A Study on Predicting Coal Market Price in China Based on Time Sequence Models

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Abstract

Coal is the life-blood of the Chinese economy and is crucial to China's energy consumption and economic growth. Since January 1, 2002, China has canceled governmental controls on coal prices and adopted the market-oriented price-setting mechanism for electric coal management. Therefore, developing a long-term and accurate coal price forecast is a major challenge for policymakers to plan future energy consumption mix and to make investment decisions in China in the market era. This paper applies time sequence models to study the characteristics of time data with time variation by historical data to predict coal price. The study uses the closing price of Datong gifted mixed coal (>25.12MJ) in Qingdao Harbor from January 7, 2002 to December 27, 2010, which includes China's reform of the coal price formation mechanism. The results show that the time sequence models can fit relatively well into the alteration process of the national coal price in China.

Keywords: Time Sequence Models; Prediction; Coal Price; China

1. Introduction

Coal occupies a stable prime position in China's resource production and consumption structure, and will for quite some time. It comprises over 50% of China's energy mix and is therefore in an irreplaceable position (Peng, 2011). The fluctuations of coal prices relate closely to the routine production activities of companies and the macro-adjustments of the government. Hence, the accurate prediction of coal market price trends and alterations of coal prices, especially the current alteration trend, will positively affect business strategies of companies and provide theoretical support and a practical guide for the macro-adjustment of coal prices (Atkinson and Richards, 1989; Kiani, 2011; Zou and Zhang, 2010).

Historically, the formation of coal prices in China can be divided into a planned-economy period and a market-economy era (Peng, 2011). Prior to 1985, the domestic coal price was controlled by the government. At that time, the coal price control system was a little loose, and beginning in the year 1993, coal price began to open gradually, and the coal price met the market's needs and carried out a double-track price: planned price and market price. Electric coal (coal for power plants) was under the dual-price system of "planned coal" and "market coal". The National Plan Economy Committee (later called the National Development and Reform Committee) guided the electric coal price. And from January 1, 2002, the government-guided price was cancelled and electric coal reflected only the market price. However, in order to control abnormal fluctuations, the government still intervened with the dynamic coal price. See Table 1 for a summary of China's domestic coal price formation system reform.

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Table 1: Coal Price Formation System Reform Process

Time	Department in Government	Adjustment Content	Remarks
Prior to 1993	Bureau of Coal Industry Department, National Price Bureau	Coal price was set by the government	
1993- 2002	National Plan Economy Committee	Double-track price for coal; guided electric coal price	
2002-2006	National Plan Economy Committee	Market price for electric coal with governmental intervention for abnormal price fluctuations	Difference between contract and spot commodities
Dec. 2006 -	Nation Development and Reform Committee	Open dynamic coal price, retain price intervention for export quota and disputable issue	

2. *Prediction of Coal Market Price*

2.1. Prediction Models of Time Sequence ARMA

The ARMA model is a typical time sequence prediction model and a combination of AR (autoregressive) and MA (moving average) models. It is a linear combination of present value of time sequence x_t, past difference sequence ε_t, and previous sequence value. The mathematical formula is

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \qquad (1)$$

In the formula, p and q represent the order of AR and MA respectively. And φ_1, φ_2, $\cdots$, φ_p, θ_1, θ_2, $\cdots$, θ_q are coefficients of AR and MA. We call formula (1) an average mixed model, marked ARMA(p, q).

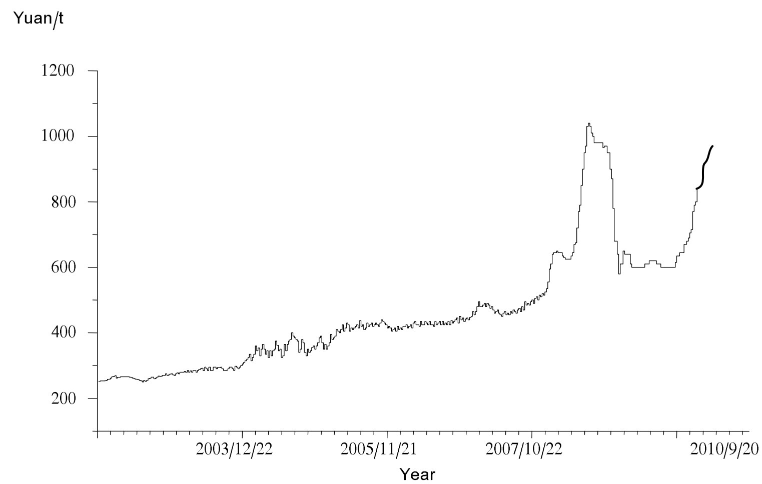
Establishing models of prediction target based on ARMA requires that the random sequence be of zero average value and stable (Koutroumannidis, et al., 2009; Zhang and Jiang, 2007). But over time, the random time sequence prediction target will constantly have an unsteady trend (rising or falling), hence an unsteady time sequence. As a result of this, before applying the model, researchers must cope with the time sequence zero average value and difference steadiness (Cabedo and Maya, 2003; Mirmirani and Li, 2004). Currently, the model has been widely used in various time sequence data predictions and achieved relatively satisfactory results (Zhang and Jiang, 2007; Zhang, et al., 2008). This paper combines the process of Chinese domestic coal price formation mechanism reform, uses the time sequence model on historical data to reveal time data features over time and establishes prediction models which analyze Chinese domestic coal price trends.

2.2. Prediction Model Qualitative Analysis and Option

Qinhuangdao coal exchange center is China's largest coal exchange market at present. Billions of tons of coal produced in Shanxi are chiefly transported via Qinhuangdao to major Chinese cities. In recent years, the market exchange data is exposed in time and accuracy, which reflects the market change tendency of coal prices and provides a real-time picture of supply and demand change (Bai, 2008). However, under the circumstance of immaturity of the domestic coal market, we chose Qinhuangdao coal exchange market price as our representative data and applied the time sequence model to its price trends to conduct the analyses. In doing so, studying the state of coal industry operations has been shown to be greatly significant.

Data option: Considering the Chinese domestic coal price formation system reform course, it is rational to choose price data beginning from 2002 to do coal market price analysis. Also taking into consideration the fact that Datong quality coal (>25.12MJ) from Shanxi is the major market exchange product, this paper analyzes the changing trends of price dated from January 7, 2002 to December 27, 2010. The data source comes from Taiyuan Coal Exchange Center, and Figure 1 shows the changing trend.

Figure 1: Coal Price Changing Trend in Qinhuangdao



In Figure 1, we can see that the overall domestic coal price is on the rise, so using a random process theory to describe the domestic coal price changing process is practical.

The Box-Jenkins method demands that the prediction target time sequence be of zero average value and stable random sequence (Zhang and Jiang, 2007), so prior to establishing the ARMA(p, q) model, it is essential to analyze whether the sequence is stable. If it is not, stabilization is needed for later establishment of the model (Sun and Peng, 2000).

Observing the Qinhuangdao coal price changing trend (Figure 1), it is easy to see that the sequence is obviously on the rise. Based on ADF unit root check (Table 2), the sample sequence is non-stable.

Table 2: Sample Sequence ADF Check Results

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.165907	0.7334
Test critical values:	1% level	-2.575280	
	5% level	-1.942243	
	10% level	-1.615759	

As is shown in Table 2, the sample sequence has some differences and thus it is non-stable. Generally speaking, a different method is applied to make a non-stable sequence stable (Su, 2007), so we made some changes to the sequence, performed the first grade difference, and then used the ADF test to examine whether the first difference sequence is stable or not. The results are shown in Table 3. The new sequence, Z_t, can definitively reject the assumption of non-stability of difference sequence and the sequence can establish the ARIMA model.

Table 3 Test Results of First Grade Difference of ADF

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.762424	0.0002
Test critical values:	1% level	-2.575280	
	5% level	-1.942243	
	10% level	-1.615759	

2.3. Establishment of Prediction Model of Coal Market Price

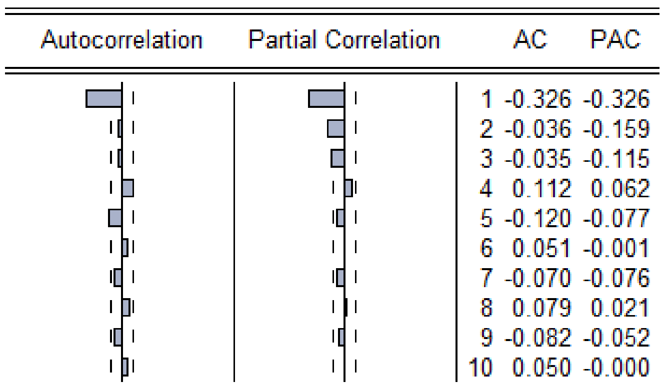
2.3.1. Calculation of sample auto-correlation and partial-correlation coefficient

After achieving stability of the sequence, it is necessary to distinguish models. Model distinction comes from the judging function of self-correlation and side-correlation; that is, to use a relatively stable estimate of AR(p), MA(q) or ARIMA(p, q) models (Zhang and Jiang, 2007). If there is a dragging end of ACF in Z_t and a cutting end of PACF, it is possible to use the AR(p) model to imitate it.

If reversed, the MA model is used. If there are no cutting ends for either ACF or PACF in Z_t, the ARMA(p, q) model is used. Figure 2 shows an analysis of stable sequence after the first grade of difference in Z_t (auto-correlation and partial correlation).

Observing the auto-correlation part of Figure 2, lagging ACF is not zero, and it has a dragging end. In the partial-correlation part, three periods lagging PACF is not zero, and it has a dragging end of PACF, considering that the advanced AR(p) model is hard to estimate. In practice, in the course of establishing model, lower-classed ARMA(p, q) is recommended to replace the corresponding higher-classed AR(p) and MA(q) models. After a comprehensive consideration, we selected ARMA(1, 1), ARMA(2, 1) and AR(3) models for further evaluation.

Figure 2: Results of ACF and PACF after First Order Difference in Z_t Sequence



2.3.2. Distinction between Models

Table 4 shows the overall test results of selected models. Based on comparison among the data in Table 4, we can see that the value R^2_{adj} of ARMA(1, 1) is 0.880694, which is the biggest, greater than 0.719797 in ARMA(2, 1) and 0.6334 in AR(3). According to the minimized criterion about information amount criterion function AIC, we chose the ARMA(1, 1) model.

Table 4 Overall Test Results of Selected Models

Model	R^2_{adj} after adjustment	Test of AIC
ARMA(1, 1)	0.880694	-1.704148
ARMA(2, 1)	0.719797	-0.914355
AR(3)	0.633488	-0.173264

2.3.3. Estimate of Model Parameter

Table 5 shows the test results and parameters estimate of the selected model ARMA(1, 1). Hence, the stable sequence Z_t model is as follows:

$$(1+0.430868\ B)Z_t = (1-0.879966\ )\varepsilon_t \qquad (2)$$

Z_t model that by means of first order difference sequence is (p, d, q) order and ARIMA(1,1,1) model (the d in brackets represents the number of times of difference; here d=1).

$$(1+0.430868\ B)(1-B)Z_t = (1-0.879966\ )\varepsilon_t \qquad (3)$$

Let $Z_t = \log(y_t)$ in formula (3), the result comes from the original sequence y_t, for which the model is as follows:

$$(1+0.430868\ B)(1-B)\log(y_t) = (1-0.879966\ )\varepsilon_t \qquad (4)$$

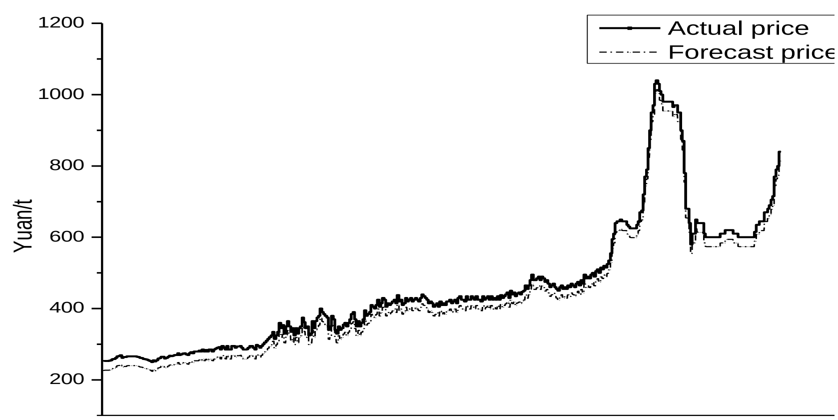
Table 5: Parameters Estimate and Test Results of Model ARMA(1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.430868	0.091633	-4.702132	0.0015
MA(1)	0.879966	0.225466	3.902871	0.0045
R-squared	0.904556	Mean dependent var		-0.043580
Adjusted R-squared	0.880694	S.D. dependent var		0.266741
S.E. of regression	0.092134	Akaike info criterion		-1.704148
Sum squared reside	0.067909	Schwarz criterion		-1.595631
Log likelihood	12.37281	Durbin-Watson stat		1.318407

2.3.4. Imitation and Test of Models

By applying the above-motioned prediction model, we can predict coal market prices and compare them with historical data. As you can see from Figure 3, the value of the difference is relatively small and the time sequence prediction model is almost the same as the practical value. So we can use the ARMA(1, 1) model to predict Chinese domestic coal prices, and similarly we can apply the model to other price predictions of coal trade in different markets.

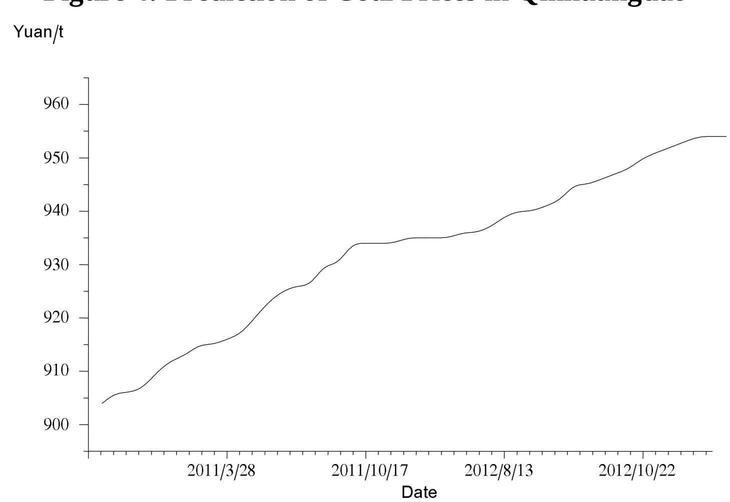
Figure 3: Comparison of Forecast Price and Actual Price



2.3.5. Price Prediction

For our application of Eviews5.0 software to predict the Datong quality coal price in Qinhuangdao Harbor in 2011 and 2012, see Figure 4. In Figure 4, we can clearly see a rising trend in coal price in 2011 and 2012. This will offer some foresight for related departments, and in the meantime, we can still use the model to predict other coal prices in different coal trade markets.

Figure 4: Prediction of Coal Prices in Qinhuangdao



3. Conclusion

Time sequence models have been widely applied in a variety of time sequence data prediction situations and achieved superior results (Koutroumanidis, et al., 2009; Sun and Peng, 2000). This study has shown that time sequence models can accurately predict the alteration process of coal prices in China. This research is valuable in that China's coal market is transitioning from "planned coal" to "market coal," and development of a predictive model of coal price trends is important for governmental macro-adjustments, as well as planning the nation's energy mix and economic development. Because of the dynamic nature of the market economy, companies can also use this tool to assess market opportunities and make their business decisions.

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