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The Effect of Oil Price Uncertainty on Industrial Production in the Major European Economies - Methodologies Based on the Bayesian Approach

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Abstract

This paper investigates how oil price uncertainty affects industrial production (IP) in six developed European countries – Germany, UK, France, Italy, Spain and Norway. In the research process, we use several methodologies based on the Bayesian technique – MS-GARCH model and quantile regression. Estimated quantile parameters show that the magnitude of volatility transmission from oil to IP is not high in higher quantiles, but for the majority of the net oil consuming countries the negative effect is around 20% when IP is very low, which is relatively high. However, this result should be taken with a caution, because all quantile parameters are statistically significant at 70%. The results indicate that the U.K. suffers the weakest, while Spain the strongest impact from the oil price uncertainty. The reason for this finding probably lies in daily oil consumption vis-à-vis GDP, since UK has the lowest, whereas Spain has the highest oil consumption ratio. Also, it should be said that four fifth of the U.K. GDP is composed of services, which also speaks in favour why British IP suffers relatively weak impact. Besides Spain, Germany and Italy also have relatively high 0.05th quantile parameters. This indicates that these countries also endure relatively significant impact from oil price uncertainty when their economies are in recession.

1. Introduction

Oil is the world's largest energy source that provides around 33% of global primary energy consumption (see e.g. Ho and Huang, 2016; van Eyden et al. 2019). Because of that, the impact of oil on the economy have been widely discussed in the literature (see e.g. Sodeyfi and Katircioglu, 2016, Pinho and Madaleno, 2016; Maghrebi et al., 2018; Bildirici and Sonustun, 2018). In addition, it should be said that global oil prices are very susceptible to the huge price swings that is particularly characteristic for the last two decades (see Figure 1), and that happens due to numerous factors such as regional wars, OPEC oil-price shocks, political conflicts, global economic crisis, changes in global oil demand and supply, etc., as Oladosu et al. (2018) asserted. Left plot in Figure 1 clearly shows that at the beginning of the

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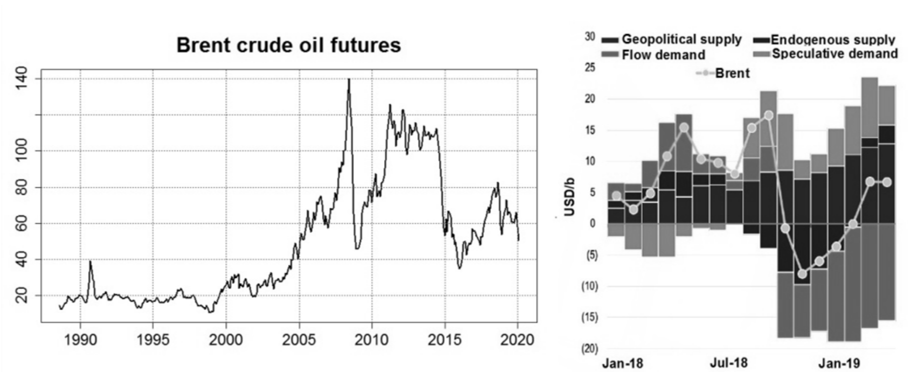
century, the price of oil was well below $40 per barrel, up to July 2008 it was around $140 per barrel, while in November 2008 price of crude oil was under $50 per barrel. Yet another oil price roller-coaster occurred in February 2012, when the price of crude oil was beyond $120 per barrel, whereas up to December 2015, oil was sold below $40 per barrel. Right plot in Figure 1 gives an illustration of various factors that affect oil price dynamics, which indicates that oil prices are under constant and complex influence from different sources.

Generally speaking, analysing oil dynamics is important for governments and companies, because oil price swings can affect the economy *via* variety of conduits. Most important factor reflects in a fact that rising oil prices directly impact costs of production due to rise in the relative price of energy inputs, which lowers companies' profit. On the other hand, numerous other factors arise from the oil price increase and hit the economy indirectly. For instance, rise in inflation, as a consequence of increasing oil prices, induces lower profit of companies and forces them to reduce the workforce and production, which increases unemployment and decreases GDP. Following repercussion of rising inflation is also a response of monetary authorities, who increase interest rates, making borrowing money more expensive, which reflects to lower investments and lower production. Higher interest rates, as a consequence of rising inflation, directly affect financial markets, i.e. equity and bond valuations, which brings insecurity in these markets and hinders normal functioning of the economy. Therefore, rising and unstable oil prices can have very detrimental effects on the economies across the globe.

Figure 1 Empirical Dynamics of Brent Crude Oil Futures Prices and Its Drivers



Notes: Left-hand plot presents empirical dynamics of Brent crude oil futures prices in dollars per barrel (source: authors' calculation). Right-hand plot denotes oil price drivers from January 2018 (source: Fattouh and Economou, 2019).

Cheng et al. (2019) added that oil price oscillations raise the alarm to private companies primarily owing to two widely accepted reasons. First of all, oil stands as a crucial input in many production processes, which means that changing oil prices, expressed as oil price shocks (first-moment measure), inevitably affect company's production costs. On the other hand, oil price uncertainty[1], defined as unanticipated change in future price (second-moment measure), impacts company's expectations regarding current production and investment decisions. Therefore, it is very important to make a clear difference between first and second-moment variability, because these changes are not necessarily harmonized, since volatility rise in both periods of price increase and decrease. Punzi (2019) asserted that oil price uncertainty can affect GDP growth because companies postpone their investment decisions in uncertain conditions about the future cost of oil, whereas households delay their present consumption for precautionary savings reasons. Maghyereh and Abdoh (2020) also contended that oil price uncertainty can cause a decline in the investments and capacity utilization, which inevitably spills over to lower output growth. This happens because companies delay immutable investment expenditures in order to do more analysis and gather more information about future oil prices in order to avoid potentially costly reallocation of resources. In practical sense, in this way, companies buy themselves more time before committing their resources irreversibly. However, as a consequence of these actions, output falls.

According to the above, this paper tries to add to the literature by investigating the impact of Brent oil futures price uncertainty on industrial production in the six major European countries – Germany, France, the United Kingdom, Italy, Spain and Norway. The five largest European economies are intentionally selected, because all these countries are net oil consumers (see Table 1). In addition, we include Norway in the sample, although Norway is not the sixth largest European economy, but Norway is net oil producer, and this country serves for comparison purposes. We observe industrial production rather than GDP, because industrial output is narrower aggregate, and as such, is more dependent on oil fluctuations. We opt for oil futures prices rather than oil spot prices, because futures prices by definition incorporate all available information and thus provide a more realistic oil dynamics in comparison with the spot prices, as Cipra (2010) and Natanelov et al. (2011) contended. Besides, Brent crude oil is chosen rather than WTI oil, because this energy commodity is the most traded oil in the current global oil market, and as such, portrays the evolution of the global oil prices in the best way. Also, the selected countries primarily consume Brent oil.

Table 1 Nominal GDP Rank and Daily Oil Production and Consumption in Barrel of Oil in 2019

	Germany	*U.K.*	*France*	*Italy*	*Spain*	*Norway*
Global GDP rank*	4	6	7	8	13	29
Oil production**	46 839	939 760	16 418	70 675	2 667	1 647 975
Oil consumption**	2 447 000	1559000	1606000	1262000	1226000	255 200
Net position	-2 400 161	-780 760	-1 589 582	-1 191 325	-1 223 333	1 392 775

Source: *International monetary fund, **U.S. Energy Information Administration

[1] It should be said that uncertainty is different term from variability, according to Grier and Perry (1998), because uncertainty can be regarded as unpredictable fluctuations, whereas variability captures both unpredictable and predictable fluctuations. However, in the paper, we do not make a difference between these two terms and use them interchangeably.

Besides the fact that very few papers have addressed the role of oil price uncertainty on industrial production (see Punzi, 2019), our motivation to do this research is also based on the usage of two unconventional methodological approaches – Bayesian Markov switching GARCH (BMS-GARCH) model and Bayesian quantile regression (BQR), which have never been done before in this topic/context. Therefore, our study differentiates from the existing papers in a sense that we put an emphasis on the Bayesian estimation technique rather than maximum likelihood or least squares methodologies, because this approach is potentially more capable of dealing with identification issues, parameter uncertainty, misspecification and a number of computational matters (see e.g. Hamilton and Susmel, 1994; Ardia, 2009; Klacso, 2015; Fičura and Witzany, 2016; Živkov et al., 2020). We consider the Bayesian Markov switching GARCH model and Bayesian quantile regression in the main computational process, while the vector autoregression (VAR) model serves as complementary analysis.

BMS-GARCH model is applied, because we want to measure oil price uncertainty as accurate as possible, and this model can recognize regime changes in conditional volatility endogenously. In order to add more precision in the estimation process, we combine MS-GARCH model with six different distribution functions – normal, skewed normal, Student t, skewed Student t, GED and skewed GED. The best model is chosen based on the Deviance Information Criterion (DIC) of Spiegelhalter et al. (2002). From the best BMS-GARCH specification, we derive regime-switching conditional volatility, which serves as proxy for oil price uncertainty. Our assumption is that oil time-series are polluted with structural breaks[2], and it is well known in the literature that estimates of the GARCH type models can be biased due to this nuisance in the volatility dynamics (see Bauwens et al., 2010). If this is the case, the sum of the estimated GARCH coefficients is close to or even exceeds one, as Klaassen (2002) explained. This issue could produce a non-stationary volatility in a single-regime GARCH models, biased conclusions and poor risk predictions, as Frommel (2010) argued. An efficient way to resolve this problem is to estimate Markov switching GARCH model, which can change parameters over time according to a discrete latent (unobservable) variable. We estimate MS-GARCH model with the Bayesian procedure instead of maximum likelihood method, because Virbickaite et al. (2015) contended that maximum likelihood approach presents some limitations when the errors are heavy tailed, when the convergence rate is slow or when the estimators is not asymptotically Gaussian.

After creation of the Bayesian regime-switching conditional volatilities, we combine industrial production time-series with this oil price uncertainty proxy in the Bayesian quantile regression model. This particular procedure can provide an insight about the transmission effect from oil price uncertainty to real industrial production output in different market conditions – downturn (lower quantiles), normality (intermediate quantiles), and upturn (upper quantiles). Also, this methodology can successfully deal with extreme values and outliers in the empirical data, which prevents biased conclusions (see Lubrano and Ndoye, 2014). As in the case of the

[2] Structural break is a situation when time-series abruptly changes at some point in time, which can lead to parameter bias and unreliability of the model in general.

Bayesian MS-GARCH model, Bayesian QR uses MCMC (Markov Chain Monte Carlo) algorithm in the estimation process, which provides an exact inference about the quantile parameters. In other words, Bayesian QR can produce highly statistically significant parameters, if confidence intervals are narrow, even in low data environment. According to Sriram et al. (2013), the Bayesian QR methodology decreases the length of credible intervals and increases the accurateness of quantile estimates, comparing to the traditional quantile regression OLS approach of Koenker and Bassett (1978), which is an important feature of the Bayesian QR.

In the final stage of our investigation, we want to additionally strengthen the robustness of our quantile parameters, and in that matter, we estimate the bivariate and multivariate vector auto-regression (VAR) models. This particular methodology can indicate, *via* impulse response function, the magnitude of oil price uncertainty shocks to industrial production, and also it can show in which time-horizon this impact is the highest. The VAR model is convenient approach, because it can provide coefficient estimates that are not biased, even when the variables in the model contain unit roots. This is important for our computational process, since oil price uncertainty time-series is not mean-reverting.

Besides introduction, the rest of the paper is structured as follows. Second section provides brief literature review. Third section explains used methodologies – the Bayesian MS-GARCH model, Bayesian QR and VAR model. Fourth section presents dataset and the way how oil price uncertainty is created. Fifth section is reserved for the empirical results, while the last section concludes.

2. Brief Literature Review

At the empirical level, many papers analysed oil shocks and economic activity, such as Jiménez-Rodríguez (2008), Obadi and Korček (2014), Ratti and Vespignani (2016) and Polar (2020). On the other hand, very few studies discussed how oil price uncertainty affects output, whereby definite conclusion is not in sight, thus further research on this subject is necessary. This section briefly presents the finding of some studies on this topic. For instance, Rafiq and Salim (2014) studied the impact of oil price volatility on six major emerging economies in Asia, using time-series cross-section and time-series econometric techniques. They found that oil price volatility influenced output growth in China and affected both GDP growth and inflation in India in the short run. Oil price volatility impacts inflation in the Philippines, whereas in Indonesia, it impacts both GDP growth and inflation before and after the Asian financial crisis. As for Malaysia, oil price volatility affects GDP growth, while in Thailand, oil price volatility influenced output growth prior to the Asian financial crisis, but the impact disappeared after the crisis. Cheng et al. (2019) investigated the dynamic impacts of oil uncertainty on the Chinese economy. They used sample standard deviation and conditional standard deviation estimated from the GARCH(1,1) model, in order to calculate uncertainty in oil prices. They revealed that an increase in volatility in oil prices tends to reduce the Chinese real GDP and investment. Also, they found that an increase in oil price uncertainty reduces real GDP and investment, while a decrease in oil price uncertainty boosts the macroeconomy. The paper of Jo (2014) studied the effect of oil price uncertainty on global real economic activity. He used quarterly vector autoregressive model with stochastic volatility in mean. He found that oil price uncertainty shock has negative effects on world industrial production. In particular, he reported that a doubling of oil price volatility leads to a cumulative decline as high as 0.3 percentage points in world industrial production. The paper of Ahmed (2011) examined the impact of oil price uncertainty on Malaysian macroeconomic activities and monetary responses. They claimed that oil price volatility shock has a prolonged dampening effect on Malaysian industrial production. They also asserted that Malaysian central bank conducts an expansionary monetary policy in response to oil price uncertainty. Elder and Serletis (2010) investigated the relationship between the oil price uncertainty and investment. They reported that volatility in oil prices has had a negative and statistically significant effect on durables consumption and aggregate output. They asserted that oil price volatility tends to exacerbate the negative dynamic response of economic activity to a negative oil price shock.

Ahmed et al. (2012) examined the impact of oil price uncertainty on the US industrial production. They decomposed oil price volatility into permanent and transitory components, using component GARCH model. Their estimates showed significant asymmetric effect of oil price shock on the transitory oil price volatility. They uncovered that there is a significant and prolonged dampening impact of increased transitory oil price volatility on industrial production. Maghyereh and Abdoh (2020) investigated how oil uncertainty affects investment in the U.S., and they reported that the negative effect of crude oil price return uncertainty on investments is asymmetric. More specifically, they showed that investments are more reduced following the volatility of positive oil price changes than that of negative changes, and this asymmetric effect is more pronounced in small firms. Punzi (2019) evaluated the macroeconomic implications of energy price volatility, using a dynamic stochastic general equilibrium (DSGE) model in 10 Asian economies. He found that energy price volatility shocks generate an increase in GDP in the short-run and a reversal in the long-run. He asserted that market volatility leads households to cut consumption for precautionary savings motives, which in turn increases investment. However, he concluded that both energy price and uncertainty fluctuation lead to high macroeconomic volatility in the business cycle. Elder (2018) researched the effect of oil price volatility on disaggregated measures of industrial production, which are the special aggregates by market groups calculated by the Federal Reserve Board. He found that among energy-related market groups, the effects of oil price volatility are concentrated in activities related to primary energy generation and oil and gas drilling. While for non-energy-related market groups, oil price volatility affects a broad range of special aggregates, including consumer goods and business equipment.

3. Research Methodologies

3.1 Bayesian Markov Switching Approach

Our first task involves the construction of conditional volatility of Brent oil, which serves as proxy for oil price uncertainty. Since we assume the presence of structural breaks in monthly oil time-series, which can produce spurious estimates of conditional volatilities, we opt for Markov switching GARCH model, which can recognize structural breaks endogenously in the variance. In order to further enhance accurateness of the assessed oil conditional volatility, we apply MS-GARCH model with the Bayesian technique.

Ardia (2009) asserted that the Bayesian statistical method efficiently obtain the posterior distribution of any non-linear function of the model parameter. On the contrary, the classical maximum likelihood procedure has a problem to easily perform inferences on non-linear functions of the model parameters, while the convergence rate could prove slow, with the serious limitations when the residuals are heavy tailed. Virbickaite et al. (2015) contended that the state variables are treated as random variables in the Bayesian context, which enables researchers to construct the likelihood function without difficulty. In other words, a posterior distribution is constructed using priors, which integrate the posterior density function with respect to parameters and state variables.

In this study, we assume an AR(1) process for the conditional mean of Brent oil, where residuals of the model follow some form of the iid process $\varepsilon_t \sim iid(0, h_{it})$. In other words, we try to find out the bets fitting distribution in the Bayesian MS-GARCH model, and in that effort, we consider six different distribution functions – normal, skewed normal, Student t, skewed Student t, GED and skewed GED. 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 $\varepsilon_{t-1,st}^2$ and $h_{t-1,st}$ are ARCH and GARCH effect under regime st. The non-negativity of h_t is ensured if we set following restrictions: $\omega_{st} \geq 0$, $\alpha_{st} \geq 0$ and $\beta_{st} \geq 0$. Volatility persistence in state i is measured by $\alpha_i + \beta_i$.

We estimate the Bayesian MS-GARCH model[3] with Markov Chain Monte Carlo (MCMC) procedure, which requires the evaluation of the likelihood function. Referring to Ardia (2008), we define $y_t \in \mathbb{R}$ as the log return of oil at time t, and regroup the model parameters into the vector $\mathbf{\Psi}$. Accordingly, the conditional density of y_t in state $st = k$, given $\mathbf{\Psi}$ and I_{t-1}, is presented as $f(y_t|st = k, \mathbf{\Psi}, I_{t-1})$. The discrete integration is subsequently obtained as follows:

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

where $\eta_{i,t-1} = \mathrm{P}(s_{t-1} = i|\, \mathbf{\Psi}, I_{t-1})$ 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:

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

Following Ardia (2008), in the case of MCMC estimation, the likelihood function is combined with a diffuse (truncated) prior $f(\mathbf{\Psi})$ to build the kernel of the

[3] Estimation of the Bayesian MS-GARCH model was done via 'MSGARCH' package in 'R' software.

posterior distribution $f(\mathbf{\Psi}|\mathrm{y})$. Since 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 monthly oil regime-switching conditional volatilities, we combine this dynamic time-series with the industrial production of the selected countries in the Bayesian quantile regression framework[4]. Referring 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 sophisticated view about the interlink between the dependent variable and the covariates, because it gives an evaluation 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 (see e.g. Choi and Min, 2015; Borraz et al., 2015; Vilerts, 2018; He et al., 2020).

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 industrial production time-series is a dependent variable, while 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):

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

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 τ^{th} regression quantile. When $\tau = 0.5$, it corresponds to median regression. In the Bayesian estimation process, efficient QR parameters are obtained with the usage of the Markov Chain Monte Carlo algorithm. A primary reason why we choose Bayesian QR and not traditional QR of Koenker and Bassett (1978) is the fact that this process provides accurate and reliable estimates of the quantile parameters $\hat{\beta}(\tau)$, if confidence intervals around estimated BQR parameters are relatively narrow.

3.3 Vector Auto-Regression Model

In order to boost the robustness of quantile regression results, we additionally calculate vector autoregression model in bivariate and multivariate form. Using a bivariate VAR model, we can measure the effect of oil price uncertainty on industrial production *via* impulse response functions and see in which time-horizon this effect is most pronounced. Also, this model can serve as a robustness check for estimated Bayesian quantile parameters. We get an idea to use VAR model in our research

[4] Bayesian quantile parameters were calculated via 'bayesQR' package in 'R' software.

from the papers such as Jo (2014), Jimenez-Rodriguez (2008) and Ratti and Vespignani (2016). A given structure of a bivariate VAR model has a form like in equations (6) and (7).

$$Y_t^{IP} = \omega_0 + \sum_i^m \omega_i Y_{t-i}^{IP} + \sum_i^m \omega_i X_{t-i}^{OU} + \varepsilon_{1,t} \tag{6}$$

$$X_t^{OU} = \varpi_0 + \sum_i^m \varpi_i X_{t-i}^{OU} + \sum_i^m \varpi_i Y_{t-i}^{IP} + \varepsilon_{2,t} \tag{7}$$

where Y_t^{IP} and X_t^{OU} are industrial production and oil uncertainty variables, respectively. ω and ϖ are parameters to be estimated, whereas m denotes proper lag length determined based on the lowest AIC.

Based on the fact that industrial production is affected by numerous external shocks, which means that our basic bivariate model could be biased due to consideration of only two variables, we extend bivariate VAR by adding two more fundamental variables in the model – inflation and long-term interest rate. The inclusion of these variables in the model is based on the papers of Ratti and Vespignani (2016) and Serletis and Liu (in press), who investigated the impact on inflation and interest rate on output. The four-variate VAR model looks like in equation (8).

$$Y_t = C_0 + \sum_{i=1}^{m} \phi_i Y_{t-i} + \epsilon_t \tag{8}$$

where Y_t is 4×1 vector of endogenous variables – industrial production (IP), inflation (INF), interest rate (IR) and oil uncertainty (OU), and the order of variables is set in our VAR model according to logical influence between the variables, i.e. OU → IR → INF → IP. C_i is constant term, and ϵ_t is 4×1 vector of residuals that are not correlated with each other. ϕ denotes VAR coefficients.

4. Dataset and Preliminary Calculations

This study uses monthly data of industrial production of six developed European economies – Germany, France, the United Kingdom, Italy, Spain and Norway. Also, we use the prices of monthly Brent oil futures traded on Chicago Mercantile Exchange. In the Bayesian QR model, which is our primary methodological tool, we analyse spillover effect from oil price uncertainty to industrial production. Additional analysis considers VAR model, where we add inflation and long-term interest rate. All industrial production, inflation and interest rate time-series are seasonally adjusted, using filter-based methods of seasonal adjustment, known as X11 style method. Data for industrial production, inflation and interest rate are retrieved from *OECD statistics* website, while Brent oil futures prices are collected from *investing.com* website. The samples range from 1988:M7 to 2020:M2. Industrial production, inflation and interest rate time-series are collected from the site as rates, while Brent oil futures price is transformed to rate of return according to the expression $r_{i,t} = 100 \times ln(P_t/P_{t-1})$, where P is Brent futures oil price.

Table 2 presents descriptive statistics for industrial production time-series. It can be seen that Germany has the highest average industrial production, while Norway follows. On the other hand, Norway has the highest variability of industrial production, whereas Germany and Spain follow. All IP time-series have relatively modest skewness and kurtosis coefficients, thus all values for the Jarque-Bera tests of normality are relatively low, which means that all IP time series follow normal distribution or they are near normal distribution. Figure 2 gives graphical plots of the empirical IP time-series.

Table 2 Descriptive Statistics of Seasonally Adjusted Industrial Production Time-Series

	Germany	*U.K.*	*France*	*Italy*	*Spain*	*Norway*
Mean	0.132	0.020	0.054	0.000	0.031	0.128
St. dev.	1.550	0.855	1.337	1.411	1.480	2.973
Skewness	-0.351	-0.806	-0.068	-0.314	-0.179	0.532
Kurtosis	5.360	7.081	4.142	4.135	5.478	6.096
JB	95.7	304.0	20.9	26.6	99.0	169.2

Notes: JB stands for Jarque-Bera test of normality.

The second step in our computational process considers creation of oil uncertainty time series. For that purpose, we use the Bayesian MS-GARCH model, which gives robust estimates of the GARCH parameters and standard errors, because we assume that oil rate of returns is polluted with structural breaks. In order to further increase the accurateness of the estimated model, we couple the Bayesian MS-GARCH model with the six different distribution functions – normal, skewed normal, Student t, skewed Student t, GED and skewed GED. The optimal model is selected based on the lowest Deviance information criterion of Spiegelhalter et al. (2002). Figure 3 presents smooth probabilities of two regimes in the variance, estimated *via* Bayesian MS-GARCH model. Figure 3 clearly shows existence of two regimes – low volatility (stage 1) and high volatility (stage 2). It can be seen that oil volatility is more than 70% in higher volatility mode. Finding two different regimes, indicates that BMS-GARCH model has successfully recognized structural breaks in the conditional variance.

Figure 2 Seasonally Adjusted Industrial Production of the Selected Economies

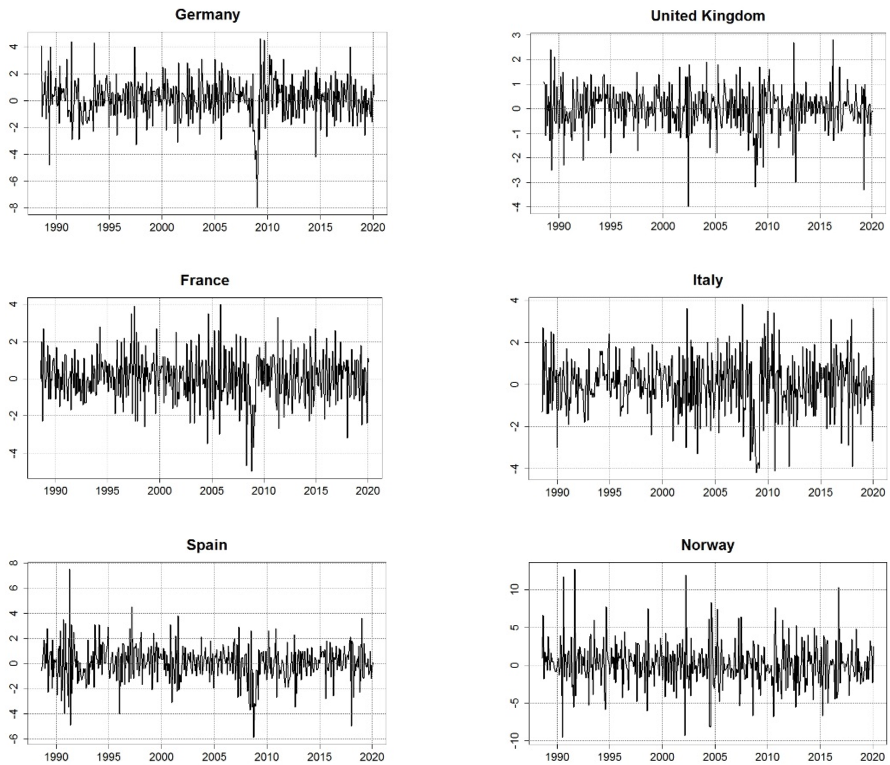
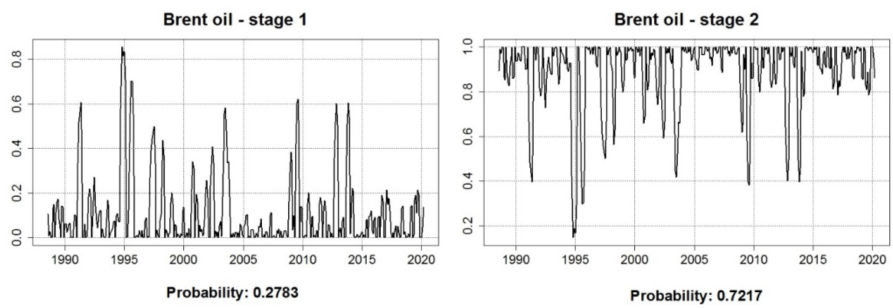


Figure 3 Smooth Probabilities of Brent Oil Futures for Two Regimes and Their Probabilities



As can be seen in Table 3, model with skewed normal distribution is the best-fitting, and this model is used to generate regime switching conditional variance, which serves as oil price uncertainty proxy.

Table 3 Deviance Information Criterion for Different Bayesian MS-GARCH Specifications

	Normal	*Skew-normal*	*Student*	*Skew-Student*	*GED*	*Skew-GED*
Brent oil	2711.6	2704.1	2708.7	2704.7	2709.5	2704.9

Figure 4 Regime-Switching Conditional Volatility of Brent Oil Futures

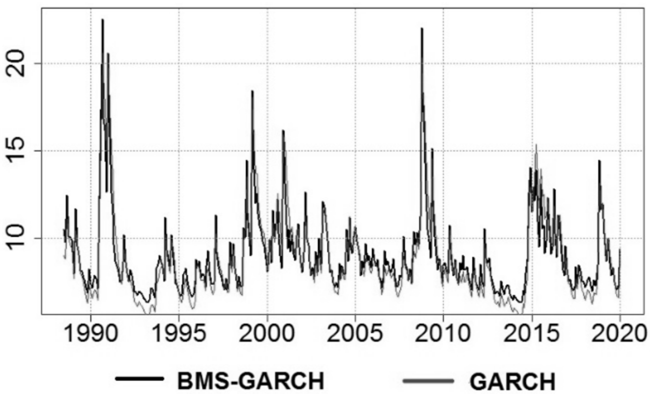
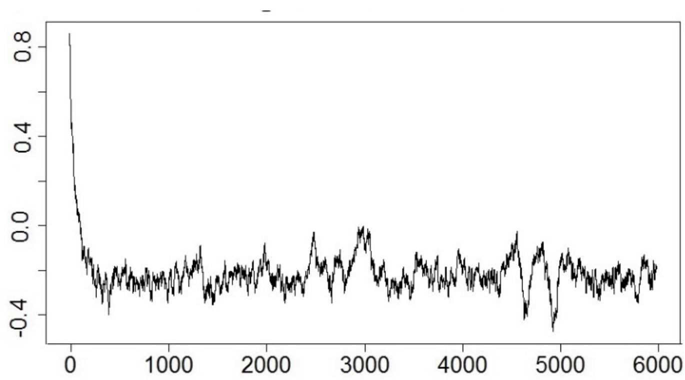


Figure 4 presents graphical illustration of conditional volatility dynamics, created *via* the BMS-GARCH model with the skewed normal distribution and simple GARCH-normal model, which serves for comparison purposes. It can be seen that dynamics of conditional volatilities is similar, but not equal between BMS-GARCH and GARCH models. Probable reason is the fact that BMS-GARCH model can recognize structural breaks in the variance, and thus better fit to the empirical series. Therefore, it could be said that estimation of conditional volatility *via* BMS-GARCH model contributes to the accurateness of the computation.

In the Bayesian QR framework, we can preliminarily check the validity of the estimated Bayesian QR parameter. In that goal, we apply a visual inspection of the MCMC chain convergence for Germany IP that can be seen in Figure 5. This plot presents the evolution of the MCMC draws over the 6000 iterations, that have been used in this research. The number of burn-in draws that have been discarded is 1000. Applying relatively high number of iterations in MCMC chain *vis-à-vis* the size of our sample (379 empirical observations), gives us a confidence that estimated Bayesian QR parameters could be reliable. Figure 5 displays the trace-plots of the MCMC chain of the median quantile, $\hat{\beta}(\tau) = 0.5$. It is obvious that presented trace-plot has good performance, which means that the effect of the initial values of the MCMC chains wears off very fast, while the MCMC sampler quickly reduces to the stationarity. This result indicates the absence of (large) bias of the estimated parameters. However, it should be said that MCMC chain convergence does not say undoubtedly anything about statistical significance of the estimated parameters. This can be assessed rather by credible intervals of the estimated parameters. Due to the fact that all trace-plots of all other countries across all quantiles are very similar, we portray in Figure 5 only trace-plots for the median quantile of German IP, while all other trace-plots can be obtained by request.

Figure 5 Trace Plot for Median Quantile of Germany Industrial Production



5. Empirical Results

5.1 Bayesian quantile regression results

This subsection presents the Bayesian quantile regression results, regarding how oil price uncertainty affects industrial production in the cases when this output is low, moderate and high. The results are presented in Table 4 *via* seven quantile parameters.

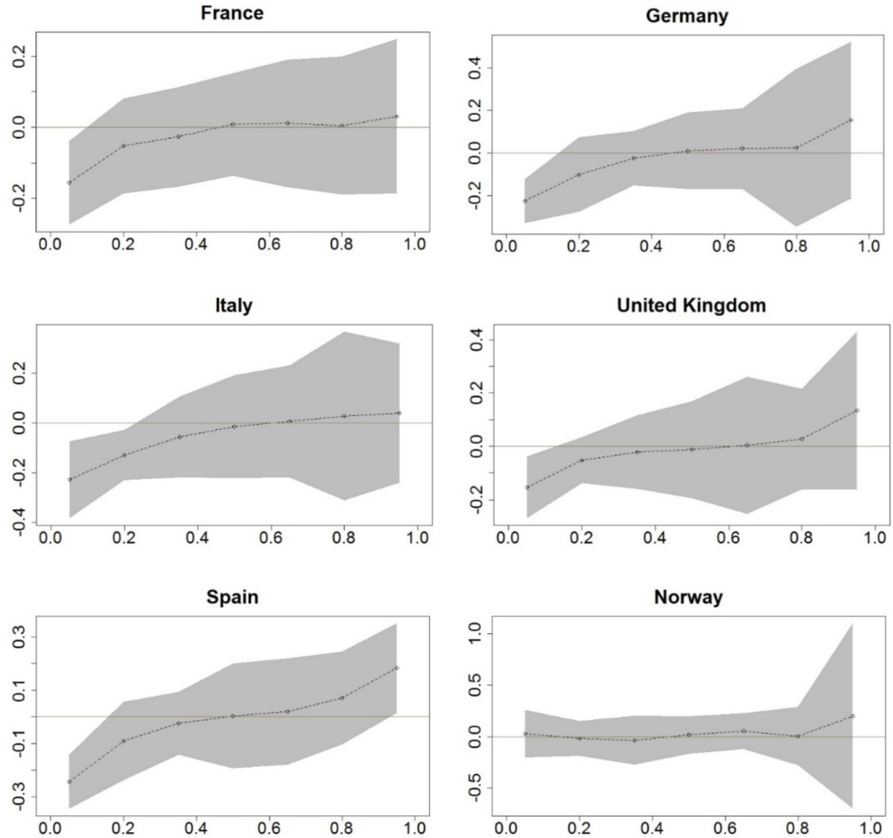
Figure 6 presents estimated quantile parameters with 70% confidence band for each country. Looking at Figure 6, it can be noticed that, confidence interval at right-tail quantile is relatively wide in relation to the left-tail quantile confidence band. Wider credible intervals at right tail quantile indicate that right tail quantiles are less reliable than left tail quantiles.

Table 4 Results of Quantile Parameters Estimated with the Bayesian Quantile Regression

	Estimated Bayesian quantiles						
	0.05	***0.2***	***0.35***	***0.5***	***0.65***	***0.8***	***0.95***
Germany	-0.239	-0.116	-0.034	0.001	0.006	0.008	0.122
UK	-0.163	-0.060	-0.031	-0.025	-0.017	0.009	0.106
France	-0.169	-0.059	-0.039	-0.002	-0.005	-0.010	0.030
Italy	-0.237	-0.136	-0.067	-0.032	-0.012	0.007	0.0
Spain	-0.247	-0.102	-0.035	-0.011	0.008	0.054	0.183
Norway	0.014	-0.025	-0.051	0.007	0.048	-0.011	0.189

Note: All quantile parameters are statistically significant at 70%.

Figure 6 Plots of the Estimated Bayesian QR Parameters



Notes: The shaded area indicates credible intervals at 70% probability.

Table 4 shows that all estimated Bayesian QR parameters are relatively low, which means that oil volatility shocks do not have substantial effect on industrial production of the selected countries. The highest negative effect goes little bit over 20% for Germany, Italy and Spain, and this is recorded in the conditions when industrial production is very low ($\tau^{0.05}$ quantile). It can be seen that all net consuming countries have relatively high negative effect from oil price uncertainty at left tail, which means that these volatility shocks decrease IP in conditions when IP is in downturn, but this effect is not particularly high. This assertion is confirmed by other quantile parameters (from $\tau^{0.2}$ to $\tau^{0.5}$), which shows that 100% increase in oil volatility reduces IP only by 10% or less. In moderate market conditions (median quantile), the transmission effect goes around 3% or less. Our findings are well in line with the paper of Jo (2014), who investigated how oil price uncertainty affects global real economic activity during 1958Q2–2008Q3. Using Bayesian VAR model, he determined that a 100% increase in oil price uncertainty over a 12-quarter results in a drop of the industrial production growth rate by approximately 0.11 percentage points in the same quarter. This percentage is relatively low and coincides with our QR finding in great deal. In addition, Maghyereh et al. (2019) reported that oil price uncertainty had very low effect on the real economic activity in Jordan and Turkey (around 1%) during the period 1986:01–2014:12, which is not quite consistent with our findings, because our results are higher. However, the reason for the discrepancy probably lies in the used methodologies. Maghyereh et al. (2019) used structural VAR model, which provides a measure only of an average impact, while we apply quantile regression, which can gauge the spillover effect in different quantiles, i.e. when IP is very high or very low. Regarding our median quantile results, we also report very low impact, which is in line with Maghyereh et al. (2019) findings.

Also, it is noticeable that QR parameters bear both positive and negative signs. Negative signs indicate that higher oil uncertainty reduces industrial production, which is in accordance with expectations, since oil price uncertainty affects firm profitability and postpones investment decisions. On the other hand, positive QR parameters are recorded from $\tau^{0.65}$ to $\tau^{0.95}$ quantile, i.e. in conditions when IP records growing rates. Positive quantile parameters may seem counterintuitive, because it means that rising oil volatility increases industrial production. However, this finding is not so unusual, because the paper of Henriques and Sadorsky (2011) supports our results. These authors investigated how oil price volatility affects the strategic investment decisions in a large panel of US firms. They asserted that for annual oil price volatility values below particular point, an increase in oil price volatility reduces investment. On the other hand, for annual oil price volatility values above, so called inflection point, an increase in oil price volatility increases investment. In addition, we refer to Chowdhury et al. (2018), who researched the link between inflation uncertainty and GDP in the UK and US cases, but the explanation made in this paper can easily be implemented to our study. In particular, they contended that, during the period of economic upturn, cash flows to the firms are relatively high, which is a favourable situation for them regardless of the changes in inflation uncertainty or, in our case, oil uncertainty. Taking into account these conditions, companies are willing to finance new investment projects, without worrying what future inflation or oil volatility might be, which positively influences output growth. This explanation seems logical, because the majority of the estimated $\tau^{0.65}$ to $\tau^{0.95}$ Bayesian quantile parameters are positive, whereas almost all $\tau^{0.05}$ to $\tau^{0.5}$ quantile coefficients are negative. However, as we have said earlier, higher quantile parameters bear wider confidence intervals, so their interpretation must be done with great caution.

As for the size of the effect between the countries, it can be seen that the United Kingdom suffers the lowest impact from oil uncertainty when its IP is very low ($\tau^{0.05}$ quantile). The spillover effect from oil uncertainty to the U.K. is in magnitude around 16%, whereas for the majority of other net-consuming countries, this effect goes between 17-24%. The reason for this finding probably lies in the size of relative use of oil *vis-à-vis* nominal GDP. Table 5 shows the value of coefficient Φ, which represents the share of daily net oil consumption, expressed in barrels, relative to the daily nominal GDP. According to Table 5, the United Kingdom has the lowest Φ coefficient, which means that the U.K. is the least dependent on oil consumption, comparing to all other net oil consuming countries. All other countries have Φ coefficient more than twice as large in comparison to the U.K. coefficient. This argument explains very well our findings in Table 4, regarding the lowest $\tau^{0.05}$ quantile that the U.K. has. Also, it should be said that 79.2% of the U.K. GDP is composed of services, regarding sectoral share in GDP, whereas for Germany, it amounts 68.6[5]. This argument also can support our BQR findings, because sector of services consumes less oil. In other words, the more dependent country is on oil consumption, the greater the impact of oil price uncertainty on its industrial production will be. Spain has the largest Φ coefficient, as can be seen in Table 4, and Spain also has the largest 0.05th quantile parameter ($\tau^{0.05} = -0.247$). This indicates that oil uncertainty impacts industrial production in Spain relatively hard. On the other hand, industrial production of the U.K., country that is the least dependant on oil consumption, is affected the weakest by oil price uncertainty in 0.05th quantile parameter ($\tau^{0.05} = -0.163$).

Table 5 Calculation of Relative Daily Oil Consumption Vis-à-Vis Daily GDP for the Net Oil Consuming Countries

	*(1) Annual GDP in billions**	*(2) GDP per day*	*(3) Net oil consumption in barrels***	*(4) F = (3) / (2)*
Germany	3 863 344	10 584 504 110	2 400 161	0.000227
U.K.	2 743 586	7 516 673 973	780 760	0.000104
France	2 707 074	7 416 641 096	1 589 582	0.000214
Italy	1 988 636	5 448 317 808	1 191 325	0.000219
Spain	1 397 870	3 829 780 822	1 223 333	0.000319

Source: *International monetary fund.

Notes: **See Table 1

At the end, we comment the finding for net oil producer – Norway. As can be seen in Table 4, all Bayesian quantile parameters for Norway are by far the lowest in comparison to all other countries. In addition, the estimated quantile parameters bear both positive and negative signs across the seven quantiles, which is inconclusive in a sense whether oil uncertainty impacts Norwegian IP positively or negatively.

Table 6 Renewable Energy Consumption for the Selected Countries

	GER	*GBR*	*FRA*	*ITA*	*ESP*	*NOR*
Renewable energy consumption in %	14.2	8.71	13.5	16.5	16.3	57.8

Source: The world bank for 2015.

Due to such findings, this suggests that Norway is the least susceptible to oil uncertainty shocks, which is somewhat counterintuitive, because it could be expected that oil-exporting countries react more intensively to oil price uncertainty (see e.g. Živkov et al., in press). One explanation of such findings could be the fact that Norway uses significant amount of renewable energy sources (see Table 6). Because

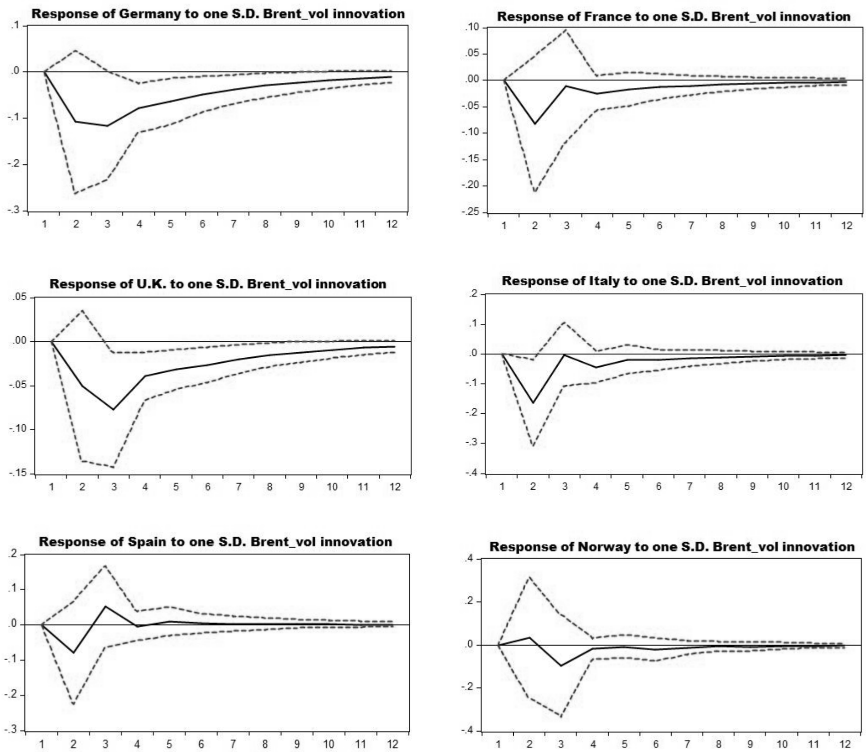
[5] Source: The World Factbook - GDP composition by sector of origin *for 2017.*

of that, Norway is less affected and less susceptible to oil price shocks and oil volatility shocks, which Bayesian quantile parameters clearly show.

5.2 Vector Autoregression Results – the Robustness Check

In order to further strengthen our quantile regression results, we present in this subsection the findings of the impulse response functions (IRFs), calculated with the bivariate and four-variate VAR models. Figures 7 and 8 contain bivariate and four-variate impulse response plots for every country. VAR models serve as complementary analysis, because they can confirm/refute the QR findings, but they also can give us a new insight about how persistent oil volatility shocks are, i.e. in which time-horizon they die out.

Figure 7 Bivariate Impulse Response Functions of the Selected Countries



Notes: X axis denotes the 12-month time-horizon. Red lines portray confidence intervals.

According to Figure 7, it can be seen that the size of the effect, measured *via* IRFs, is in line with the previously estimated Bayesian quantile parameters in the majority of cases. In other words, the impact of oil uncertainty on IP in net oil consuming countries is negative and relatively weak, which coincides with BQR parameters and adds to their robustness. However, we find by far the strongest effect in Italy, which somewhat deviate from the BQR results, because Spain and Germany recorded stronger negative effect from oil price uncertainty. This discrepancy could be an aftermath of inclusion only two variables in VAR model, thus, a misspecification of VAR model might be a reason for such findings. This assertion will be tested later, when we present the results of four-variate VAR model.

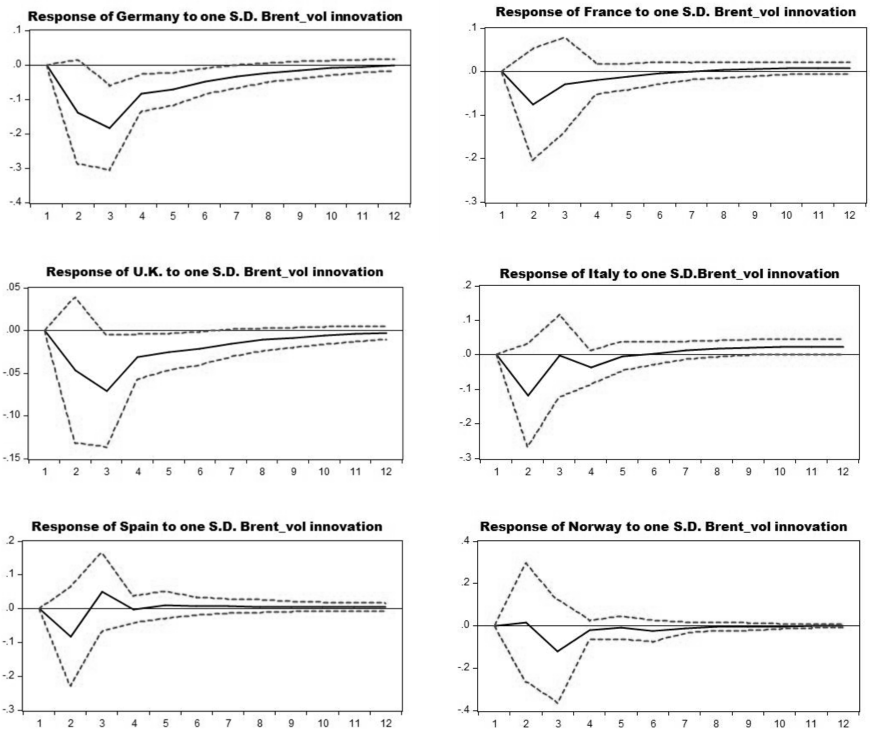
Impulse response functions are useful tool, because they give us an information in which time-horizon oil price uncertainty shocks come to the fore, complementing in this way the BQR results. According to IRFs, the highest volatility shocks manifest in relatively short time-span (two months) for Germany, France, Italy and Spain, whereas for the U.K. and Norway, it happens in third month. Very quickly after the initial impact, the effect of volatility shocks subsides significantly as time progresses. Therefore, it can be said that the persistence of oil uncertainty on IP is low. In other words, up to fourth month, the effect is below 5% for the majority of net oil consuming countries, while up to eighth month, the effect is almost non-existent for France, Italy, Spain and Norway, while for Germany and the U.K. it is below 3%. These findings coincide very well with the paper of Jo (2014), who reported *via* impulse response analysis that oil price uncertainty shock has an immediate and negative effect on global quarterly economic activity.

As for net oil producing Norway, impulse response function suggests that oil volatility shocks initially have low and positive effect on Norwegian IP (around 3%), whereas in third month, this effect reaches its negative maximum around 7%. Comparing with the quantile parameters, it can be seen that impulse response estimates also have low value and interchangeable sign, which is in line with the computed Bayesian quantile parameters. In addition, it can be noticed that the effect of impulse response function in the case of Norway is below the effect of five net oil consuming countries, which also concurs pretty much with the quantile parameter findings.

In order to avoid misspecification and possible biasedness of bivariate VAR model, we additionally estimate four-variate VAR, adding inflation and long-term interest rate in the model. The results of impulse response functions for the extended VAR model are presented in Figure 8. As can be seen, IRF results in four-variate VAR model are improved, and now they coincide better with BQR parameters than the previous IRF findings. In other words, we find very strong effect in the case of Germany, which concur very well with BQR results, while the effect in the case of Italy is reduced, which is also in line with the quantile parameters. For France, the U.K., Spain and Norway, four-variate IRFs are very similar to bivariate IRFs, so we do not find significant differences in these cases.

All in all, it can be said that impulse response findings corroborate the Bayesian quantile regression results in great deal, which contributes significantly to the robustness of our overall results.

Figure 8 Four-Variate Impulse Response Functions of the Selected Countries



Notes: X axis denotes the 12-month time-horizon. Red lines portray confidence intervals.

6. Conclusion

This paper investigates the effect of oil uncertainty on industrial production in six developed European countries. In the research process, we apply Bayesian technique in the estimation of MS-GARCH model and quantile regression, because MCMC algorithm can deal successfully with number of estimation issues. In particular, we employ the Bayesian MS-GARCH, which can recognize structural breaks endogenously, in order to construct oil uncertainty proxy. Transmission effect from oil price uncertainty toward IP is gauged *via* BQR that can provide confident quantile estimates. In addition, bivariate and four-variate VAR models are used as complementary analysis, and they provide estimates of impulse response functions, i.e. they give a picture of size and time-horizons in which the effect is the strongest.

According to estimated Bayesian quantile parameters, the magnitude of oil price uncertainty spillover towards industrial production is not high, and for the majority of the net oil consuming countries the negative effect is around 20% when IP is relatively low. Although these results are in line with other studies, which researched this topic, the result should be taken with a caution, because all quantile parameters are statistically significant at 70%. On the other hand, we also find wide confidence intervals, so they cannot be regarded as reliable. As for the relative effect between the countries, we report that the U.K. experiences the least effect from oil uncertainty, and the rationale probably lies in the fact that the U.K. has the lowest Φ ratio (daily oil consumption per daily GDP), and this finding is also in line with the fact that four fifth of the U.K. GDP is composed of services. On the other hand, Spain has relatively low $\tau^{0.05}$ and $\tau^{0.2}$ quantile parameters and relatively low value of impulse response function, which suggests that oil uncertainty hit Spain the strongest, comparing to all other countries. These results coincide very well with the Spanish daily oil consumption, since Spain has the highest Φ coefficient. Besides Spain, Germany and Italy also have relatively high $\tau^{0.05}$ BQR parameters, which indicates that these countries also endure relatively significant impact from oil price uncertainty when their economies are in recession. As for net oil producing Norway, quantile parameters offer inconclusive results, because we find both positive and negative quantile estimate across the seven quantiles, while impulse response function also shifts between positive and negative values. In addition, quantile parameters for Norway are very low. These findings indicate that Norway is the least susceptible to oil volatility shocks, probably because Norway is not so dependent on oil, since over 50% of their energy consumption come from renewable sources.

Based on the results, we can conclude that global oil price uncertainty does not affect industrial production of the net oil consuming European countries very hard, although they are highly dependent on import of fossil fuels. This means that these countries are not necessarily obliged to increase fossil fuel inventories in order to protect themselves from the potential impact of oil price uncertainty on domestic economy or to move away from fossil fuels towards renewable energy sources.

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