Time-Varying Volatility Feedback of Energy Prices: Evidence from Crude Oil, Petroleum Products, and Natural Gas Using a TVP-SVM Model

Yong Jiang 1, Chao-Qun Ma 1,2,* Xiao-Guang Yang 3,* and Yi-Shuai Ren 1,2,*

1 Business School, Hunan University, Changsha 410082, China; jiangyonghnu@hnu.edu.cn
2 Center for Resource and Environmental Management, Hunan University, Changsha 410082, China
3 Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China
* Correspondence: cqma1998@hnu.edu.cn (C.-Q.M.); xgyang@iss.ac.cn (X.-G.Y.); yishuai_hnu@hnu.edu.cn (Y.-S.R.)

Received: 24 October 2018; Accepted: 5 December 2018; Published: 10 December 2018

Abstract: In this paper, the time-varying volatility feedback of nine series of energy prices is researched by employing the time-varying parameter stochastic volatility in mean (TVP-SVM) model. The major findings and conclusions can be grouped as follows: Significant differences exist in the time-varying volatility feedback among the nine major energy productions. Specifically, crude oil and diesel’s price volatility has a remarkable positive time-varying effect on their returns. Yet the returns, for natural gas and most petroleum products are negatively affected by their price volatility over time. Furthermore, obvious structural break features exist in the time-varying volatility feedback of energy prices, which coincide with the breakpoints in the energy volatility. This indicates that some factors such as major global economic and geopolitical events that cause the sudden structural breaks in the energy volatility may also affect the volatility feedback of the energy price. Moreover, the volatility feedback in energy price will become weak and even have no impact on energy returns in some special periods when the energy price volatility is extremely high.

Keywords: crude oil; natural gas; petroleum product; structural breaks; time-varying volatility feedback; TVP-SVM model

1. Introduction

The crucial role of energy in the macro economy is undeniable [1–6]. As one of the world’s most frequently traded commodities, huge and sharp volatile energy prices often result in a significant impact on production capacity, which causes further economic fluctuations [7]. And it will influence the energy price itself if energy price volatility persists [8]. Moreover, there are significant substantial risks to both producers and consumers via unlimited increases in the costs of inventory, transportation, and production [9]. Therefore, a scientific and rational evaluation of the feedback effect of energy price volatility on the energy price itself is of essential significance for both investors and policymakers, especially under circumstances of large swings in energy price in recent decades. Motivated by this aim, one natural question is posed: How does the volatility of the energy price affect the energy price itself in the energy market at present? It is of significance to answer this question for managing risk, hedging, and making investment decisions.

At the present time, a great deal of literature has been concerned with the measuring of energy price volatility, volatility forecasting [10–14], and the volatility spillover effect of energy prices on other financial markets, such as the stock market, the non-energy commodity market and exchange rate market [15–20]. However, it is surprising that there is little literature investigating the volatility feedback of energy prices [8,21,22]. For example, Chan and Grant [8] proved that the stochastic
Sustainability 2018, 10, 4705

...Sustainability volatility in mean (SVM) model outperforms the GARCH-M model in evaluating the volatility feedback of energy prices and show that crude oil (WTI and Brent), petroleum products, and gas price volatility have a negative side for their returns. However, there are few studies that investigate the volatility feedback of petroleum products and natural gas prices and consider the structural breaks of energy prices when estimating the feedbacks of energy price. Moreover, numerous studies have proved that in energy productions, such as crude oil, volatility presents some structural breaks during the sample time [23–28], and the break feature may affect the estimation of the volatility feedback effects on the energy price under the framework of the conditional mean models with constant coefficients [29]. Recently, Balcilar and Ozdemir [30] investigated the relationship between oil price and its volatility risk in a stochastic volatility in the mean model with time-varying parameters, they find that oil volatility has a time-vary and positive impact on oil returns. However, whether the existence of a structural break features in the time-varying volatility feedback of energy prices is not clear. Therefore, it needs to further analyze the volatility feedback of the energy price combining structural break test. In addition, for natural gas and petroleum productions, what is the volatility feedback for them? Up to now, litter literature answers this problem.

To address the above problems, considering the influences of structural breaks of energy price volatility, this paper examines the time-varying volatility feedback of the energy prices by employing the TVP-SVM model recently proposed by Chan [29]. Because the TVP-SVM model with the time-varying parameter can correct the estimated errors due to the structural break in the energy returns, we can better address the structural instability. Unlike the SVM model of Koopman and Hol Uspsensky [31], the TVP-SVM model’s volatility enters the conditional mean as a covariate and affects the variable of interest directly and time variably. Therefore, this study is better able to assess whether the nexus between the energy returns and the energy price volatility has changed over time, especially for natural gas and petroleum product prices. According to the above considerations and discussions, this study yields some noteworthy results and enriches related research in the following forms. First, significant differences are found in the price volatility feedback among nine energy products. More specifically, the price volatility of crude oil has a remarkable positive time-varying effect on its returns, while natural gas has a negative time-varying volatility feedback. In the petroleum products market, the returns on heating oil, jet fuel, and propane are negatively affected by the price volatilities over time; and for diesel, there exists a positive time-varying volatility feedback. Differing from all the above, for gasoline, no time-varying feature for the volatility feedback is found. Second, structural breaks exist in the price volatility of nine energy products corresponding to some major global economic and geopolitical events. Based on this, obvious structural features are found in the time-varying volatility feedback of energy prices, which coincide with the structural breaks in the energy volatility. This indicates factors, such as the major global economic and geopolitical events that cause a sudden break in the energy volatility, can also affect the volatility feedback of the energy prices. Third, we find the volatility feedback in energy returns will become weak and even have no impact on the energy returns in some special periods when the energy price volatility is extremely high. Finally, this paper estimates the time-varying volatility feedback of energy prices, especially the natural gas and petroleum products. However, there is little attention paid to this for a long time. Of particularly note is that there is little study investigating the time-varying nexus between the volatility for natural gas and petroleum products and their returns.

The remainder of the paper is organized as follows. Sections 2 and 3 describe the empirical methodologies and the data description. Section 4 concludes the empirical results. Section 5 summarizes the main findings.

2. Methodology

In this paper, we build a two-stage approach in which we first test the existence of structural breakpoints in the volatility of the nine energy products by using the iterated cumulative sum of squares algorithm (ICSS) [32] and found that there exist multiple structural breakpoints in energy...
volatility. Hence, it may not be appropriate to estimate the volatility feedback of energy prices by using the traditional constant parameter model such as the GARCH-M model [33] and SVM model [31]. To this end, secondly, we employ the TVP-SVM proposed by Chan [29], which can handle the structural instability and acquire the time-varying influence of the energy price volatility on the energy returns.

2.1. Structural Break Test

The ICSS algorithm approach [32] is employed in order to check the structural breaks in energy volatility. The approach has been widely applied to detect the sudden changes in the volatility of the energy returns series by some scholars, like Hammoudeh and Li [23], Kang et al. [24], Arouri et al. [16], Kumar and Maheswaran [25], Wen et al. [27].

We assume a stable time series

\[ y_t = \mu + \epsilon_t \]  

where \( \mu \) denotes the mean return for time series; \( \epsilon_t \) is the residual series, and its mean and variance are zero and \( \sigma^2 \) respectively. The null hypothesis is that the unconditional variance of \( y_t \) is constant for \( k = 1, \ldots, T \), which is contrary to the alternative hypothesis of a break in the unconditional variance. To test the null hypothesis, Inclan and Tiao [32] provided the following test statistic,

\[ IT = \sup_k \left| \sqrt{T/2} D_k \right| \]  

where, \( D_k = C_k^{1/2} - \frac{k}{T} \) and \( D_0 = D_T = 0; \) \( C_k = \sum_{t=1}^{k} \epsilon_t^2 \), \( k = 1, \ldots, T \) is the cumulative sum of squares of \( \epsilon_t \) from the whole sample period.

If breakpoints do not occur in the variance in the iteration process, the value of \( D_k \) statistic will be different about zero. With this just the opposite occurs, if there are one or more breakpoints in a sequence, the value of the statistic \( D_k \) will deviate significantly upward or downward from 0.

2.2. TVP-SVM Model

TVP-SVM model is proposed by Chan [29], in which the coefficients in the conditional mean is permissible to be time-varying. This model can reduce the estimated errors caused by the structural break in the energy returns.

In this paper, \( y_t \) denotes the time series of energy returns and then we consider

\[ y_t = X_t' \beta_t + \alpha_t \epsilon_{hi} + \epsilon_{ti}^\gamma, \quad \epsilon_t^\gamma \sim N(0, \Omega) \]  

\[ h_t = \mu + \varphi(h_{t-1} - \mu) + \epsilon_t^\varphi, \quad \epsilon_t^\varphi \sim N(0, \sigma^2) \]  

where \( X_t \) indicates a \( k \times 1 \) vector of covariates and \( \beta_t \) indicates the \( k \times 1 \) vector of time-varying parameters. The disturbances \( \epsilon_t^h \) and \( \epsilon_t^\gamma \), which are not correlate mutually and serially. The log-volatility \( h_t \) following a stationary AR (1) process with \(|\varphi| < 1 \), which is initialized with \( h_1 \sim N(\mu, \sigma^2/(1 - \varphi^2)) \), and \( \sigma^2 \) is the conditional variance. Model (3)–(4) generalizes the original setup in Koopman and Hol Uspensky [31], which permits the conditional mean of \( y_t \) to have time-varying parameters, namely both \( \beta_t \) and \( \alpha_t \) are also time-varying. The vector of coefficients \( \gamma_t = (\alpha_t, \beta_t)' \) evolves based on a random walk process as shown in (5):

\[ \gamma_t = \gamma_{t-1} + \epsilon_{\gamma t}, \quad \epsilon_{\gamma t} \sim N(0, \Omega) \]  

In (5), \( \Omega \) denotes a \((k+1) \times (k+1)\) covariance matrix. This model allows a generic correlation structure between innovations and random-walk coefficients. The random walk process in (5) is initialized with \( \gamma_1 \sim N(\gamma_0, \Omega_0) \) for constant matrices \( \gamma_0 \) and \( \Omega_0 \).

When \( \alpha_t = 0 \) for \( t = 1, \ldots, T \), the model in (3)–(5) simplifies to a standard TVP regression with stochastic volatility. Since \( \alpha_t \) is allowable to nonzero, the model allows an additional channel of
where, also due to the log-volatility, which follows an AR (1) process, and when a shock to h_{t-1} affects h_t, which in turn affects the conditional mean of y_t directly. As shown below, this channel is empirically meaningful for both the model comparison exercise and the forecasting exercise. Also, (3)–(5) define a Gaussian state-space model with two types of states; i.e., γ_t and h_t.

Since Equations (3) and (4) define a nonlinear Gaussian state-space model, the traditional Maximum Likelihood (ML) approach, which has the intractability of the likelihood function and cannot provide reliable estimates for the parameters. Based on the latest progress of band and sparse matrix algorithms, the efficient MCMC sampling approach is proposed by Chan [29]. Since this approach uses the fact that the Hessian of the log conditional density of the log-volatilities is a band matrix algorithms, the efficient MCMC sampling approach is proposed by Chan [29]. Since this approach uses the fact that the Hessians of the log conditional density of the log-volatilities is a band matrix which contains only a few nonzero elements lined along a diagonal band, it can simulate each type of state individually.

For notational convenience, let x denote the covariates (in Equation (3)); y = (y_1, · · · , y_T)' and h_t = (h_1, · · · , h_T)'. Then, posterior draws are acquired by sequentially sampling from:

1. \( p(h|y, x, γ, μ, ϕ, σ^2, Ω) = p(h|y, x, γ, μ, ϕ) \)
2. \( p(y|x, h, μ, φ, σ^2, Ω) = p(y|x, h) \)
3. \( p(Ω, σ^2|y, x, γ, h, μ, φ) = p(Ω|γ)p(σ^2|h, μ, φ) \)
4. \( p(μ, φ|y, x, γ, h, σ^2, Ω) = p(μ, φ|h, σ^2) \)

In order to complete the model specification, the independent priors are assuming as follows:

\[
\begin{align*}
μ & \sim N(μ_0, V_μ), \quad φ \sim N(φ_0, V_φ)I(|φ| < 1), \\
σ^2 & \sim IG(ν_σ^2, S_σ^2), \quad Ω \sim IW(ν_Ω, S_Ω)
\end{align*}
\]

where IG(·, ·) denotes the inverse-gamma distribution and IW(·, ·) denotes the inverse-Wishart distribution. Also, following Chan (2017), we impose the stationary condition |φ| < 1 on the prior for φ.

According to the TVP-SVM model, see Equations (3)–(5), following Chan [29], we further use the unobserved components model (UC) [34] to decompose the energy returns into a trend and a transitory component, and at the same time it is assumed that the transitory component has stochastic volatility, however, the variance of the trend is constant. Meanwhile, it is assumed that the energy price volatility may have an effect on the energy returns over time; and additionally, the past energy returns can affect the current energy price volatility. As a result, we particularly consider the following TVP-SVM model:

\[
\begin{align*}
y_t &= τ_t + α_t e^{h_t} + ε_t^y, \quad ε_t^y \sim N(0, e^{h_t}) \\
h_t &= μ + φ(h_{t-1} - μ) + β y_{t-1} + ε_t^h, \\
γ_t &= γ_{t-1} + ε_t^γ, \quad ε_t^γ \sim N(0, Ω)
\end{align*}
\]

where \( y_t \) is the returns of energy, \( τ_t \) denotes the trend of energy returns, and \( Ω \) is a 2 × 2 covariance matrix. \( σ^2 \) is the conditional variance. As the associated coefficient in the conditional mean equation, \( α_t \) may be explained as the impact of the transitory volatility on the energy returns for \( e^{h_t} \) is the variance of the transitory component. Moreover, \( y_{t-1} \) is a covariate in the conditional variance equation, which is the past return. Its associated parameter \( β \) enters the MCMC algorithm as an extra block, which is samples it from its full conditional distribution: \( (β|y, h, μ, φ, σ^2) \sim N(\hat{β}, D_β) \)

where, \( D_β^{-1} = V_β^{-1} + X'_β X_β / σ^2 \) and \( \hat{β} = D_β^T(V_β^{-1} β_0 + X'_β z_β / σ^2) \) with \( X_β = (y_1, · · · , y_{T-1})' \) and \( z_β = (h_2 - φ h_1 - μ(1 - φ), · · · , h_T - φ h_{T-1} - μ(1 - φ))' \). More detailed model settings can be seen in Chan et al. (2017).
3. Data

This paper aims to study the time-varying volatility feedback effects of energy prices on the level of energy returns by using the TVP-SVM model. We select nine energy products as the research objects (see Table 1) and further divide these nine products into three categories: crude oil (S1 and S2), petroleum products (S3–S8), and natural gas (S9). This paper uses weekly data for the nine energy products obtained from the U.S Energy Information Administration (EIA) (www.eia.gov). The full sample ranges from 10 January 1997 to 11 November 2016. We calculate energy returns by $100 \times \ln(p_t/p_{t-1})$, where $p_t$ is the energy price at time $t$.

Table 1. The energy price data of the nine energy products.

<table>
<thead>
<tr>
<th>Panel 1. Crude Oil (US Dollars per Barrel)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
</tr>
<tr>
<td>S2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel 2. Petroleum Products (US Dollars per Gallon)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S3</td>
</tr>
<tr>
<td>S4</td>
</tr>
<tr>
<td>S5</td>
</tr>
<tr>
<td>S6</td>
</tr>
<tr>
<td>S7</td>
</tr>
<tr>
<td>S8</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel 3. Natural Gas (US Dollars per Million Btu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S9</td>
</tr>
</tbody>
</table>

Notes: The data come from the EIA.

The dynamics of the nine energy prices are shown in Figure 1. Note that the prices of energy products are basically consistent with each other, which indicates that there exists a risk spillover effect among the products in the energy market. Specifically, the prices of WTI and Brent crude oil roughly follow the same dynamic trend with that of the petroleum products. This is because petroleum products are the derivatives of crude oil. However, the dynamic price trend of natural gas is different from that of the crude oil and petroleum products; and its dynamic curve is not very smooth and there are more sudden changes than that of other energy products. For example, under the influence of the 911 terrorist attacks, natural gas prices tumbled during the US economic recession in 2001. However, the price of natural gas rose between 2003 and 2005, which is due to the Iraq war in 2003. The trends of crude oil and petroleum products were relatively small. During the global financial crisis of 2008, the prices of crude oil, petroleum products, and natural gas all plummeted, while global energy prices experienced ups and downs in 2014.

The summary statistics of the variables have been reported in Table 2. It notes that the means of the return series for the nine energy prices are quite small and close to zero. The corresponding standard deviations of returns are substantially different between each other, and natural gas has the largest standard deviations among the nine energy products. As the skewness, kurtosis, and Jarque–Bera tests indicate, the distribution of energy returns is not normal. Along with the time lags from 10 to 20 increasing, the Ljung–Box Q statistics reject the null hypothesis of no serial correlation in the return series.
The return series of the nine energy product prices with the structural breakpoints for energy volatility of sustainability are shown in Table 3. In addition, the periods of structural changes in volatility identified by the ICSS algorithm for WTI and Brent are shown in Table 3.

Table 2. Descriptive statistics for returns of the nine energy products price.

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
<th>S7</th>
<th>S8</th>
<th>S9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.05</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.06</td>
<td>0.00</td>
<td>-0.05</td>
</tr>
<tr>
<td>Median</td>
<td>0.16</td>
<td>0.18</td>
<td>0.35</td>
<td>0.26</td>
<td>0.11</td>
<td>0.14</td>
<td>0.23</td>
<td>0.21</td>
<td>0.00</td>
</tr>
<tr>
<td>Maximum</td>
<td>25.13</td>
<td>20.10</td>
<td>37.36</td>
<td>35.25</td>
<td>36.17</td>
<td>27.14</td>
<td>21.24</td>
<td>42.05</td>
<td>64.21</td>
</tr>
<tr>
<td>Minimum</td>
<td>-19.23</td>
<td>-23.16</td>
<td>-22.49</td>
<td>-23.91</td>
<td>-29.14</td>
<td>-17.93</td>
<td>-22.82</td>
<td>-34.69</td>
<td>-43.97</td>
</tr>
<tr>
<td>Std.Dev.</td>
<td>4.36</td>
<td>4.37</td>
<td>4.95</td>
<td>5.40</td>
<td>4.44</td>
<td>4.66</td>
<td>4.40</td>
<td>5.07</td>
<td>7.47</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.21</td>
<td>-0.24</td>
<td>0.04</td>
<td>-0.02</td>
<td>0.18</td>
<td>0.27</td>
<td>-0.05</td>
<td>-0.34</td>
<td>0.17</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>5.66</td>
<td>5.12</td>
<td>6.83</td>
<td>6.12</td>
<td>10.35</td>
<td>5.43</td>
<td>5.02</td>
<td>12.67</td>
<td>11.63</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>312.29*</td>
<td>204.66*</td>
<td>632.55*</td>
<td>419.07*</td>
<td>2336.71*</td>
<td>267.60*</td>
<td>177.01*</td>
<td>4054.75*</td>
<td>3209.7*</td>
</tr>
<tr>
<td>Q(10)</td>
<td>61.14*</td>
<td>73.16*</td>
<td>49.51*</td>
<td>62.31*</td>
<td>94.89*</td>
<td>115.05*</td>
<td>63.65*</td>
<td>63.97*</td>
<td>32.66*</td>
</tr>
<tr>
<td>Q(20)</td>
<td>78.16*</td>
<td>79.92*</td>
<td>57.06*</td>
<td>75.56*</td>
<td>104.93*</td>
<td>136.20*</td>
<td>69.37*</td>
<td>71.70*</td>
<td>49.18*</td>
</tr>
</tbody>
</table>

Notes: The Jarque–Bera corresponds to the test statistic for the null hypothesis of normality in sample returns distribution. The Ljung–Box statistics, Q(n), is used to check the serial correlation of the return series. * indicates a rejection of the null hypothesis at the 1% significance level.

4. Empirical Results and Discussions

4.1. Multiple Structural Breakpoints

Firstly, using the ICSS algorithm, we test whether the structural break characteristics for the volatility of the nine major important products that exist in the energy market. Compared to the modified ICSS recently used, the ICSS proposed by Inclan and Tiao [32] can find more structural points and actual events can be found to correspond to these breakpoints. Since the ICSS algorithm can calculate the standard deviations among the breakpoints to determine the number of structural changes, the ICSS algorithm can perfectly capture the structural breaks of the energy price volatility. The return series of the nine energy product prices with the structural breakpoints for energy volatility corresponding with some major global economic and geopolitical events is illustrated in Figure 2. In addition, the periods of structural changes in volatility identified by the ICSS algorithm for WTI and Brent are shown in Table 3.
Figure 2. Structural breakpoints in the dynamic price changes of the nine energy prices (including crude oil, petroleum products, and the natural gas). (By using the ICSS algorithm, the structural breakpoints are estimated. And the red dashed line denotes the location of breakpoints. The shaded regions represent NBER recessions).
Table 3. Structural break tests for WTI and Brent.

<table>
<thead>
<tr>
<th>Energy</th>
<th>Number of Breaks</th>
<th>Breakpoint Dates</th>
<th>Major Event-Related Potentials</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTI</td>
<td>5</td>
<td>23 May 2003</td>
<td>2nd Gulf war</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5 September 2008</td>
<td>Sub-prime war and global financial crisis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3 April 2009</td>
<td>European sovereign debt crisis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>14 August 2009</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>28 November 2014</td>
<td>International crude oil plunged at the end of 2014</td>
</tr>
<tr>
<td>Brent</td>
<td>8</td>
<td>20 March 1998</td>
<td>Asian economic and financial crisis; the Russian crisis of 1998</td>
</tr>
<tr>
<td></td>
<td></td>
<td>28 September 2001</td>
<td>911 terrorist attacks and U.S. economy recession</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 March 2005</td>
<td>2nd Gulf war</td>
</tr>
<tr>
<td></td>
<td></td>
<td>19 September 2008, 16 January 2009</td>
<td>Sub-prime and global financial crisis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30 October 2009, 10 August 2012</td>
<td>European sovereign debt crisis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>28 November 2014</td>
<td>International crude oil plunged at the end of 2014</td>
</tr>
</tbody>
</table>

Notes: The structural break points are estimated by the ICSS algorithm for nine energy prices over the period from 10 January 1997 to 11 November 2016. (Due to limited space, we only list the periods of structural changes in volatility identified for WTI and Brent in Table 3).

Figure 2 and Table 3 show that there are five and eight breakpoints for the volatility of WTI and Brent prices respectively during the sample period (from 10 January 1997 to 11 November 2016). By observing the location of these structural breakpoints, we can clearly see that, these breakpoints are associated with some major global economic and financial activities or some regional political events. Specifically, the first breakpoint for Brent crude oil on 20 March 1998, corresponded to the Asian economic and financial crisis as well as the Russian crisis of 1998. For WTI crude oil, the first breakpoint happened in March 2003, which corresponded to the outbreak of the Iraq wars. Moreover, Brent crude oil has a structural breakpoint in March 2005. These breakpoints all occurred during the Iraq war. Crude oil production declined in the oil-producing countries of the Middle East during the Iraq war, and the BP data shows that since 2004, the crude oil price climbed significantly until 2008, reaching $150 per barrel. The second breakpoint for Brent crude oil volatility was on 28 September 2001, affected by the 911 terrorist attacks, when the oil prices plummeted. During the global financial crisis in 2008–2009, the volatility of WTI and Brent prices showed two structural breakpoints, respectively. Affected by the debt crisis in Europe, WTI and Brent price fluctuations were increasingly intensified, and it is easy to see the structural breakpoints that are a result of the 14 August 2009, 30 October 2009, and 10 August 2012. Afterward, on 28 November 2014, it is observed that for the price volatility of WTI and Brent oil, there exists a structural breakpoint, respectively. Their corresponding event is the opening of the OPEC conference, in which OPEC decided not to cut production.

We also detect some structural breakpoints for the volatility of petroleum products prices (see Figure 2). Overall, we find that the volatility of petroleum products has more breakpoints than crude oil, which suggests that petroleum product prices may be more sensitive to major economic and political events. Specifically, except that diesel, which only has three structural breakpoints, the other five petroleum products exhibit at least six structural breakpoints over the full sample period. During the Iraq war from 2003 to 2005, the global supply of crude oil was reduced, and heating oil possessed one breakpoint in 2005. Gasoline (NY Harbor Conventional Gasoline Regular and US Gulf Coast Conventional Gasoline Regular) and Jet Fuel have two breakpoints in 2005. The volatility of the propane price shows six breakpoints during the periods of 2003–2005. In addition, the volatility of the petroleum products shows at least two structural breakpoints during the financial crisis. Notably, in line with the WTI and Brent crude oil, some breakpoints were found during the debt crisis of Europe in 2012. Afterward, on 28 November 2014, and the global energy market freeze, we find some breakpoints in petroleum products.

We detect ten structural breakpoints for the volatility of natural gas prices. In particular, during the Iraq war in 2003, the volatility of natural gas has two breakpoints. One is at the beginning of the Iraq war of 2003, and the other one is in 2005. During the global financial crisis from 2008 to 2009, there exists a structural break in the volatility of natural gas. Similarly, most energy prices experienced a severe rise and fall in 2014. Natural gas is no exception, and it experienced four structural breaks in
volatility during this time, corresponding to the price rises in April, 2014 and when the price plunged at the end of 2014.

4.2. The Volatility Feedback Effect of Energy Prices

In this section, we employ the TVP-SVM model to assess the time-varying effects of energy prices volatility on their returns. All the posterior moments are based on 50,000 draws from the MCMC algorithm after a burn-in of 5000.

Table 4 displays the posterior trends of the model parameters. It can be seen that coefficient $\beta$ is associated with the lagged energy returns, which is estimated to be different among the nine energy prices. It is noted that the coefficient associated with the lagged crude oil price movements is estimated to be a positive value. Its 90% confidence interval excludes zero, indicating that the past crude oil returns affect current log-volatility negatively. The lag of the petroleum product returns including heating oil, jet fuel and propane has a positive impact on the current log-volatility of the prices, with its 90% confidence interval excluding zero. This means that the current returns for jet fuel and propane have significantly increased the current log-volatility. Nevertheless, the lag of diesel returns has a negative impact on the current log-volatility, and its 90% confidence interval excludes zero, indicating that the estimate is credible. From the persistence of energy price volatility, the posterior mean of $\phi$ for WTI and Brent is estimated to be 0.965 and 0.968 with a 90% confidence interval (0.949, 0.977) and (0.954, 0.981), respectively. The 90% confidence interval excludes zero, indicating that the estimates are credible as well. Compared to the petroleum products, natural gas price volatility persistence is the weakest; the posterior mean of $\mu$ estimated for natural gas is just 0.941, whereas it is different from zero with the test of the 90% confidence intervals. This suggests that the parameter estimates are significant.
Table 4. Estimated posterior moments.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
<th>S7</th>
<th>S8</th>
<th>S9</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>2.487</td>
<td>2.371</td>
<td>2.779</td>
<td>2.868</td>
<td>2.416</td>
<td>2.503</td>
<td>2.426</td>
<td>2.507</td>
<td>3.421</td>
</tr>
<tr>
<td></td>
<td>(2.262, 2.704)</td>
<td>(2.098, 2.642)</td>
<td>(2.556, 2.993)</td>
<td>(2.629, 3.107)</td>
<td>(2.147, 2.688)</td>
<td>(2.253, 2.750)</td>
<td>(2.141, 2.714)</td>
<td>(2.269, 2.746)</td>
<td>(3.196, 3.641)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$-0.026$ (−0.030, −0.021)</td>
<td>$-0.025$ (−0.029, −0.021)</td>
<td>0.004 (−0.020, 0.019)</td>
<td>0.003 (0.014, 0.026)</td>
<td>0.02 (−0.025, −0.017)</td>
<td>0.018 (0.012, 0.024)</td>
<td>0.019 (0.013, 0.025)</td>
<td>0.013 (0.008, 0.018)</td>
<td></td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.965</td>
<td>0.968</td>
<td>0.955</td>
<td>0.958</td>
<td>0.963</td>
<td>0.961</td>
<td>0.965</td>
<td>0.941</td>
<td>0.941</td>
</tr>
<tr>
<td></td>
<td>(0.949, 0.977)</td>
<td>(0.954, 0.981)</td>
<td>(0.933, 0.974)</td>
<td>(0.937, 0.976)</td>
<td>(0.944, 0.979)</td>
<td>(0.944, 0.977)</td>
<td>(0.947, 0.981)</td>
<td>(0.918, 0.961)</td>
<td>(0.919, 0.961)</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>0.018</td>
<td>0.019</td>
<td>0.024</td>
<td>0.027</td>
<td>0.027</td>
<td>0.024</td>
<td>0.028</td>
<td>0.057</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>(0.013, 0.023)</td>
<td>(0.014, 0.026)</td>
<td>(0.016, 0.034)</td>
<td>(0.018, 0.038)</td>
<td>(0.020, 0.036)</td>
<td>(0.017, 0.031)</td>
<td>(0.020, 0.037)</td>
<td>(0.041, 0.075)</td>
<td>(0.035, 0.064)</td>
</tr>
<tr>
<td>$\omega_2^2$</td>
<td>0.005</td>
<td>0.008</td>
<td>0.004</td>
<td>0.004</td>
<td>0.005</td>
<td>0.007</td>
<td>0.005</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.003, 0.008)</td>
<td>(0.005, 0.012)</td>
<td>(0.003, 0.006)</td>
<td>(0.003, 0.006)</td>
<td>(0.003, 0.007)</td>
<td>(0.004, 0.010)</td>
<td>(0.003, 0.007)</td>
<td>(0.003, 0.007)</td>
<td>(0.002, 0.004)</td>
</tr>
<tr>
<td>$\omega_{\alpha\tau}$</td>
<td>$-0.002$ (−0.010, 0.005)</td>
<td>$-0.001$ (−0.012, 0.009)</td>
<td>$-0.004$ (−0.011,0.002)</td>
<td>$-0.003$ (−0.012, 0.002)</td>
<td>$-0.004$ (−0.012, 0.008)</td>
<td>$-0.001$ (−0.012, 0.002)</td>
<td>$-0.004$ (−0.010, 0.002)</td>
<td>$-0.003$ (−0.006, 0.001)</td>
<td>$-0.002$ (−0.006, 0.001)</td>
</tr>
<tr>
<td>$\omega^2_\tau$</td>
<td>0.087</td>
<td>0.102</td>
<td>0.102</td>
<td>0.998</td>
<td>0.084</td>
<td>0.107</td>
<td>0.083</td>
<td>0.073</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.043, 0.159)</td>
<td>(0.050, 0.186)</td>
<td>(0.047, 0.193)</td>
<td>(0.045, 0.195)</td>
<td>(0.041, 0.155)</td>
<td>(0.047, 0.223)</td>
<td>(0.046, 0.157)</td>
<td>(0.038, 0.131)</td>
<td>(0.039, 0.122)</td>
</tr>
</tbody>
</table>

Notes: Confidence interval denotes 90% confidence interval, if the credible interval including zero, it implies not pass the test of significance.
4.2.1. Crude Oil

The price volatility \( (h_t) \) and time-varying volatility feedback \( (a_t) \) for WTI (S1) and Brent (S2) are shown in Figure 3. Note that WTI and Brent demonstrate the same volatility trend, and these two crude oil price volatilities reached their peak during the global financial crisis of 2008. Especially, in the second half of 2014, there was a significant increase in crude oil price volatility due to a tremendous drop in price. Furthermore, it can be seen from the right panel of Figure 3 that all crude oil price volatilities affect the time-varying feedback effect on crude oil returns positively, which means the greater the volatility of crude oil prices, the more likely the crude oil prices are to rise. The test results of the 90% confidence intervals show that the positive nexus between oil price volatility and oil returns is statistically different from zero during most of the sample time. This finding accords with the conclusion of Antoniou and Foster (1992) and Day and Lewis (1993) who have provided evidence that oil price volatility has a positive impact on the level of oil returns. However, they cannot detect the time-varying volatility feedback and provide more information that is useful for investors in the energy market. Our empirical results are not consistent with the finding of Chan and Grant (2016). They employ the constant coefficient SVM model and provide evidence that WTI crude oil price volatility affects WTI returns negatively during the sample period, from 3 January 1997 to 6 February 2015. The differences lie in the fact that Chan and Grant (2016) use a constant coefficient SV model, whereas we employ a TVP-SVM model that allows for time-variation on the impact of oil price volatility and that analyzes this structural instability better. Meanwhile, we find that the time-varying feedback effect of Brent price volatility is higher than that of the WTI price as a whole.

\[ \text{Figure 3. Crude oil (S1 and S2) price volatility (h_t) and volatility feedback effect for crude oil (a_t) (The solid lines are the volatility and the time-varying volatility feedback of energy prices, and the dashed lines are the associated 90% credible intervals. The shaded regions represent NBER recessions. Vertical dashed line denotes the break points that as same as the Figure 2).} \]

In addition, the time-varying volatility feedback of the crude oil price has structural break characteristics, namely, there exists a turning point for the volatility feedback of the crude oil price in the location of the crude oil volatility breaks at the same time. For example, in the location of these breakpoints for WTI and Brent volatility, the volatility feedback reaches the minimum value during
the global financial crisis of 2008, which closes to zero and some parts are insignificant for the test of 90% credible intervals. This indicates that when the oil price volatility is large enough, for instance, the extreme volatility during the global financial crisis of 2008, the feedback effects of oil volatility on its returns will tend to be zero, indicating the volatility will have no impact on the crude oil returns. Likewise, in the location of the structural breakpoint for oil volatility, there is a large volatility in the crude oil price and the volatility feedback of the oil price tends to be zero as well in the second half of 2014. These two special periods coincided with the recessions in the international oil market, in which the oil prices plummeted and the price volatility was higher than at other times. This reveals that the volatility feedback in crude oil prices will become weak and even have no impact on its returns when the price volatility is extremely high.

4.2.2. Petroleum Products

Figure 4 plots the dynamic evolution of energy price volatility ($h_t$) and volatility feedback ($\alpha_t$) for two types of gasoline (NY Harbor Conventional Gasoline Regular (S3) and US Gulf Coast Conventional Gasoline Regular (S4)) and one heating oil (S5) (NY Harbor No. 2 Heating Oil). Specifically, for gasoline, the volatility of gasoline prices increased and reached a peak in 2005 since the outbreak of the Iraq war in 2003. Thereafter, the volatility gradually stabilized, and the financial crisis erupted and the price volatility reached a peak again in 2008. The right panel of Figure 4 shows that the volatility feedback of gasoline price is negative over the sample time, but the corresponding 90% confidence intervals include zero. This suggests that there is no time-varying volatility feedback effect for the gasoline returns. In other words, the volatility of the gasoline price has no impact on the level of gasoline returns.

Heating oil has a similar price volatility curve to that of gasoline, but as a whole, it is relatively stable with no obviously sharp peak for the volatility. The volatility feedback ($\alpha_t$) estimated for heating oil displays a negative time-varying path overall, which indicates that the volatility of heating oil price has a negative impact on the level of heating oil returns over the sample period. Its 90% confidence interval excludes zero, which means that the parameter estimate is significant and credible. The finding is in line with the conclusion of Chan and Grant [8] and Kristoufek [35]. Likewise, we also find that the time-varying volatility feedback effect of the heating oil price shows the structural break characteristics as well. For example, at the beginning of 2000, the volatility feedback of the heating oil price has a turning point and closes to zero in the location of the two breakpoints for heating oil volatility. The volatility feedback of the heating oil price gradually decreased until reaching its lowest value in June 2009 during the global financial crisis in 2008. This finding is similar to that of crude oil, that is, if the volatility of energy prices is particularly higher in a severe economic recession, the impact of price volatility on the level of returns will become smaller, even close to zero. Similar evidence is found in 2014: the price volatility of heating oil increased at the end of 2014, but the volatility feedback effect of prices gradually decreased.

The results of energy price volatility ($h_t$) and volatility feedback ($\alpha_t$) for diesel (S6), jet fuel (S7) and propane (S8) are presented in Figure 5. First, we note that diesel has similar volatility feedback dynamics with WTI and Brent crude oil. The time-varying parameter estimate of $h_t$ for diesel is positive and its 90% confidence interval excludes zero, indicating that the parameter estimate is significant and credible. We find that diesel price volatility affected its returns positively. At the location of the structural breakpoint, the diesel volatility has weak or not any effect on its returns if it reaches a peak. For example, the diesel price volatility reached a peak and yet the volatility feedback fell to the bottom close to zero during the global financial crisis in 2008. Likewise, in November 2014, this finding also can be proved. Second, in the case of jet fuel (S7), it shows that the price volatility of jet fuel has a significant and time-varying negative feedback effect on its returns. The corresponding 90% confidence intervals are excluded from zero, and the estimated results are significant. Besides, the volatility feedback effect of the jet fuel price on its returns shows the characteristics of a structural break. For instance, during the Iraq war, the volatility of jet fuel has two breakpoints in 2005. Under the location
of breakpoints, the price volatility reaches a peak, whereas the volatility feedback effect gradually declined and neared to zero. All these indicate the volatility lost its effects on the returns. Similarly, when the global financial crisis broke out in 2008, the feedback effect of jet fuel price volatility on its returns reached an extremum (the feedback level less than zero), which indicates that the volatility has a smaller impact on jet fuel returns. Third, we can easily find that the propane price volatility (S8) has a negative effect on its returns. However, when considering the 90% confidence interval, most of the time it includes zero, which suggests that the estimated results are inaccurate.

![Figure 4](image-url)

**Figure 4.** Energy (S3–S5) price volatility ($h_t$) and volatility feedback ($a_t$) (The solid lines are the volatility and the time-varying volatility feedback of energy prices, and the dashed lines are the associated 90% credible intervals. The shaded regions represent NBER recessions. Vertical dashed line denotes the break points that as same as the Figure 2).
To sum up, some convincing findings are demonstrated in this section. On the one hand, during the sample period, although petroleum products are the derivatives of crude oil, the volatility feedbacks of most petroleum product prices are different from that of crude oil. Besides, there exist significant differences in volatility feedback effects among petroleum products. In particular, the volatility feedback of five petroleum products among the six is less than zero (only diesel is positive), indicating that the volatility in petroleum products leads to a decline in returns. On the other hand, there exist the structural break and time-varying characteristics in the volatility feedback of petroleum products price, which is influenced by major global economic or politic events. The turning points of volatility feedback will appear in the location of the breakpoint in their volatility. When the price volatility of petroleum products reaches a high peak, the price volatility of the petroleum products will have a weak even nonexistent impact on their returns.

4.2.3. Natural Gas

The evolution of price volatility ($h_t$) and time-varying feedback ($a_t$) for natural gas are plotted in Figure 6. Generally, the volatility of the natural gas price has a negative time-varying impact on its returns, which is diametrically opposed to crude oil. The parameter is obviously different from zero only in some special periods when it comes to considering the 90% confidence intervals. During the U.S. economic recession of 2001, the price volatility of natural gas has a significant negative effect on
its returns. And the price volatility of natural gas reached the bottom of the dynamic curve and the volatility of the natural gas price has a greater and significantly negative impact on its returns during the U.S economic recession of 2008–2009. We also provide evidence to back up the structural break characteristics in the volatility feedback of the natural gas price. For example, under the location of breakpoints for the volatility of natural gas, the volatility feedback of natural gas price was close to zero (not pass the test of 90% confidence intervals) during the Iraq war from 2003 to 2005. This reveals that volatility has no influence on the level of returns. The finding is in accordance with Goor and Scholtens [13], who find that the volatility-in-mean effect in the GARCH-in mean model is insignificant between for natural gas in October 2001 and December 2003. Another example is at the beginning of 2010 the European debt crisis erupted and the price volatility reached a peak, yet the volatility feedback of gas price was close to zero. This indicates the highest volatility has no influence on the level of returns. Under the locations of the breakpoints for gas volatility in 2014, some characteristics of structural break can still be detected for the time-varying volatility feedback. In May 2014, the volatility of the natural gas price reached a peak, and the impacts of gas price volatility on the level of returns are also close to zero. This means that when gas price volatility is extremely high, the volatility feedback in gas returns will become weak and may even have no impact on returns.

![Volatility Feedback](image)

**Figure 6.** Natural gas (S9) price volatility ($h_t$) and volatility feedback effect ($\alpha_t$) (The solid lines are the volatility and the time-varying volatility feedback of energy prices, and the dashed lines are the associated 90% credible intervals. The shaded regions represent NBER recessions. Vertical dashed line denotes the break points that as same as the Figure 2).

5. Conclusions

The purpose of this paper is to shed light on whether energy price volatility has a time-varying impact on the level of energy returns, and then analyze whether the structural characteristics in the volatility feedback of the energy prices existed. To this end, we set nine energy products as the samples and employ the TVP-SVM model proposed by Chan [29] to investigate the time-varying volatility feedback of energy prices. Our main findings are soundly drawn as follows.

First, there exist significant differences in the price volatility feedback among the nine energy products. Specifically, the price volatility for the crude oil and diesel has a remarkably positive time-varying feedback effect on their returns. Nevertheless, for most of the petroleum products such as heating oil, jet fuel, propane and natural gas, their returns are negatively affected by the price volatility over time. However, for gasoline, there is no time-varying feature for the volatility feedback.

Second, structural break features are existed in the volatility feedback of energy prices. That is to say, in the location of structural breakpoints for the energy volatility, there exist turning points in the volatility feedback of the energy prices, which indicates that some factors, such as major global economic and geopolitical events that cause a sudden break in the energy returns, can also affect the volatility feedback of the energy prices.
Finally, we find that when the energy prices volatility is extremely high, for example, in a bearish market, the volatility feedback effect of energy prices will become weak and even have no impact on the energy returns in some special periods.

Our results suggest some important implications for policymakers and global investors in the energy market. For example, our results show that the price volatility for crude oil and diesel has a remarkably positive time-varying effect on their returns. However, for heating oil, jet fuel, propane and natural gas, the returns are negatively affected by price volatility over time. Therefore, when investing in the international energy market, investors should recognize the different effects of volatility in different energy products, and then take pertinent countermeasures to guard against market risks. In addition, when major and extreme global events occur around in the world, and the energy price fluctuations are extremely high, investors do not need to panic because it has proved in this paper, at this time, energy prices volatility tends to have a weak feedback effect on energy returns.

Author Contributions: All authors designed the research and wrote the paper. Y.J. and Y.-S.R. collected and analyzed the data, and co-revised the paper. C.-Q.M. and X.-G.Y. controlled the quality assurance. All authors read and approved the final manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, the three grant numbers are 71431008, 71521061, 71790593 respectively. This research was also funded by the Department of Science and Technology of Hunan province, the grant number is 2018GK1020.

Acknowledgments: We gratefully acknowledge the financial support from the National Natural Science Foundation of China (Nos. 71431008, 71521061, 71790593) and Major special Projects of the Department of Science and Technology of Hunan province (no. 2018GK1020). The authors would like to thank the anonymous referees for their careful reading of this article and valuable suggestions.

Conflicts of Interest: The authors declare no conflict of interest.

References
14. Klein, T.; Walthier, T. Oil price volatility forecast with mixture memory GARCH. *Energy Econ.* 2016, 58, 46–58. [CrossRef]
17. Ewing, B.T.; Malik, F. Volatility transmission between gold and oil futures under structural breaks. Int. Rev. Econ. Financ. 2013, 25, 113–121. [CrossRef]
27. Wen, F.; Gong, X.; Cai, S. Forecasting the volatility of crude oil futures using HAR-type models with structural breaks. Energy Econ. 2016, 59, 400–413. [CrossRef]