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Oil price volatility and macroeconomic fundamentals: A regime switching GARCH-MIDAS model☆

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Abstract

We introduce a regime switching GARCH-MIDAS model to investigate the relationships between oil price volatility and its macroeconomic fundamentals. Our model takes into account both effects of long-term macroeconomic factors and short-term structural breaks on oil volatility. The in-sample and out-of-sample results show that macroeconomic fundamentals can provide useful information regarding future oil volatility beyond the historical volatility. We also find the evidence that the structural breaks cause higher degree of GARCH-implied volatility persistence. Two-regime GARCH-MIDAS models can significantly beat their single-regime counterparts in forecasting oil volatility out-of-sample.

Keywords: Crude oil, Volatility, Regime switching, Mixed-frequency data sampling, Forecasting

JEL Classification: C32, C58, E32, Q41, Q47

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Highlights

- We propose a regime switching GARCH-MIDAS model to account for structural breaks.
- Oil fundamentals can provide useful information regarding future volatility.
- Structural breaks cause higher degree of GARCH-implied volatility persistence.
- Our two-regime models perform significantly better than the single-regime model out-of-sample.

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Abstract

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1. Introduction

Modeling and forecasting asset price volatility is an important issue in the area of financial economics. The reason is that volatility forecast is crucial for many studies such as portfolio optimization, value at risk computation and option pricing. Notably, how to obtain accurate volatility forecasts of crude oil prices is of particular interest for academics. The motivation is that crude oil is the main input in the modern industry and high oil price uncertainty can depress future investment according to the theory of real option, further producing negative impacts on the real economy (Elder and Serletis, 2010). Therefore, accurate oil price volatility forecasts are required by both oil market participants and the central banks.

In recent years, a large number of studies contribute to modeling oil price volatility. A strand of studies employs GARCH-class models to capture oil market volatility dynamics (see, e.g., Chan and Grant, 2016; Nomikos and Pouliasis, 2011; Wang and Wu, 2012; Wang et al., 2016; Sadorsky, 2006), while the other strand of papers uses realized volatility models (Haugom et al., 2014; Sévi, 2014). Both types of models draw predictive information from historical volatility or prices. In this paper, we improve upon the literature by using oil market fundamental information besides the historical volatility.

The predictive content of fundamental variables can be explained by the efficient market hypothesis of Fama (1970). Commodity market is not as efficient as developed financial markets (Chen et al., 2010). In particular, some studies also find that crude oil market is not efficient in the weak-form (Tabak and Cajueiro, 2007; Wang and Liu, 2010). In this sense, current oil price cannot reflect all available fundamental information. We can reasonably suspect that current oil price volatility does not contain all available past information from macroeconomic uncertainty. Although supply and demand fundamentals have been employed to explain and forecast oil price changes (Baumeister and Kilian, 2012; Boffelli et al., 2015), to the best of our knowledge, the economic sources of price volatility have not been considered in the literature except the notable paper of Conrad et al. (2014). Conrad et al. (2014) investigate the effect of macro variables on oil volatility from the in-sample perspective. As an extension, we revisit this issue from out-of-sample perspective by analyzing whether the incorporation of macro variables in volatility models can obtain more accurate forecasts. Furthermore, it is possible that oil price level and volatility do not share the same determinant because the former one is the first moment while the latter one belongs to the second moment of price and they display quite different statistical properties. Moreover, high price volatility does not necessarily imply that oil price change is large. As the evidence, the descriptive statistics of logarithmic changes of oil prices in Table 1 show that the mean values are rather close to zero but the standard deviation is much larger.

Table 1 about here

We focus on daily volatility which is more concerned by market participants such as option market traders. However, it is difficult to incorporate macroeconomic information in a GARCH or realized volatility model because the data frequencies of oil price and its fundamental variables are not consistent. In detail, since the frequency of the available oil price data is daily, oil production and demand data are obtained at monthly or even lower frequency. Fortunately, the GARCH-MIDAS class specifications proposed by Engle et al. (2013) can well solve the mixed-frequency problem in volatility modeling. This model decomposes daily conditional volatility into two components, a short-term volatility component following the standard daily GARCH process (Bollerslev, 1986) and a long-term component captured by a mixed-frequency data sampling (MIDAS) regression with monthly, quarterly or even lower frequency variables (Ghysels et al., 2004). In recent years, the GARCH-MIDAS models become more and more popular for detecting the linkages between high-frequency volatility and low-frequency macroeconomic variables (Conrad et al., 2014; Conrad and Loch, 2015a,b).

A shortcoming of GARCH-MIDAS is that it does not accommodate structural breaks, which has been considered a "stylized fact" in volatilities of financial asset and commodity prices. A series of exogenous events such as Gulf War and financial crisis are found to produce structural breaks in oil volatility (Miller and Ratti, 2009). According to the argument of Lamoureux and Lastrapes (1990), structural break can cause the spurious finding of volatility persistence implied by GARCH models. Due to this motivation, we also contribute to the literature by modifying the GARCH-MIDAS specification. We introduce a regime switching GARCH-MIDAS (RS-GARCH-MIDAS) which allows for the change of the state of short-term volatility component between two different regimes caused by structural breaks. The proposed RS-GARCH-MIDAS model can deal with both mixed-frequency data and the effect of structural breaks.

We investigate the predictive ability of levels and volatilities of oil supply and demand to WTI and Brent oil price volatility from 1986 to 2015. Our in-sample evidence suggests that fundamental variable levels produce negative impacts on oil volatility, whereas their uncertainties have positive effects on oil volatility. The finding of oil-demand relationship is consistent with Conrad et al. (2014) who reveal the counter-cyclical behavior of long-term oil volatility. Oil volatility dynamics display two significantly different regimes, high-volatility regime and low-volatility regime. Some events such as the geopolitical events in the Middle East and financial crisis trigger volatility regime switching. Interestingly, we find that after adding the fundamental variables to RS-GARCH-MIDAS, the model-implied volatility persistence becomes moderately weaker. The degree of persistence revealed by our two-regime GARCH-MIDAS is much lower than that suggested by the single-regime model. This evidence indicates that macroeconomic effect and short-term structural breaks are the two important sources of volatility persistence.

We also investigate the usefulness of macroeconomic information and the importance of regime switching out-of-sample. Two criteria of loss functions are employed to evaluate the forecasting performance. We use the statistical test of Diebold and Mariano (1995) to examine whether the differences of loss functions of two models are significant. We find that our two-regime GARCH-MIDAS can significantly beat the single-regime model for both WTI and Brent oil volatility, indicating that allowing for regime switching can improve the predictive ability. The incorporation of fundamental variables in a RS-GARCH-MIDAS model does not necessarily improve the out-of-sample forecasting performance. More consistent finding comes from the model with oil demand level, which can beat the model without macro variables consistently. Furthermore, we find that a combination of RS-GARCH-MIDAS models with each of four fundamental variables outperforms the benchmark model significantly. This evidence highlights the importance of macroeconomic variables in oil volatility forecasting. Oil fundamental variables can provide useful information regarding future volatility beyond the historical volatility.

The remainder of this paper is organized as follows: Section 2 presents the methodology of our RS-GARCH-MIDAS model. Section 3 provides the data description. We show the in-sample and out-of-sample empirical results in Section 4. The last section concludes the paper.

2. The regime switching GARCH-MIDAS model

2.1. The model specification

Motivated by Engle and Rangel (2008) and Engle et al. (2013), the return, $r_{i,t}$, with mean zero on high-frequency i (say day) in low-frequency t (say month) is modeled as

$$\begin{aligned} r_{i,t} &= \sqrt{\tau_t \times h_{i,t}}\epsilon_{i,t}, \quad \forall i = 1, \cdots, N_t, \\ \epsilon_{i,t}|\mathcal{F}_{i-1,t} &\sim \mathcal{N}(0,1), \end{aligned} \tag{1}$$

where $\mathcal{F}_{i-1,t}$ denotes the information set available at day $i-1$ of period t. Obviously, the volatility is decomposed into tow parts: τ_t which captures the long-run behaviors and $h_{i,t}$ describes the short-run fluctuations.

The GARCH-MIDAS of Engle et al. (2013) uses the GARCH process of Bollerslev (1986) to model the short-term volatility component $h_{i,t}$, given as,

$$h_{i,t} = (1-\alpha-\beta) + \alpha\frac{r_{i-1,t}^2}{\tau_t} + \beta h_{i-1,t}. \tag{2}$$

In order to account for the role of structural breaks, we modify the short-term volatility process by considering the following regime switching structure:

$$h_{i,t}^{(j)} = \omega(s_{i,t} = j) + \alpha\frac{r_{i-1,t}^2}{\tau_t} + \beta\bar{h}_{i-1,t}, \tag{3}$$

where $s_{i,t}$ is a latent variable with two regimes ($j = \{0,1\}$)[1], i.e., $\omega(0)$ indicates the low volatility regime while $\omega(1)$ denotes the high volatility regime. The state variable $s_{i,t}$ is governed by following transition matrix,

$$P = \begin{bmatrix} p_{00} & 1-p_{11} \\ 1-p_{00} & p_{11} \end{bmatrix}, \tag{4}$$

[1]Strictly, choosing the number of states for regime switching model should be based on some test. However, the test procedure is complicate (see, e.g., Hansen, 1992; Conrad et al., 2014 and among others) and two states are enough in application and practicable because of the smaller number of parameters (Kim et al., 2008).

where $p_{j_0 j_1} = Pr(s_{i,t} = j_1 | s_{i,t} = j_0)$ means the probability that regime j_0 will be followed by regime j_1. As pointed out by Cai (1994) and Hamilton and Susmel (1994), our specification for $h_{i,t}^{(j)}$ in (3) suffers from the path-dependence problem. To avoid the shortcoming, we follow Gray (1996)'s suggestion by using the information observable at lags 2 for integrating out the unobserved states as,

$$\bar{h}_{i-1,t} = E_{i-2,t}[h_{i-1,t}^{(j)}] = Pr(s_{i-1,t} = 0|\mathcal{F}_{i-2,t})h_{i-1,t}^{(0)} + Pr(s_{i-1,t} = 1|\mathcal{F}_{i-2,t})h_{i-1,t}^{(1)}. \tag{5}$$

Note that we do not allow the changes in all parameters of $h_{i,t}$ process because of two considerations. First, based on the finding in Marcucci (2005), the differences of parameters α and β between two regimes are not likely to be significant. Second, the non-convergence problem caused by the increment of the number of parameters will happen according to Guérin and Marcellino (2013).

We assume that the component, τ_t, is driven as

$$\tau_t = \exp(\theta_0 \sum_{i=1}^{K} \varphi_i(\kappa) RV_{t-i}), \tag{6}$$

where RV_t is smoothing realized volatility with the fixed-span,

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2. \tag{7}$$

where N_t is the number of days in month t. The specification of long-term volatility component expressed by (6) is different from the standard GARCH-MIDAS of Engle et al. (2013) such that it does not include a constant. The reason is that we have put a constant in the short-term volatility process (3) to account for structural breaks. If the constant appeared in both short-term and long-term volatility component equations, the parameters would be not identified. In order to incorporate macroeconomic information, we extend equation (6) as

$$\tau_t = \exp(\theta_0 \sum_{i=1}^{K} \varphi_i(\kappa_0) RV_{t-i} + \theta_1 \sum_{i=1}^{K} \varphi_i(\kappa_1) X_{t-i}), \tag{8}$$

and X_t represents the macroeconomic factors of interest such as production and demand for crude oil. One-parameter Beta polynomial is chosen as the weighting scheme since it is flexible and common (see, e.g., Colacito et al., 2011),

$$\varphi_i(\kappa_d) = \frac{[1 - i/(K+1)]^{\kappa_d - 1}}{\sum_{j=1}^{K}[1 - j/(K+1)]^{\kappa_d - 1}}, \quad d = 0, 1 \tag{9}$$

The weights $\varphi_i(\kappa_d)$ sums up to one such that the parameters, $\{\theta_0, \theta_1, \kappa_0, \kappa_1\}$, are identified. Taking *exp* guarantees that the long-run variance is always positive, which is also used in Engle et al. (2013).

2.2. Parameter estimation

We use the the conventional quasi-maximum likelihood method to estimate the parameters since it is popular and valid for regime switching model (Hamilton, 1989; Guérin and Marcellino, 2013). Let $f(r_{i,t}|s_{i-1,t} = j, \mathcal{F}_{i-1,t}; \Theta)$ be the conditional density of $r_{i,t}$ given by regime $s_{i-1,t} = j$, and

$$\begin{aligned} \eta_{i,t} &= \begin{bmatrix} f(r_{i,t}|s_{i-1,t} = 0, \mathcal{F}_{i-1,t}; \Theta) \\ f(r_{i,t}|s_{i-1,t} = 1, \mathcal{F}_{i-1,t}; \Theta) \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{\sqrt{2\pi\tau_t h_{i,t}^{(0)}}} \exp\big(-\frac{r_{i,t}^2}{2\tau_t h_{i,t}^{(0)}}\big) \\ \frac{1}{\sqrt{2\pi\tau_t h_{i,t}^{(1)}}} \exp\big(-\frac{r_{i,t}^2}{2\tau_t h_{i,t}^{(1)}}\big) \end{bmatrix}, \end{aligned} \tag{10}$$

where $\Theta = (\omega(0), \omega(1), \alpha, \beta, \bar{\tau}, \theta_0, \theta_1, \kappa_0, \kappa_1, p_{00}, p_{11})$. The log-likelihood function $\mathfrak{L}(\Theta)$ can be expressed as

$$\mathfrak{L}(\Theta) = \sum_{t=1}^{T}\sum_{i=1}^{N_t} \log f(r_{i,t}|\mathcal{F}_{i-1,t}; \Theta), \tag{11}$$

and

$$f(r_{i,t}|\mathcal{F}_{i-1,t}; \Theta) = \mathbf{1}'(\hat{\xi}_{i,t|i-1,t} \odot \eta_{i,t}), \tag{12}$$

where $\mathbf{1}$ denotes a 2×1 vector with element ones, $\odot$ is element by element multiplication and the filtered probability

$$\hat{\xi}_{i,t|i-1,t} = \begin{bmatrix} Pr(s_{i,t} = 0|\mathcal{F}_{i-1,t}) \\ Pr(s_{i,t} = 1|\mathcal{F}_{i-1,t}) \end{bmatrix}. \tag{13}$$

Hamilton (1994) gives the solution to obtain $\hat{\xi}_{i,t|i-1,t}$ by iterating on the following pair of equations:

$$\hat{\xi}_{i,t|i,t} = \frac{\hat{\xi}_{i,t|i-1,t} \odot \eta_{i,t}}{\mathbf{1}'(\hat{\xi}_{i,t|i-1,t} \odot \eta_{i,t})} \tag{14}$$

$$\hat{\xi}_{i+1,t|i,t} = P \times \hat{\xi}_{i,t|i,t} \tag{15}$$

with initial value $\hat{\xi}_{0|0}$:

$$\hat{\xi}_{0|0} = \begin{bmatrix} \frac{1-p_{11}}{2-p_{00}-p_{11}} \\ \frac{1-p_{00}}{2-p_{00}-p_{11}} \end{bmatrix}. \tag{16}$$

Finally, through maximizing the $\mathfrak{L}(\Theta)$ in equation (11), we will yield the estimator, $\hat{\Theta}$.

2.3. The standard errors of the estimates

In this section, we sketch how to obtain the standard errors of the estimates in our proposed model. Bollerslev and Wooldridge (1992) and Wooldridge (1994) have established the asymptotic properties for the quasi-maximum likelihood estimation (QMLE). More specifically, Wang and Ghysels (2008) have shown the asymptotic behavior of GARCH-MIDAS model. Our estimates can be involved in their theoretical framework. That is, under some standard regularity conditions, we have:

$$\sqrt{T}(\hat{\Theta} - \Theta_0) \xrightarrow{d} \mathcal{N}(0, J^{-1}IJ^{-1}), \tag{17}$$

where Θ_0 is the true values of Θ, J and I are the expected Hessian and the covariance of the scores of log-likelihood function (11), respectively. Both are numerically calculated as

$$\hat{J}_{i,j} \approx \frac{1}{T}\frac{\mathfrak{L}(\hat{\Theta} + e_i s_i + e_j s_j) - \mathfrak{L}(\hat{\Theta} + e_i s_i) - \mathfrak{L}(\hat{\Theta} + e_j s_j) + \mathfrak{L}(\hat{\Theta})}{s_i s_j}, \tag{18}$$

and

$$\hat{I} = \frac{1}{T}\frac{\partial \mathfrak{L}(\hat{\Theta})}{\partial \Theta}' \frac{\partial \mathfrak{L}(\hat{\Theta})}{\partial \Theta}, \tag{19}$$

where

$$\frac{\partial \mathfrak{L}(\hat{\Theta})}{\partial \Theta} \approx \frac{\mathfrak{L}(\hat{\Theta} + e_i s_i) - \mathfrak{L}(\hat{\Theta})}{s_i} \tag{20}$$

and s_i is a scalar step size, e_i denotes a vector of zeros except for element i. See Flannery et al. (1992) for more details on numerical derivative, and Sheppard (2007) for implementation using Matlab software.

Furthermore, we have the standard errors for estimators as

$$s.e.(\hat{\Theta}) = \sqrt{diag(\hat{J}^{-1}\hat{I}\hat{J}^{-1}/T)} \tag{21}$$

where $diag$ denotes the diagonal elements of the matrix. As the transition probability matrix (4) has the restriction, i.e., $0 \leq p_{00}, p_{11} \leq 1$, we use the transform function in the estimating process: $p_{00} = \frac{\exp(x_{00})}{1+\exp(x_{00})}$, where $x_{00} \in (-\infty, \infty)$, and the same as p_{11}. Then, the standard errors of p_{00} and p_{11} are obtained through the delta method.

3. Data

We choose daily spot price data of West Texas Intermediate (WTI) and Brent crude oil from Energy Information Administration (EIA) of the U.S.. Due to the data availability, our sample data for WTI price covers the period from January 2, 1986 to December 31, 2015, while Brent price sample starts from January 4, 1988 and ends at the same date. The monthly data reflecting oil supply and demand fundamentals are also selected accordingly. We use global oil production obtained from EIA as the proxy of world oil supply. We follow recent oil market studies (see, e.g., Kilian and Park, 2009; Baumeister and Kilian, 2012) in using the index of Kilian (2009) as the signal for oil demand. The index is constructed based on the percentage growth rates obtained from a panel of single voyage bulk dry cargo ocean shipping freight rates measured in dollars per metric ton. The data are downloaded from Kilian's personal website[2].

Our econometric model is built on the return of oil prices, i.e., the first order difference of log prices. The squared daily return is taken as the proxy of actual volatility as a standard way of doing volatility forecasting. The graphical representations of oil prices, returns and volatilities of WTI and Brent oils are illustrated as Figure 1 and Figure 2, respectively.

[2] http://www-personal.umich.edu/∼lkilian/

Figure 1 and Figure 2 about here

Table 1 shows the descriptive statistics of WTI and Brent oil returns. The means of both returns are close to zero, whereas the variances are much larger. Both return series display the similar statistical properties. For example, the augmented Dickey and Fuller statistics significantly reject the unit root null, in favor of the stationary time series. The Ljung-Box statistics suggest the significant autocorrelations in both returns and squared returns. As a well-known stylized fact, the Jarque-Bera statistics reveal the fat-tailed distribution. Being of our interest, Engle (1982)'s ARCH test results indicate the significant ARCH effect, highlighting the appreciation of GARCH-type models in capturing oil volatility dynamics.

We investigate the effects of level and volatility of fundamental variables on oil volatility. In order to construct the volatility of macroeconomic variables, we follow the standard approach taken by Schwert (1989) and Engle et al. (2013) using the regression:

$$X_t = \sum_{j=1}^{12} \alpha_j D_{jt} + \sum_{j=1}^{12} \beta_j X_{t-j} + \epsilon_t \tag{22}$$

where D_{jt} is the monthly dummy variable. The squared residuals ϵ_t^2 are taken as the proxy of volatility of macroeconomic variable X_t. The summary statistics of explanatory variables are also given in Table 1.

4. Empirical results

In this section, we first present in-sample evidence on the roles of long-term macroeconomic fundamentals and short-term structural breaks in driving oil price volatility dynamics. Furthermore, we investigate whether the incorporation of macroeconomic information can improve the oil volatility forecasts out-of-sample. We use five GARCH-MIDAS-type models to detect the effects of macroeconomic variables. The first is the standard GARCH-MIDAS which takes monthly RV as the driver of long-term component. The other four models additionally incorporate different macroeconomic variables (see equation (8)). In these models, we consider four fundamental variables of oil volatility which are supply and demand levels and their volatilities. To take into account the role of structural breaks, we further allow for regime switching in the process of short-term component of conditional volatility.

4.1. In-sample estimation results

Table 2 reports the parameter estimates of regime switching GARCH-MIDAS (RS-GARCH-MIDAS) models for WTI oil price volatility. All the macro variables are standardized. We first look at the effects of fundamental variables. The estimate of θ_1 is significantly negative at 1% level for oil production and global economic activity levels, indicating that an increase in oil supply or demand can lead to a decrease in crude oil return volatility. In particular, this result is qualitatively consistent with the finding in Conrad et al. (2014) about the relationship between oil price volatility and US aggregate demand. The authors show that long-term oil volatility behaves counter cyclically, i.e., increases during recessions and decreases during expansions. The parameter θ_1, together with the weighting parameter κ_1 can tell us the quantitative effects of oil fundamentals. For example, the estimate of θ_1 is -0.093 for oil demand level. Since the weighting function with 11.933 puts 0.6946 on the first lag, we find that a one standard deviation increase in oil demand at the current month would lead to a decrease in the long-term component of the next month's volatility by $e^{0.6946\times0.093} \approx 0.0667$ or 6.67%. This magnitude is moderately lower than the value reported in Conrad et al. (2014) who find that a one standard deviation increase in the leading index reflecting business condition this month leads to a 14.03% decrease in long-term oil market volatility. The plausible explanation about the difference of reported values comes from two sources. Firstly, we use a global economic activity index proposed by Kilian (2009) to reflect oil demand, while Conrad et al. (2014) employ a leading index signaling US business condition. Secondly and more importantly, the sample periods are not consistent such that we use data for the period from January 1986 through December 2015, while Conrad et al. (2014) paper considers the period from January 1993 to December 2011. From 1986 to 1992, the role of oil demand was relatively weak (Kilian, 2009) and the changes in oil prices were mainly driven by oil supply shocks. For example, Iraqi invasion to Kuwait and the subsequent Gulf War resulted in large fluctuations of oil prices during this period. Baumeister and Kilian (2016) also argue that the effects of production changes on oil prices become more prominent after 2014. Therefore, it is possible that the use of longer period dilutes the impacts of demand on oil price volatility.

Table 2 about here

The influences of oil supply and demand uncertainties on oil price volatility are both positive, with the close magnitude. Similarly, if current month's supply volatility (demand volatility) increased by one standard deviation, we would see 7.08% (7.46%) increase in the long-term component of the next month's WTI market volatility. These values are much higher than that reported in Engle et al. (2013) when investigating the macroeconomic sources of stock volatility (1.3%-2.6%). The plausible explanation is that the price elasticities of oil supply and demand are very low and close to zero (see, e.g., Alquist and Kilian, 2010; Hamilton, 2009). A minor change in oil supply or demand can cause a relatively large change in oil price. We also report the estimation results of RS-GARCH-MIDAS for Brent oil return in Table 3. Generally speaking, the consistent evidence about the significant effects of macroeconomic fundamentals on Brent oil volatility is also available.

Table 3 about here

Second, we turn to the situation of structural breaks. It is clear that the short-term volatility process can be captured by two regimes, low volatility regime and high volatility regime. Our t-statistics suggest that $\omega(1) - \omega(0)$ is significantly positive, indicating that the average volatilities of these two regimes are significantly different. The state probabilities p_{00} and p_{11} revealed by each model are close to 1 for both WTI and Brent oil volatility, implying the high degree of state persistence. In other words, if current volatility belongs to the high-volatility regime, next day's volatility is more likely to stay in the same regime. Interestingly, we find that the parameter estimates $\alpha + \beta$ of RS-GARCH-MIDAS models without fundamental variables are higher than 0.7, while the estimates from the models with macroeconomic variable are always lower than this value. This evidence implies that macroeconomic effect is a potential source of oil volatility persistence, consistent with the argument in Beltratti and Morana (2006) about stock market that macroeconomic factors drive long memory in volatility. Actually, we also find that the parameter estimate $\alpha + \beta$ of single-regime GARCH-MIDAS is about 0.99 for both WTI and Brent oil returns[3]. When the structural breaks are accounted for in our regime switching model, the degree of volatility persistence is much lower, indicating that structural break can cause the volatility persistence. This evidence is consistent with the finding in Lamoureux and Lastrapes (1990) that the ARCH-implied long memory in volatility is possible to be a fiction due to structural breaks, rather the than the "genuine" one.

In order to see how volatility regimes change over time, we give the posterior probabilities of high volatility regime for WTI and Brent oil volatilities in Figure 3 and Figure 4, respectively. If the probability is higher than 0.5, the volatility during that period is considered to be in the high volatility regime. We can find that our RS-GARCH-MIDAS model can well capture the regime changes in oil volatility. For example, the transition probability is always higher than 0.5 when the US economy undergone a recession. That is, oil volatility is more likely to turn to a high-volatility regime when the economy switches from an expansion to a recession, intrinsically consistent with the counter-cyclical behavior of oil volatility shown by Conrad et al. (2014).

Figure 3 and Figure 4 about here

4.2. Out-of-sample forecasting results

In this subsection, we investigate whether macroeconomic information is helpful to predict oil return volatility out-of-sample. Also, we try to find whether accounting for regime switching in the short-term component can improve the forecasting performance of GARCH-MIDAS. The motivation is that in comparison with in-sample performance, market participants are more concerned about out-of-sample performance because they are more like to know how the model works in the future. The key step for generating out-of-sample volatility forecasts of RS-GARCH-MIDAS is the calculation of the forecast of short-term volatility

[3]To save space, we do not report the estimation results about single regime GARCH-MIDAS but they are available upon request.

component because the process of producing forecasts of long-term volatility component is the same to single-regime GARCH-MIDAS. We first obtain the volatility forecasts from GARCH-MIDAS in Regime 0 and Regime 1 as $\hat{h}^{(0)}_{i+1,t}$ and $\hat{h}^{(1)}_{i+1,t}$, respectively. The filtering probability $\hat{\xi}_{i+1,t|i,t}$ is also available using equation (15). Then, we calculate the short-term volatility forecast as the weighted average of volatility forecasts in two regimes:

$$\hat{h}_{i+1,t} = Pr(s_{i+1,t} = 0|\mathcal{F}_{i,t}) \times \hat{h}^{(0)}_{i+1,t} + Pr(s_{i+1,t} = 1|\mathcal{F}_{i,t}) \times \hat{h}^{(1)}_{i+1,t}. \tag{23}$$

The forecast of total volatility is defined as the product of the forecasts of short-term and long-term volatility components.

We forecast 1-day-ahead oil return volatility from January 2, 2001 using the scheme of rolling window, where the initial window for parameter estimation covers the period before this date. Figure 5 and Figure 6 show the volatility forecasts generated by RS-GARCH-MIDAS models, as well as the actual daily volatility of WTI and Brent oil prices, respectively. For comparison, the forecasts from single-regime GARCH-MIDAS models are also plotted. We can see that comparing with our two-regime models, single-regime models are likely to amplify the lagged effect of macroeconomic variables. As the piece of evidence, during the short period after the financial crisis in 2009, single-regime models heavily over-predict volatility, while two-regime models can generate the forecasts closer to the true values because they are flexible to regime changes in volatility.

Figure 5 and Figure 6 about here

Various forecasting criteria or loss functions can be considered to assess the predictive accuracy of a volatility model. Obviously, the value of loss function may be affected by the choice of the proxy of actual volatility heavily. Patton (2011) shows that shows that two popular loss functions, mean squared predictive error (MSE) and Gaussian quasi-likelihood (QLIKE), are more robust to the imperfect volatility proxies. These two loss functions are given by,

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\sigma_i^2 - \hat{\sigma}_i^2)^2, \tag{24}$$

and

$$QLIKE = \frac{1}{N}\sum_{i=1}^{N}(\log(\hat{\sigma}_i^2) + \frac{\sigma_i^2}{\hat{\sigma}_i^2}) \tag{25}$$

where σ_i^2 and $\hat{\sigma}_i^2$ are the actual value and forecast of volatility, respectively. N is the total number of volatility forecasts.

Table 4 reports the performances of RS-GARCH-MIDAS models in forecasting oil return volatility. For simplicity, we give the loss function ratios of our two-regime GARCH-MIDAS relative to the single-regime counterparts. Therefore, a loss ratio lower than 1 indicates that the two-regime model forecasts display lower loss function than the single-regime model forecasts, generating more accurate forecasts under the pre-specified loss criterion. We use the Diebold and Mariano (1995) method to test for the null hypothesis that the loss function of two-regime model forecasts are higher than or equal to the single-regime model forecasts. We find that under both two loss criteria, the loss ratios are lower than 1, indicating that our two-regime models perform better than their existing single-regime counterparts. Moreover, the p-values of DM tests show that the outperformance of two-regime model is significant for almost all cases. The superiority of regime switching model is evident in forecasting both WTI and Brent oil volatilities.

Table 4 about here

To investigate the predictive content of macro variables for oil volatility out-of-sample, we calculate the ratio of loss functions of RS-GARCH-MIDAS with macro variables relative to the loss function of the model without macro variables. In the literature, it has been well documented that an individual macro variable is difficult to successfully predict return or volatility because of some problems such as model uncertainty (e.g., Welch and Goyal, 2008; Avramov, 2002; Paye (2012)). For example, Conrad and Loch (2015a) find that almost all specifications based on macro variables perform worse than the benchmark of GARCH-MIDAS-RV model in forecasting long-term stock market volatility for the horizon of a quarter. To address the issue of model uncertainty, we employ the popular method of forecast combination, which has been considered a powerful tool in handling with multivariate predictive information. The forecast combination takes the weighted average of forecasts from individual models where the weight of each model is determined by a scheme. For simplicity, we use the mean forecast combination, i.e., the equal-weighted average of forecasts. Although the weighting scheme is simple, it is difficult to find a more sophisticated combination which can beat the mean combination (Graefe et al., 2014; Smith and Wallis, 2009; Claeskens et al., 2016).

Table 5 reports the evaluation results. We find that the forecasting performance of individual macro variables rely on which loss criterion is employed and on which oil volatility is predicted. For example, when forecasting WTI oil volatility, RS-GARCH-MIDAS with oil demand or supply level performs better than the benchmark model without macro variables under the criterion of QLIKE, but performs worse under the MSE criterion. When using the criterion of MSE, adding the levels of fundamental variables to RS-GARCH-MIDAS can improve the predictability of Brent oil volatility, but fail to obtain significantly more accurate forecasts of WTI oil volatility. The uncertainty of fundamental variables is helpful to improve forecasting performance for some cases but the improvement is not significant. More consistent result comes from oil demand level model, which can outperform the benchmark model for all cases and outperformance is significant except WTI oil volatility forecasting under MSE criterion. The out-of-sample performance of forecast combination is more encouraging. We find that the forecast combination can significantly outperform the benchmark model without macro variables for both loss criteria and for both oil price volatilities. This evidence highlights the importance of fundamental variables for oil volatility forecasting out-of-sample. In general, our out-of-sample findings show that a combination of macroeconomic variables indeed provides useful predictive information about future oil return volatility beyond long-term realized volatility.

Table 5 about here

5. Conclusions

We have revealed the predictive relationships between oil price volatility and its fundamentals using a newly proposed regime switching GARCH-MIDAS model. Our model accommodates both the long-term macroeconomic effect and short-term structural breaks. The in-sample results show that both levels and volatilities of oil supply and demand have significant impacts on oil price volatility. Long-term effect and short-term structural breaks are the two important sources of high persistence in oil volatility. Out-of-sample findings suggest that using a combination of fundamental information can improve the predictive ability of RS-GARCH-MIDAS significantly. Our two-regime GARCH-MIDAS models significantly outperform their single-regime counterparts.

We would like to conclude this paper by outlining some issues which deserve our future work. First, our RS-GARCH-MIDAS model allows for the regime switching in the constant of short-term volatility process. One can consider to impose regime switching in the long-term component, which dynamics are captured by a MIDAS regression. Solving the severe problem of non-convergence in the process of parameter estimation (Guérin and Marcellino, 2013) is a key step. Second, the regime switching can be imposed on the multivariate GARCH-MIDAS models such as DCC-MIDAS (Asgharian et al., 2015; Conrad et al., 2014) and DECO-MIDAS (Boffelli et al., 2015) to investigate the conditional correlations at different frequencies. Third, because intraday high-frequency data of oil spot price is not available, we have to use daily data. One can further consider regime switching realized volatility model for intraday high-frequency data of other assets (e.g., oil futures data) with MIDAS regressors.

Table 1: Descriptive statistics of crude oil returns.

	WTI(return)	Brent(return)	Prod.	Dem.	volProd.	volDem.
mean	0.005	0.010	0.098	-0.117	0.794	0.815
var.	6.384	5.240	1.147	58.219	5.342	5.791
min	-40.640	-36.121	-7.083	-41.046	0.000	0.000
max	19.151	18.130	4.527	36.540	35.587	32.536
skewness	-0.720	-0.627	-1.238	-0.666	10.707	8.972
kurtosis	17.291	17.550	12.827	8.934	149.269	101.954
JB stat($\times 10^4$)	6.504***	6.310***	0.154***	0.055***	32.780***	15.171***
ADF(5) stat	-38.464***	-36.330***	-9.375***	-8.753***	-5.769***	-5.792***
Q(5) stat	35.496***	14.673**	10.263*	44.722***	14.750**	22.134***
Q^2(5) stat	461.609***	578.683***	6.969	105.317***	2.781	14.038**
ARCH(5) stat	333.085***	465.563***	5.929	71.895***	2.765	14.488**

Notes: JB stat, ADF stat, Q stat and ARCH stat are the statistics testing for normal distribution, stationarity, serial correlation and heteroskedastic effects, respectively. Q^2 performs the serial correlation for squared returns. The selected lag number is in parentheses. *,** and *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Table 2: Estimation results of RS-GARCH-MIDAS for WTI oil volatility

	RV	RV+Prod.	RV+Dem.	RV+volProd	RV+volDem
$\omega(0)$	0.172	0.554***	0.531***	0.536***	0.536**
	(0.113)	(0.195)	(0.199)	(0.201)	(0.242)
$\omega(1)$	2.591***	3.389***	3.493***	3.420***	3.419***
	(0.925)	(1.313)	(0.932)	(1.008)	(1.078)
α	0.025	0.056**	0.049***	0.047**	0.047**
	(0.021)	(0.026)	(0.014)	(0.020)	(0.021)
β	0.715***	0.619***	0.712***	0.617***	0.618***
	(0.059)	(0.074)	(0.053)	(0.064)	(0.068)
θ_0	0.002***	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
θ_1	−−	-0.096***	-0.093***	0.109***	0.109***
	−−	(0.025)	(0.009)	(0.024)	(0.022)
κ_0	19.655***	21.985***	20.672***	21.937***	21.935***
	(3.748)	(4.653)	(6.190)	(3.479)	(3.582)
κ_1	−−	9.419***	11.933***	9.783***	10.782***
	−−	(1.689)	(0.579)	(1.318)	(1.439)
p_{00}	0.972***	0.991***	0.991***	0.993***	0.993***
	(0.276)	(0.205)	(0.062)	(0.206)	(0.222)
p_{11}	0.957***	0.975***	0.973***	0.975***	0.975***
	(0.438)	(0.241)	(0.180)	(0.155)	(0.155)
$\omega(1) - \omega(0)$	2.420**	2.835**	2.962***	2.883***	2.883***
	(1.002)	(1.169)	(0.895)	(0.852)	(0.880)

Notes: The table shows the estimation results for WTI oil volatility. The first row corresponds to the MIDAS regressors, that are, realized volatility (RV), realized volatility and oil production level (RV+Prod.), realized volatility and demand level (RV+Dem.), realized volatility and oil production volatility (RV+volProd) and realized volatility and oil demand volatility (RV+volDem). Standard errors are reported in parentheses. *,** and *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Table 3: Estimation results of RS-GARCH-MIDAS for Brent oil volatility

	RV	RV+Prod.	RV+Dem.	RV+volProd	RV+volDem
$\omega(0)$	0.304*	0.488**	0.510**	0.745	0.769
	(0.164)	(0.225)	(0.231)	(0.488)	(0.522)
$\omega(1)$	2.664***	2.915*	2.842***	4.040**	4.549*
	(0.728)	(1.630)	(0.643)	(2.208)	(2.377)
α	0.043***	0.071***	0.051***	0.062**	0.061*
	(0.010)	(0.019)	(0.008)	(0.024)	(0.032)
β	0.728***	0.585***	0.649***	0.437**	0.407**
	(0.080)	(0.119)	(0.064)	(0.187)	(0.206)
θ_0	0.001*	0.001**	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
θ_1	−−	-0.076**	-0.127***	0.070***	0.063***
	−−	(0.033)	(0.011)	(0.017)	(0.017)
κ_0	26.846***	20.272**	12.610**	23.604***	28.818***
	(6.125)	(8.146)	(5.169)	(5.622)	(5.671)
κ_1	−−	9.477***	13.376***	10.952	8.925
	−−	(2.840)	(0.896)	(1.568)	(2.328)
p_{00}	0.990***	0.989***	0.990***	0.978***	0.975***
	(0.136)	(0.211)	(0.052)	(0.104)	(0.100)
p_{11}	0.972***	0.985***	0.986***	0.952***	0.953***
	(0.216)	(0.364)	(0.092)	(0.334)	(0.326)
$\omega(1) - \omega(0)$	2.361***	2.427*	2.332***	3.295**	3.780*
	(0.667)	(1.444)	(0.448)	(1.800)	(1.975)

Notes: See Table 2.

Table 4: Forecasting performances of RS-GARCH-MIDAS models: the role of regime switching

	WTI oil volatilitty		Brent oil volatility	
MIDAS regressor	MSE	QLIKE	MSE	QLIKE
RV	0.699***	0.988**	0.938***	0.925***
	(0.000)	(0.038)	(0.000)	(0.000)
RV+Prod.	0.695***	0.985**	0.930***	0.928***
	(0.000)	(0.011)	(0.000)	(0.000)
RV+Dem.	0.902***	0.999	0.681***	0.915***
	(0.000)	(0.795)	(0.000)	(0.000)
RV+volProd.	0.765***	0.987**	0.961**	0.937***
	(0.000)	(0.041)	(0.030)	(0.000)
RV+volDem.	0.771***	0.988*	0.945***	0.937***
	(0.000)	(0.062)	(0.003)	(0.000)

This table reports the forecasting performances of RS-GARCH-MIDAS models evaluated by the loss functions of MSE and QLIKE. The numbers provided are the ratios of loss functions of two-regime GARCH-MIDAS models over the single-regime counterparts. The Diebold and Mariano (1995) (DM) method is applied to examine the null hypothesis that the loss function of single-regime model forecasts is lower than or equal to the two-regime counterpart under a specific criterion. The numbers in parentheses are the p-values of the DM test. The asterisks *, ** and *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Table 5: Forecasting performances of RS-GARCH-MIDAS models: the role of macro information

	WTI oil volatilitty		Brent oil volatility	
MIDAS regressor	MSE	QLIKE	MSE	QLIKE
RV+Prod.	1.002	0.997*	0.989**	0.999
	(0.536)	(0.092)	(0.031)	(0.275)
RV+Dem.	0.997	0.994**	0.979*	0.995**
	(0.413)	(0.044)	(0.053)	(0.032)
RV+volProd.	0.984	0.997	1.011	0.998
	(0.197)	(0.132)	(0.892)	(0.191)
RV+volDem.	1.015	0.999	1.003	0.999
	(0.761)	(0.333)	(0.659)	(0.341)
Forecast	0.983*	0.994***	0.990***	0.996***
combination	(0.064)	(0.000)	(0.004)	(0.003)

This table reports the evaluation results about the usefulness of macro information in improving crude oil volatility forecasting performances based on the loss functions of MSE and QLIKE. The numbers provided are the ratios of loss functions of RS-GARCH-MIDAS models with macro variables relative to the model without macro variables. The forecast combination takes the equal-weighted average of volatility forecasts from volatility models with macro variables. The Diebold and Mariano (1995) (DM) method is applied to examine the null hypothesis of equal forecasting performance. The numbers in parentheses are the p-values of the DM test. The asterisks *, ** and *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

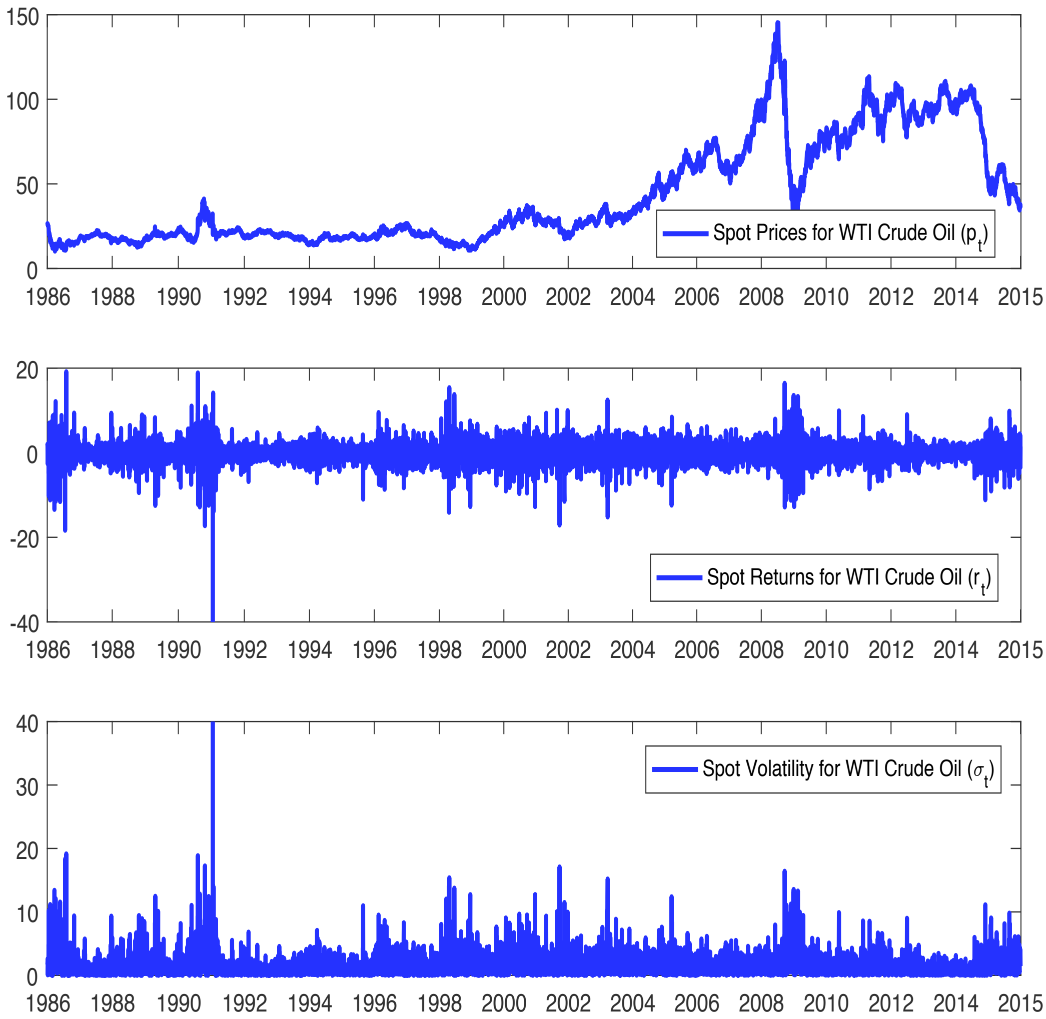

Figure 1: WTI oil prices, returns and volatilities

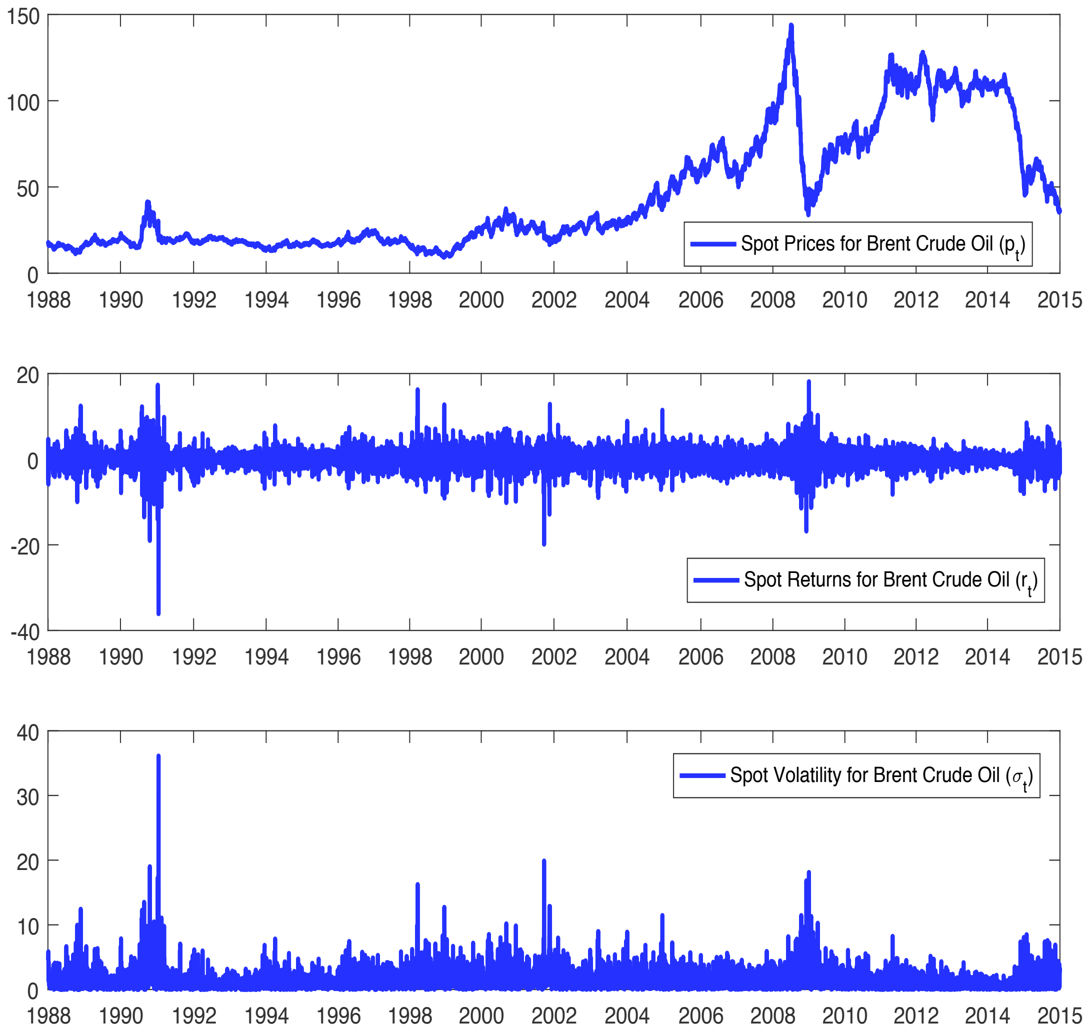

Figure 2: Brent oil prices, returns and volatilities

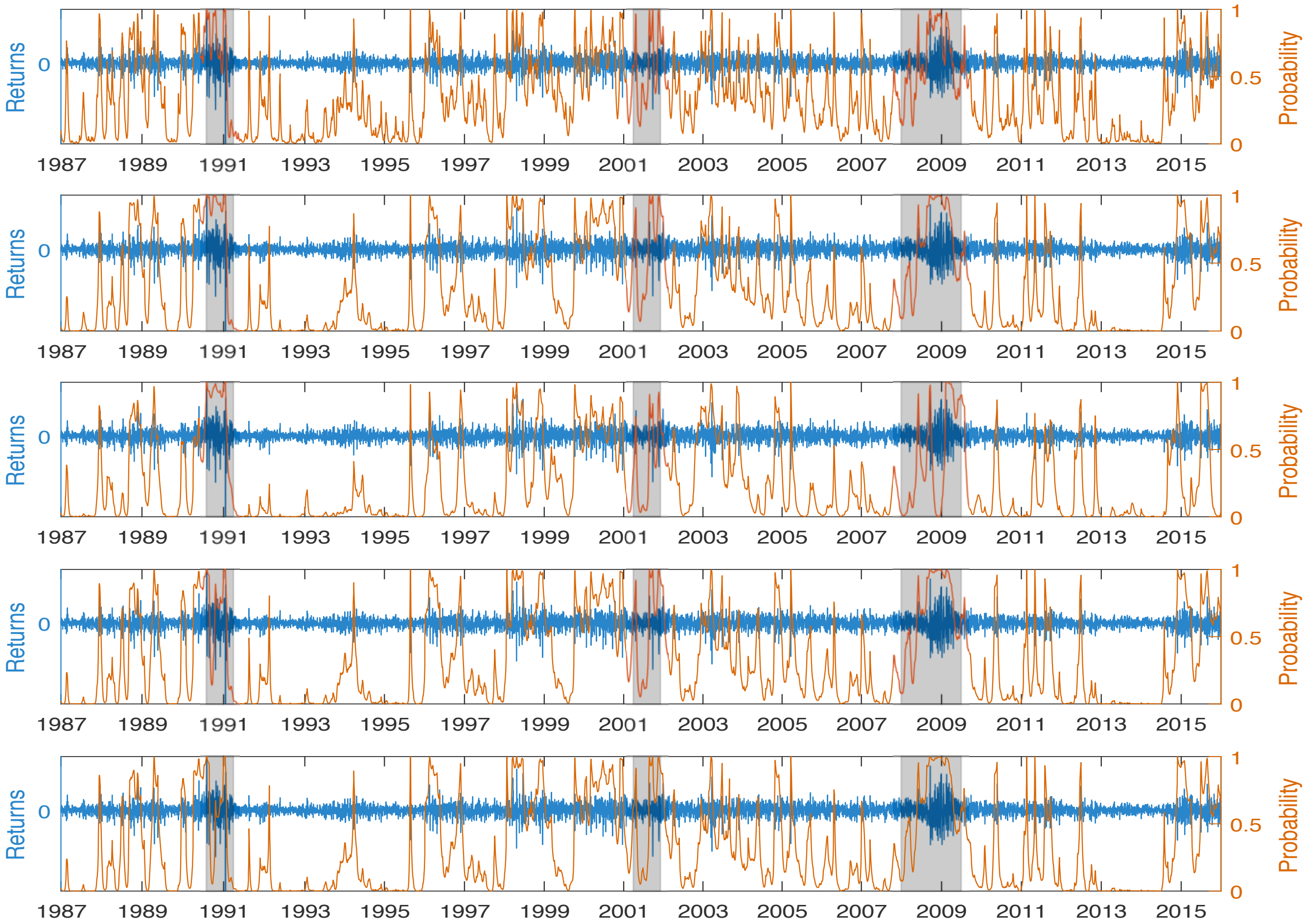

Figure 3: The returns of WTI crude oil (left side) and the posterior probability of high-volatility regime (right side). The probabilities are generated by the RS-GARCH-MIDAS models with different macroeconomic information. From the top to bottom, the information is realized volatility (RV), realized volatility and oil production level (RV+Prod.), realized volatility and demand level (RV+Dem.), realized volatility and oil production volatility (RV+volProd) and realized volatility and oil demand volatility (RV+volDem).

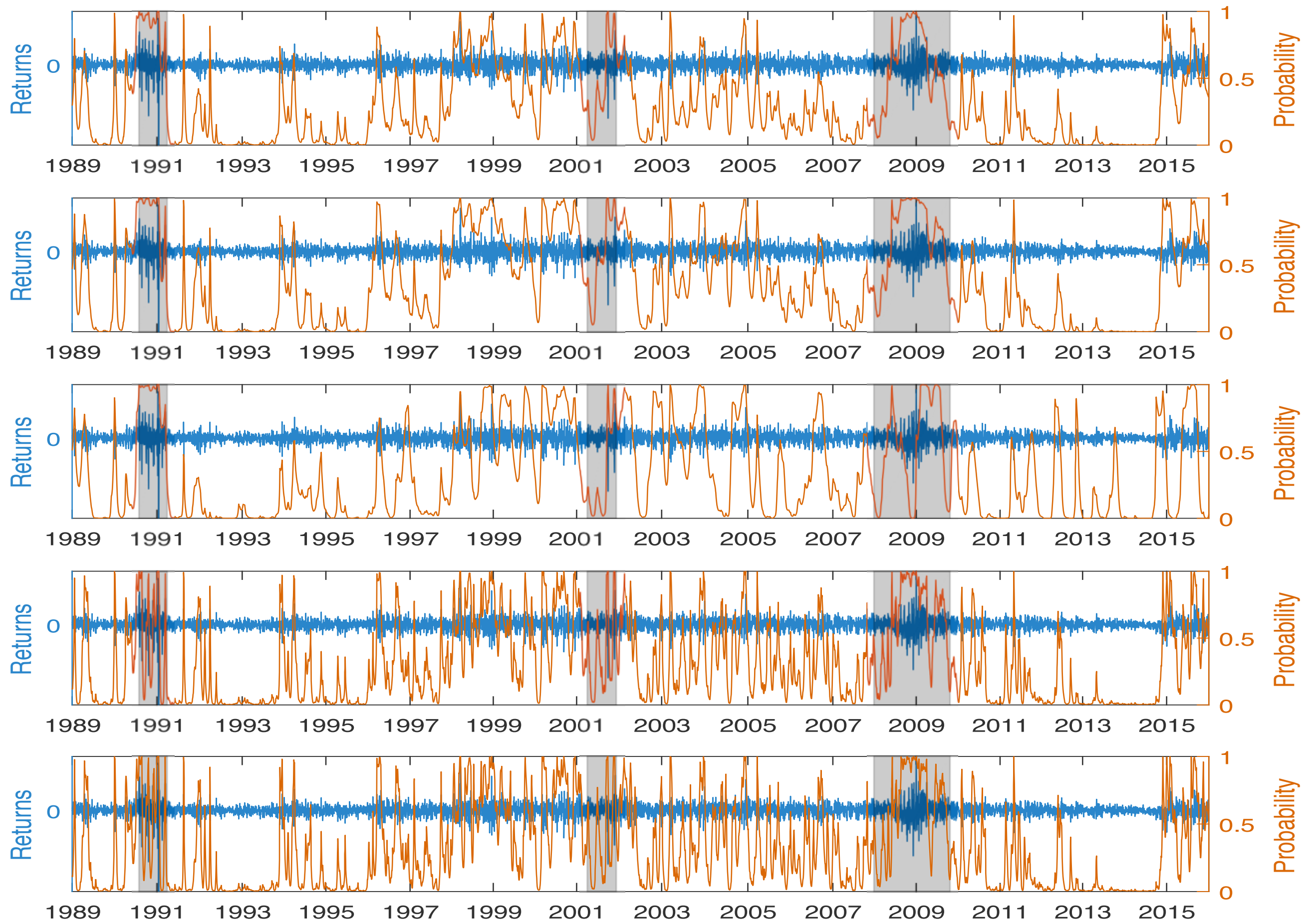

Figure 4: The returns of Brent crude oil (left side) and the posterior probability of high-volatility regime (right side). The probabilities are generated by the RS-GARCH-MIDAS models with different macroeconomic information. From the top to bottom, the information is realized volatility (RV), realized volatility and oil production level (RV+Prod.), realized volatility and demand level (RV+Dem.), realized volatility and oil production volatility (RV+volProd) and realized volatility and oil demand volatility (RV+volDem).

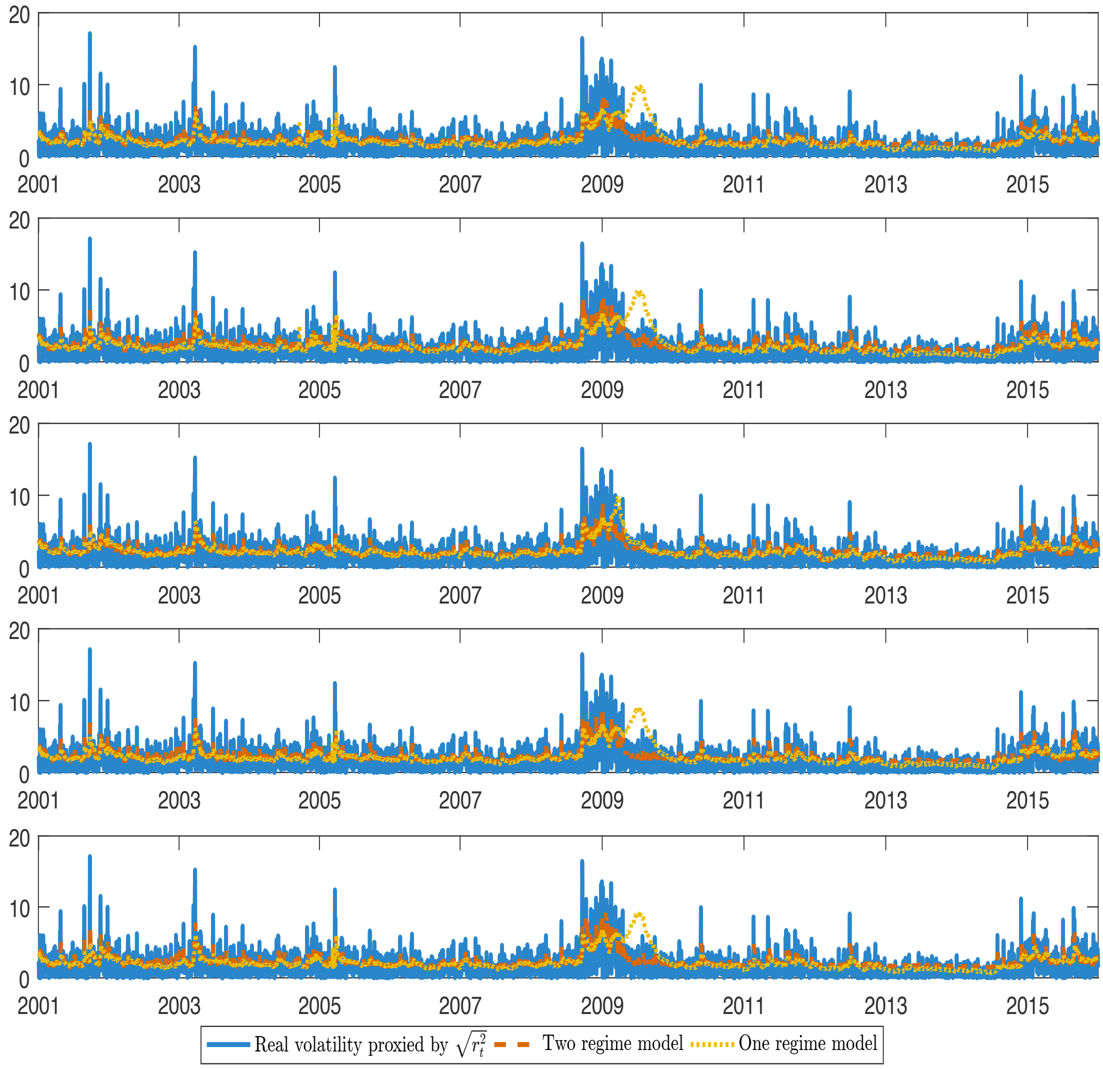

Figure 5: Volatility forecasts of WTI oil prices.The volatility forecasts are generated by the two-regime and single-regime GARCH-MIDAS models with different macroeconomic information. From the top to bottom, the information is realized volatility (RV), realized volatility and oil production level (RV+Prod.), realized volatility and demand level (RV+Dem.), realized volatility and oil production volatility (RV+volProd) and realized volatility and oil demand volatility (RV+volDem).

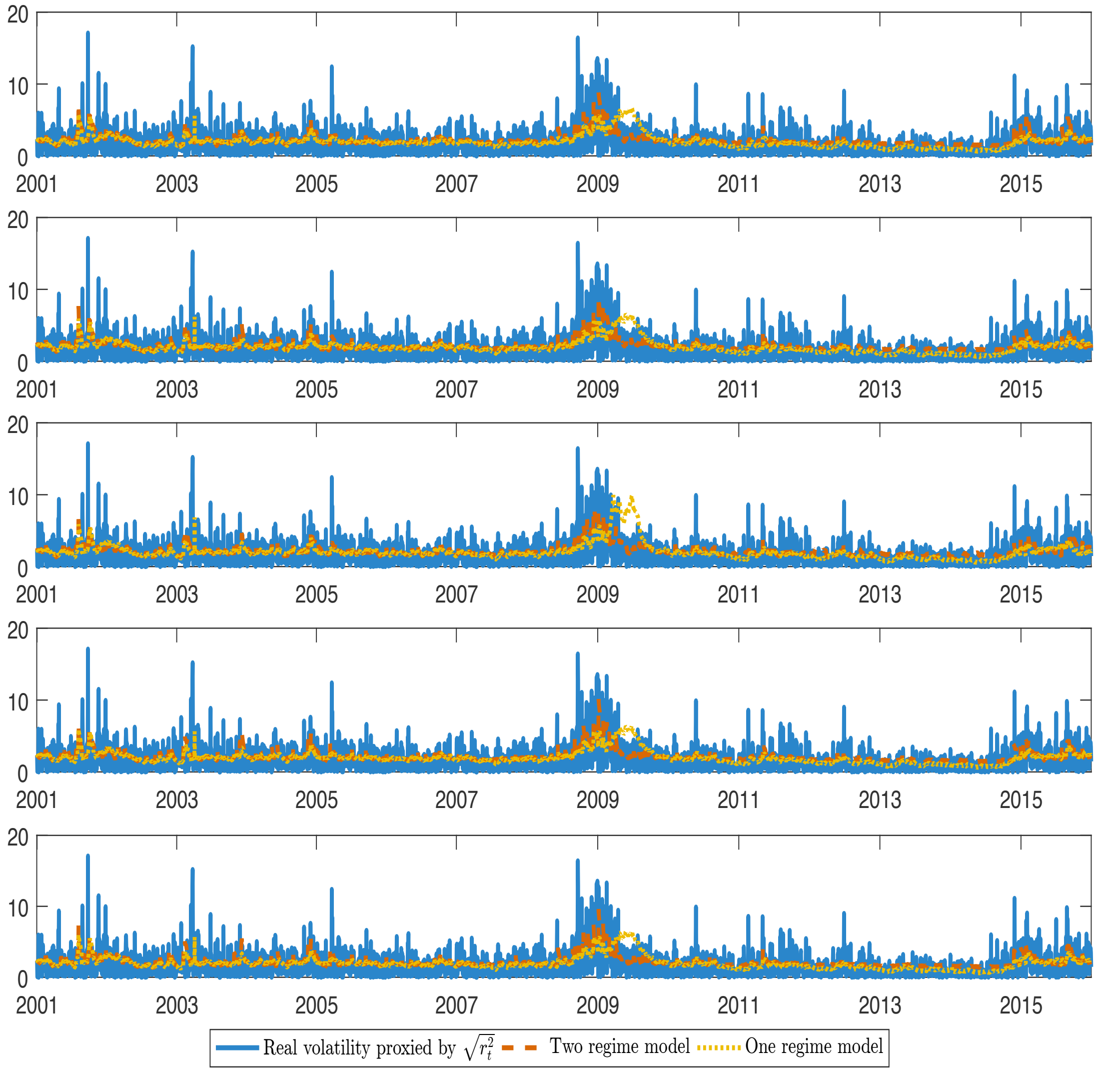

Figure 6: Volatility forecasts of Brent oil prices. The volatility forecasts are generated by the two-regime and single-regime GARCH-MIDAS models with different macroeconomic information. From the top to bottom, the information is realized volatility (RV), realized volatility and oil production level (RV+Prod.), realized volatility and demand level (RV+Dem.), realized volatility and oil production volatility (RV+volProd) and realized volatility and oil demand volatility (RV+volDem).

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