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ORIGINAL PAPER

Factors affecting the pilot trading market of carbon emissions in China

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Abstract
Climate change and carbon emissions are major problems which are attracting worldwide attention. China has had its pilot carbon emission trading markets in seven regions for more than 3 years. What affects carbon emission trading market in China is a big question. More attention is paid to how China promotes the carbon emission trading schemes in the whole country. This paper addresses concerns about the functioning of carbon emission trading schemes in seven pilot regions and takes the weekly data from November 25, 2013, to March 19, 2017. We employ a vector autoregressive model to study how coal price, oil price and stock index have affected the carbon price in China. The results indicate that carbon price is mainly affected by its own historical price; coal price and stock index have negative effects on carbon price, while oil price has a negative effect on carbon price during the first 3 weeks and then has a positive effect on carbon price. More regulatory attention and economic measures are needed to improve market efficiency, and the mechanisms of carbon emission trading schemes should be improved.

Keywords Carbon emission trading market · Carbon price · VAR model · China

1 Introduction

China is the largest carbon emitter contributing 27.3% of the world's total in 2015, while its coal consumption is 50.0% and oil consumption is 12.9% of the world's total (BP 2016). According to BP, China's carbon emissions rose from 489 Mt in 1965 to 9154 Mt in 2015. Meanwhile the nation's consumption of oil and coal rose from 11.0 and 114 Mt in 1965 to 560 and 1920 Mt in 2015, respectively. As Fig. 1 shows, we can see that oil consumption, coal consumption and carbon dioxide emissions have similar increasing trends from 1965 to 2015.

The National Development and Reform Commission issued a "Notice on starting the national carbon emission trading market" and pointed out that it would start the national carbon emission trading market and ensure its implementation of carbon emission trading system in 2017. China's pilot carbon emission trading programs began operating in the second half of 2013 in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen (Zeng et al. 2017) The carbon emission trading schemes in 7 regions in China marked a watershed in the history of Chinese climate policy (Ren and Lo 2017; Tan and Wang 2017). At the end of 2015, the cumulative turnover in seven pilot carbon trading markets was nearly 80 million tons and the cumulative payment was more than 2.5 billion RMB (Zhou et al. 2016). These pilot experiences laid a good foundation for the establishment of China's carbon emission trading market. Compared to the international emissions trading market, China's is currently in its initial stage and has some significant problems including unreasonable carbon price and imperfect carbon emission trading mechanisms (Zeng et al. 2017). Therefore, a study of the carbon trading market has become necessary. How to rationalize the pricing of various products in the carbon market is the key to the normal operation of the whole market. It is important to study the factors influencing carbon price in China's carbon trading pilot and promote the rational pricing of China's carbon trading schemes.

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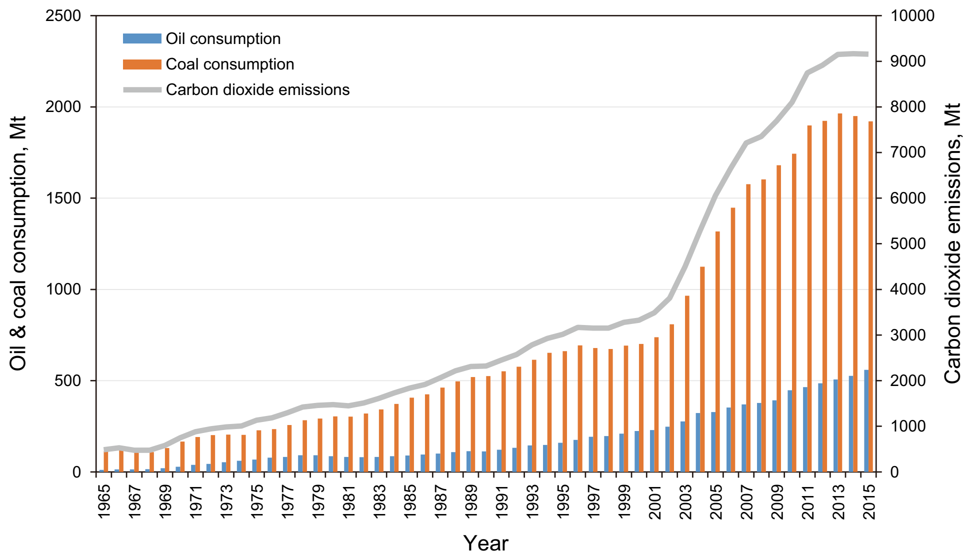

Fig. 1 Oil consumption, coal consumption and carbon dioxide emissions in China from 1965 to 2015

This paper is structured as follows: a review of the relevant literature is presented in Sect. 2. Section 3 introduces the study's methodology and data sources. Section 4 discusses the empirical results and analysis. Conclusions and policy implications are presented in Sect. 5.

2 Literature review

Scholars have done extensive research on the factors influencing carbon price in emission trading system in European Union (ETS EU), mainly from the perspectives of the relationship between macroeconomic markets and energy price.

2.1 The relationship between carbon price and the stock market

From a macroperspective, some studies have analyzed how economic activities affected carbon emission trading. Chen et al. (2016) analyzed the effect of industrial economic activities on carbon price in China and finds a significant relationship between industrial economic activities and carbon price. Wang and Lu (2015) focused on the differences in the 6 pilot regions and found that the macroperspective has a positive effect on carbon price. Chevallier (2009) identified several macroeconomic drivers of European Union Allowances (EUA) prices. Economic activity and financial market shocks have been revealed to be among the fundamental drivers of carbon prices (Segnon et al. 2017). Bredin and Muckley (2011) reported a significant correlation between carbon prices and stock prices and an index of industrial production. It appears from these and related studies that the influence of compliance and the large list of potential fundamentals makes the carbon market more complex than other commodity markets and explains the significant attention that is paid to this market (Ellerman and Buchner 2007; Convery and Redmond 2007; Chevallier 2013; Zhang and Wei 2010), especially for an accurate review on the carbon price development in the EU ETS and its operating mechanism and economic effect. Alberola et al. (2008a, b, c), Chevallier (2009) and Alberola and Chevallier (2009) had analyzed in detail the effects of institutional decisions (the emissions shortfall factor and banking restrictions) on the price path of carbon. Chevallier (2012) studied how banking instruments can be used to manage the stock of allowances in the European Union Emissions Trading Scheme (EU ETS).

2.2 The relationship between carbon price and energy price

Many studies have focused on the role of energy prices (oil, gas, coal and electricity prices) in the determination of carbon prices. Examples include Christiansen et al. (2005), Mansanet-Bataller et al. (2007), Bunn and Fezzi (2009), Kim and Koo (2010), Hintermann (2010), Keppler and Mansanet-Bataller (2010), Bredin and Muckley (2011), Mansanet-Bataller et al. (2011), Creti et al. (2012), Aatola et al. (2013) and Hammoudeh et al. (2014a, b). In all these papers, the authors find a strong relationship between energy prices and the price of EUA (Bunn and Fezzi 2009; Keppler and Mansanet-Bataller 2010; Mansanet-Bataller et al. 2011). Chen et al. (2016) focused on the impact of energy prices on the carbon trading market and found that coal prices have a strong effect on carbon price. Kanen

(2006) studied the effects of the prices of oil, gas and electricity and found that oil, gas and electricity prices have a positive effect on the carbon price. Mansanet-Bataller et al. (2007) used multiple regression to study the relationship between carbon price and prices of gas and crude oil and found that the energy price has a positive effect on carbon price. Alberola et al. (2008a, b, c) used structural vector autoregression (SVAR) analysis to analyze the energy price affecting the EUA and found that energy price is the main driver of EUA in the first period. Wei et al. (2008) suggested that the energy price is in equilibrium with carbon price for the long term and the magnitudes of influencing factors are different. Kanamura (2016) investigated the volatility structure and dynamic linkage between two carbon prices and found energy price had stronger effect on EUA prices than sCER prices using a mean-reverting log normal process for energy prices.

Zhang (2015) used the theory of equilibrium price and found that a co-integrating relationship exists between the carbon price and market fundamentals. More specifically, economic environment is significant, but the impact of energy prices does not have the same conclusion pending further examination, unexpected events bring shocks to the carbon price and even lead to suspension of trading. Tan and Wang (2017) focused on the quantile-based dependence and influence paths between European Union allowance (EUA) and its drivers (energy prices and macroeconomic risk factors) during the three phases of the European Union Emissions Trading Scheme (EU ETS) and showed that the reaction in fluctuation in carbon price in relation to its drivers across its conditional distribution in different phases is highly heterogeneous. Fan et al. (2017) used the event study method to assess the impacts of different policy adjustments on the EUA returns in the European Union Emissions Trading Scheme (EU ETS) since 2005. Some papers have investigated the relationship between carbon emission spot and futures prices. For example, Arouri et al. (2012) employed vector autoregressive (VAR) models to investigate the dynamic relationships between the EU Emission Allowances (EUA) spot and futures prices during phase II.

Since the market for European Union Allowances (EUAs) was launched on January 1, 2005, it has become by far the largest market for CO_2 emissions worldwide. Empirical studies of price formation in the carbon market are almost exclusively based on data collected for EUAs. A large number of studies have investigated factors that may affect the carbon price in the European Union Emissions Trading Scheme (EU ETS). However, less attention has been paid to modeling the carbon price in China, and few studies have investigated factors affecting the carbon price in China although there is the pilot experiment of 7 regions for a carbon emission trading. Therefore, to fill this research gap, we use the VAR model with a pulse response function and a variance decomposition technique to understand the effects of carbon price and we also study the degrees to which these factors affect the carbon price so that we can provide a decision-making basis for national policy makers.

3 Methodology and data sources

3.1 VAR model

The VAR (vector autoregressive) model as proposed by Sims (1980) is an alternative to large-scale macroeconometric models and does not rely on ''incredible'' identifying assumptions. It takes the form of multiple simultaneous equations, and the endogenous variables in each equation form a regression with the lagged values of all endogenous variables to estimate the dynamic relationships between all the endogenous variables. Moreover, it allows us to consider both long-run restrictions and short-run restrictions justified by economic considerations (Magkonis and Tsopanakis 2014). Consequently, we employ the VAR model to study how coal price, oil price and stock index have affected carbon price in China. The VAR model is constructed using the statistical properties of the data. The mathematical expression of the general VAR model is as follows:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + \varepsilon_t \quad t = 1, 2, \ldots, T \tag{1}$$

where y_t, $t = 1, 2,\ldots T$, is a $K \times 1$ time series vector and A is a $K \times K$ parametric matrix. x_t is an $M \times 1$ vector of exogenous variables, and B is a $K \times M$ coefficient matrix to be estimated. ε_t represents the random error term.

In the formula (1), the endogenous variable has a lag period (p), so it can be called a VAR (p) model which can fully reflect the dynamic characteristics of the constructed model. However, the longer the lag period is, the less freedom the parameters need to be estimated. Therefore, it should be necessary to seek a balance between the lag periods and the freedom. When the Schwarz criterion (SC) and Akaike information criterion (AIC) (Sims 1980) are the lowest, we get suitable lag periods. The formulas of these two statistics are expressed as follows:

$$\mathrm{AIC} = -\frac{2l}{n} + \frac{2k}{n} \tag{2}$$

$$\mathrm{SC} = -\frac{2l}{n} + k\frac{\ln n}{n} \tag{3}$$

where $k = m\ (qd + pm)$ represents the number of parameters to be estimated. n is the sample size and meets the following formula:

$$1 = -nm(1 + \ln 2\pi)/2 - n \ln \left[\det \left(\sum_t \hat{\varepsilon}_t \hat{\varepsilon}_t' / n \right) \right] \Big/ 2. \quad (4)$$

3.2 Data sources

According to an analysis of the literature, this paper selects the carbon price as the dependent variable and assumes that the carbon price (PC) is mainly affected by the coal price (COAL), oil price (OIL) and the stock price. This paper selects the data sample interval of November 25, 2013, to March 19, 2017, based on daily data transformed into weekly data. The carbon price is derived from the official website (www.tanpaifang.com). China's pilot carbon emission trading programs began operating in the second half of 2013 in 7 regions. Compared to the international emissions trading market, China's carbon emission trading market is in its initial stage and has some significant problems (Zeng et al. 2017). This paper uses the average carbon price of 7 regions as the variable of carbon price. The oil price is from the statistics of the EIA (www.eia.org). This paper selects the Qinhuangdao coal price as the coal price used, which is obtained by the official coal market website (www.cctd.com). The stock price of the Shanghai Composite Index is from the Shanghai Stock Exchange (www.sse.com.cn). In order to eliminate the heteroskedasticity possibly existing in the model and facilitate hypothesis testing, all the factors take logarithmic form.

4 Results and discussion

4.1 Unit root test

We should check whether a sequence is stationary using a unit root test. This paper uses the Augmented Dickey–Fuller (ADF) (Dickey and Fuller 1979) test which can avoid the effects of higher-order serial correlation when a lagged difference term of the dependent variables is added into the regression equation. The unit root test lag length is determined by the Schwarz information criterion (SIC). The ADF unit root test results in Table 1 suggest that the variables are not all a stationary sequence, but their first-order difference is a stationary sequence. Therefore, PC, COAL, OIL and STOCK are all integrated of order 1.

4.2 Co-integration test

In this paper, the trace statistic and maximum eigenvalue test are used to determine whether there is a co-integration relationship. The results of co-integration tests between PC, COAL, OIL and STOCK are presented in Tables 2 and 3. As we can see, a co-integration relationship exists between the PC and COAL, OIL and STOCK.

4.3 VAR model

4.3.1 Optimal lag order analysis

The explanatory power is weak when the lag period is long. In this paper, lags of 1–6 are selected as a result of the logarithmic likelihood ratio (LogL), AIC, SC, sequential modified LR test statistic (lR), FPE (final prediction error) and HQ (Hannan–Quinn) information criterion, as shown in Table 4. We find that the lag of 3 is the best, and we select the lag of 3.

4.3.2 VAR estimates and stability tests

Based on the unit tests and the co-integration tests, there is a co-integration relationship between PC and COAL, OIL and STOCK. Therefore, the VAR model can be estimated using the AIC and SC criteria. The vector autoregression estimates are indicated in Table 5. Figure 2 shows that the characteristic roots are less than 1 and lie inside the unit circle which indicates that the model satisfies the stability condition.

4.3.3 Impulse response functions

As observed in Fig. 3, COAL has a negative response to PC; OIL has a negative response to PC value fluctuation in the short term but then gets a stable positive response in the long term; STOCK shows a negative response. When a standard deviation innovation is attached to carbon price in China, OIL responds to it in two directions. In the first period, OIL has a negative effect on PC. By contrast, from the second to the fourth period, the positive response turns into a constant positive response.

4.4 Variance decomposition

The variance decomposition results are shown in Table 6. We can see that carbon price changes as the variance contribution gradually decreases, from 97.6% to 80.1% from the 1st period to the 20th period. The carbon price is mainly affected by its own historical price. The contribution of coal price to the carbon price increases from 2.02% to 4.83% at the first 4th period and then drops to 3.09% from 5th period to the 11th period, and increases to 5.41% in the 20th period. The contribution rate of oil price fluctuates during the periods to this analysis, but the contribution rate is very small and it becomes steady near 0.35%.

Table 1 Results of the unit root test

Variables	1% Critical value	5% Critical value	10% Critical value	t statistic	Prob.
Levels					
PC	− 3.469	− 2.878	− 2.576	− 2.867	0.051
COAL	− 3.469	− 2.878	− 2.576	− 1.422	0.571
OIL	− 3.469	− 2.878	− 2.576	− 1.432	0.565
STOCK	− 3.469	− 2.878	− 2.576	− 1.490	0.537
First difference					
PC	− 3.469	− 2.878	− 2.576	− 10.423	0.000
COAL	− 3.469	− 2.878	− 2.576	− 6.089	0.000
OIL	− 3.469	− 2.878	− 2.576	− 10.078	0.000
STOCK	− 3.469	− 2.878	− 2.576	− 9.874	0.000

Table 2 Unrestricted co-integration rank test (trace)

Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	5% Critical value	Prob.[b]
None[a]	0.142	42.045	40.175	0.032
At most 1	0.066	16.015	24.276	0.379
At most 2	0.023	4.406	12.321	0.652
At most 3	0.003	0.440	4.130	0.570

Trace test indicates 1 co-integrating eqn(s) at the 5% level

[a]Rejection of the hypothesis at the 5% level

[b]MacKinnon–Haug–Michelis (1999) p values

Table 3 Unrestricted co-integration rank test (maximum eigenvalue)

Hypothesized no. of CE(s)	Eigenvalue	Max eigen statistic	5% Critical value	Prob.[b]
None[a]	0.142	26.030	24.159	0.028
At most 1	0.066	11.609	17.797	0.331
At most 2	0.023	3.965	11.225	0.634
At most 3	0.003	0.440	4.130	0.570

Max eigenvalue test indicates 1 co-integrating eqn(s) at the 5% level

[a]Rejection of the hypothesis at the 5% level

[b]MacKinnon–Haug–Michelis (1999) p values

Table 4 Lag selection criteria for carbon price

Lag	LogL	LR	FPE	AIC	SC	HQ
0	193.780	NA	1.21E−06	− 2.272	− 2.198	− 2.242
1	1423.373	2385.558	5.90E−13	− 16.807	− 16.433[a]	− 16.655
2	1458.694	66.834	4.68E−13	− 17.038	− 16.366	− 16.765[a]
3	1478.098	35.788[a]	4.50e−13[a]	− 17.079[a]	− 16.108	− 16.685
4	1487.859	17.536	4.86E−13	− 17.004	− 15.735	− 16.489
5	1492.969	8.933	5.55E−13	− 16.874	− 15.305	− 16.237
6	1501.653	14.769	6.08E−13	− 16.786	− 14.919	− 16.028

[a]Lag order selected using the criterion

The contribution rate of stock price increases from 0.01%, and it gets its peak of 14.1% in the 20th period. We can draw the conclusion that carbon price is predominately influencing itself and the contribution rate surpasses 80%. The influence of oil price is very small. The coal and stock price have a similar impact on carbon price, and stock price will have greater impact on carbon price than coal price.

Table 5 Vector autoregression estimates

	COAL	OIL	PC	STOCK
COAL(-1)	1.464	− 0.040	− 0.194	− 0.086
	− 0.076	− 0.174	− 0.149	− 0.139
	[19.331]	[− 0.232]	[− 1.301]	[− 0.622]
COAL(-2)	− 0.776	− 0.194	0.257	− 0.111
	− 0.123	− 0.282	− 0.242	− 0.226
	[− 6.313]	[− 0.689]	[1.061]	[− 0.490]
COAL(-3)	0.315	0.259	− 0.024	0.222
	− 0.077	− 0.175	− 0.151	− 0.141
	[4.118]	[1.477]	[− 0.157]	[1.580]
OIL(-1)	− 0.038	1.195	− 0.041	0.016
	− 0.035	− 0.079	− 0.068	− 0.064
	[− 1.097]	[15.052]	[− 0.599]	[0.253]
OIL(-2)	0.060	− 0.256	0.107	− 0.046
	− 0.053	− 0.122	− 0.105	− 0.098
	[1.136]	[− 2.098]	[1.024]	[− 0.471]
OIL(-3)	− 0.017	− 0.004	− 0.069	0.022
	− 0.034	− 0.077	− 0.066	− 0.062
	[− 0.511]	[− 0.046]	[− 1.036]	[0.351]
PC(-1)	− 0.077	− 0.0818	1.210	0.003
	− 0.039	− 0.090	− 0.077	− 0.072
	[− 1.958]	[− 0.909]	[15.638]	[0.039]
PC(-2)	0.135	0.111	− 0.557	− 0.184
	− 0.059	− 0.135	− 0.116	− 0.108
	[2.299]	[0.829]	[− 4.818]	[− 1.704]
PC(-3)	− 0.085	0.004	0.285	0.168
	− 0.038	− 0.087	− 0.075	− 0.070
	[− 2.232]	[0.050]	[3.795]	[2.393]
STOCK(-1)	− 0.009	− 0.136	− 0.016	1.264
	− 0.042	− 0.097	− 0.083	− 0.078
	[− 0.209]	[− 1.405]	[− 0.188]	[16.220]
STOCK(-2)	− 0.020	0.211	0.088	− 0.390
	− 0.067	− 0.153	− 0.131	− 0.123
	[− 0.306]	[1.382]	[0.673]	[− 3.176]
STOCK(-3)	0.008	− 0.113	− 0.114	0.097
	− 0.042	− 0.098	− 0.084	− 0.079
	[0.190]	[− 1.151]	[− 1.358]	[1.236]
C	0.222	0.288	0.307	0.160
	− 0.109	− 0.249	− 0.214	− 0.200
	[2.042]	[1.157]	[1.433]	[0.801]
R^2	0.990	0.989	0.987	0.981
Adj. R^2	0.990	0.988	0.986	0.980
Sum sq. resids	0.049	0.258	0.190	0.166
SE equation	0.018	0.041	0.035	0.033
F-statistic	1352.091	1125.277	974.879	674.333
Log likelihood	451.459	310.553	336.389	347.759
Akaike AIC	− 5.158	− 3.501	− 3.805	− 3.938
Schwarz SC	− 4.919	− 3.261	− 3.565	− 3.699
Mean dependent	6.143	4.052	3.406	7.974
SD dependent	0.174	0.364	0.292	0.227

Standard error is shown in parentheses, and *t* statistics are in parentheses

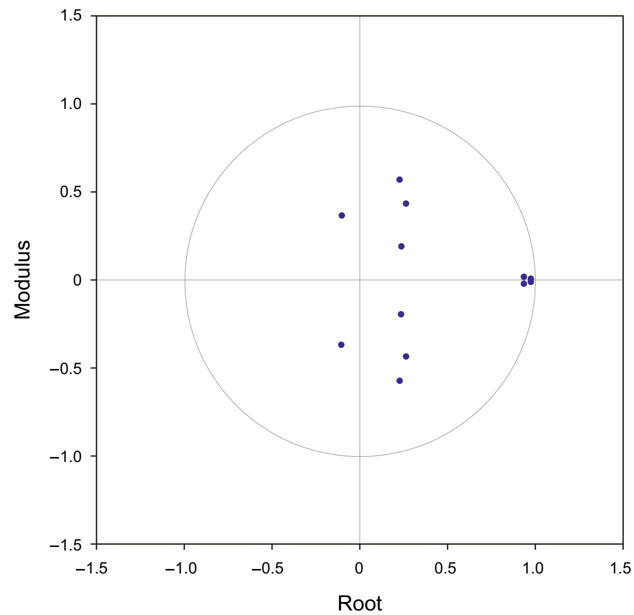

Fig. 2 VAR roots of characteristic polynomial. *Note*: blue dots indicate characteristic roots

5 Conclusions and policy implications

This study attempts to examine empirically the factors influencing carbon price in China using weekly data over the 2013–2017 period. Before testing the relationship among variables within a VAR system, a co-integration analysis is conducted. The results show that there is a long-term equilibrium relationship among carbon price, coal price, oil price and stock index.

(1) Carbon price is negatively correlated with the price of coal price because coal is a non-clean energy source and a rise in coal price will cause the enterprises to reduce their use of coal, and furthermore, the carbon price will decrease for reducing the demand of the use of coal. Meanwhile, the enterprises transform their uses of coal to oil and gas so that the oil price will increase as the carbon price rises.

(2) The contribution rate of oil price fluctuates during the periods, and the contribution rate is very small, and it becomes steady near 0.35%. That is to say, the

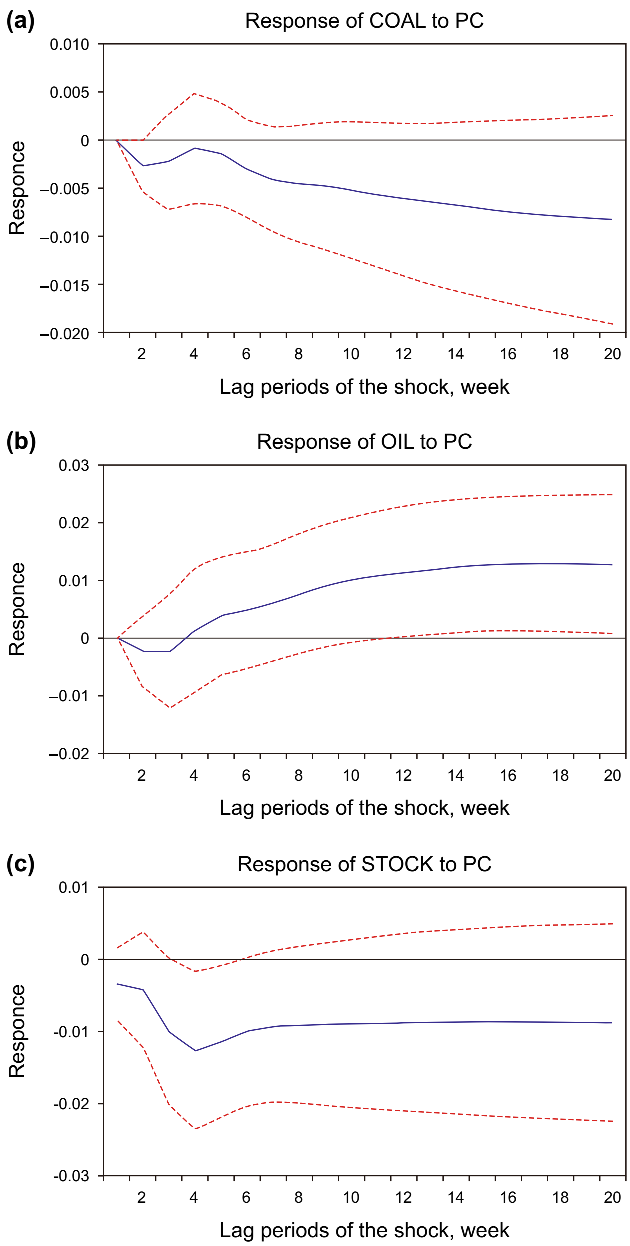

Fig. 3 Responses of COAL, OIL and STOCK to PC. The solid lines indicate mean responses to a one-standard deviation shock, while the dotted lines represent ± 2 standard deviations of the responses

oil price has a slight and unstable effect on carbon price. The oil price decreases in the first three periods and then rises. The oil price has a positive effect on the carbon price. That is to say, when the carbon price rises, the enterprises transform their use of coal to oil sources and this increases the oil price. Furthermore, the government encourages the enterprises to utilize cleaner sources or renewable sources. In contrast, a rise in the oil price will lead to more use of coal and promote an increase in carbon price.

(3) Stock price has a negative effect on carbon price. Stock price rises when the economy is getting better. However, China's stock market is more affected by interest rate policy and capital costs. The stock index shows the opposite factor of the real economy. Therefore, the stock price has a negative impact.

From a policy perspective, our findings highlight that energy prices and macroeconomic risk factor variations have significant but different influences on carbon price. Moreover, only oil price has a positive effect on the carbon price. Thus, close but unstable dependences of coal price and macroeconomy have decreased the complexity of carbon price volatility regulation. China has established a national carbon emission trading market since 2017, and it has been predicted that the scale of this market will reach one trillion RMB after 2020. The establishment of this national carbon emissions trading market will help the carbon price to become more market-oriented, which will facilitate essential future research into the mechanisms of price fluctuation and the factors that influence the price of carbon emissions price in China (Zeng et al. 2017). To promote the carbon emission trading market at the national level, the government may establish market-oriented regulations and enhance low carbon development to make sure that the carbon emission trading market is efficient. Meanwhile, the government policymakers should strengthen macrocontrol of the macroeconomy and energy market.

Energy pricing reform plays a decisive role in China's low carbon transition. On one hand, rapid economic growth requires sufficient and cheap energy; on the other hand, large incremental energy demand would unavoidably make emissions reduction more difficult and costly (Ouyang and Lin 2017). Energy price is a key factor affecting clean energy development. Energy pricing reform makes the market more competitive. The government should establish the inspection of the carbon emission trading market and increase the carbon emission credits to encourage enterprises to cut carbon emissions and trade in the carbon emission trading market. The investors should pay more attention to energy pricing reform such as coal price and oil price. As for the investors, the volatility of macroeconomic risk factors can be used to forecast the volatility of carbon price up to a certain extent. When the carbon price is high, a rise in stock index can lead to an increase in carbon price. In addition, the investors should take price-induced energy-saving innovation and technology advancement in reducing the carbon content in each unit of goods production to reduce the cost of the carbon price. Furthermore, the investors should pay more attention to renewable energy such as geothermal energy (Jiang et al. 2016) and carbon

Table 6 Variance decomposition of PC

Period	COAL	OIL	PC	STOCK
1	2.018	0.334	97.648	0.000
2	3.727	0.152	96.112	0.009
3	4.812	0.272	94.828	0.088
4	4.830	0.512	94.523	0.135
5	4.506	0.602	94.763	0.129
6	4.144	0.592	95.013	0.251
7	3.804	0.559	95.127	0.510
8	3.509	0.529	95.086	0.876
9	3.286	0.504	94.853	1.357
10	3.146	0.480	94.397	1.977
11	3.082	0.457	93.718	2.743
12	3.092	0.436	92.827	3.645
13	3.178	0.418	91.737	4.667
14	3.338	0.401	90.464	5.797
15	3.566	0.386	89.024	7.024
16	3.852	0.372	87.440	8.336
17	4.188	0.361	85.735	9.716
18	4.565	0.351	83.932	11.152
19	4.975	0.343	82.053	12.629
20	5.411	0.336	80.121	14.132

capture, utilization and storage to cut carbon emissions to promote a cleaner society.

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