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Research article

Impact of COVID-19 on energy prices and main macroeconomic indicators—evidence from China's energy market

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Abstract: With the COVID-19 pandemic sweeping the world, the development of China's energy industry has been hampered. Although previous studies have shown the global influence of COVID-19 on energy prices and macroeconomic indicators, very few of them examined the impact on China independently, considering the special role of China in this pandemic and economy. In this study, we investigate the impact of the pandemic on several major China energy prices using the ARIMA-GARCH model. Combined with the Value-at-Risk (VaR) theory, we further explore the market risk, which indicates an increase in the tail risk of energy price volatility and the dramatic turbulence in energy markets. In addition, a Vector Autoregressive (VAR) model is developed to analyze how the main macroeconomic indicators are affected when energy prices fluctuate. According to the model results, energy price fluctuations caused by the COVID-19 have a negative impact on economic growth and inflation, with a higher contribution to the latter changes. Based on the modeling analysis results, this paper makes constructive suggestions on how to stabilize energy prices and recover the economic development in the context of the COVID-19 pandemic.

Keywords: COVID-19 pandemic; China energy industry; energy price volatility; main macroeconomic indicators; ARIMA-GARCH model; Value-at-Risk; VAR model

JEL Codes: C32, C51, E31, Q43

1. Introduction

The COVID-19 pandemic, which broke out at the end of 2019, has spread rapidly around the world and led to severe disruption to global activities. Considering its threat to people's lives, many countries imposed restrictions on public activities and kept lockdowns on global transport and aviation activity, resulting in negative shocks to energy demand. According to Global Energy Review 2020 by the International Energy Agency (IEA), in the first quarter of 2020, the global energy demand has experienced a significant decline of 3.8%, with a fall of 8%, 5%, 20% in coal, oil, electricity demand respectively. The imbalance between energy supply and demand has led to fluctuations in energy prices, exposing the energy sector to increasing risks of instability. From March 2020 to April 2020, Brent crude oil prices dropped from $32.25 per barrel to $18.11 per barrel. Similarly, WTI slipped from $31.72 per barrel to as low as $19.23 per barrel. The price volatility has significantly affected investment activities. Compared to 2019, the investment in energy sectors was estimated to experience a sharp fall in 2020, especially in the oil sector (Hendrawaty and Kesumah, 2020).

As the first country to officially report the infection case, China has been struggling with the pandemic storm. In order to prevent the increase in infection cases, the Chinese government decided to shut down Wuhan with restrictions on unnecessary public activities. As a result, in the first quarter of 2020, the GDP in China declined by 6.8%. Lockdown policy also significantly influenced China's daily oil consumption, which slipped from 0.9 million barrels in the last quarter of 2019 to 0.6 million barrels in the first quarter in 2020 (OPEC, 2020). Generally, China was considered the key player on the demand side in the world energy market (Adedeji et al., 2021; U.S. Energy Information Administration, 2020). Undoubtedly, as a major global energy consumer and importer, the dramatic fluctuations in energy prices and the tremendous reduction in energy consumption due to the COVID-19 would pose a significant threat to the China energy market stability (Sun et al.,2020; Sun et al.,2020; Shen et al., 2020).

In this paper, we aim to quantify the impact of COVID-19 on energy price volatility and market risk. Considering the important role of energy economy in the national economy, there is a growing concern about whether the energy price volatility would cause a trail of damage to the macroeconomic growth, so we also study the impact of the energy price volatility caused by the COVID-19 on main macroeconomic indicators.

The main contributions of our study are illustrated as follows. (1) We focus on the impact of COVID-19 on China, the major global energy importer and the second largest economy. Our analysis of its energy market stability and economic development under COVID-19 would contribute to the trend prediction of the global economy. (2) Our study takes a broader scope to explore the pandemic impact on different fuel types, while many other researchers paid less attention to the price volatility of other energy types other than oil (Adedeji et al., 2021; Liu et al., 2020; Szczygielski et al., 2021). (3) Our study not only explores the pandemic shock on energy price fluctuations but further investigates its impact on economic growth and inflation, which would provide insightful implications to investors and governments.

The rest of this paper is organized as follows. Section 2 provides a brief introduction to relevant studies. Section 3 and section 4 describe research methods and research data respectively. The results and discussion are presented in section 5. Finally, section 6 concludes our main findings.

2. Literature review

Recently, as the extreme event of COVID-19 spread rapidly around the world, it has pushed a profound impact on different domains, including a negative shock to the energy sector (Mofijur et al., 2021). Several studies have investigated the impact of COVID-19 on energy prices and stock returns and their conclusions exhibit certain regional differences. Szczygielski et al. (2021) argued that the impact of COVID-19 related uncertainty varied across countries, with a greater degree of impact in countries further west from China. Adedeji et al. (2021) focused on oil markets in China and Nigeria. According to the results, the impact of the pandemic accounted for the smallest shares of movement in oil prices. More interestingly, when Liu et al. (2020) cast their attention to US markets, they found that the COVID-19 actually exerted a positive effect on oil and stock returns.

As an extreme event, the occurrence of COVID-19 has also significantly affected the financial and non-financial investment risk (Sukharev, 2020). Particularly, lockdown measures on the energy system posed a threat to the stability of energy markets, resulting in an increased need to assess the risk in energy markets. Akhtaruzzaman et al. (2020) found that the COVID-19 shock moderated the oil price risk exposure of financial and non-financial industries. On the contrary, Wen et al. (2021) concluded that the response of the oil price risk to the epidemic was significantly negative. A traditional method to study the risk evaluation under extreme events is the Value-at-Risk method, which can also be applied in the energy market (Liu, 2014; Marimoutou et al., 2009; Echaust and Just, 2021). Several studies adopted GARCH-based models to aid analysis, such as AR-GARCH and E-GARCH, which have gained a good performance in the assessment of Value-at-Risk (Hendrawaty and Kesumah, 2021; Omar et al., 2020).

It's believed that there was an interaction between energy prices and economic development (Cunado and Perez de Gracia, 2005; Sodeyfi and Katircioglu, 2016; Jeris and Nath, 2020; Teng and Huo, 2019). Previous studies showed that the way how oil price shocks affect inflation and economic growth varied considerably across countries and sectors, which can be examined by VAR family methods, the Granger test and impulse response analysis (Cologni and Manera, 2008; Berument et al., 2010; Teng and Huo, 2019). Trang (2017) found that in Vietnam, a rise in oil prices would lead to higher inflation. However, Chatziantoniou et al. (2013) drew a different conclusion. The empirical results provided evidence to suggest that aggregate demand shocks had a significantly positive influence on tourism income and the economy, while oil specific demand shocks exercised a significant negative impact on inflation.

Since the outbreak of COVID-19, increasing attention has been paid to studies of the impact of the pandemic. However, the relevant research was still at an immature stage. Many studies focused on the pandemic shock to the price volatility in the oil market but failed to investigate the impact on other energy sectors and further explore the influence of energy price volatility on economic development. Considering this problem, our study takes a step forward. In addition, there were few studies conducted for China, the country that played an influential role in global energy consumption and imports but first experienced COVID-19 catastrophe. Our study can be regarded as an effective complement to the existing literature.

3. Methods

The research in this paper follows three processes. We first collect relevant data and perform some necessary pre-processing. To quantify the impact of COVID-19 on energy prices, we employ the classic ARIMA-GARCH model to fit the energy price series and compute the Value-at-Risk. The third part is the analysis of the national macroeconomic impact caused by energy price volatility, which involves the VAR model and its derivative applications.

3.1. ARIMA and GARCH models

ARIMA models, i.e., summated Autoregressive Moving Average models, are mainly used to fit differential stationary series. The ARIMA (p, d, q) model represents that a series after the d-order differencing process is stationary, and the ARMA (p, q) model can be further fitted to it. In general, the ARIMA (p, d, q) model has the following structure

$$\begin{cases} \Phi(B)\nabla^d x_t = \Theta(B)\varepsilon_t \\ E(\varepsilon_t) = 0, \mathrm{Var}(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t\varepsilon_s) = 0, \forall s \neq t \\ E(x_s\varepsilon_t) = 0, \forall s < t \end{cases} \quad (1)$$

where B represents the delay operator, $\nabla^d = (1-B)^d$. $\Phi(B) = 1 - \phi_1 B ... - \phi_p B^p$ and $\Theta(B) = 1 - \theta_1 B ... - \theta_q B^q$ represent the autoregressive coefficient polynomial and the moving smoothing coefficient polynomial of the stationary and reversible ARMA (p, q) model. $\{\varepsilon_t\}$ is the zero-mean white noise series.

Some series, although passing the stationarity test, will exhibit sharp fluctuations at certain periods. The clustering effects have brought inconvenience to the prediction of time series in macroeconomic and financial areas, such as interest rates and stock prices. In order to fit such series whose variance is essentially homogeneous but will differ from the expected variance at a certain time, the Autoregressive Conditional Heteroskedasticity (ARCH) model has been proposed (Engle and Robert, 1982). However, ARCH model is generally only applicable to the process of short-term autocorrelation of heteroskedasticity functions. Considering this problem, people further explored the p-order autocorrelation of the heteroskedasticity function and proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev and Tim, 1986). Usually, the structure of the GARCH (p, q) model can be displayed as

$$\begin{cases} x_t = f(t, x_t, x_{t-1}, x_{t-2}, \ldots) + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} e_t \\ h_t = \omega + \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \eta_i h_{t-i} \end{cases} \quad (2)$$

The GARCH model is fitted with a premise that $\{\varepsilon_t\}$ is a zero-mean, purely random, heteroscedastic series. When it is not satisfied, an Autoregressive model (AR) is fitted to $\{\varepsilon_t\}$ first, and then a GARCH (p, q) model is employed to the residual series $\{v_t\}$. In the end, an AR(m)-GARCH (p, q) model is constructed, with the structure

$$\begin{cases} x_t = f(t, x_t, x_{t-1}, x_{t-2}, \ldots) + \varepsilon_t \\ \varepsilon_t = \sum_{k=1}^{m} \beta_k \varepsilon_{t-k} + v_t \\ v_t = \sqrt{h_t} e_t \\ h_t = \omega + \sum_{j=1}^{q} \lambda_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \eta_i h_{t-i} \end{cases} \quad (3)$$

where $e_t \sim N(0, 1)$. As a major method to fit the series with heteroskedasticity, GARCH class models have been widely applied in studies on energy price volatility (Hou and Suardi, 2012; Kang et al., 2009; Mohammadi and Su, 2010; Pan and Zhang, 2005; Wei et al., 2010).

3.2. VAR model

The Vector Autoregressive model, known as the VAR model, assumes that the change of a variable is not only affected by its own lagged value but also related to the lagged values of other variables. By constructing an unstructured system of Equations model, the dynamic relationship of all endogenous variables can be explored. If the number of variables is n and the maximum lag order is p, the VAR model can be expressed as

$$Y_t = A_0 + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + B x_t + \varepsilon_t \tag{4}$$

where $Y_t, \ldots, Y_{t-p}$ are p endogenous variable vectors of size n*1 and are uncorrelated with the random error term ε_t. x_t is a vector of the exogenous variable. $A_0, A_1, \ldots, A_p, B$ are coefficient matrices.

In recent years, the VAR model has been widely applied in the time series forecasting and dynamic structure analysis among variables for its loose application prerequisites and outstanding capabilities. Although not based on the strict economic theory, it requires two things: first, a correlation among the variables entering the model, and second, a suitable lag order under which the residuals are not autocorrelated.

The VAR model indicates that changes in Y_t are influenced by the past state of itself and other variables, while the Granger causality test examines whether there is a lead-lag causality between variables and whether it is bidirectional. If the variable x can Granger cause y, it means that adding the lagged value of x to the Equation will lead to a higher degree of explanation.

In addition to the Granger causality test, another important application is impulse response analysis and variance decomposition. The impulse response function reflects the response of an endogenous variable to a residual shock. Specifically, it measures the dynamic effect on the current and future values of the endogenous variable after applying a shock of standard size to the random error term. On this basis, the variance decomposition further estimates the contribution of each endogenous variable to the prediction variance so as to obtain the importance of different structural shocks.

4. Data

4.1. Data source

To explore the status of China energy market, three series are selected to represent energy prices level of coal, petroleum and hydroelectricity, which are the top three fuel types in China total primary energy consumption (BP, 2021). We obtain the monthly data of energy prices from the Industry Zone of CEInet Statistics Database. The deadline for data collection is December 2020. But the start dates of data collection for coal, petroleum, and hydroelectricity are January 2014, January 2006, and January 2001, respectively, with corresponding sample sizes of 84, 180, and 240.

In order to assess the impact on the economic development, the current value and growth rate of GDP and CPI for each quarter are collected from the Macroeconomic Zone of CEInet Statistics Database. The GDP data covers the period from March 1992 to December 2020, with 116 records. And the CPI data is collected for the period from March 1990 to December 2020, with 124 records.

4.2. Data pre-processing and description

4.2.1. Energy price

Although coal and petroleum include many types of energy sources, the prices under the same broad category show similar trends, which means we only need to select one representative for the modeling analysis. Therefore, the more completely documented coke and unleaded gasoline (89#) series are adopted as representatives for coal and petroleum. As to the electricity price, it is measured by the consumer price index for hydroelectric fuel. Figure 1 illustrates the level of monthly price for three selected energy types. Other than fluctuating randomly around the average line, they show a certain trend.

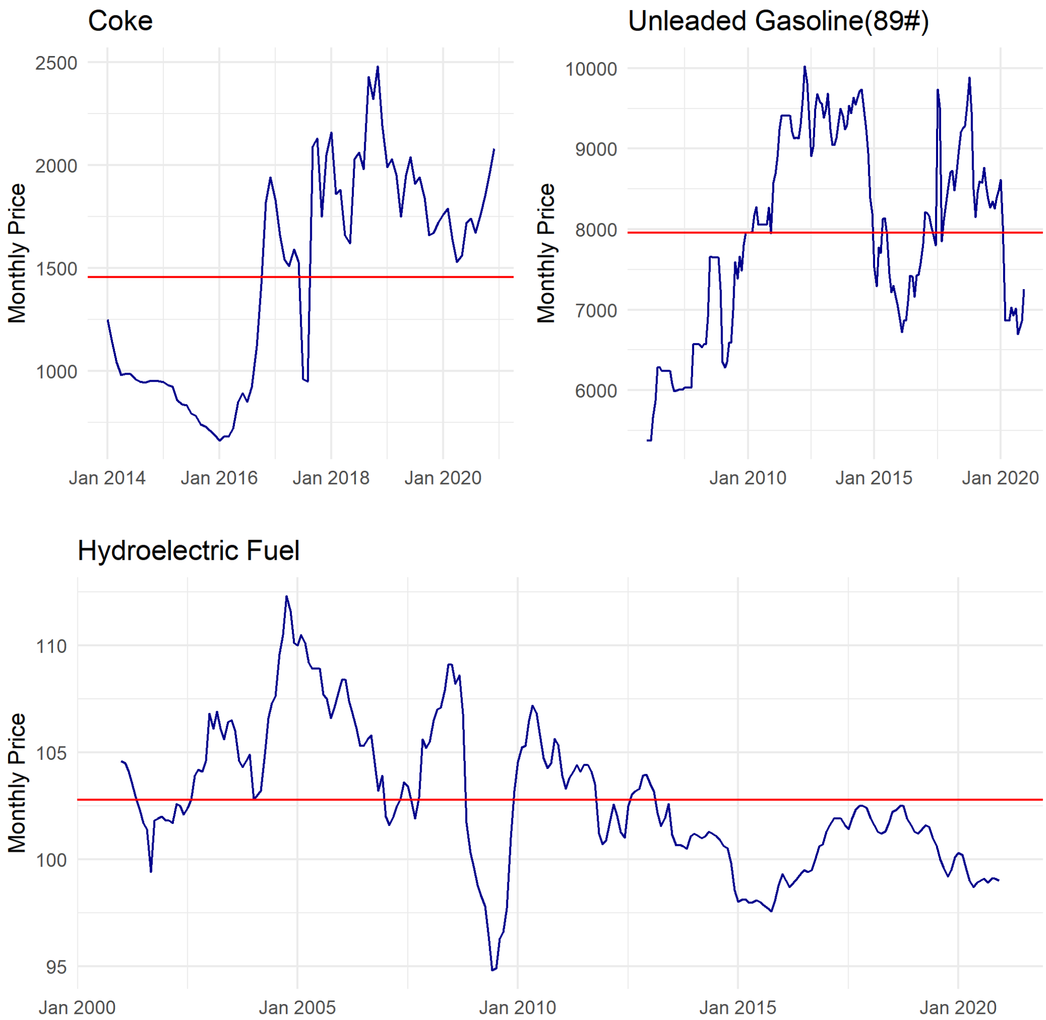

Figure 1. Price line chart of coke, unleaded gasoline (89#), and hydroelectric fuel (from left to right, from top to bottom).

Considering the importance of the yield value in the energy market, this paper uses the logarithmic percent formula to transform the energy price series into the yield series. Let P_t represents the energy price in the t^{th} cycle, the yield r_t is

$$r_t = 100 * \log(\frac{P_t}{P_{t-1}}) = 100 * (\log(P_t) - \log(P_{t-1})) \tag{5}$$

After removing the missing values, the sample sizes of coke, unleaded gasoline (89#), and hydroelectric fuel are 83, 179, and 239, respectively.

Table 1 shows the descriptive statistics for the energy price yield series. The coke yield series have a larger standard deviation and a wider range, which implies its high volatility. In contrast, yields of hydroelectricity fuel vary smoothly around the average value.

It is worth noting that the null hypotheses of the normal distribution are all rejected at the significance level of 0.001 in the Jarque-Bera test. Moreover, the kurtosis values of all three series are significantly non-zero and positive, indicating characteristics of a heavy tail. As shown in Figure 2, the energy yield distribution is more like a t-distribution than a normal distribution, which is consistent with some previous studies (Liu, 2016; Omari et al., 2020). Therefore, this study decides to take the t-distribution as the theoretical distribution of energy price yields.

Table 1. Descriptive statistics for energy price yield series.

Yield Series	Coke	Unleaded Gasoline (89#)	Hydroelectric Fuel
Mean	0.614	0.168	−0.023
Median	−0.479	0.018	0
Standard deviation	13.154	4.024	0.817
Minimum	−46.609	−19.254	−4.893
Maximum	79.162	22.174	3.322
Skewness	2.192	−0.226	−0.420
Kurtosis	14.997	8.551	6.329
Jarque-Bera	893***	564***	416***

Note: *** means the p-value for Jarque-Bera test statistic is below 0.001.

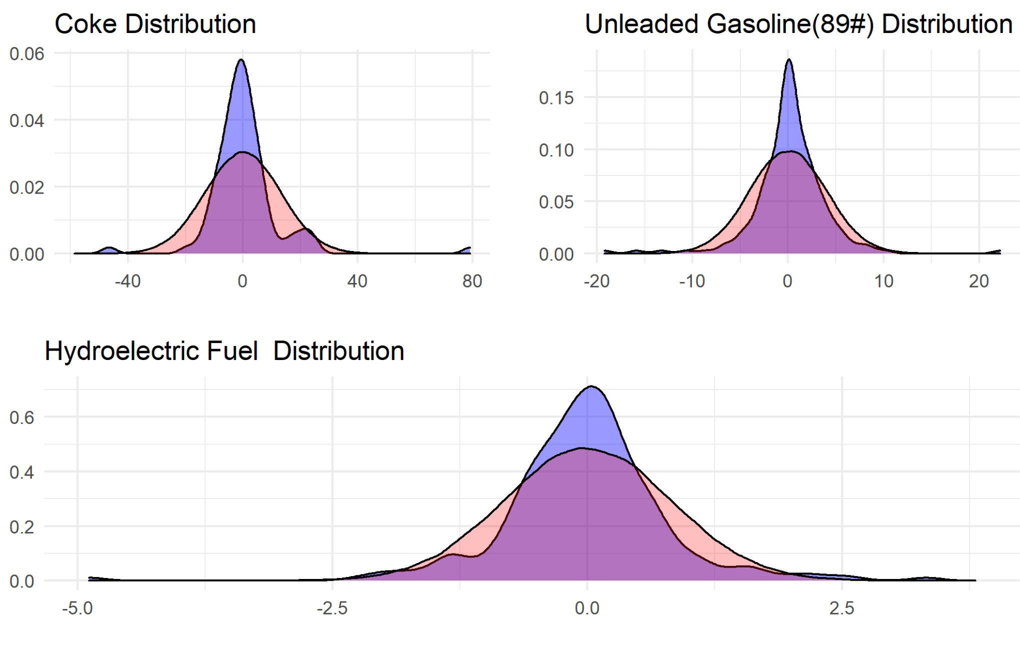

Figure 2. Yield series distribution of coke, unleaded gasoline (89#) and hydroelectric fuel (from left to right, from top to bottom). The blue one is the probability density curve of the energy yield distribution and the red one is the probability density curve of the normal distribution.

In addition to the distribution, another crucial issue in the energy yield series is the stationarity.

According to Figure 3, the yields fluctuate randomly around the mean but exhibit a dramatic variation in specific periods, implying the stationarity with clustering effects. The ADF test is additionally adopted to draw a more reliable conclusion, whose results are shown in Table 2. Since p-values are under 0.05, the original hypothesis is rejected at the 0.05 significance level, which means that all series can be considered stationary.

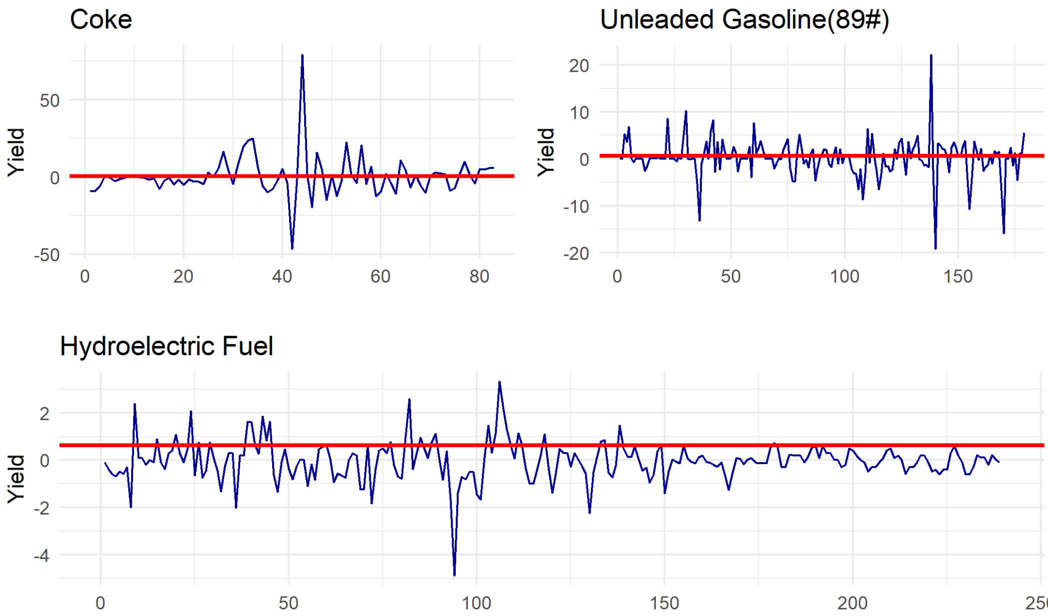

Figure 3. Time series chart for energy price yield of coke, unleaded gasoline (89#), and hydroelectric fuel (from left to right, from top to bottom).

Table 2. Results of ADF test for yield series.

Yield Series	Null Hypothesis	Statistic of Test	Lag Order	P Value
Coke	Non-Stationary	−3.785	4	0.024
Unleaded Gasoline (89#)	Non-Stationary	−6.089	5	0.010
Hydroelectric Fuel	Non-Stationary	−5.524	6	0.010

4.2.2. Macroeconomic indicators

In order to explore the relationship between energy price volatility and main macroeconomic indicators, it is necessary to calculate the growth rate of energy prices to ensure that the variables in the model have the same magnitude. Using the year-ago prices as the benchmark, the growth rate is calculated according to the formula, which is

$$Y_t = 100 * \frac{P_t - P_{t-12}}{P_{t-12}} \tag{6}$$

After removing the missing values, the effective sample sizes of price growth rates corresponding to coke, unleaded gasoline (89#), and hydroelectric fuel are 72, 168, and 228, respectively.

As displayed in Table 3, the growth rate of coke fluctuates dramatically but that of hydroelectric fuel has a much smaller range of variation. As to the unleaded gasoline (89#), its growth rate demonstrates certain fluctuations but overall obeys a normal distribution according to the Jarque-Bera test. Besides, the growth rate series of GDP and CPI have a large positive mean and small standard deviation, implying a growing trend with a moderate variation.

Table 3. Descriptive statistics for growth rate series.

Yield Series	Coke	Unleaded Gasoline (89#)	Hydroelectric Fuel	GDP	CPI
Mean	18.096	2.086	−0.094	9.297	4.010
Median	2.411	2.022	−0.523	9	2.350
Standard deviation	51.938	12.504	3.897	2.970	5.554
Minimum	−32.661	−22.784	−13.107	−6.800	−2.100
Maximum	181.159	32.921	12.690	2.817	2.446
Skewness	1.619	0.068	0.031	−0.989	2.285
Kurtosis	1.749	−0.416	1.519	5.831	5.328
Jarque-Bera	43***	1	23***	193***	265***

Note: *** means the p-value for Jarque-Bera test statistic is below 0.001.

5. Results and discussions

5.1. Impact of the COVID-19 on energy prices

Based on the ADF test results in Table 2, there is no necessity for the differential operation in the ARIMA modeling, so we select the ARMA model to fit the yield series. Before establishing the ARMA model, the Box Test is employed to ensure the series are not purely random. As shown in Table 4, the null hypothesis of white noise can be rejected at the significance level of 0.05, which indicates that the yield series contain meaningful information.

Table 4. Results of white noise test for yield series.

Yield Series	Lag Order	Null Hypothesis	Q Statistic	P Value
Coke	5	White Noise	15.45	0.009
Unleaded Gasoline (89#)	4	White Noise	10.54	0.032
Hydroelectric Fuel	6	White Noise	38.46	<0.001

In order to identify the appropriate order, we compare the AIC and BIC of models corresponding to different orders, whose range is roughly determined in advance by drawing autocorrelation (ACF) and partial autocorrelation (PACF) plots. Under the AIC and BIC criteria, we establish ARMA models. Results are shown in Table 5.

Table 5. Results of ARMA model fitting yield series.

Yield Series	ARMA(p,q)	Model	P Value for Residuals
Coke	ARMA (2,2)	$(1+0.81B+0.64B^2)x_t=(1-1.18B-0.57B^2)\varepsilon_t$	0.973
Unleaded Gasoline (89#)	ARMA (0,2)	$x_t=(1-0.18B+0.16B^2)\varepsilon_t$	0.977
Hydroelectric Fuel	ARMA (1,0)	$(1-0.36B)x_t=\varepsilon_t$	0.746

To ascertain that the model results are plausible, the next step is to test the significance of the model and the parameters. On the one hand, the significance of the model is tested using the LB statistic, which is to determine whether the residual series holds pure randomness. As shown in Table 5, the residual series can be considered as white noise series at the significance level of 0.05, which implies that the model has extracted almost all information from the samples. On the other hand, the t-statistic is constructed to test the significance of the parameters, which is calculated by dividing the parameter estimated value by the corresponding standard deviation. As shown in Tables 6–8, since the p-values are less than 0.05, the parameters pass the significance test, demonstrating that they are significantly non-zero.

Figure 3 exhibits an apparent clustering effect, which often appears in the returns and volatility series, causing trouble in model fitting and forecasting. Considering this problem, this study further adopts a GARCH model to fit the residual series. Table 9 shows the results of the Lagrangian (LM) test for the ARCH effect. Since the LM test statistics are significantly non-zero at the level of 0.05, the clustering effect exists in the residual series.

Taking the stability of the model into account, the model order should not be too high. Combined with the AIC and BIC criteria, we choose the appropriate GARCH models to fit the three series, as shown in Table 10. Using test methods similar to those in the ARMA process, we conclude that at the 0.05 level, the parameters of the GARCH models are significant and the residuals are white noise.

Table 6. Parameter test results of ARMA (2,2) model for coke series.

Parameter	Value	t Statistic	P Value
ar1	−0.81	−3.67	<0.001
ar2	−0.64	−3.74	<0.001
ma1	1.18	5.54	<0.001
ma2	0.57	2.08	0.02

Table 7. Parameter test results of ARMA (0,2) model for unleaded gasoline (#89) series.

Parameter	Value	t Statistic	P Value
ma1	0.18	2.33	0.01
ma2	−0.16	−2.04	0.02

Table 8. Parameter test results of ARMA (1,0) model for hydroelectric fuel series.

Parameter	Value	t Statistic	P Value
ar1	0.36	6.08	<0.001

Table 9. Results of ARCH effect test.

Yield Series	LM Statistic	Lag Order	P Value
Coke	14.107	5	0.015
Unleaded Gasoline (89#)	11.479	5	0.043
Hydroelectric Fuel	54.252	12	<0.001

Table 10. Results of GARCH model fitting.

Yield Series	GARCH(p,q)	Model
Coke	GARCH (1,1)	$\varepsilon_t = \sqrt{h_t}e_t, h_t = 4.575 + 0.255\varepsilon_{t-1}^2 + 0.744h_{t-1}$
Unleaded Gasoline (89#)	GARCH (0,1)	$\varepsilon_t = \sqrt{h_t}e_t, h_t = 0.036 + 0.999h_{t-1}$
Hydroelectric Fuel	GARCH (1,1)	$\varepsilon_t = \sqrt{h_t}e_t, h_t = 0.075\varepsilon_{t-1}^2 + 0.923h_{t-1}$

With respect to energy price yields, there has been an increasing interest in the risk associated with price volatility. Extrapolation of the Value-at-Risk of energy yields from historical data allows people to evaluate the stability of the energy market after the epidemic and accordingly hedge potential investment risks.

According to the definition on the CFA website, Value-at-Risk (VaR) is the expected maximum amount of loss over a certain holding period under normal market fluctuation. In the context of this paper, the value that satisfies

$$\mathrm{Prob}(\Delta\mathrm{P}_{\mathrm{month}} \leq \mathrm{VaR}) = 0.05 \tag{7}$$

is defined as the Value-at-Risk (VaR) with a confidence level of 0.95, where $\Delta\mathrm{P}_{\mathrm{month}}$ represents the monthly loss of energy assets. The definition requires the identification of the yield distribution. As illustrated in Section 4.2.1, it is more appropriate to select the t-distribution.

Under the assumption of the t-distribution, the Equation can be rewritten as

$$\mathrm{Prob}(\frac{\Delta\mathrm{P}_{\mathrm{month}}-\mu}{\sigma} \leq \mathrm{t}_{0.05}) = 0.05 \tag{8}$$

and the dynamic Value-at-Risk can be inferred as

$$\mathrm{VaR}_{\mathrm{dynamic}} = \mu + \sigma * \mathrm{t}_{0.05} \tag{9}$$

where $\mu = 0$, and σ is the estimated value derived from the GARCH model fitting. Compared with the traditional static Value-at-Risk

$$\mu + \mathrm{sd}(\Delta\mathrm{P}_{\mathrm{month}}) * \mathrm{z}_{0.05} \tag{10}$$

based on the normal distribution and the standard deviation of the series, the dynamic Value-at-Risk takes into account the characteristics of the series distribution and the clustering effect, thus being a more accurate indicator of the market risk.

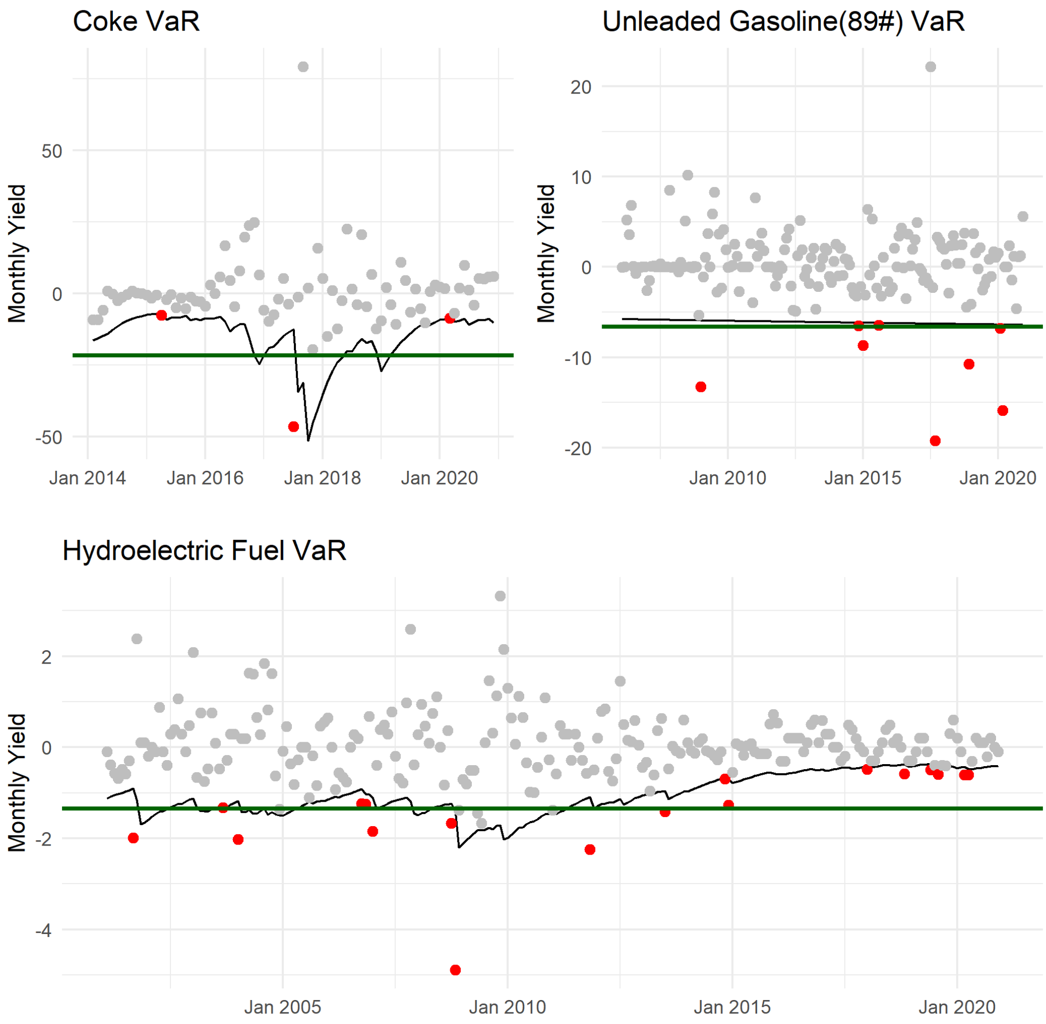

Figure 4. The Value-at-Risk (VaR) line for yield series of coke, unleaded gasoline (89#) and hydroelectric fuel (from left to right, from top to bottom). The green line represents the static VaR and the black line indicates the dynamic VaR.

Figure 4 shows the static and dynamic VaR for three yield series. Compared to the former, the dynamic risk is able to adapt to the market fluctuations and is more sensitive to extreme events. As a result, it captures the market trends in a more timely manner. As displayed in Figure 4, the occurrence of the epidemic did not significantly affect the level of VaR, which remained at a normal position. In 95% of cases, the losses caused by energy price volatility were supposed to be within an acceptable range. However, people generally tend to be more concerned about the maximum loss that is likely to occur in the remaining 5% of cases. The static VaR and the dynamic VaR of the coke series showed a significant difference, implying the significant effect caused by the heteroskedasticity and the thick tail distribution. Since there were almost no outliers below the line, the market risk exposed to coke yield was not out of control. As to the hydroelectric fuel yield, although more outliers appeared under the dynamic VaR line, they only experienced a minor drop compared to the normal level. In contrast, the frequency of the outliers of the unleaded gasoline (89#) yield increased dramatically after the outbreak, raising the uncertainty in the petroleum energy market. It suggests that the extreme event

COVID-19, while not affecting the level of VaR, increased the tail risk in the energy market. Just like a Black Swan event, it did not make a significant change in the magnitude of conventional losses, but exacerbated the instability of the energy market, raising the possibility of massive losses in investment.

With the ARIMA-GARCH model, the yield values for the coming year can be predicted. Take the monthly yield of coke as an example. We estimate the average level of monthly yield in 2021 by the ARMA (2, 2) model and apply the GARCH (1, 1) model to predict the future variance of the monthly yield series. Combined with the quantiles of t-distribution, the confidence interval of the future yield estimate with a confidence level of 0.95 can be acquired. According to the prediction results displayed in Figure 5, the coke yield will hover around 0 with certain volatility in 2021, which means coke prices would be relatively stable. Despite optimistic forecasts, it is essential to invest cautiously in case the outliers pose an adverse shock to enterprises in this particular context.

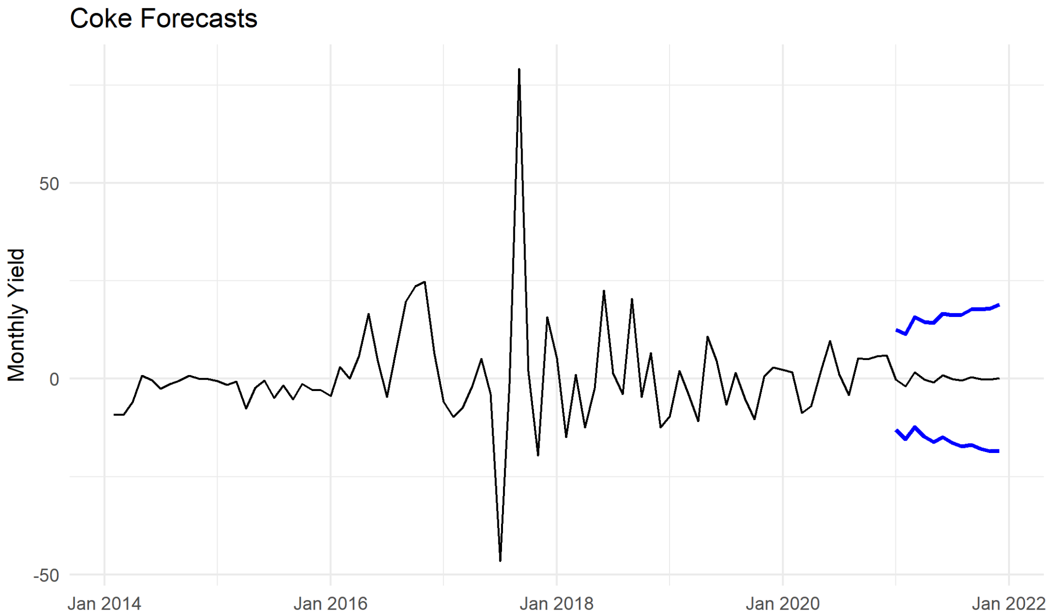

Figure 5. Coke yield forecast in 2021. Blue lines represent the upper and lower limits of the 95% confidence interval.

Notably, the response of the three energy price yields to the pandemic storm is different, which can be explained by the energy demand difference and the special pricing mechanism in China. Due to the lockdown policy, people were forced to stay at home, resulting in an increasing demand for electricity consumption. In China, the hydroelectricity resource is abundant to provide a sufficient supply (Penghao et al., 2019). The balance of supply and demand and the government's regulatory role in pricing contributed to minimal fluctuations in electricity prices.

To curb the spread of the COVID-19, factories experienced a shutdown for operations, causing a reduction in coal demand. However, considering the outbreak was close to the Chinese New Year, at which time the coal demand was already at a low level, the pandemic impact was not obvious. As lockdowns keep going, a decrease in coal prices is expected in the future, which requires the government to take regulation measures. Unlike the coal and electricity prices, the petroleum price was deeply influenced by the epidemic. Undoubtedly, with less usage of public transportation such as road or air transportation, the dramatic drop in petroleum demand was the major reason. Besides, the pricing mechanism also accounted for market conditions. On the one hand, compared to the other two energy prices, the petroleum pricing has established a closer interaction with the market, thus exhibiting greater volatility. On the other hand, the regulation measures by the government may induce a delayed and long-lasting response to external shocks (Chen and Sun, 2021). In the post-epidemic era, petroleum prices could experience a more dramatic decline.

5.2. Impact of energy price volatility on main macroeconomic indicators

The epidemic has exacerbated the instability of energy prices. As an important input source in the production chain, energy is likely to significantly affect national economic development. Since there are fewer observations of the coke series and the price of hydroelectric fuel is regulated by the government, this study mainly takes the growth rate of unleaded gasoline (89#) price to represent the energy price situation. Utilizing the GDP growth rate and CPI growth rate to measure the economic growth situation and inflation situation respectively, the Vector Autoregressive (VAR) model is constructed to investigate their interactions.

Combining the results of AIC, SC, and other criteria, the VAR (1) model is built under the principle of lower order priority. After the parameter estimation, the model can be written as

$$\begin{cases} \mathrm{GDP_t} = 2.21 + 0.76\mathrm{GDP_{t-1}} - 0.13\mathrm{CPI_{t-1}} - 0.02\mathrm{Oil_{t-1}} \\ \mathrm{CPI_t} = -1.11 + 0.21\mathrm{GDP_{t-1}} + 0.79\mathrm{CPI_{t-1}} - 0.03\mathrm{Oil_{t-1}} \\ \mathrm{Oil_t} = -5.93 + 0.6\mathrm{GDP_{t-1}} + 0.49\mathrm{CPI_{t-1}} + 0.64\mathrm{Oil_{t-1}} \end{cases} \tag{11}$$

To make sure the stability of the model parameters, the cumulative sum of the residuals curve is plotted to aid in the judgment. As shown in Figure 6, the cumulative sum of residuals for the corresponding parameters of the three variables do not exceed the critical line, indicating that the model results are stable and the subsequent analysis is of significance.

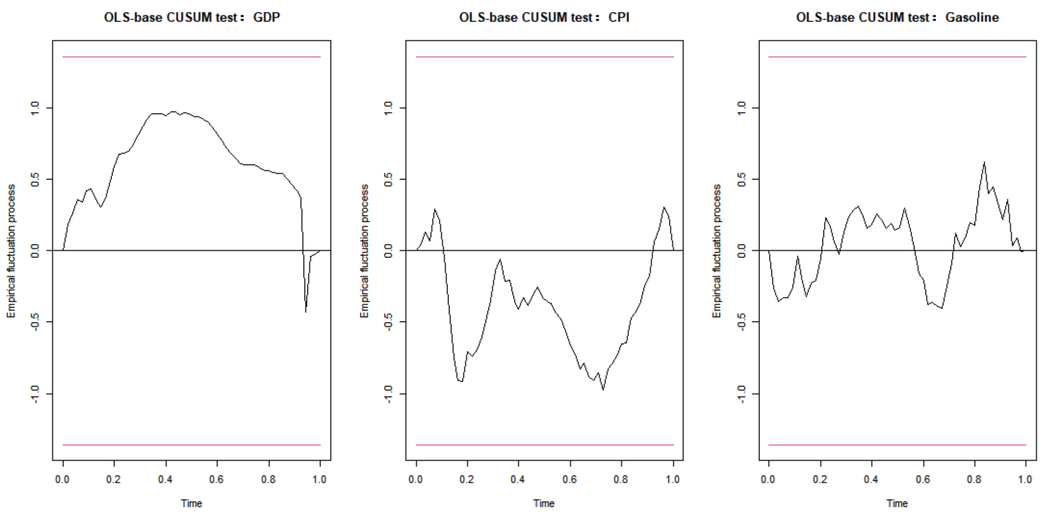

Figure 6. The cumulative sum of residuals curve for VAR (1) model for the growth rate of GDP, CPI and unleaded gasoline (89#) (from left to right).

In order to confirm that changes in energy prices cause economic fluctuations to some degree, the

Granger causality test is employed to explore whether a causal relationship holds in a statistical sense. Since the corresponding p-value of the test is 0.034, the growth rate of unleaded gasoline (89#) price is the Granger cause of GDP and CPI growth rate, which means the gasoline price volatility would affect the growth rate of main macroeconomic indicators.

In addition, we adopt impulse response analysis and variance decomposition to evaluate the magnitude of the impact. Impulse response analysis provides a way to know how the growth of GDP and CPI would change when a positive shock from energy prices is applied on the random error term. Figure 7 clearly illustrates that a positive shock from the unleaded gasoline (89#) price would cause a small reverse change in the GDP growth rate, which becomes a small positive change within a short period and then dissipates to zero at around 20 days. As a comparison, the CPI growth rate, under the influence of a positive energy price shock, shows a large reverse change and also tends to zero at around 20 days.

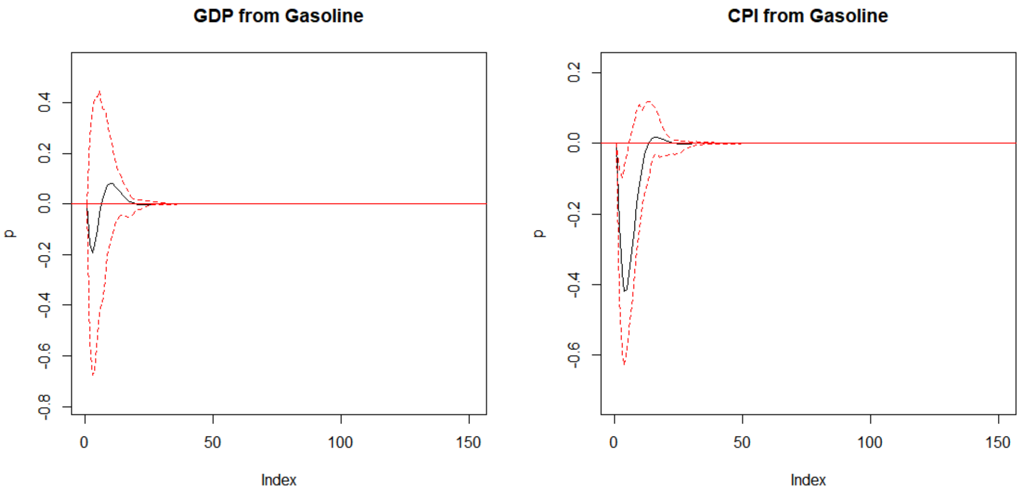

Figure 7. Results of impulse response analysis for the growth rate of GDP and CPI (from left to right) when a positive shock from the unleaded gasoline (89#) price is applied on the random error term. Red lines represent the upper and lower limits.

With the help of the variance decomposition, people could effectively understand the extent to which energy price fluctuations contribute to the predicted variance of GDP and CPI. Figure 8 displays the results of the variance decomposition, which implies that the contribution of unleaded gasoline (89#) price fluctuations gradually increase in a short period of time and stabilizes at about 20 days. What's more, the contribution to GDP growth is low at about 1.4%, while the contribution to CPI growth is high, reaching about 20%.

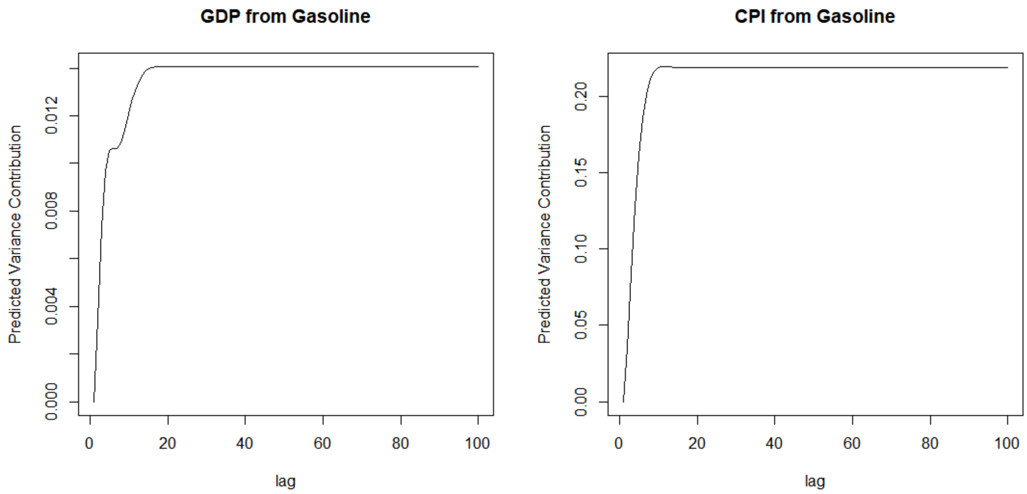

Figure 8. Results of variance decomposition for the growth rate of GDP and CPI (from left to right) when a positive shock from the unleaded gasoline (89#) price is applied on the random error term.

It is noteworthy that the model results imply that changes in energy prices cause an inverse movement in the CPI, which deviates from traditional economic theory. Generally, they will move in the same direction. An increase in energy prices, especially oil prices, will lead to higher input costs, which forces companies to pass on part of their costs to consumers, raising the price of products and causing inflation. The reason for this conclusion, which conflicts with common sense, is most likely associated with the COVID-19. Since the outbreak of the epidemic, production activities have been severely restricted. Various products have experienced varying degrees of imbalance in supply and demand, with food products being particularly notable. Excessive demand and insufficient supply led to rapid growth in food prices, which pushed the CPI up significantly. In addition, there was also an imbalance between supply and demand for energy products, but mainly in the form of a considerable demand reduction. Due to the blockade caused by the epidemic, the public transportation and tourism sectors sharply reduced their energy consumption demand, triggering a decline in energy prices. As a result, it led to an unusual inverse movement of the CPI and energy prices.

According to the above analysis, the volatility of energy prices caused by the epidemic will have a short-term impact on economic growth and inflation, with a higher contribution to the latter changes. Based on the forecast using the VAR (1) model, the GDP growth rate will gradually recover from the negative growing state to steadily positive. Since the growth rate of CPI and unleaded gasoline (89#) price indicate an ascending trend, certain inflation may occur. Therefore, the economic impact of energy fluctuations caused by the epidemic will remain, requiring the government to take appropriate precautions against possible recession and inflation.

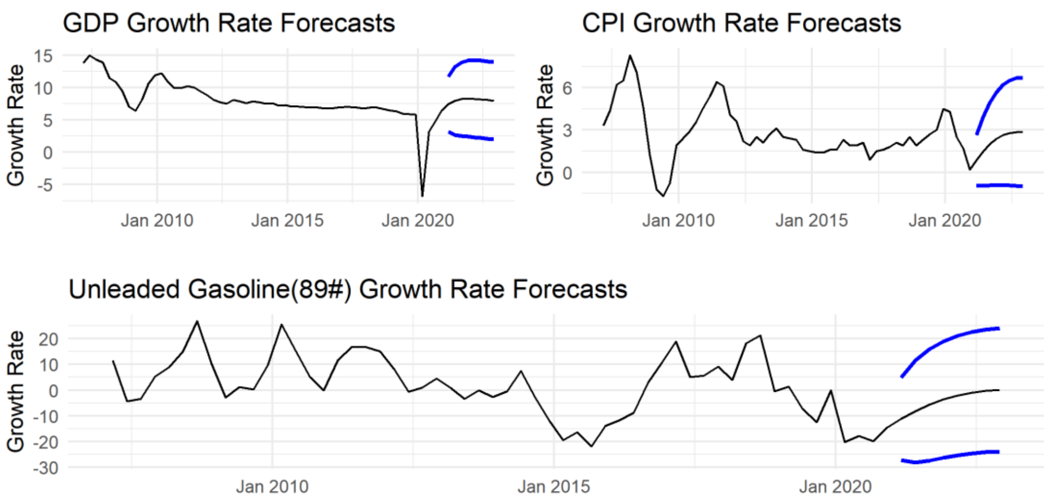

Figure 9. Growth rate forecast for the next 2 years for the growth rate of GDP, CPI and unleaded gasoline (89#) (from left to right, from top to bottom). Blue lines represent the upper and lower limits of the 95% confidence interval.

In section 5, we found that due to the occurrence of COVID-19, there was an increase in the risk in the energy market. Moreover, the pandemic shock also slowed economic growth and raised the potential for inflation emergence. To help the economy come back to normal, the primary task is to curb the pandemic spread and promote vaccination. Additionally, the government can formulate certain policies to optimize the structural configuration of the energy market. For example, during the 14th Five-Year Plan period, China issued policies related to the energy transition and renewable energy development, improving the efficiency of energy use and lower energy costs and eliminating the adverse effects caused by energy price fluctuations. At the same time, in order to cope with the energy price shock, appropriate fiscal stimulus policies can be implemented to boost energy consumption. On the premise that the epidemic is under control, it is necessary to take measures to resume work and production in an orderly manner, pulling up energy demand. What's more, in order to stabilize the energy supply, energy enterprises need to be given substantial assistance to resume normal operations as soon as possible. Although the sudden outbreak of the COVID-19 pandemic has brought a rare adverse impact to the energy industry in history, with the efforts of the government and enterprises, economic development will get back on track.

6. Conclusions and future works

This paper focuses on the impact of the occurrence of the COVID-19 on energy price yields, and the consequential effects on main macroeconomic indicators. Based on the ARIMA-GARCH model, this paper calculates the dynamic VaR of the energy price yield series to estimate the energy market risk. The response to the pandemic shock varies across different energy types, which can be attributed to the energy demand and pricing mechanism difference. Due to the regulatory role of the Chinese government, the dynamic Value-at-Risk remained stable at normal levels. However, the appearance of outliers far below the VaR line indicated an increase in the tail risk of energy prices and the dramatic turbulence in energy markets, especially for the petroleum market. In the particular context, the government is suggested to pay more attention to those energy types with more demand reduction and less regulation in pricing. And enterprises should invest prudently after taking into full consideration their asset size, asset and liability levels, and actual financing capacity to avoid extreme losses effectively.

Another focus of this research is how main macroeconomic indicators are affected when energy prices fluctuate. According to the Granger causality test results, there is an interaction between energy price volatility and main macroeconomic indicators. The impulse response analysis and variance decomposition results suggest that energy price fluctuations caused by the COVID-19 have a short-term impact on economic growth and inflation for about 20 days, with a higher contribution to the latter changes. Since energy prices are still at low levels at present, there will be minor fluctuations in economic growth and slight inflation in the future.

In conclusion, the epidemic has generated a negative impact on the energy market and economic development. To increase the energy demand and recover the economic development, the government should make efforts to control the pandemic spread and resume production activities.

As the COVID-19 continues to strike a blow to the economic development and tends to produce more complex variants, we will conduct an ongoing study on the long-term impact in the future. We will also consider using more frequent data and applying the state-of-the-art models to gain more reliable insights.

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Conflicts of interest

All authors declare no conflicts of interest in this paper.

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