Price Risk Control of Natural Resource Commodities through Behavioral Finance Analysis: An Information Transfer Perspective

Zehui Liu

1School of Economics and Finance, Xi’an Jiaotong University, Xi’an 710061, China
2School of Management, Yulin University, Yulin 719000, China

Correspondence should be addressed to Zehui Liu; liuzehui@yulinu.edu.cn

Received 25 January 2022; Revised 1 March 2022; Accepted 3 March 2022; Published 30 March 2022

1.Introduction

In the age of economic globalization, countries across the world are striving to develop their economy, and therefore demanding more international natural resources [1–7]. Hence, the price volatility of natural resource commodities (NRCs) has a great impact on global economic development and national stability [8–13]. With the emergence of sudden incidents like financial crisis, national debt crisis, and trade friction, uncertain financial risks are on the rise [14–19]. In-depth research on how to define and quantify the effects of uncertain risk factors on NRC price would help to fully understand the price volatility mechanism of NRCs, and facilitate the policymaking of controlling NRC price volatility.

The price dynamics of the energy futures market is an important factor affecting the global economy, such as crude oil futures, gold futures and agricultural product futures. Wang et al. [20] introduced a new stochastic interactive energy futures price model to simulate the price dynamic mechanism of that market, and studied the price volatility and c fluctuation dynamics of the model with two statistics: daily logarithmic yield, and volatility duration average intensity (VDAI). Through complementary ensemble empirical mode decomposition (CEEMD), Chen and Pan [21] divided the Chinese stock index futures price series into residual items, low-frequency items, and high-frequency items, revealing the volatility of the series on different time scales, and predicted the Chinese stock index futures price by combining the decomposition method with the support vector machine (SVM) based on particle swarm optimization (PSO). Wan et al. [22] analyzed the fractal features of International Energy Exchange (INE) crude oil market through rescaled range (R/S) analysis, multifractal detrended fluctuation analysis, and multifractal spectrum analysis. The results show that the price yield of INE crude oil carries significant multifractal features. Ames et al. [23] introduced the regression structure to expand the multi-factor random model of the structural dynamics of commodity futures price period, and discovered that the expanded model helps to explain the main observable factors of the structure of commodity futures price period (e.g., dollar index,
inventory, and commodity index) and facilitates the risk avoidance by financial intermediaries. Weron [24] proposed a jumping-diffusion model, which restores the main features of the power spot price in the Nordic market, including seasonality, mean regression, and spikes. Kakeu and Bouaddi [25] empirically demonstrated the correlation between the long-term risks impacted by uncertainty, and the future growth prospects, and integrated dynamic factor analysis into an econometric approach to estimate the pricing equation of oil inventory. Sadorsky [26] developed a model to estimate the conditional expected return of oil futures price under time-varying risks, and empirically proved the strong predictive power of macroeconomic risk factors for the oil futures market. Korotayev et al. [27] evaluated the social-political instability risks of oil exporters that might be induced by oil price decline, and analyzed the relationship between oil price changes and political crises in economies.

Based on behavioral financial theory, it is possible to establish a transaction decision-making model reflecting the actual market situation of the natural resources like crude oil futures, gold futures, and agricultural product futures. The model can replace the traditional mathematical method and questionnaire survey to study the price volatility features of natural resources. Meanwhile, the existing studies have not included the uncertainty of risk factors to the research of the factors affecting NRC price, but carry on with the traditional price impact mechanism. Therefore, this paper decides to explore the price risk control of NRCs from the perspective of financial theories. Section 2 empirically examines the specific impacts of uncertain risk factors on NRC price, and the directions of the impacts; Section 3 discusses the price volatility and transaction risks of NRCs brought by information transmission, and constructs an information transmission model for NRC trading market; Section 4 builds up a dynamic price model for NRCs based on the theory of behavioral finance. The effectiveness of the proposed model was verified through experiments, and the relevant results were analyzed.

2. Influence of Risk Factors on NRC Price

Empirical method is needed to reveal the impacts of uncertain risk factors on NRC price, and the directions of the impacts. This paper chooses the vector autoregression (VAR) model with time-varying parameters to analyze the effects of risk factors on NRC price, aiming to describe the time dynamics of model parameters.

Let \( r \) be the lag period of tradable NRCs; \( q \) be time; \( b_\phi \) be an \( r \times 1 \) vector composed of \( l \) observable variables; \( X, G_1, \ldots, G_r \) be an \( r \times l \) coefficient matrix; \( \xi_\phi \) be an \( r \times 1 \) structural impact. Then, the basic VAR model can be constructed:

\[
X_{t+1} = G_1 b_{t,q-1} + G_2 b_{t,q-2} + \ldots + G_r b_{t,q-r} + \xi_{t+1}, \quad \phi = r + 1, \ldots, m. \quad (1)
\]

This paper divides the NRC market allowing free contract transactions into agricultural product market (APM), energy market (EM), and non-ferrous metal market (NFMM). From each of the three markets, three representative commodities with high trade volumes were selected to study the impact mechanism of uncertain risk factors on the core commodity prices in these markets. The three commodities from each market correspond to three vectors. The three vectors plus a risk factor make the number of variables 4, i.e., \( l = 4 \).

The three commodities from APM are soybean, wheat, and cotton. The corresponding three variables are the price to earnings (P/E) ratios of soybean, wheat, and cotton, denoted as \( YR_{SO}, YR_{WH}, \) and \( YR_{CO} \), and the corresponding uncertain risk factor is denoted as \( URF_{APM} \). The three commodities from EM are crude oil, natural gas, and coal. The corresponding three variables are the P/E ratios of crude oil, natural gas, and coal, denoted as \( YR_{CR}, YR_{GA}, \) and \( YR_{COA} \), and the corresponding uncertain risk factor is denoted as \( URF_{EM} \). The three commodities from NFMM are gold, silver, and cooper. The corresponding three variables are the P/E ratios of gold, silver, and cooper, denoted as \( YR_{GO}, YR_{SI}, \) and \( YR_{CO} \). The corresponding uncertain risk factor is denoted as \( URF_{NFMM} \).

Let \( \varepsilon \) be standard deviation. The structural impact \( \xi_\phi \) satisfies \( \xi_\phi \sim M(0, \Phi) \), where

\[
\Phi = \begin{pmatrix}
\varepsilon_1 & 0 & 0 \\
0 & \varepsilon_2 & 0 \\
0 & 0 & \varepsilon_3 \\
0 & 0 & \varepsilon_4
\end{pmatrix}. \quad (2)
\]

Suppose coefficient matrix \( X \) is a lower triangular matrix (3), in which all the elements on the main diagonal are 1

\[
X = \begin{pmatrix}
1 & 0 & 0 & 0 \\
x_{31} & 1 & 0 & 0 \\
x_{32} & x_{33} & 1 & 0 \\
x_{41} & x_{42} & x_{43} & 1
\end{pmatrix}. \quad (3)
\]

Let \( \rho_\phi \) be the residual items; \( f_i \) be the unit matrix; \( \mu_j = X^{-1} G_j, \quad i = 1, 2, \ldots, r \). In this case, the model is a recursive structural VAR model. Then, formula (1) can be converted into

\[
b_\phi = \mu_1 b_{\phi-1} + \mu_2 b_{\phi-2} + \ldots + \mu_r b_{\phi-r} + \Psi^{-1} \delta_\phi \rho_\phi \sim M(0, J_f). \quad (4)
\]

The elements in each row of matrix \( \mu_i \) need to be processed to convert the matrix into the form of a \( 16r \times 1 \)-order vector \( \alpha \). Let us define \( A_\phi = f_i \bigcirc (b_{\phi-1}, \ldots, b_{\phi-r}) \), with \( \bigcirc \) being the Kronecker product. Then, formula (4) can be further transformed into

\[
b_\phi = A_\phi \alpha_\phi + \Psi^{-1} \delta_\phi \rho_\phi, \quad (5)
\]

where \( \alpha_\phi, \Psi_\phi, \) and \( \delta_\phi \) are all time-varying parameters. Since the determinant of time-varying parameter matrices is
nonzero, the matrices are all reversible. Let $x_1 = (x_{21}, x_{31}, x_{32}, x_{41}, \ldots, x_{4j})'$ be the lower triangular elements of conversion matrix $S$; $f_{ij} = f_{2j}\phi_1, f_{3j}\phi_1, f_{4j}\psi$, $\prod f_{ij} = l_n e^{2j\psi}$; $j = 1, 2, 3, 4,$ $\phi = \tau + 1, \ldots, m$ be the logarithmic random fluctuation matrix. If formula (6) obeys the random walk, then

$$
\begin{align*}
\alpha_{\phi+1} &= \alpha_\phi + \zeta_\phi, \\
\beta_{\phi+1} &= \beta_\phi + \zeta_\phi, \\
f_\phi+1 &= f_\phi + \zeta_\phi,
\end{align*}
$$

where $\alpha_{\tau+1} \sim M(\zeta_{\tau0}, \delta_{\tau0}); \beta_{\tau+1} \sim M(\zeta_{\tau0}, \delta_{\tau0}); h_{\tau+1} \sim M(\zeta_{\tau0}, \delta_{\tau0}).$

Then, the parameters can be estimated more accurately based on the Markov chain Monte-Carlo (MCMC) method.

### 3. Information Transmission Model of NRC Transaction Market

The NRC market is featured by a large scale, advanced transaction techniques, and a complex group of traders. Drawing on behavioral finance theories, the following can be discovered from the behavioral patterns of different traders: during free contract transactions, the traders of different information acquisition channels, knowledge backgrounds, and energies exhibit different behavioral features.
price. This paper discusses the influence of the two parameters through empirical analysis.

Based on the continuous seepage theory, the intensity of the critical Poisson process that is strong enough to induce a seepage between points is denoted as $\chi$. The critical probability of the seepage can be defined as the probability $GV^d$ of satisfying the corresponding attributes. Let $GV^v$ and $GV^c$ be the buy-in and sell-out probabilities of the transaction information transmission in the seepage string, respectively. Relative to critical probability $GV^d$, $GV^v$ and $GV^c$ satisfy

$$GV^v (R^*_\min) = GV^d \quad GV^c (R^*_\max) = GV^d,$$

where $R^*_\min$ and $R^*_\max$ are the top and bottom NRC prices under the above conditions, respectively. Different from $R^*_\min$ and $R^*_\max$, $R^*_\min$ and $R^*_\max$ are the critical values of NRC price, and estimated based on the frequently occurred probabilities. In the actual NRC market, when the commodity price fluctuates greatly, a rational trader would choose buy-in at $R < R^*_\min$ and choose sell-out at $R > R^*_\max$ aiming to eliminate the NRC market overshoot induced by sudden occurrence of non-systematic risks. $R^*_\min$ and $R^*_\max$ can be expressed as

$$R^*_\min = R^* \pm \sqrt{-\frac{1}{\xi} \ln GV^d} \quad R^*_\max = R^* \pm \sqrt{-\frac{1}{\eta} \ln GV^d}.$$

Formula (14) shows that the top and bottom of NRC price can be estimated by determining empirical parameters $\xi$ and $\eta$. The relationship between these two empirical parameters can be expressed as

$$\eta = \xi \frac{(R - R^*)^2}{(R - R^*)^2}.$$

### 4. Dynamic Price Model Based on Behavioral Finance Theory

Following traditional finance theory, all models for the NRC market are equilibrium models. Unlike traditional finance, behavioral finance views the mentality of traders differently. The logic of behavioral finance is the reverse of that of traditional economics. The traditional economics theory firstly creates ideals, and then moves gradually towards reality, focusing on what should happen under ideal conditions. In contrast, behavioral finance focuses on experience and its underlying reasons.

Figure 2 compares the differences between traditional finance and behavioral finance. Based on behavioral finance theory, this paper summarizes the research objects as independent traders, group behavior of traders, ineffective market, and effective market.

The buy-in/sell-out decision-making of independent traders in the window $[\psi, \psi + 1]$ of a transaction is apparently a static game in a unit period. The price of the commodity mix at time $\psi$ can be denoted by $O_\psi$.

![Figure 2: Differences between traditional finance and behavioral finance.](image-url)

Figure 3 shows the response of commodity price to different types of information. It can be inferred that bear information transmission impacts the market more significantly than bull information transmission.

When information is being transmitted in the market, the number of people that underreact to the transaction information, and that of the people that overreact are denoted as $M_1$ and $M_2$, respectively. Then, the proportion of underreacting people can be calculated by

$$\lambda_\psi = \frac{M_1}{M_1 + M_2}.$$

Correspondingly, the overreacting traders are $\theta_\psi = 1 - \lambda_\psi$. The NRC market is normally ineffective. Excluding the value of NRCs, the volatility of transaction price is essentially a game between traders possessing different types of transaction information. Therefore, the actual price of natural resources can be expressed as the competition between the decision-making of two kinds of traders. The actual price $O_\psi$ of commodity mix can be expressed as:

$$O_\psi = \lambda_\psi O^*_\psi + (1 - \lambda_\psi) O^\phi_\psi,$$

$$O_\psi = \lambda_\psi g(\phi) + (1 - \lambda_\psi) \omega(\phi).$$

If $\lambda_\psi = 0$, then $O_\psi = \omega(\phi)$. In this case, all the traders in the market overreact to the transaction information; If $\lambda_\psi = 1$, then $O_\psi = g(\phi)$. In this case, all the traders in the market underreact to the transaction information. The proportions of the two types of traders jointly shape the investment sentiment in the market. Figure 4 presents the game intervals of transactors of different transaction information. The x-axis is time, and the y-axis is commodity price.

To build a more realistic dynamic NRC price model, this paper introduces the other investment features of traders to the proposed static price model. The actual rate of yield of NRCs can be calculated by

$$E_\psi = \frac{O_\psi - O_{\psi-1}}{O_{\psi-1}}.$$

If the expected rate of NRCs $H(E_{\psi+1}) > E_\psi$, i.e., the expected rate of yield of NRCs in $\psi + 1$ is greater than that in
φ, then the traders would choose buy-in; if \( H(E_{\varphi+1}) < E_{\varphi} \), i.e., the expected rate of yield of NRCs in \( \varphi + 1 \) is smaller than that in \( \varphi \), then the traders would choose sell-out.

\[
H(E_{\varphi+1} | H(E_{\varphi}) > E_{\varphi}, H(E_{\varphi-1}) > E_{\varphi-1}, \ldots, H(E_{\varphi-j}) > E_{\varphi-j})
\]

\[
> H(E_{\varphi+1} | H(E_{\varphi}) > E_{\varphi}, H(E_{\varphi-1}) > E_{\varphi-1}, \ldots, H(E_{\varphi-m}) > E_{\varphi-m}).
\]  \( (19) \)

If the actual expectation of NRCs consistently trails the expected rate of rate of traders, as shown in formula (20), then \( \varphi > j > m > 0 \). In this case, the traders would be unconfident with the selected NRC mix and the buy-in behavior, and more likely to choose sell-out.

\[
H(E_{\varphi+1} | H(E_{\varphi}) < E_{\varphi}, H(E_{\varphi-1}) < E_{\varphi-1}, \ldots, H(E_{\varphi-j}) < E_{\varphi-j})
\]

\[
< H(E_{\varphi+1} | H(E_{\varphi}) < E_{\varphi}, H(E_{\varphi-1}) < E_{\varphi-1}, \ldots, H(E_{\varphi-m}) < E_{\varphi-m}).
\]  \( (20) \)

According to our hypothesis, when \( E_{\varphi-1} \) is known, the underreacting traders expect the rate of return in \( \varphi \) to be \( H(E_{\varphi}) < E_{\varphi-1} \), and the overreacting ones expect the rate of return in that period to be \( H(E_{\varphi}) > E_{\varphi-1} \). Table 1 summarizes the behaviors of different types of traders.

\[
\begin{align*}
\lambda_{\varphi} &= \lambda_{\varphi-1} + \theta_{\varphi-1}GV(\lambda(\theta_{\varphi-1})|\omega_0)GV(\omega_0^1) - \lambda_{\varphi-1}GV(\theta(\lambda_{\varphi-1})|\omega_0)GV(\omega_0^2), \\
\theta_{\varphi} &= \theta_{\varphi-1} - \theta_{\varphi-1}GV(\lambda(\theta_{\varphi-1})|\omega_0)GV(\omega_0^1) + \lambda_{\varphi-1}GV(\theta(\lambda_{\varphi-1})|\omega_0)GV(\omega_0^2),
\end{align*}
\]  \( (21) \)

If the actual expectation of NRCs consistently surpasses the expected rate of rate of traders, as shown in formula (19), then \( \varphi > j > m > 0 \). In this case, the traders would be confident with the selected NRC mix and the buy-in behavior, and more likely to choose buy-in again.

If the commodity price fluctuates oppositely to trader’s expectation, the traders with different expectations will shift their positions. Let \( GV(\omega_i') \) be the occurrence probability of a transfer event; \( GV(\chi(\theta_{\varphi-1})|\omega_0') \) be the transfer probability of condition \( i \) after the event. Then, the proportion of the two types of traders can be expressed as...
Then, \( GV(\omega_0^0) \) depends on the proportion of independent traders in the market:

\[
\begin{align*}
&GV(\omega_0^0) = \lambda_{\psi-1}, \\
&GV(\omega_2^0) = \theta_{\psi-1},
\end{align*}
\]

(22)

Combining formulas (21) and (22)

\[
\begin{align*}
\lambda_{\psi} &= \lambda_{\psi-1} + \theta_{\psi-1}GV(\theta(\theta_{\psi-1})|\omega_0^1)\lambda_{\psi-1} - \lambda_{\psi-1}GV(\theta(\theta_{\psi-1})|\omega_2^1)\theta_{\psi-1}, \\
\theta_{\psi} &= \theta_{\psi-1} - \lambda_{\psi-1}GV(\theta(\theta_{\psi-1})|\omega_0^1)\lambda_{\psi-1} + \lambda_{\psi-1}GV(\theta(\theta_{\psi-1})|\omega_2^1)\theta_{\psi-1},
\end{align*}
\]

(23)

Substituting \( \theta_{\psi-1} = 1 - \lambda_{\psi-1} \) into formula (23)

\[
\begin{align*}
\Delta_i &= GV(\theta(\theta_{\psi-1}) | \omega_0^0_i) - GV(\theta(\theta_{\psi-1}) | \omega_0^0_i),
\end{align*}
\]

(25)

where \( GV(\theta(\theta_{\psi-1}) | \omega_0^0_i) \) actually means the price hike of NRCs make traders to expect earnings, and reduce the number of underreacting traders/increase the number of overreacting traders, i.e., the emotional disposition exists in the market; \( GV(\theta(\theta_{\psi-1}) | \omega_0^0_i) \) actually means the price fall of NRCs make traders unconfident with their commodities, and increase the number of underreacting traders/reduce the number of overreacting traders, i.e., the casual attribution exists in the market.

Formula (25) can be extended into

\[
\begin{align*}
\lambda_{\psi} &= \lambda_{\psi-1} + \theta_{\psi-1} \sum_{\phi_i=1}^i GV(\theta(\theta_{\phi_i-1})|\omega_0^1_{\phi_i-1})GV(\omega_0^1_{\phi_i-1}) - \lambda_{\psi-1} \sum_{\phi_i=1}^i GV(\theta(\theta_{\phi_i-1})|\omega_2^1_{\phi_i-1})GV(\omega_2^1_{\phi_i-1}), \\
\theta_{\psi} &= \theta_{\psi-1} - \lambda_{\psi-1} \sum_{\phi_i=1}^i GV(\theta(\theta_{\phi_i-1})|\omega_0^1_{\phi_i-1})GV(\omega_0^1_{\phi_i-1}) + \lambda_{\psi-1} \sum_{\phi_i=1}^i GV(\theta(\theta_{\phi_i-1})|\omega_2^1_{\phi_i-1})GV(\omega_2^1_{\phi_i-1}).
\end{align*}
\]

(26)

Similarly

\[
\begin{align*}
\lambda_{\psi} &= \lambda_{\psi-1} \sum_{i=1}^i \Delta_i \lambda_{\phi_i-1} + \left( 1 - \sum_{i=1}^i \Delta_i \right) \lambda_{\psi-1}, \\
\theta_{\psi} &= -\theta_{\psi-1} \sum_{i=1}^i \Delta_i \theta_{\phi_i-1} + \left( 1 - \sum_{i=1}^i \Delta_i \right) \theta_{\psi-1},
\end{align*}
\]

(27)

\[
\Delta GV_i = GV(\theta(\theta_{\psi-1}) | \omega_0^0_{\phi_i-1}) - GV(\theta(\theta_{\psi-1}) | \omega_0^0_{\phi_i-1}),
\]

(28)

where \( \Delta GV \) is the transfer probability difference between a market of emotional disposition and a market of casual attribution. Combined with the previous analysis results, the proportions of different types of traders change dynamically from the initial moment \( \psi_0 \), as the commodity rate of return varies from period to period. In other words, \( \lambda_{\psi} \) is a function \( \lambda_{\phi}(\psi) \) of time \( \psi \). Let \( \lambda_{\psi} \) be the \( \lambda_{\psi} \) at the initial moment. Then, the NRC price mechanism function of the dynamic model can be expressed as

\[
GV_1 = \lambda_{\phi} GV_0 + (1 - \lambda_{\phi}) GV^2_0, \\
= \lambda_{\phi} g_0(0) + (1 - \lambda_{\phi}) \omega(0), \\
= \lambda_{\phi} \frac{\sigma_1}{\psi_1} + \frac{\sigma_2}{\psi_2} + \lambda_{\phi} \rho_0^1 + (1 - \lambda_{\phi}) \rho_0^2, \lambda_{\phi} \in [0,1],
\]

(29)

whereas \( \lambda_0 = \Omega(\lambda_0, Y_0) \), period \( \psi \) satisfies

\[
\beta_0 = \Omega(X_\phi, Y_\psi), \\
GV_{\phi+1} = \lambda_\phi GV_{\phi+1} + (1 - \lambda_\phi) GV^2_{\phi+1}, \\
= \lambda_\phi g(\phi) + (1 - \lambda_\phi) \omega(\phi) + \lambda_\phi \rho_0^1 + (1 - \lambda_\phi) \rho_0^2, \\
\lambda_\phi \in [0,1], \lambda_\phi \rho_0^1, \lambda_\phi \rho_0^2 \sim \lambda_{\phi}.
\]

(30)

Therefore, as transaction information propagates in the market, all traders would judge the commodity value based on historical information and psychological behaviors. Then, the traders whose expected price is above the actual price would enter a price game in the market with those whose expected price is below the actual price. The proportions of the two types of traders would change continuously until the actual price reaches their target price.

5. Experiments and Result Analysis

Since the traders would the commodity value based on historical information and psychological behaviors, this paper assigns greater weights to more recent transaction information and psychological behaviors. Figure 5 compares the incomes of different NRC markets. It can be seen that the exponential weight is strongly correlated with the rate of return of commodities. In most cases, the correlation is positive, but difficult to quantify.

To verify the income of our model, this paper constructs a short-term transaction strategy of traders. Firstly, a stop loss line was set up to prevent heavy losses based on the support and resistance levels. When the composite index becomes positive twice in a row, the traders choose buy-in;
when that index becomes negative twice in a row, the traders choose sell-out. Figure 6 compares the income of our model with that of the short-term transaction strategy. It can be observed that our model could effectively avoid the price decline of the overall market. The comprehensive rate of return was -16.75% for the overall market. The rates of return for short-term transaction strategies were simulated as 17.54%, 8.51%, and 7.33%, all falling in the ideal range.

The parameter estimations of APM, EM, and NFMM obtained by MCMC are displayed in Tables 2–4, respectively, including the posterior mean, standard deviation, CD, invalidity factor, 95% confidence interval, etc. The data in the tables only cover the estimations for the first diagonal elements in matrices $k_s$, $k_r$, and $k_u$. Judging by the CD values, the null hypothesis that the estimated parameters converge to its posterior distribution remains valid, even at the significance level of 1%. Since the MCMC sampling was conducted for more than 10,000 times, the maximum invalidity factors in the tables were relatively small. The largest value was merely 74.35. That is, at least 133 uncorrelated samples could be obtained. It can also be learned that the selected MCMC method effectively estimated all the parameters, and the proposed model achieved a high goodness-of-fit.

Figures 7–9 present the curves for the time-varying features of stochastic price volatility for commodities in APM, EM, and NFMM, respectively. Under the influence of uncertain risk factors, the prices of APM and NFMM commodities fluctuated similarly: both of them increased with fluctuations in 2014–2016, and dropped with fluctuations from the end of 2016 to the start of 2017. Compared with that of EM and NFMM, the commodity price of APM was weakly impacted by uncertain risk factors through the study period. The APM commodity price volatility reached...
the peak near 2013, mainly due to the decline in the output of agricultural products across the market, which is driven by droughts.

Figure 10 reports the time-varying features of stochastic price volatility of commodity price under the impact of economic policy risks. It can be seen that the economic policy risks had 3-4 clear peaks near 2013-2014, 2017-2018, and 2019-2020. In the real world, the European debt crisis occurred in 2013-2014, Brexit happened in 2016-2017, and COVID-19 broke out and spread in 2019-2021. These sudden events significantly push up the uncertainty of economic policies, bringing the peaks of economic policy risks. To sum up, the stochastic volatility features of the uncertain risks induced by real-world events correspond well with those of commodity price.
term, it is suggested mitigating the price volatility risks by adding bonds. In the long run, it is suggested focusing on the variation of domestic interest level.

Therefore, our model fits well with the time-varying features of actual volatilities, which demonstrates the feasibility and effectiveness of the model.

6. Conclusions

This paper explores the risk control strategies for NRC commodity price from the angle of financial theory and constructs the relevant model to analyze the risk control. The authors investigated how NRC price is impacted by uncertain risk factors, such as supply risk, demand risk, macroscopic price risk, political price risk, policy price risk, seasonal price risk, and sudden price risks, and what are the directions of the impacts. After that, an information transmission model as created for NRC trading market, and a dynamic price model was developed for NRCs based on the theory of behavioral finance. Through experiments, the authors compared the incomes of different NRC markets, and the income of our model with that of short-term transaction strategy. The comparison shows that our model could effectively avoid the price decline of the overall market. It was concluded that the energy market price fluctuates similarly to the nonferrous metal market price, under the effects of uncertain risks. The results confirm that our model fits well with the time-varying features of actual volatilities, which demonstrates the feasibility and effectiveness of the model.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the project of Shaanxi Provincial Federation of Social Sciences: Poverty Alleviation Effect of Rural Financial Development in Shaanxi Province, China (2021ND0440).

References


[22] F. Wang, X. Ye, and C. Wu, “Multifractal characteristics analysis of crude oil futures prices fluctuation in China,”