

# Analyzing and Predicting the Economic Growth, Energy Consumption and CO<sub>2</sub> Emissions in Shanghai

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## Abstract

Based on the data from 1978-2010, this paper analyzes the causal relationships between carbon emissions, energy consumption, and economic growth in Shanghai, adopting the co-integration and vector error correction methods. The Grey prediction model is applied to forecast three variables for the period between 2011 and 2020. As the empirical results showed, in the long-run equilibrium, there is a positive relationship of a long-term equilibrium between carbon emission and energy consumption in Shanghai. However, between carbon emission and real GDP, there is a negative correlation. Besides, in the short-run equilibrium, energy consumption is the important impact on carbon emission. The causality results show that there is a bidirectional causality relationship between carbon emission, real GDP and energy consumption. For the purposes of reducing carbon emissions and not adversely affecting economic growth, Shanghai should optimize the structure of energy consumption and develop new energy. In addition, the optimal forecasting models of real GDP, energy consumption and carbon emissions have good prediction precision with MAPEs of less than 3%.

**Keywords:** carbon emissions, energy consumption, economic growth, co-integration, grey prediction

## 1. Introduction

For the last 30 years, China's economy grows rapidly and ranks second in the world. However, economic growth is mainly driven by investment, which brings a lot of energy consumption and greenhouse gas emissions. Currently, China's total greenhouse gas emissions rank second in the world, and may surpass the United States to become the first in the next two or three decades. Thus in the international negotiations on climate change, China now faces great pressure on reducing its energy consumption and CO<sub>2</sub> emissions. In Sep. 2009, President Hu made solemn commitment to the world on the United Nations Summit on Climate Change that China would unswervingly take practical steps to meet the challenge of climate change, integrate action on climate change into its economic and social development plan, and endeavor to cut CO<sub>2</sub> emissions per unit of GDP by a notable margin by 2020 from the 2005 level.

The studies on the relationship between economic growth, energy consumption and environmental pollutants may be divided into three lines of research. The first line of research focuses on the relationship between economic growth and environment, which are mainly devoted to examining the inverted U-shaped relationship between environmental pollutants and economic growth, i.e. testing the validity of environmental Kuznets curve (EKC) hypothesis. That is, in the initial stages of economic development, environmental pollutant emissions increase with economic growth, but begin to decline as economic growth pass beyond a turning point. Researchers have carried out a large number of empirical studies in which different conclusions have been drawn. For example, Selden and Song (1994), Stern (2004), Galeottia and Lanza (2005), Managi and Jena (2008), Pao and Tsai (2011) concluded that there was carbon dioxide environmental Kuznets curve. However, Agras and Chapman (1999), Richmond and Kaufmann (2006), Coondoo and Dinda (2008), He and Richard (2010) concluded that there was no carbon dioxide environmental Kuznets curve.

The second line of research focuses on the relationship between economic growth and energy consumption.

Economic growth is closely related to energy consumption since more energy consumption may promote economic development more effectively. Likewise, higher level of economic development may bring about greater technology advancement and enhance energy use efficiency, then reduce the wastage of energy. Therefore, whether there exists a causal relationship and the direction of causality between economic growth and energy consumption have become a long-term issue concerned by the academic field (Ozturk, 2010). The idea of causal relationship between energy consumption and economic growth was first introduced in the seminal study of Kraft and Kraft (1978), who examined the relationship between these variables for USA. Since their study, Granger causality test and co-integration model have been employed to study the relationship between energy consumption and economic growth in different countries, e.g. Yu and Hwang(1984), Yu and Choi (1985), Masih (1996), Asafu-Adjaye (2000), Wolde-Rufael (2005), Soytas et al. (2007).

For the past few years, researches in this field have made further progress. To investigate the relationship between economic growth, energy consumption and CO<sub>2</sub> emissions under the the unified framework has become the new study trends in this field (Halicioglu, 2009; Lean & Smyth, 2010). Soytas et al. (2007) combined several techniques such as Granger causality test and forecast variance decomposition analysis to conduct a study on the dynamic relationship between economic growth, energy consumption and CO<sub>2</sub> emissions in the years from 1960 to 2004 in America. The analysis showed that no obvious causal relationship existed between output and CO<sub>2</sub> emissions or between output and energy consumption, but energy consumption does cause CO<sub>2</sub> emissions. On the other hand, Apergis and Payne (2009) adopted PVECM (panel vector error correction model) to study the relations between output, energy consumption and CO<sub>2</sub> emissions in the years from 1971 to 2004 in six Central American countries. The study found that a bi-directional causality existed between the long-term energy consumption and CO<sub>2</sub> emissions. Soytas and Sari (2009) employed Granger causality test and a few other techniques to observe the mutual influence among economic growth, energy consumption and CO<sub>2</sub> emissions in the years from 1960 to 2000 in Turkey. It indicated that there was a one-way Granger causality from CO<sub>2</sub> emissions to energy consumption. Under the multi-variable co-integration framework, Ghosh (2010) used such techniques as Granger causality test and forecast variance decomposition analysis to inspect the the dynamic relations from 1971 to 2006 among five variables like economic growth, energy supply and CO<sub>2</sub> emissions in India. Besides, Lean and Smyth (2010) adopted PVECM to carry out an in-depth study on the relationship between economic growth, electricity consumption and CO<sub>2</sub> emissions in the years from 1980 to 2006 in five ASEAN member countries. The analysis results manifested that a long-term one-way causality existed from electricity consumption and CO<sub>2</sub> emissions to economic growth.

For all literature available now, there is no real research on the relationship between economic growth, energy consumption and carbon emissions for Shanghai. Shanghai, as the most developed area, features dominantly in China's economy with its highest economic growth speed. Especially in post economic crisis age, the rapid economic development of Shanghai can promote the economic and social improvement of the whole Yangtze River Delta, the East China area and its hinterland--the Yangtze Valley. In the "Twelfth Five-Year Plan", Shanghai government set the target of reducing its energy consumption per unit of GDP by 18% and carbon emissions by 19%. As a result, the study and prediction of CO<sub>2</sub> emissions, energy consumption and economic development comprise a vital part of Shanghai's environment energy policy.

## 2. Method

In this paper, GDP stood for the level of economic growth; the components of energy consumption mainly refer to coal, petroleum and natural gas. CO<sub>2</sub> emission data is calculated by the formula, which is recommended by the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. The basic data on economy, energy and carbon came from Shanghai Statistical Yearbook and China Energy Statistical Yearbook.

We collected annual data for Shanghai on real GDP (in constant 1978, local currency billion YUAN), energy use (million tons of standard coal equivalent) and CO<sub>2</sub> emissions (million tons) over the period 1978-2010. In order to eliminate the heteroscedasticity as well as enable the model to have practical significance, all of the data was converted into natural logarithms before conducting the empirical analysis. Thus, the coefficient of the variables indicated the elastic relations between them.

### 2.1 Econometric Methodology

In order to avoid that non-stationary time series regression leads to a spurious regression result, two different unit root tests, namely Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) are used to investigate the stationarity and the order of the integration of the variables. If the variables have the same order of integration, their linear combination can constitute a stationary time series and co-integration relationship, namely, long-term equilibrium relationship exists among the variables. Co-integration test methods include the Engle-Granger and

Johansen tests. EG co-integration test is based on linear regression residual test and is applied only for single variable regression model. Therefore, Johansen maximum likelihood method is used to test the co-integration relation between the variables rather than Engle-Granger method. Furthermore, the existence of co-integration indicates that there are long-term equilibrium relationships among the variables, but not that there must be a causal relationship among them. Granger causality test is used to test the causal relationship between the variables.

This paper selects GDP and energy consumption as the impact factors of carbon emission, as follows:

$$LCO_t = \alpha_0 + \alpha_1 LGDP_t + \alpha_2 LEC_t + \mu_t \quad (1)$$

where  $LCO$ ,  $LGDP$  and  $LEC$  represent natural logarithms of CO<sub>2</sub> emissions, real GDP and energy consumption respectively.  $\alpha_1$ ,  $\alpha_2$  represent the elasticity of GDP and energy consumption respectively. The expected sign of the energy consumption is positive because of the greater energy consumption and the greater CO<sub>2</sub> emissions. The random error term,  $\mu_t$ , is assumed to be independent and identically distributed with a zero mean and a constant variance.

According to the Granger theory, if co-integration exists among the non-stationary variables, the short-run fluctuation and long-run equilibrium can be described with an error correction model (ECM). When cointegration relationships exist between carbon emissions, energy consumption and real GDP, it is reasonable to test the Granger causal relationships between the three variables. The ECMs for (1) can be specified as follows:

$$\Delta LCO_t = \gamma_{10} + \sum_{i=1}^{m_1} \gamma_{11i} \Delta LCO_{t-i} + \sum_{i=1}^{n_1} \gamma_{12i} \Delta LGDP_{t-i} + \sum_{i=1}^{k_1} \gamma_{13i} \Delta LEC_{t-i} + \delta_1 ECT_{t-1} + \mu_{1t} \quad (2)$$

$$\Delta LGDP_t = \gamma_{20} + \sum_{i=1}^{m_2} \gamma_{21i} \Delta LCO_{t-i} + \sum_{i=1}^{n_2} \gamma_{22i} \Delta LGDP_{t-i} + \sum_{i=1}^{k_2} \gamma_{23i} \Delta LEC_{t-i} + \delta_2 ECT_{t-1} + \mu_{2t} \quad (3)$$

$$\Delta LEC_t = \gamma_{30} + \sum_{i=1}^{m_3} \gamma_{31i} \Delta LCO_{t-i} + \sum_{i=1}^{n_3} \gamma_{32i} \Delta LGDP_{t-i} + \sum_{i=1}^{k_3} \gamma_{33i} \Delta LEC_{t-i} + \delta_3 ECT_{t-1} + \mu_{3t} \quad (4)$$

where  $m_i$ ,  $n_i$  and  $k_i$  are the lag lengths for the differenced variables of the respective equations and can be determined on the basis of Akaike's information criteria (AIC).  $\gamma$  and  $\delta_i$  represent the short-run and the long-run dynamic relationships between the variables respectively.  $\mu_{it}$  is the serially uncorrelated error term. The error correction term in (2)-(4) can be derived from the long-run equilibrium (1) as follows:

$$ECT_{t-1} = LCO_{t-1} - \alpha_0 - \alpha_1 LGDP_{t-1} - \alpha_2 LEC_{t-1} \quad (5)$$

## 2.2 Grey Prediction Model

The grey system theory is used to study an uncertain problem with small sample and poor information that is partially known. GM (1,1) model is based on applying the accumulated generating operation of any series to a non-negative increasing sequence and thus weakening the randomness of the original data sequence, and highlighting the trend.

The modeling procedure is summarized as follows (Kayacan et al., 2010; Lin et al., 2009):

Step 1: Suppose  $x^{(0)}$  is GM (1,1) modeling original data sequence,

$$x^{(0)} = [x^{(0)}(0), x^{(0)}(1), \dots, x^{(0)}(i), \dots, x^{(0)}(n)] \quad (6)$$

Step 2: By taking the first-order accumulated generating operation on  $x^{(0)}$ , we can obtain a new data series, which is:

$$x^{(1)} = [x^{(1)}(0), x^{(1)}(1), \dots, x^{(1)}(i), \dots, x^{(1)}(n)] \quad (7)$$

$$x^{(1)}(k) = \sum_{i=0}^k x^{(0)}(i), k = 0, 1, \dots, n; n \geq 3 \quad (8)$$

Step 3: Calculate the background value  $z^{(1)}$ , which is generated by closely mean value of  $x^{(1)}$ ,

$$Z^{(1)}(k) = 0.5 [x^{(1)}(k) + x^{(1)}(k-1)] \quad (9)$$

Step 4: Establish the grey differential equation,

$$x^{(0)}(k) + aZ^{(1)}(k) = b, k = 1, 2, \dots, n \quad (10)$$

where  $a$  is development coefficient, and  $b$  is the grey control variable.

Step 5: The ordinary least squares method (OLS) is used to calculate the parameters  $a$  and  $b$ ,

$$(a, b)^T = [B^T B]^{-1} B^T y_n \quad (11)$$

Where

$$B = \begin{bmatrix} -Z^{(1)}(1) & 1 \\ -Z^{(1)}(2) & 1 \\ \dots & \dots \\ -Z^{(1)}(n) & 1 \end{bmatrix}, \quad y_n = \begin{bmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \dots \\ x^{(0)}(n) \end{bmatrix}$$

Step 6: Take  $x^{(1)}(0) = x^{(0)}(1)$ , the solution of the grey differential equation yields:

$$\hat{x}^{(1)}(k+1) = \left[ x^{(0)}(0) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a}, k = 0, 1, \dots \quad (12)$$

Step 7: Perform the inverse accumulated generating operation technique to get the predicted values  $\hat{x}^{(0)}(k+1)$ .

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad (13)$$

$$\hat{x}^{(0)}(k+1) = (1 - e^{-a}) \left( x^{(0)}(0) - \frac{b}{a} \right) e^{-a(k+1)}, k = 0, 1, \dots \quad (14)$$

In order to evaluate the out-of-sample forecast capability, the predictive accuracy of the model requires to be examined by calculating three different evaluation statistics: the root mean square error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE).

$$\begin{aligned} RMSE &= \sqrt{\sum_{i=1}^n (P_i - A_i)^2 / n} \\ MAE &= \sum_{i=1}^n |P_i - A_i| / n \\ MAPE &= \sum_{i=1}^n |(P_i - A_i) / A_i| / n \end{aligned} \quad (15)$$

where  $P_i$  and  $A_i$  are the  $i$ th forecasting and actual values respectively, and  $n$  is the total number of predictions. The MAPE result is used as a means to judge the accuracy of the forecast: less than 10% is a highly accurate

forecast, 10-20% is a good forecast, 20-50% is a reasonable forecast, and more than 50% is an inaccurate forecast (Pao & Tsai, 2011).

### 3. Empirical Results

#### 3.1 Unit Roots Test

The time series properties of the variables are checked through two different unit root tests, namely ADF and PP. The results are displayed in Table 1.

Table 1. Result of unit root tests

	ADF		PP	
	Level	1st diff.	Level	1st diff.
LCO	0.2049	-4.0861*	-2.4304	-5.8350*
LGDP	-2.1321	-4.0565*	-2.3001	-2.9744**
LEC	-1.9566	-3.8484**	-2.7335	-3.1524**

\* and \*\* mean that the null of the unit root test is rejected at a 1% and 5% level

All of the original sequences have a unit root, but their first-order difference sequences are stationary, which indicates that the variables are integrated at first-order. Thus, there may be a long-run equilibrium relationship between carbon emissions, energy consumption and real GDP for Shanghai.

#### 3.2 Johansen Co-integration Test

Whether co-integration relationship exists among the same order series, they are checked through maximum eigenvalue test and trace test of Johansen and co-integration test. The results are displayed in Table 2.

Table 2. Result of Johansen's co-integration test

Eigen value	Trace statistics	5%Critical value	Max-Eigen. statistics	5%Critical value	Number of co-integrations
Variable: LCO, LGDP and LEC					
0.7936	60.984	29.797	44.188	21.132	None*
0.4301	16.796	15.495	15.743	14.265	At most 1*
0.0369	1.0529	3.8415	1.0529	3.8415	At most 2

\* indicates the rejection of a null hypothesis at 5% level of significance.

Both maximum eigenvalue statistics and trace statistics are significant at 5% level of significance. It indicates that there is a long-run equilibrium relationship between carbon emissions, energy consumption and real GDP for Shanghai. Then we can obtain the following long-run co-integrating equation by estimating (1):

$$LCO = -0.7904 * LGDP + 0.0340 * LEC \quad (16)$$

(0.2738)                      (0.5459)

Figures in parenthesis indicate standard error of the estimated coefficient.

In term of (16), there were negative correlation between carbon emissions and real GDP and positive correlation between carbon emissions and energy consumption in Shanghai. Moreover, the elastic coefficient of real GDP and energy consumption that changed to carbon emissions is 0.2738 and 0.5459 respectively.

That carbon emission was negatively correlated with real GDP may be related with the economic development scale of Shanghai. The high-speed rise of economy in Shanghai leads to the marginal decreasing of carbon emissions, which accord with the environmental Kuznets curve theory. And energy consumption is an important influencing factor for carbon emissions.

#### 3.3 Granger Causality Test

If co-integration relationship does not exist among non-stationary variables, the causal relationship can be

described by the difference model. If co-integration relationship exists among non-stationary variables, the causal relationship can be described by the error correction model. According to the previous result, the variables are non-stationary and there exist co-integration relationships among them. Long-run co-integration relationship indicates that there is at least one direction of causality. However, the direction of the causal relationship is unclear. Therefore, in order to clarify the direction of causality, ECM based Granger causality tests are made. The short-run t-statistics, long-run t-statistics and joint F-statistics for (2)-(4) are reported in Table 3.

Table 3. Result of causality test

Dependent variable	Source of causation (independent variables)						
	Short-run			Long-run	Joint(short-run/long-run)		
	t-statistics			t-statistics	F-statistics		
	$\Delta$ LCO	$\Delta$ LEC	$\Delta$ LGDP	ECT	$\Delta$ LCO/ECT	$\Delta$ LEC/ECT	$\Delta$ LGDP/ECT
$\Delta$ LCO		3.388*	3.261*	6.767*		10.425*	9.826*
$\Delta$ LEC	3.388*		2.526**	-2.637**	3.614**		3.459**
$\Delta$ LGDP	3.261*	2.526**		-2.254**	6.182*	4.683**	

\*, \*\* Indicate a 1%, 5% level of significance, respectively

Short-run dynamic relationship implied that there were mutual causal relationships between energy consumption, real GDP and carbon emissions. In the long-run dynamic relationships, the coefficient of all ECT were significant, and changes in any variable can affect other variables through the feedback mechanism. It implied that there was a bidirectional causal relationship between them and all three variables readjust towards a common equilibrium relationship after a shock occurs.

### 3.4 Forecasting CO<sub>2</sub> Emissions, Energy Consumption and Real GDP

The grey forecasting model requires less in-sample data. It is generally believed that the number of original in-sample data used to build model should be not less than five. The intermediate loss data may use the interpolation method to make up neat, but the selected data must be equal interval, adjacent, and no leap. However, if the number of the in-sample data is different, the precision of the forecasting model also has a slight difference. Therefore, we took three different time period datasets, namely five-year (GP-5, 2000-2004), six-year (GP-6, 1999-2004) and seven-year (GP-7, 1998-2004) datasets, as the in-sample data. This in-sample period is used to build models and the out-of-sample period (2005-2010) is used to evaluate the prediction accuracy by using RMSE, MAE and MAPE statistics.

The optimal forecasting models of real GDP, energy consumption and carbon emissions have a good prediction precision, because all of the MAPE are less than 3%. The results are shown in Table 4. The optimal GP model was used to forecast carbon emissions, energy consumption and real GDP for Shanghai from 2011 to 2020.

Table 4. Out-of-sample comparisons GPs models, 2005-2010

	GP-5	GP-6	GP-7
Forecasts of CO <sub>2</sub> emissions(million tons)			
RMSE	5.99	5.57	4.41
MAE	4.76	4.38	3.72
MAPE	2.21%	2.03%	1.82%*
Forecasts of energy consumption(million tons)			
RMSE	3.83	2.34	3.58
MAE	3.55	2.05	3.43
MAPE	3.59%	2.12%*	3.59%
Forecasts of real GDP(constant 1978 billion Yuan)			
RMSE	22.37	7.38	12.05
MAE	15.15	5.60	10.38
MAPE	2.69%	1.15%*	2.08%

\* indicates the optimal model.

The grey prediction model for carbon emissions, energy consumption and real GDP are as follows:

$$\begin{aligned}
 CO^{(0)}(k+1) &= (1 - e^{-0.0606}) \left( CO^{(0)}(0) + \frac{195.46}{0.0606} \right) e^{0.0606k}, k = 0, 1, \dots \\
 EC^{(0)}(k+1) &= (1 - e^{-0.0449}) \left( EC^{(0)}(0) + \frac{90.47}{0.0449} \right) e^{0.0449k}, k = 0, 1, \dots \\
 GDP^{(0)}(k+1) &= (1 - e^{-0.0889}) \left( GDP^{(0)}(0) + \frac{413.52}{0.0889} \right) e^{0.0889k}, k = 0, 1, \dots
 \end{aligned}
 \tag{17}$$

The forecasts data, together with the actual data, is presented in Figures 1-3.

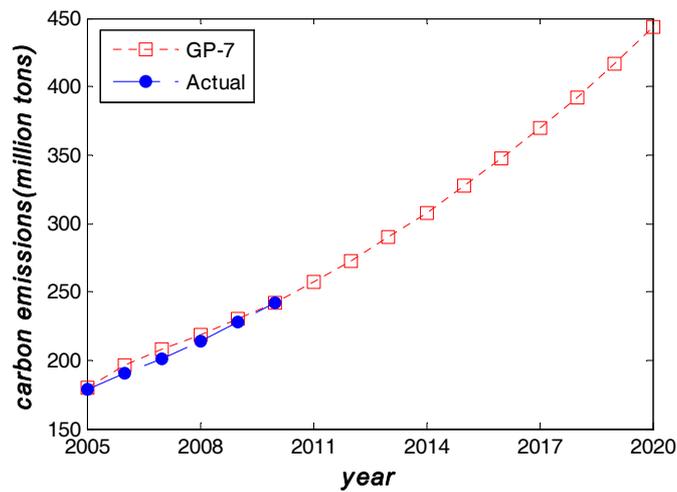


Figure 1. Forecasts of carbon emissions (million tons) for Shanghai, 2005-2020

Note: The small dot is actual values and the square is forecast values

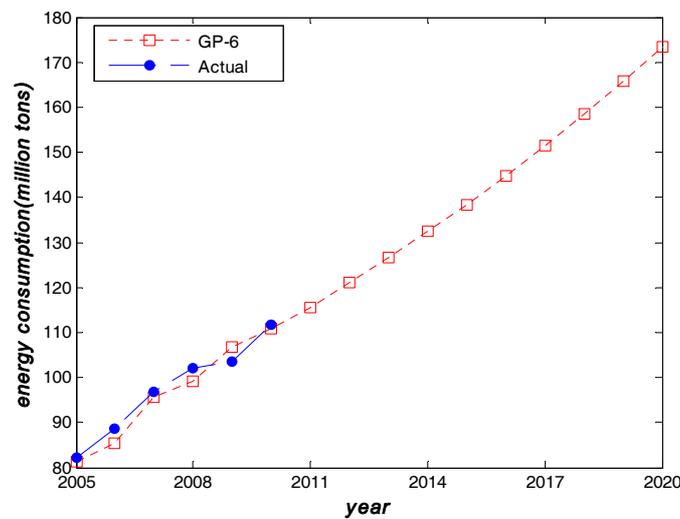


Figure 2. Forecasts of energy consumption (million tons) for Shanghai, 2005-2020

Note: The small dot is actual values and the square is forecast values

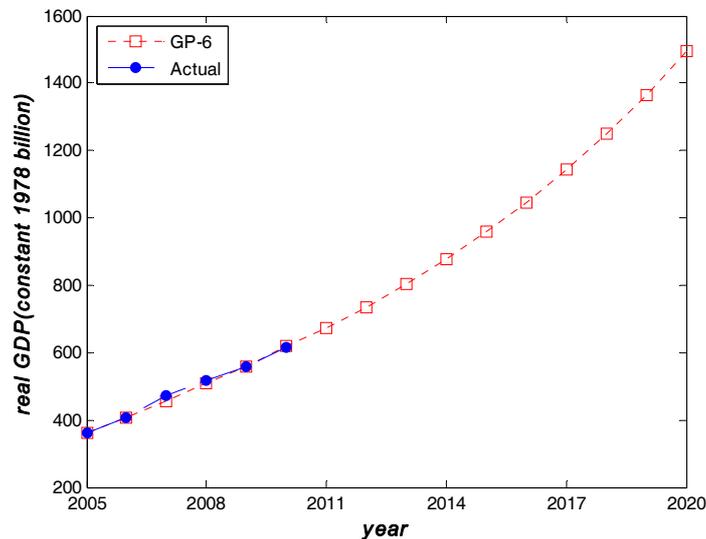


Figure 3. Forecasts of real GDP (constant 1978 billion) for Shanghai, 2005-2020

Note: The small dot is actual values and the square is forecast values

#### 4. Conclusion

This paper analyses the long-term equilibrium relationship and short-term interaction between carbon emissions, real GDP and energy consumption for Shanghai based on the 1978-2010 annual data. In the long-run equilibrium, carbon emission was positively correlated with energy consumption, which implies that an increase in energy consumption leads to an increase in carbon emissions. However, carbon emission was negatively correlated with real GDP, which implies that rapid economic growth leads to carbon emissions diminishing marginal. The result supports the environmental Kuznets curve hypothesis that environmental pollution levels increase as economy develop, but begin to decrease as rising incomes pass beyond a turning point. That is, Shanghai's economy has a high-level development, and carbon emissions relative to the influence of economic growth have passed over the turning point and decreased gradually.

Causality test results indicated that energy consumption Granger-causes real GDP and vice versa in the long-run, which implies that an increase in energy consumption leads to an increase in economic growth and vice versa. But the finding that energy consumption will boost economic growth does not necessarily mean that energy-saving will hinder economic development. In fact, a reduction in energy consumption due to improvements in energy efficiency may raise productivity, which in turn may stimulate economic development. Therefore, the transformation on energy consumption from low-efficiency and high-pollution pattern to high-efficiency and low-pollution pattern may stimulate rather than hinder economic growth.

Based on recent years' data, the grey prediction model is applied to forecast carbon emissions, energy consumption and real GDP for Shanghai during 2011-2020. The optimal forecasting models have a good prediction precision with MAPEs of less than 3%. These results can be applied to adjust the energy and environmental policies dynamically to achieve the best economic development.

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