_2+\beta_2$	0.843	0.951
	p-value	0.57	0.91

In the MS-GARCH estimation process, we consider two regimes – the low volatility regime (Regime 1) and high volatility regime (Regime 2). It can be seen that probability values in the first regime, regarding both quarterly and monthly data, are higher than their counterparts in the second regime. This indicates that the low volatility regime occurs more frequently throughout the observed sample. Figure 2, which portrays smoothed probabilities for quarterly and monthly data, confirms this assertion. Visually, it can be seen that Regime 1 is much more dominant than Regime 2 in both quarterly and monthly data.

After estimation of MS-GARCH and GARCH models, we construct conditional volatilities for quarterly and monthly data. Table 3 contains their statistical properties, while Figure 3 presents a graphical illustration of the conditional volatility MS-GARCH model. It is obvious that conditional volatilities are considerably lower when they are estimated with the Bayesian MS-GARCH model, taking into account both quarterly and monthly data. The same applies to their standard deviations. As for skewness and kurtosis, the deviations are not so conspicuous between the two models, as in the cases of the first two moments. Generally, it seems that the regime-switching GARCH model better recognizes empirical Brent oil volatility in terms of volatility persistence and its overall level.

Table 4 provides descriptive statistics of seasonally adjusted real GDP and industrial production of the selected CEECs. It is worth of noting that the majority of real GDP growth

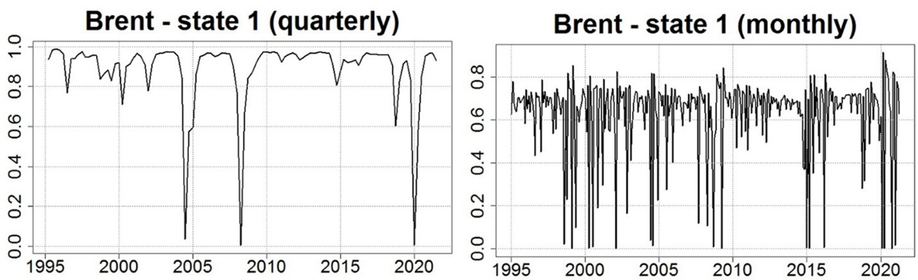


Figure 2.
Smoothed probabilities for Brent oil of the Regime 1

and industrial production time-series have kurtosis values higher than the benchmark value of 3. Because real GDP and industrial production are dependent variables in the Bayesian QR model, this characteristic justifies the usage of QR methodology because Bayesian QR estimator is robust to deviations from normality, meaning that it performs very well in an extreme value environment.

5. Research results

This section presents the results of the transmission effect from oil price uncertainty towards real GDP and industrial production in the selected CEECs. Bayesian QR model enables us to gauge the spillover effect in different market conditions – recession/stagnation (lower quantiles), normality (intermediate quantiles) and economic prosperity (upper quantiles). However, before we present the quantile estimates, we need to be sure about the validity of the estimated Bayesian QR parameters. This can be done by a visual inspection of the MCMC chains' convergence, which shows the evolution of the MCMC draws over the

	Quarterly data					Monthly data				
	Mean	St. dev.	Skewness	Kurtosis	JB	Mean	St. dev.	Skewness	Kurtosis	JB
Brent-GARCH	364.682	170.794	2.998	13.335	571.0	86.539	49.957	2.256	9.689	781.2
Brent-BMSG	17.463	3.372	2.033	7.675	153.6	9.052	1.318	2.335	11.265	1081.4

Note: BMSG denotes Bayesian MS-GARCH model

Table 3. Descriptive statistics of conditional volatilities

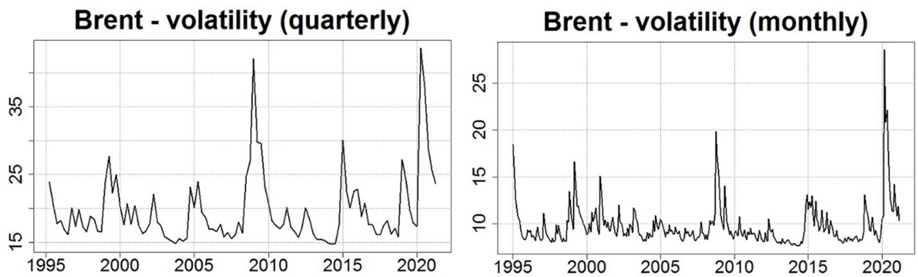


Figure 3. Time-varying conditional volatilities estimated with MS-GARCH models

	GDP – quarterly data					Industrial production – monthly data				
	Mean	St. dev.	Skewness	Kurtosis	JB	Mean	St. dev.	Skewness	Kurtosis	JB
CZE	0.642	0.883	−0.928	7.287	87.3	0.306	1.605	−0.179	3.287	2.0
POL	1.035	1.147	0.514	5.483	28.9	0.445	1.799	−0.065	5.208	46.3
HUN	0.623	0.897	−2.642	12.903	504.0	0.362	2.541	−0.515	6.060	98.6
SLK	0.983	1.633	−1.832	19.930	1,200.1	0.515	3.125	2.337	22.502	3,804.1
LIT	1.050	1.908	−4.212	32.799	3,835.7	0.516	5.133	0.082	4.777	30.1
LAT	0.980	2.016	−0.485	5.015	20.0	0.338	1.970	−0.459	4.323	24.5
EST	1.007	1.994	−1.768	9.670	228.0	0.458	2.608	−0.332	4.383	22.3
SLO	0.679	1.089	−1.758	10.018	246.5	0.240	2.244	−1.110	10.183	534.6

Note: JB stands for Jarque-Bera test of normality

Table 4. Statistical properties of GDP and industrial production for the selected countries

iterations. Figure 4 displays the trace plots of the MCMC chain for the median quantiles, $\hat{\beta}(\tau) = 0.5$, for quarterly and monthly data, regarding the Polish case. We use 3,000 iterations in the MCMC estimation process. It can be seen that all trace plots have a good performance, meaning that the effect of the initial values of the MCMC chains wears off relatively fast, while the MCMC sampler quickly moves to the stationary distribution. These findings cannot suggest reliably that estimated median Bayesian quantile parameters are statistically significant, but they can indicate an absence of (large) bias in the estimated parameters. Because all trace plots of all other countries across all quantiles are very similar, we portray in Figure 4 only trace plots for the median quantile of Polish GDP and industrial production, whereas all other trace plots can be obtained by request.

Table 5 presents the results of the estimated Bayesian quantile parameters for quarterly and monthly data. Following Živkov *et al.* (2020), we estimate all BQR parameters under

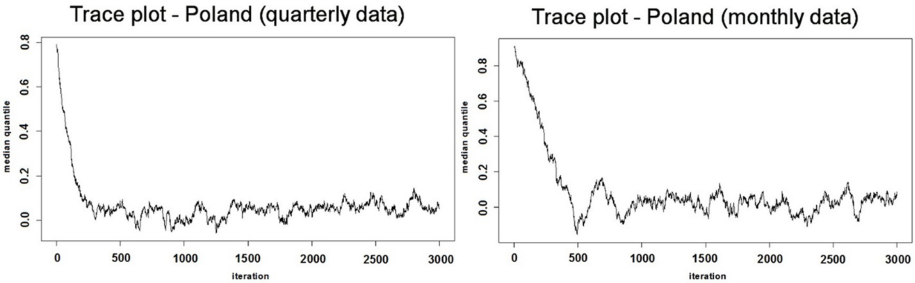


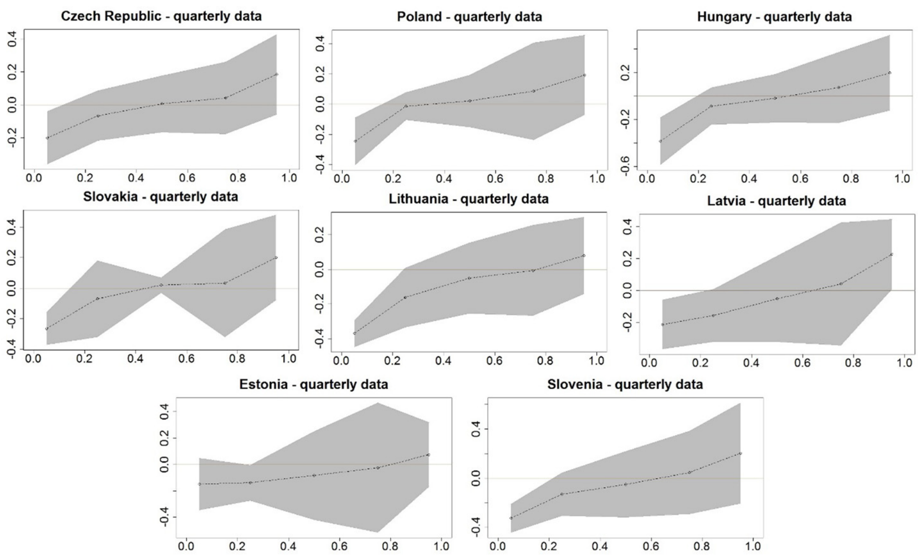
Figure 4.
Trace plots for median quantile of Polish GDP and industrial production

Table 5.
Estimated quantile parameters for quarterly and monthly data

GDP – quarterly data Quantile estimates					Industrial production – monthly data Quantile estimates				
0.05th	0.25th	0.5th	0.75th	0.95th	0.05th	0.25th	0.5th	0.75th	0.95th
Czech Republic									
−0.210	−0.077	−0.009	0.022	0.153	−0.747	−0.130	0.020	0.159	0.970
Poland									
−0.251	−0.021	0.007	0.060	0.163	−0.619	−0.082	0.014	0.139	0.601
Hungary									
−0.407	−0.100	−0.035	0.044	0.164	−1.170	−0.165	−0.020	0.239	1.030
Slovakia									
−0.268	−0.081	0.014	0.005	0.170	−1.090	−0.114	0.053	0.253	1.370
Lithuania									
−0.379	−0.177	−0.067	−0.026	0.051	−0.912	−0.138	0.071	0.175	0.207
Latvia									
−0.220	−0.169	−0.072	0.015	0.198	−0.343	−0.106	0.017	0.113	0.192
Estonia									
−0.158	−0.154	−0.105	−0.055	0.053	−0.418	−0.169	−0.009	0.099	0.453
Slovenia									
−0.338	−0.147	−0.070	0.018	0.169	−0.684	−0.154	−0.003	0.106	0.460

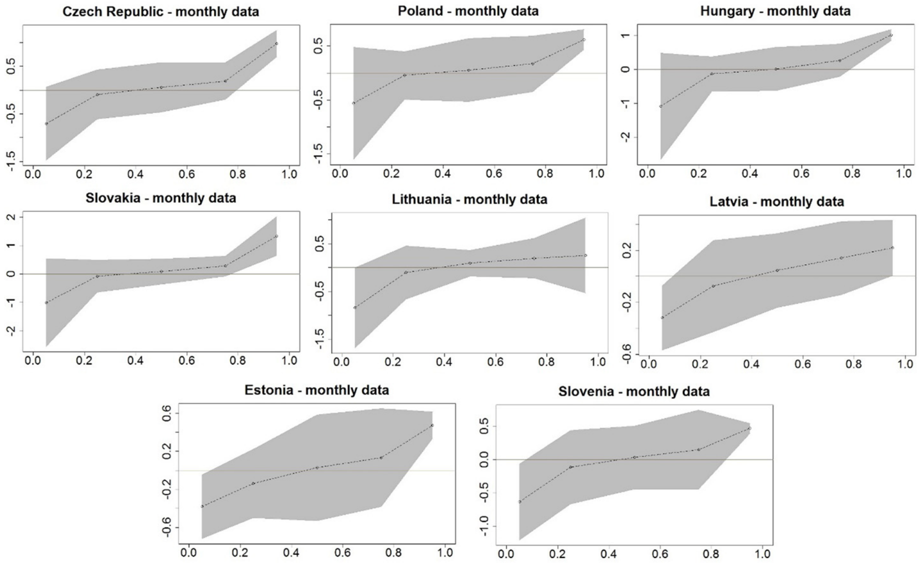
70% confidence level, and Figures 5 and 6 graphically illustrate these results. It can be seen that QR parameters are heterogeneous in magnitude across the quantiles and the selected countries, and they bear both positive and negative signs. It is interesting to note that only periphery quantiles, i.e. left and right tail quantiles, are relatively high, whereas near tail and median quantile parameters are low in magnitude. This characteristic applies for both quarterly and monthly data. This finding suggests that in moderate economic conditions, oil price uncertainty has a very low, in some cases almost negligible, effect on real GDP and industrial production in the selected countries. However, under the extreme market circumstance, which is portrayed by the tail quantiles, the magnitude of QR parameters is relatively high.

Additionally, it should be said that negative sign is found dominantly in the left tail quantiles, which depicts the situation of recession and economic downturn, whereas from median quantile and onwards, QR parameters are overwhelmingly positive. These findings suggest the existence of the asymmetric effect over contractions and expansions in the business cycle in all the countries. Results indicate that in periods of deep economic crises, an increase in the oil price uncertainty reduces output, whereas when the economy is in progression mode, oil price uncertainty has no influence on output whatsoever. It means that in periods of economic prosperity, when all economic sectors record growth, which is described by the right tail quantile ($\tau^{0.95}$), the uncertainties that come from the oil market are not strong enough to exert a negative effect on output. In other words, in cyclical stages of economic well-being, the negative effect of increased oil price uncertainty is offset notably by all other positive things that are inherent for one growing economy, such as increased domestic consumption, growing export, rising incomes and positive expectations about the future. In these circumstances, the negative effect of oil price uncertainty on the output is counterweighted and its effect cannot be found in the Bayesian QR framework, as Table 5 suggests. Punzi (2019) also reported the positive affect of oil volatility on output, but she



Note: The shaded area gives the adjusted credible intervals at 70% probability

Figure 5. Graphical presentation of the estimated quantile parameters – quarterly data



Note: The shaded area gives the adjusted credible intervals at 95 % probability

Figure 6.
Graphical presentation of the estimated quantile parameters – monthly data

found another explanation of this phenomenon. She claimed that energy price volatility can actually galvanize an improvement in GDP growth in the short-run because it can be an omen for a real increase in the future energy price. Thus, firms accelerate the production process in the short-run, under increased volatility, because oil prices can skyrocket in the following period. In addition, Chowdhury *et al.* (2018) studied the nexus between inflation uncertainty and GDP in the UK and USA, but the explanation in this paper can easily be implemented in our study. In particular, they asserted that cash flows of companies are relatively high in the period of economic prosperity, which is a favourable situation for them regardless of the changes in inflation uncertainty or, in our case, oil uncertainty. In these advantageous conditions, firms are willing to enter new investment projects, without particular concern about what incoming oil volatility might be, which positively affects output growth. This explanation is in line with our results because Table 5 shows that the majority of the estimated $\tau^{0.65}$ to $\tau^{0.95}$ BQR are positive, whereas almost all $\tau^{0.05}$ to $\tau^{0.5}$ quantile coefficients are negative.

On the other hand, when the economy is in struggle, which is depicted by the left tail quantile ($\tau^{0.05}$), we reveal that increase in oil price uncertainty has a negative effect on output, and it applies to all the countries. These findings suggest that in the period of an economic downturn, falling incomes and depressed production, oil price uncertainty only adds "oil to the fire", amplifying in this way the problems which one economy already encounters. Elder and Serletis (2009) analysed the case of Canada via the structural VAR model and found that increases in oil price uncertainty tend to reduce output in industries that use imported energy. Bernanke (1983) asserted that the probable explanation lies in the fact that oil-dependent companies postpone some investment decisions if they suspect that the decrease in energy prices may be quickly reversed. These actions have negative implications on the economy. This explanation totally fits in with our results, because in the period of economic contraction, companies are already reluctant to invest in new projects, while uncertainties in the oil market only additionally convince companies to wait for better times. A direct aftermath of the falling investments is a drop in GDP growth and industrial production. Also, our findings of an asymmetric effect coincide very well with the results of Serletis and Xu (2019), who investigated the US case and reported an asymmetric effect from oil price uncertainty towards economic activity. These authors contended that the negative effect of oil price uncertainty is significantly larger during periods of contraction when large oil price changes occur. They also asserted that oil price uncertainty shocks are more persistent during contractions and they increase the negative dynamic response of the economic growth rate.

Regarding the idiosyncratic effect of oil volatility on the output, it can be seen that increased oil uncertainty has a more negative effect on industrial production than on real GDP. This finding applies for all the selected countries and it is expected because GDP involves wider range of sectors, which not all directly relate their activities to the oil consumption. On the other hand, industries that find oil as indispensable input for their production, are directly and more severely hit by the increased volatility in the oil market. This discrepancy is well documented in Table 5, and in some instances, such as Czech, Polish, Lithuanian, Latvian and Slovenian, this difference is quite substantial. As for the effect of oil uncertainty on the countries, we try to find a viable reason why a particular country experiences an impact from oil uncertainty in the amount found in Table 5. In that regards, Tables 6 and 7 should help in the analysis, and they contain empirical information about net fuel import and GDP sector composition, respectively.

According to Table 5, the biggest economies, such as Polish and Czech, sustain the least effect on real GDP, whereas smaller economies suffer more profound impact from oil volatility. Probable explanation lies in the fact that larger economies are more diversified and as such are less susceptible for uncertainties that come from the oil market. In addition, both Poland and the Czech Republic have relatively high weight of industrial production in their GDPs, which explains relatively high impact of oil uncertainty on this aggregate at the economic downturn, i.e. $\tau^{0.05}$ quantile. Two other Visegrad countries – Hungary and Slovakia, are smaller economies than the Czech and Polish, and they endure a somewhat bigger effect on GDP from oil uncertainty. These two economies have relatively high weight of industry sector in their GDP, around 31% and 35%, respectively, which might explain

	CZE (%)	POL (%)	HUN (%)	SLK (%)	LIT (%)	LAT (%)	EST (%)	SLO (%)
Fuel import◆	4.61	5.95	6.21	6.14	14.65	14.96	10.42	6.6
Fuel export◆	0.63	0.96	1.91	2.2	13	3.13	6.49	3.41
Net import of fuel	3.98	4.99	4.3	3.94	1.65	11.83	3.93	3.19

Note: ◆Fuel involves crude petroleum, petroleum gas and refined petroleum
Source: https://oec.world/en/profile/country/cze

Table 6. Fuel import and export of the selected CEECs in 2018

	CZE	POL	HUN	SLK	LIT	LAT	EST	SLO
Agricultural in %	2.3	2.4	3.9	3.8	3.5	3.9	2.8	1.8
Industrial in %	36.9	40.2	31.3	35.0	29.4	22.4	29.2	32.2
Service in %	60.8	57.4	64.8	61.2	67.2	73.7	68.1	65.9

Note: ◆CIA World Factbook, 2017

Table 7. GDP Sector composition of the selected countries in 2017◆

relatively high impact of oil uncertainty on their industrial productions. Lithuania, Estonia and Slovenia also have relatively high share of the industrial sector in their GDPs, which can explain very well the negative left-tail quantile parameters. On the other hand, Latvia has the highest net fuel import, according to Table 6, but sustains the least effect from oil uncertainty when industrial production is in concern. A probable explanation lies in the fact that Latvia has the lowest share of industrial production in its GDP, which is around 22%.

6. Conclusion

This paper tries to answer how oil price uncertainty affects two different aggregate levels – real GDP and industrial production in eight CEECs. We put an emphasis on the accurateness of the obtained results, thus we use the Bayesian method of inference for two applied methodologies – the Markov switching GARCH model and quantile regression. In the first stage, we estimate conditional variance via the MS-GARCH model, which serves as a proxy for oil price uncertainty. In the second stage, we measure how this uncertainty impacts GDP and industrial production in the quantile regression framework.

The estimated quantile parameters give us an opportunity to assess how oil uncertainty affects output in different market conditions. The results indicate that only left and right tail quantiles, are relatively high and have economic significance, whereas the majority of the near tail and median quantile parameters are really low in magnitude. This is a clear indication that in moderate economic conditions, oil price uncertainty has a very low, in some cases almost negligible, effect on output in the selected countries. However, in the explicit phases of contraction and expansion, which is portrayed by the tail quantiles, we find negative and positive QR parameters, which are relatively high in magnitude. These results indicate that in periods of deep economic crises, an increase in the oil price uncertainty reduces output, amplifying in this way the downfall of one economy. On the other hand, when the economy is in expansion, oil price uncertainty has no influence on output, because the negative effect of oil volatility is not strong enough to offset all other positive developments in the economy. Our results provide additional evidence that increased oil uncertainty has a more negative effect on industrial production than on real GDP, whereas industrial share in GDP plays an important role in how strong some CEEC is impacted by an oil uncertainty.

This paper could be interesting for policymakers of the selected countries to gain an insight whether and how oil uncertainty affects their output. Generally, we do not find the strong and negative influence of oil uncertainty on output in all market conditions. This only happens in the cases when economies slip into a deep recession, and some policy implications may emerge from these results. For instance, in the cases of Hungary, Slovakia and Lithuania, which suffer the most from oil volatility in downturn cyclical episodes, governments of these countries may take some measures to act as a counterweight for the second-moment changes in oil prices. Fiscal measures could help more directly to those who suffer from adverse oil uncertainty impacts. More specifically, a different form of subsidies could be given for companies that are directly and solely depend on oil consumption if these companies have a key role in country’s export, provide important public services or use significant amount of people.

Notes

1. Estimation of the Bayesian MS-GARCH model was done via “MSGARCH” package in “R” software.
2. Bayesian quantile parameters were calculated via “bayesQR” package in “R” software.

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