A Comparison Research on Dynamic Characteristics of Chinese and American Energy Prices

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ABSTRACT

This study compares the dynamic characteristic of Chinese and American energy prices from the perspectives of learning expectation, volatility, persistence, and so on. First, the most suitable learning speeds for energy prices are determined and the energy price expectations are calculated by the learning models. Second, volatility characteristics and Granger-spillover effects among different energy prices and expectations are examined using the stochastic models based on the coefficient significance and DIC criteria. Third, the dynamic correlation coefficients are obtained by the selected stochastic models that have the lower DIC values. Fourth, expectation, volatility, and foreign energy price are introduced into the persistence model, and the persistence characteristics and reasons behind Chinese and American energy prices are empirically tested and compared. Finally, conclusions and suggestions are given based on the theoretical analysis and empirical results.

KEYWORDS

Energy Price, Learning Expectation, Learning Speed, Persistence, Volatility

INTRODUCTION

The literature concerning energy price expectation, volatility characteristics, and persistence is extensive. In terms of price learning expectation, it presumes that the public know the energy price prediction model, but they do not know the parameters of the model exactly, and thus estimate the unknown parameters according to the newest information they can obtain at the time. Milani (2005) examines learning expectation from the viewpoint of the influences of the learning speed on the
inflation expectation and the best speed. Milani (2007) compares the learning expectation with the rational expectation using the DSGE model and argues that learning can enhance the model fitting effect. Fan and Gao (2016) investigate the adaptive learning expectation of Chinese inflation and examine empirically the roles of inflation expectation and persistence on equilibrium inflation. Recently, machine learnings are also researched deeply. Zhu et al. (2022a) investigate the ability of the opposition-based learning salp swarm algorithm in price prediction and Zhu et al. (2022b) investigate the classification ability of extreme learning machines (ELMs) with rapid learning rates.

Second, regarding the volatility characteristics and the spillover effect between different countries, under no arbitrage, the volatility of prices is equal to that of information flow (Ross, 1989). With the integration of the world economics and the intensification of globalization, volatility and its spillover between different countries’ financial markets, especially in the asset portfolio construction, and how the volatility setting influences the market information flow and its transmission among different markets are of great significance (Huang, 2012; Song et al., 2020). Using the GARCH model, Pindyck (2004) investigates the price volatility of American oil and gas. Huang (2012) adopts the bivariate GARCH model to examine the volatility of different countries’ stock index futures markets. GARCH volatility models set the conditional variance as the function of the variable’s past value. On the other hand, stochastic volatility models introduce the error term into the conditional variance and thus not only does the variance have stochastic characteristics, but the model flexibility is also greatly increased (Asai and et al., 2006). Asai et al. (2006) conduct a systematic literature review on multivariate stochastic volatility. Granger (1969, 1980) determines the causal relationship between the variables, but does not consider such relationship between the variables’ volatility. Yu and Meyer (2006) summarize the typified characteristics of the financial variable and argue that the multivariate stochastic volatility model is suitable for portraying the financial variable’s volatility. The authors construct the multivariate stochastic volatility model with Granger effect in volatility and the multivariate stochastic volatility model with dynamic volatility correlation coefficient. Zhang et al. (2021) empirically tests oil and stock markets’ volatility using the DGC-MSV-t Model. In addition, there is extensive research on price fluctuation synchronization. Ruan et al. (2021) examine the stock price volatility synchronization of different companies and the market, and the influence of the synchronization on information dealing efficiency. Cui et al. (2021) investigates volatilities of natural resources commodity prices and economic growth and their correlations. Zhang, Ding et al. (2022) examine the relationship of absorptivities of stock price indexes in different countries using spillover network and Granger causality test. Zhang, Yang et al. (2022) examines risk spillover effects among different commodity markets in different market conditions based on the network topology approach. Ma et al. (2022) empirically investigates the relationship between natural resources tax volatility and economic performance.

Third, retrospective and forward-looking factors play a role in reducing the price persistence. Taylor (2000) explores the relationship between the inflation persistence reducing and the low inflation level. Willis (2003) finds that the structural changes in the economy can partly explain the reduction in inflation persistence. Milani (2005) empirically tests the effect of adaptive learning on inflation persistence and finds that the learning expectation is one of the main sources. Milani (2007) further examines learning expectation and the persistence source of the macro variable, and argues that learning is one such source and introducing the learning expectation can reduce persistence. Chen et al. (2021) empirically investigate the persistence of Chinese real estate prices.

The current study examines the learning expectation and volatility characteristics of energy price and expectations. The work of the study embodies mainly the following aspects. First, learning expectations of Chinese and American energy prices and the optimal learning speeds of the Chinese and American public are calculated based on the learning expectation model. Second, the volatility characteristics and spillover effects among the aforementioned energy prices and expectations are analyzed using the stochastic volatility models. Third, learning expectation, volatility, and foreign energy price are introduced into the traditional persistence model, and the roles of pre- and post-factors in reducing the energy price persistence are empirically tested.
The rest of the paper is arranged as follows. Section 2 outlines the learning expectations of Chinese and American energy prices. The volatility characteristics and spillover effects among different countries’s energy prices and expectations are presented in Section 3. Section 4 introduces the volatility, learning expectation, and foreign energy price into the energy price persistence model, and empirically tests the roles of different factors in reducing the price persistence. Finally, concluding remarks and suggestions are given in Section 5.

LEARNING EXPECTATIONS OF CHINESE AND AMERICAN ENERGY PRICES

Expectation is one of the most important characteristics of prices. The authors calculate the expectation of energy price based on the learning expectation theory. The learning expectation assumes that the public know the price expectation formation model but do not exactly know the model’s coefficient, and they renew the coefficient information based on the newest information they can obtain at that time. The authors hypothesize that the public apply only the energy price, namely the public form the energy price expectation according to the following formulas (Milani, 2005; Milani, 2007):

\[
ep_t = \alpha_{0,t} + \alpha_{1,t}ep_{t-1} + \varepsilon_t, \\
\hat{\alpha}_t = \hat{\alpha}_{t-1} + sH_{t-1}^{-1}X_t(ep_t - X_t^T\hat{\alpha}_{t-1}) \\
H_t = H_{t-1} + s(X_{t-1}X_{t-1}^T - H_{t-1})
\]

Where \(ep_t\) represents energy price, \(\hat{\alpha}_t = [\alpha_{0,t}, \alpha_{1,t}]^T\) represents the time-varying coefficient matrix, \(s\) represents the learning speed, \(X_t = \{[1, ep_{t-1}]^T\}_{t=0}^{t-1}\), and \(H_t\) is the second moment matrix of the stacked variable \(X_t\). The superscript -1 and \(T\) represent the inversion and transposition of the matrix, respectively. Equation (1) indicates how the public form their energy price expectation according to the former energy price, and equation (2) and (3) indicate how the public renew the time-varying coefficients using the newest information they can get over time.

Regarding the index selection, the authors apply the energy part of the Producer Price Index (PPI) to reflect the energy price. Namely, Chinese and American energy prices are reflected by energy parts in the Chinese and American PPI, respectively. All the variables are in the form of year-on-year growth rate. For brevity and conveniently, the authors use the abbreviations listed in Table 1 to represent the variables investigated herein.

\(cep\) represents Chinese energy prices in the form of the year-on-year growth rate, and the other abbreviations are analogous. The time span is from January 2003 to June 2021, and the data comes from China Economic Net, National Bureau of Statistics of China, and the Organisation for Economic Co-operation and Development (OECD).

The expectations of energy prices can be calculated based on equation (1)–(3), and then the prediction residual errors at different speeds can be derived (see figure 1).

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Variable</th>
<th>Abbreviation</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>cep</td>
<td>Chinese energy price</td>
<td>aep</td>
<td>American energy price</td>
</tr>
<tr>
<td>ecep</td>
<td>Expectation of Chinese energy price</td>
<td>eaep</td>
<td>Expectation of American energy price</td>
</tr>
<tr>
<td>vcep</td>
<td>Volatility of Chinese energy price</td>
<td>vaep</td>
<td>Volatility of American energy Price</td>
</tr>
<tr>
<td>vcepe</td>
<td>Volatility of Chinese energy price expectation</td>
<td>vaepe</td>
<td>Volatility of American energy price expectation</td>
</tr>
</tbody>
</table>
The graphs of both energy price prediction residual errors on different learning speeds are U-shaped. For Chinese energy prices when the learning speed \( g \) is from 0.175 to 0.181, the prediction residual error is 0.0193, which is the minimum. Considering the fact that the greater learning speed corresponds to the more unstable expectation formulation model, the authors take \( g = 0.175 \) as the most optimal learning speed for China energy price. For American energy prices, when the learning speed \( g \) is from 0.118 to 0.135, the prediction residual error is 0.0355, which is the minimum, and the best learning speed is \( g = 0.118 \). The Chinese public’s energy price learning speed is higher than that of the American public’s, and thus the weights assigned to the new information of the former is more than that of the latter.

Considering the fact that the public can only hold the information of time t-1 at time t, and expectations are formulated using the following formula (Milani, 2005, 2007):

\[
E_t(ep_{t+1}) = \frac{ep_{t+1}}{I_{t-1}} = \frac{(\alpha_{0,t+1} + \alpha_{1,t+1} ep_t)}{I_{t-1}} = \frac{(\alpha_{0,t+1} + \alpha_{1,t+1} (\alpha_{0,t} + \alpha_{1,t} y_{t-1}) )}{I_{t-1}}
\]

\[
= \alpha_{0,t-1} + \alpha_{1,t-1} \alpha_{0,t} + \alpha_{1,t-1} \alpha_{1,t} ep_{t-1} = \alpha_{0,t-1} (1 + \alpha_{1,t-1}) + \alpha_{1,t-1} ep_{t-1}
\]

After determining the best learning speed, the authors can calculate the expectation of Chinese energy prices (\( ecep \)) and that of American energy prices (\( eaep \)), according to equation (4). The variables are in the year-on-year form and the time span of energy price expectations is from February 2004 to June 2021. Energy price data from January to December 2003 are applied to obtain the initial data used in the iteration, and thus the time span of energy price data and that of expectation data is different.

From Table 2, the mean of Chinese energy prices (\( cep \)) is larger than that of American energy prices (\( aep \)) and the mean of expectation of the former is also larger than that of the latter. The standard deviation of \( cep \) is smaller than that of \( aep \), and the standard deviation of expectations of Chinese energy prices (\( ecep \)) is also smaller than that of expectations of America energy prices (\( eaep \)). The
and the contrary, respectively, and are the same as in the front part, \( ecep \) and \( ecep \), and this indicates that the relative volatility of \( ecep \) is smaller than that of \( ecep \). The deviation coefficients of \( ecep \) and \( ecep \) are 3.2126 and 5.4987, respective, indicating that the relative volatility of \( ecep \) is smaller than that of \( ecep \). Whether energy price or expectation, the relative volatility of China is smaller than that of America.

**VOLATILITY OF CHINESE AND AMERICAN ENERGY PRICES AND THEIR DYNAMIC CORRELATIONS**

Volatility is one of the most important characteristics of variables. It not only reflects the corresponding variable’s varying characteristics but also the information spillover effect between different variables. The energy price volatility influences market participants’ risk exposure, the positivity and motivation toward investment, storage, production, and consumption of energy materials, in addition to the value of the contingent option, and thus, the price volatility has great influence on the risk avoidance, asset configuration, and so on (Pindyck, 2004).

**Bivariate Stochastic Volatility Model with Dynamic Correlation Coefficient**

Measuring the volatility in a multivariate framework has both economic and econometric significance, and the relative volatility can not only be better applied to decision making, such as asset allocation, risk management, and so on, but can also increase the measurement efficiency (Asai et al., 2006).

After de-averaging Chinese and American energy prices, the authors construct the following stochastic volatility model (Yu and Meyer, 2006) Equation (5) (7):

\[
\begin{align*}
(cep_t, aep_t) &= \begin{pmatrix}
\exp(\theta_{1,t} / 2) & 0 \\
0 & \exp(\theta_{2,t} / 2)
\end{pmatrix}
\begin{pmatrix}
\xi_{1,t} \\
\xi_{2,t}
\end{pmatrix}
\sim \mathcal{N}
\begin{pmatrix}
0 \\
0
\end{pmatrix}
\begin{pmatrix}
1 & \rho_t \\
\rho_t & 1
\end{pmatrix}
\end{align*}
\]

\begin{align*}
(\theta_{1,t+1}, \theta_{2,t+1}) &= \begin{pmatrix}
w_1 \\
w_2
\end{pmatrix}
+ \begin{pmatrix}
\varnothing_{cep,cep} & \varnothing_{cep,aep} \\
\varnothing_{aep,cep} & \varnothing_{aep,aep}
\end{pmatrix}
\begin{pmatrix}
\theta_{1,t} - w_1 \\
\theta_{2,t} - w_2
\end{pmatrix}
+ \begin{pmatrix}
\xi_{1,t} \\
\xi_{2,t}
\end{pmatrix}
\sim \mathcal{N}
\begin{pmatrix}
0 \\
0
\end{pmatrix}
\begin{pmatrix}
\sigma_{cep}^2 & 0 \\
0 & \sigma_{aep}^2
\end{pmatrix}
\end{align*}

\[
\rho_t = [\exp(\gamma_t) - 1] \left[ \exp(\gamma_t) + 1 \right]^{-1}, \gamma_t = \lambda_0 + \lambda_{caep} (\gamma_t - \lambda_0) + \sigma_\rho \xi_t \sim \mathcal{N}(0,1)
\]

Where \( cep_t \) and \( aep_t \) are the same as in the front part, \( \exp(\theta_{1,t} / 2) \) and \( \exp(\theta_{2,t} / 2) \) represent the standard deviations of \( cep_t \) and \( aep_t \), respectively, \( \rho_t \) represents the volatility correlation coefficient of \( cep_t \) and \( aep_t \), \( \varnothing_{cep,cep} \) and \( \varnothing_{aep,aep} \) represent the persistence coefficients of \( cep_t \) and \( aep_t \), respectively, \( \varnothing_{cep,aep} \) and \( \varnothing_{aep,cep} \) represent the volatility spillover effects from \( aep_t \) to \( cep_t \) and the contrary, respectively, and \( \lambda_{caep} \) represents the persistence effect of the volatility correlation coefficient of \( cep_t \) and \( aep_t \). Equation (7) represents the dynamic change of \( \rho_t \), and

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**Table 2. Statistical characteristics of the variables**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>cep</td>
<td>0.0509</td>
<td>0.1458</td>
<td>-0.2453</td>
<td>0.361</td>
</tr>
<tr>
<td>aep</td>
<td>0.0382</td>
<td>0.1816</td>
<td>-0.4019</td>
<td>0.5753</td>
</tr>
<tr>
<td>ecep</td>
<td>0.0541</td>
<td>0.1738</td>
<td>-0.4114</td>
<td>0.7964</td>
</tr>
<tr>
<td>eaep</td>
<td>0.0395</td>
<td>0.2172</td>
<td>-0.7105</td>
<td>1.1757</td>
</tr>
</tbody>
</table>
the impacts of $\rho_t$, on the volatility of Chinese and American energy prices are derived through the equation (5) and (6).

The value of DIC is one of the most usage criterion to determine the goodness of the model (Spiegelhalter et al., 2002; Yu & Meyer, 2006).

$$DIC = \overline{D} + \rho_d$$

where $DIC$ is the information criterion, $\overline{D}$ indicates the adequacy and $\rho_d$ indicates the complexity.

To select the most suitable model to reflect the volatility characteristics and spillover effect among energy prices and energy price expectations, the authors construct the bivariate model, reduce the factor having the non-significant coefficient, and then compare the DIC values. The authors select the model with the lower DIC as the final model to reflect the volatility characteristics and dynamic relationship among the energy prices and energy price expectations. The most suitable model is selected according to the DIC criteria, and the dynamic relationship is then derived.

The empirical process is as follows: First, the authors investigate the volatility spillover effects between the variables using the stochastic volatility model with dynamic correlation coefficient and bilateral Granger Causality. Second, the authors determine the volatility characteristics of Chinese and American energy prices using the stochastic volatility model with dynamic correlation coefficient, and unilateral or no Granger Causality, removing the insignificant volatility spillover coefficient, and identify the appropriate stochastic volatility model based on the DIC criterion. Third, the authors calculate the dynamic correlations between volatility of energy prices using the above stochastic volatility model.

**Volatility Spillover Effects Between Chinese and American Energy Prices**

To empirically analyze volatility spillover effects among Chinese and American energy prices including price expectations, the authors directly use the stochastic volatility model with dynamic correlation coefficient and bilateral Granger causality without considering the coefficient significance. The Granger causality effect test coefficients of $\phi_{c,a}$ and $\phi_{a,c}$ represent the role of American energy prices ($\text{aep}$) toward Chinese energy prices ($\text{cep}$), and vice versa, respectively. $\Phi_{\text{cep,cep}}$ and $\phi_{\text{cep,cep}}$ represent that from Chinese energy price expectation ($\text{ecep}$) to Chinese energy prices ($\text{cep}$), and vice versa, respectively. $\Phi_{\text{cep,aep}}$ and $\phi_{\text{cep,aep}}$ represent that from American energy price expectation ($\text{eaep}$) to Chinese energy prices ($\text{cep}$), and vice versa, respectively. $\Phi_{\text{cep,cep}}$ and $\phi_{\text{cep,cep}}$ represent that from Chinese energy price expectation ($\text{ecep}$) to American energy prices ($\text{aep}$), and vice versa. $\Phi_{\text{aep,ecep}}$ and $\phi_{\text{aep,ecep}}$ represent that from American energy price expectation ($\text{eaep}$) to American energy prices ($\text{aep}$), and vice versa. Finally, $\Phi_{\text{cep,ecep}}$ and $\phi_{\text{cep,ecep}}$ represent that from American energy price expectation ($\text{eaep}$) to Chinese energy price expectation ($\text{ecep}$), and vice versa.

According to Table 3, there is a one-way causal spillover effect from Chinese energy prices ($\text{cep}$) to expectation ($\text{ecep}$), from American energy prices ($\text{aep}$) to Chinese energy price expectation ($\text{ecep}$), and from American energy prices ($\text{aep}$) to expectation ($\text{eaep}$). Whether Chinese or American, the volatility of energy price expectation is influenced by that of energy prices, and the volatility of Chinese energy price expectation is influenced not only by the volatility of Chinese energy prices, but also by that of American energy prices.

**Volatility Characteristics of Chinese and American Energy Prices**

To precisely measure the volatility characteristics of Chinese and American energy prices, the authors re-estimate the bivariate stochastic volatility model after removing the non-significant Granger Causality coefficients. For brevity, the authors introduce the following abbreviation to represent the corresponding model. SVB represents the stochastic volatility model with bidirectional Granger
causality, SVU represents that with unidirectional Granger cause, and SVN represents that with no Granger causality. According to the empirical process introduced above, the authors obtain the parameters of SVN of \(cep\) and \(aep\), SVU of \(cep\) and \(ecep\), SVN of \(cep\) and \(eaep\), SVU of \(aep\) and \(ecep\), and SVN of \(aep\) and \(eaep\) after removing the insignificant volatility spillover coefficients.

Taking SVN of \(cep\) and \(aep\) as an example, the parameter estimating process is introduced as follows. First, after removing the non-significant Granger causality coefficients, namely SVN of \(cep\) and \(aep\), construct the stochastic volatility model with no Granger causality. Second, all the variables are DE-averaged, and double chains are set. Third, initial values are given referring to Yu and Meyer (2006), and 100000 iterations are given. Forth, the statistical results of the parameters are obtained after deducting the beginning 10000 iterations to ensure the convergence of the posterior distribution.

Figure 2 to 5 reveal that the parameter estimation result is convergent. Figure 2 and 3 indicate that the density function posterior distribution is smooth and only one peak exists in every density function distribution. Figure 4 and 5 indicate that the double-chain results of the parameter are overlapping. All these demonstrate that the authors have excellent credibility in terms of the posterior distribute being convergent.

As seen in Table 4, \(mu_{cep}\), \(mu_{aep}\), \(phi_{cep}\), \(phi_{aep}\), and \(Psi_{cep,aep}\) are all statistically significant. The absolute value of the t-statistic is relatively large. Conversely, at the median, 5th, 10th, 90th, and 95th quantile, the coefficient signs are the same, namely \(mu_{cep}\) and \(mu_{aep}\) are negative, and \(phi_{cep}\), \(phi_{aep}\) and \(Psi_{cep,aep}\) are positive.

Regarding the volatility of \(cep\) and \(aep\), the DIC of SVN is -995.412, which is smaller than that of SVB at -950.206, indicating that SVN is superior to SVB. In addition, the bivariate stochastic volatility model, which can include the dynamic correlation between the two related variables, is more flexible than the univariate model. The authors, therefore, apply SVN to measure the volatility of \(cep\) and \(aep\), and the standard deviation of Chinese and American energy prices are represented by \(VCEPt\) and \(VAEPt\), respectively.

Further, the authors remove the insignificant volatility spillover coefficient from SVB, and apply SVU to measure the volatility of \(cep\) and \(ecep\), SVN to measure that of \(cep\) and \(eaep\), SVU to measure that of \(aep\) and \(ecep\), SVU to measure that of \(aep\) and \(eaep\), and SVN to measure that of \(ecep\) and

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Mean</th>
<th>t-statistic</th>
<th>5th quantile</th>
<th>10th quantile</th>
<th>Median</th>
<th>90th quantile</th>
<th>95th quantile</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>(phi_{cep,cep})</td>
<td>0.011</td>
<td>0.452</td>
<td>-0.026</td>
<td>-0.018</td>
<td>0.010</td>
<td>0.040</td>
<td>0.049</td>
<td>-950.206</td>
</tr>
<tr>
<td>(phi_{cep,ecep})</td>
<td>-0.382</td>
<td>-0.196</td>
<td>-2.895</td>
<td>-2.579</td>
<td>-0.251</td>
<td>2.457</td>
<td>2.940</td>
<td>-1004.4</td>
</tr>
<tr>
<td>(phi_{cep,eaep})</td>
<td>0.002</td>
<td>0.031</td>
<td>-0.094</td>
<td>-0.074</td>
<td>0.003</td>
<td>0.076</td>
<td>0.100</td>
<td>-1011.15</td>
</tr>
<tr>
<td>(phi_{aep,cep})</td>
<td>0.579</td>
<td>2.514</td>
<td>0.289</td>
<td>0.340</td>
<td>0.545</td>
<td>0.844</td>
<td>0.955</td>
<td>-897.226</td>
</tr>
<tr>
<td>(phi_{aep,ecep})</td>
<td>0.003</td>
<td>0.175</td>
<td>-0.028</td>
<td>-0.021</td>
<td>0.004</td>
<td>0.026</td>
<td>0.033</td>
<td>-804.938</td>
</tr>
<tr>
<td>(phi_{aep,eaep})</td>
<td>-1.736</td>
<td>-0.819</td>
<td>-5.068</td>
<td>-4.499</td>
<td>-0.267</td>
<td>0.357</td>
<td>0.439</td>
<td>-892.752</td>
</tr>
<tr>
<td>(phi_{cep,cep})</td>
<td>0.031</td>
<td>0.648</td>
<td>-0.044</td>
<td>-0.027</td>
<td>0.029</td>
<td>0.091</td>
<td>0.111</td>
<td>-897.226</td>
</tr>
<tr>
<td>(phi_{cep,aep})</td>
<td>0.077</td>
<td>1.675</td>
<td>0.008</td>
<td>0.022</td>
<td>0.074</td>
<td>0.137</td>
<td>0.157</td>
<td>-804.938</td>
</tr>
<tr>
<td>(phi_{aep,ecep})</td>
<td>-0.003</td>
<td>-0.050</td>
<td>-0.089</td>
<td>-0.073</td>
<td>-0.011</td>
<td>0.077</td>
<td>0.108</td>
<td>-892.752</td>
</tr>
<tr>
<td>(phi_{ecep,aep})</td>
<td>0.818</td>
<td>6.376</td>
<td>0.624</td>
<td>0.662</td>
<td>0.806</td>
<td>0.994</td>
<td>1.054</td>
<td>-995.412</td>
</tr>
<tr>
<td>(phi_{ecep,cep})</td>
<td>0.015</td>
<td>0.515</td>
<td>-0.024</td>
<td>-0.018</td>
<td>0.011</td>
<td>0.055</td>
<td>0.069</td>
<td>-892.752</td>
</tr>
<tr>
<td>(phi_{ecep,eaep})</td>
<td>0.712</td>
<td>0.612</td>
<td>0.017</td>
<td>0.039</td>
<td>0.143</td>
<td>2.694</td>
<td>3.376</td>
<td>-804.938</td>
</tr>
</tbody>
</table>
The DIC values of these binary stochastic volatility models are shown in Table 5. Comparing

Figure 2. Density function of \( \mu_{eap} \)

Figure 3. Density function of \( \mu_{eap} \)
Table 5 and 3, SVN_{cep,aep} is superior to SVB_{cep,aep}, SVU_{cep,ecep} is superior to SVB_{cep,ecep}, SVN_{cep,eaep} is superior to SVB_{cep,eaep}, SVU_{aep,ecep} is inferior to SVB_{aep,ecep}, SVU_{aep,eae} is inferior to SVB_{aep,eae}, and

Figure 4. Double-chain results of mu_{cep}

Figure 5. Double-chain results of mu_{aep}
SVN_{ecep,eaep} is superior to SVB_{ecep,eaep}; thus the authors can apply the relative better binary stochastic volatility model to measuring the dynamic volatility correlation.

**Dynamic Correlations between Volatility of Chinese and American Energy Prices and Expectations**

The dynamic correlation coefficients among Chinese and American energy prices, and expectations are obtained using the most suitable volatility model with the smallest DIC value. The maximum and the minimum of the dynamic correlation coefficients are reported in Table 6.

First, the correlations among these energy prices and expectations vary dynamically. Second, there are strong and significant correlations among energy prices and expectations. Hence, common factors affecting these may exist. Third, the volatility correlation coefficient between Chinese energy prices and expectation is the largest in these coefficients, and this indicates that the relevancy of Chinese energy prices and expectation is stronger than that of American energy prices and expectation.

**DYNAMIC CHARACTERISTICS OF CHINESE AND AMERICAN ENERGY PRICES**

By introducing the factors of expectation, volatility, and foreign energy price at the base of the general price persistence model, dynamic models of energy prices are constructed as follows:

\[ cep_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta cep_{t-i} + \beta cep_{t-1} + \varepsilon_i \]  

(9)

\[ cep_t = \alpha_0' + \sum_{i=1}^{p} \alpha_i' \Delta cep_{t-i} + \beta' cep_{t-1} + \chi cep_t + \delta vcep_t + \phi aep_t + \varepsilon_i \]  

(10)

Table 4. Estimated parameters of SVN of cep and aep

<table>
<thead>
<tr>
<th>coefficient</th>
<th>mean</th>
<th>t-statistic</th>
<th>5th quantile</th>
<th>10th quantile</th>
<th>median</th>
<th>90th quantile</th>
<th>95th quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>mu_{cep}</td>
<td>-4.183</td>
<td>-12.687</td>
<td>-4.771</td>
<td>-4.589</td>
<td>-4.147</td>
<td>-3.822</td>
<td>-3.723</td>
</tr>
<tr>
<td>phi_{cep}</td>
<td>0.937</td>
<td>25.966</td>
<td>0.871</td>
<td>0.889</td>
<td>0.942</td>
<td>0.980</td>
<td>0.987</td>
</tr>
<tr>
<td>phi_{aep}</td>
<td>0.954</td>
<td>38.577</td>
<td>0.908</td>
<td>0.921</td>
<td>0.957</td>
<td>0.983</td>
<td>0.988</td>
</tr>
<tr>
<td>Psi_{cep,eaep}</td>
<td>0.919</td>
<td>23.334</td>
<td>0.847</td>
<td>0.868</td>
<td>0.924</td>
<td>0.965</td>
<td>0.974</td>
</tr>
<tr>
<td>DIC_{cep,aep}</td>
<td>-995.412</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5. DIC values of different binary stochastic volatility models

<table>
<thead>
<tr>
<th>Models</th>
<th>SVN_{ecep,eaep}</th>
<th>SVU_{ecep,eaep}</th>
<th>SVN_{cep,ecep}</th>
<th>SVU_{cep,eaep}</th>
<th>SVN_{cep,eaep}</th>
<th>SVU_{aep,ecep}</th>
<th>SVN_{aep,eaep}</th>
</tr>
</thead>
<tbody>
<tr>
<td>DIC</td>
<td>-995.412</td>
<td>-1011.37</td>
<td>-1062.76</td>
<td>-890.827</td>
<td>-800.877</td>
<td>-912.462</td>
<td></td>
</tr>
</tbody>
</table>
Where $cep_t$ and $aep_t$ represent Chinese and American energy price, respectively. $ecep_t$ and $eaep_t$ represent Chinese and American energy price expectations, respectively. $\alpha_0, \alpha_i, \beta, \alpha_0', \beta', \chi, \delta, \phi, \phi_0, \gamma_i, \eta, \kappa, \lambda, \mu$ represent the parameters to be estimated, and $\epsilon_t, \epsilon_t', \nu_t,$ and $\nu_t'$ are resident terms.

Equations (9) and (11) are the basic persistence models for Chinese and American energy prices, and equation (10) and (12) are the extended persistence models introducing the energy price expectation, volatility, and foreign energy price for Chinese and American energy prices, respectively. Energy price volatility influences not only market participants’ risk exposure, but also the energy spot price (Pindyck, 2004). Thus, it is necessary to introduce the volatility factor into the price persistence model.

From Table 7, the authors can derive the following conclusions. First, the persistence of Chinese energy prices is very high and the persistence coefficient is 0.9554, indicating that it is necessary to take measures to reduce such persistence. Second, in terms of the fitting effect, the extended persistence model introducing the expectation term, the volatility term, and American energy prices is better than the basic persistence model. Third, the learning expectation does not have a significant effect on energy prices, and this indicates that the public’s learning ability is relatively low and thus investor education should be strengthened. Fourth, the models’ residuals are stationary and do not have serial correlation and ARCH Heteroskedasticity effects, combined with high Adjusted $R^2$. These indicate that both the basic and the extended energy price persistence model are effective.

Based on Table 8, the authors can draw the following conclusions. First, American energy prices have high persistence at 0.9098. Second, introducing the expectation term, the volatility term, and Chinese energy prices can increase the persistence model fitting effect. Third, both equation (11) and (12) pass through the residual tests including the unit test, serial correlation and ARCH Heteroskedasticity test. The adjusted $R^2$ are 0.9340 and 0.9373, respectively, and all these indicate that equation(11) and (12) are effective.

Comparing Table 7 and 8, although the persistence of Chinese energy prices is higher than that of American energy prices in the basic persistence models, that for China decreases significantly and is lower than that of America after considering the foreign energy price. In addition, the effect of
### Table 7. Dynamic characteristics of Chinese energy prices

<table>
<thead>
<tr>
<th>Explained variable: $cep_t$</th>
<th>Equation (9)</th>
<th>Equation (10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explanatory variables</td>
<td>Coefficient</td>
<td>Coefficient</td>
</tr>
<tr>
<td></td>
<td>$t$-statistic and p-value</td>
<td>$t$-statistic and p-value</td>
</tr>
<tr>
<td>Constant term</td>
<td>Non</td>
<td>Non</td>
</tr>
<tr>
<td>$\sum_{i=1}^{p} \Delta cep_{t-i}$</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$cep_{t-1}$</td>
<td>0.9554</td>
<td>0.7386</td>
</tr>
<tr>
<td></td>
<td>51.3456(0)</td>
<td>13.1768(0)</td>
</tr>
<tr>
<td>$ecep_{t}$</td>
<td>...</td>
<td>-0.0190</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>-0.6131(0.5406)</td>
</tr>
<tr>
<td>$vcep_{t}$</td>
<td>...</td>
<td>0.0511</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>1.3988(0.1637)</td>
</tr>
<tr>
<td>$aept_{t}$</td>
<td>...</td>
<td>0.2326</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>8.6130(0)</td>
</tr>
<tr>
<td>$ar(1)$</td>
<td>Non</td>
<td>0.0138</td>
</tr>
<tr>
<td></td>
<td>Non</td>
<td>0.1266(0.8994)</td>
</tr>
<tr>
<td>$ar(2)$</td>
<td>Non</td>
<td>0.6212</td>
</tr>
<tr>
<td></td>
<td>Non</td>
<td>6.2890(0)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.9595</td>
<td>0.9730</td>
</tr>
</tbody>
</table>

**Residual Tests**

- Residual unit root test: -13.7918(0), -13.8946(0)
- Serial Correlation LM Test: 0.6794(0.5083), 0.4125(0.6627)
- Heteroskedasticity Test ARCH: 1.4131(0.2360), 3.2785(0.0718)

### Table 8. Dynamic characteristics of American energy prices

<table>
<thead>
<tr>
<th>Explained variable: $aept_t$</th>
<th>Equation (11)</th>
<th>Equation (12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Explanatory variables</td>
<td>Coefficient</td>
<td>Coefficient</td>
</tr>
<tr>
<td></td>
<td>$t$-statistic and p-value</td>
<td>$t$-statistic and p-value</td>
</tr>
<tr>
<td>Constant term</td>
<td>Non</td>
<td>Non</td>
</tr>
<tr>
<td>$\sum_{i=1}^{q} \Delta aept_{t-i}$</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>$aept_{t-1}$</td>
<td>0.9098</td>
<td>0.8040</td>
</tr>
<tr>
<td></td>
<td>29.8468(0)</td>
<td>11.9617(0)</td>
</tr>
<tr>
<td>$eaept_{t}$</td>
<td>Non</td>
<td>-0.0536</td>
</tr>
<tr>
<td></td>
<td>Non</td>
<td>-1.2694(0.2060)</td>
</tr>
<tr>
<td>$vaep_{t}$</td>
<td>Non</td>
<td>-0.0034</td>
</tr>
<tr>
<td></td>
<td>Non</td>
<td>-0.1519(0.8794)</td>
</tr>
<tr>
<td>$cept_{t}$</td>
<td>Non</td>
<td>0.1733</td>
</tr>
<tr>
<td></td>
<td>Non</td>
<td>3.2982(0.0012)</td>
</tr>
<tr>
<td>Residual unit root test</td>
<td>-14.1426(0)</td>
<td>-13.6262(0)</td>
</tr>
<tr>
<td><strong>Serial Correlation LM Test</strong></td>
<td>1.6443(0.1961)</td>
<td>0.4713(0.6250)</td>
</tr>
<tr>
<td><strong>Heteroskedasticity Test ARCH</strong></td>
<td>2.1903(0.1405)</td>
<td>1.4442(0.2310)</td>
</tr>
<tr>
<td><strong>Adjusted R²</strong></td>
<td>0.9340</td>
<td>0.9373</td>
</tr>
</tbody>
</table>
American energy prices on Chinese energy price is larger than that of Chinese prices on American prices. On the one hand, the role of American energy prices in decreasing Chinese energy price persistence is greater than that of Chinese energy prices in decreasing American energy price persistence. On the other hand, the coefficient of American energy prices in the Chinese energy price persistence model is more significant than that in the American energy price persistence model. The Chinese government should, therefore, adopt the measures earlier to regulate the energy price and pay more attention to the volatility of American energy prices.

**CONCLUSION**

This study empirically examines the dynamic characteristics of Chinese and American energy prices, including their learning expectations, volatility, persistence and so on. The authors present the following main conclusions.

First, the energy price learning ability of the Chinese public is stronger than that of the American public. On the one hand, the learning speed of the former is faster than that of the latter. On the other hand, the prediction effectiveness of Chinese energy price expectation is better than that of American energy price expectation.

Second, the volatility of Chinese energy prices is smaller than that of American energy prices, and the same to energy price expectations. On the one hand, the standard deviations of Chinese energy prices and expectations are smaller than those of American energy prices and expectations. Conversely, the means of Chinese energy prices and expectations are larger than those of American energy prices and expectations, and thus, the coefficients of variations of the former are smaller than those of the latter.

Third, there are significant relationships among Chinese energy prices, expectations, and American energy prices and expectations. All the correlation coefficients of the volatility of different variables are significant and larger than 0, and whether introducing American energy prices into the Chinese energy price persistence model or vice versa, they can both increase the fitting accuracy and decrease the energy price persistence.

Fourth, the influencing role of American energy prices on Chinese energy prices is larger than that in the opposite direction. There is a significant volatility spillover effect from American energy prices to Chinese energy price expectations, but this is not the case in the opposite direction. The coefficient significance of American energy prices in the Chinese energy price persistence model is more than that in the opposite direction.

Fifth, although the persistence of both Chinese and American energy prices is high, and the learning expectations and the volatility cannot decrease the persistence, that of Chinese energy prices is stronger than that of American energy prices. This means that Chinese energy prices are mainly influenced by lagged price.

All these indicate that retrospective factors play a more important role in energy price decisions. Generally, Chinese energy price management has gained great success, the Chinese public’s learning ability is relatively high, and the volatility of Chinese energy prices and expectations are relatively small. However, energy prices and expectations are significantly influenced by American energy prices. In the future, the Chinese government should enhance energy price management ability further. First, the introducing effect of forward-looking factors should be strengthened. Second, the dynamic relationship among Chinese and American energy prices and expectations should be given more attention, with a focus on common influencing factors. Specifically, more attention should be paid to the effects of American energy prices on Chinese energy prices and expectations. When American energy prices display increased volatility, measures should be implemented in advance.
FUTURE RESEARCH

Although this paper empirically examines, learning expectations, volatilities, and volatilitary spillover effects using Chinese and American energy prices data, there is room for research additionally. The price volatility plays an important effect on resident life and social welfare and influences resident happiness, human beings at different income levels have different feeling to the same price volatility (Chen et al., 2021; He et al., 2022), and thus it is needed to examine the asymmetrical effect of the price fluctuation on resident happiness with different income levels. In addition, the micro basement of learning expectation formation will be researched in depth, the difference between Chinese and American micro basements, and reasons for forming the difference will also be analysed. Influencements of different monetary policy mechanisms on inflation expectation formation and regulation are important fields in future research.

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