Research Article

Forecasting China's CO₂ Emissions for Energy Consumption Based on Cointegration Approach

Xiangmei Li ¹, Yan Song,² Zhishuang Yao,³ and Renbin Xiao ⁴

¹School of Low Carbon Economics, Hubei University of Economics, Wuhan 430205, China

²Program on Chinese Cities, University of North Carolina at Chapel Hill, New East Building, CB No. 3140, Chapel Hill, NC 27599-3140, USA

³School of Environmental Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China

⁴School of Automation, Huazhong University of Science and Technology, Wuhan 430074, China

Correspondence should be addressed to Renbin Xiao; rbxiaohust@163.com

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Forecasting CO₂ emissions is important for climate policy decision making. The paper attempts to implement empirically the long-term forecast of CO₂ emissions based on cointegration theory under the business-as-usual scenario, by using statistical data from China over the period 1953 to 2016. We focus on the relationships between CO₂ emissions for energy consumption and influential factors: per capita GDP, urbanization level, energy intensity, and total energy consumption. The empirical results are presented as follows: (1) continuous increase of carbon pollution resulting from energy consumption (1953-2016) indicates that China has beard great pressure of carbon reduction. (2) Though reduction of carbon intensity in 2020 would account for 50.14% that of 2005, which meets the requirements announced by Chinese government in 2009, China would bear carbon emissions for energy consumption of 14.4853 billion tCO₂ by 2030, which is nearly 1.59 times that of 2016 and nearly 105 times that of 1953. The results suggest that the policymakers in China may take more effective measures such as reducing energy intensities and formulating stricter environmental regulations in order to mitigate the CO₂ emissions and realize the win-win of economic and ecological benefits.

1. Introduction

Carbon emissions and climate changes have aroused global attention. The Intergovernmental Panel on Climate Change (IPCC)'s fifth Assessment Report (AR5) affirmed that greenhouse gases (GHGs), in particular carbon dioxide emissions, from anthropogenic activities, have been major driving force of an acceleration of global warming [1]. Paris agreement on climate change adopted in COP21 (also known as the 2015 Paris Climate Conference) focuses on tackling climate change issues after the year 2020 and aims at limiting a rise in the average global temperature to below 2.0°C above the preindustrial level (United Nations Framework Convention on Climate Change (UNFCCC), 2015). Beginning in 2010, China surpassed the US to become the world's largest CO₂ emitter, accounting for 28.6% of the world's total CO₂ emissions, and nearly doubled those in the United States in 2013 [2]. Meanwhile, China is one of the most vulnerable countries

to the risks of climate change [3]. In the context, China has taken various measures for mitigating its carbon emissions facing greater pressure from international community and risk of climate change. In 2009 Copenhagen conference, the Chinese central government has set a 2020 target to reduce CO₂ emissions per unit of GDP by 40-45% from 2005 levels [4]. In 2014, China pledged to cap CO₂ output by 2030. In COP21, China also promised to strive for reaching a peak of carbon emissions as soon as possible. Obviously, the strategy of carbon emissions reductions mainly relied on from carbon emissions intensity reductions to total carbon emissions control. To achieve the goals in 2020 and 2030, it is very essential to consider as binding targets introduced into the mid-long term planning of national economy and social development. Since the carbon emissions mainly result from consumption of fossil fuels, and China's economy has gained rapid development via the path of "high energy consumption, high greenhouse gas emissions" [5], reducing

energy consumption seems to be the direct way of handling the emissions problem [6]. However, current efforts to investigate precisely the future trend of carbon emissions for energy consumption are in their infancy. Therefore, there is an urgent need to establish effective model and forecast quantitatively CO₂ emissions for energy consumption so that decisions makers can make appropriate policies to reduce and manage their carbon emissions. The work can help answer an important question that whether the continued strengthening of climate policy can lead to significant CO₂ emission reductions for energy consumption to achieve the goal of emission peaking.

Many researchers have been working on CO₂ emissions, mainly including the measurement model, the trend analysis, the impact factors, the different industrial CO₂ emissions and so on. Jakovljevic et al. [7] provided a detailed methodology for calculating CO₂ emission during the life cycles of an aircraft, with special emphasis on the use sequence and aircraft degradation. Tian et al. [8] conducted a Bibexcel and complex network analysis to identify trends and characteristics of carbon emissions research in the transportation sector for the period 1997–2016. Shi et al. [2] applied the structural decomposition analysis method and world Input-Output Database to investigate the driving factors of the changes in the carbon emissions in the Chinese construction. Cai et al. [9] investigated the nexus among clean energy consumption, economic growth, and CO₂ emissions by applying a newly developed bootstrap ARDL bounds test with structural breaks. Li et al. [10] studied the embodied CO₂ emissions in the trade of China's steel using the input-output model and the trade data of the China's steel imports and exports.

To help decision-makers track the future development trends of CO₂ emissions, researchers carried on the forecast of CO₂ emissions from national-level, provincial-level, and industrial sector and so on [2, 11, 12]. The predicting models are mainly concentrated on the IPAT model [13, 14], STIRPAT model [15, 16], EKC [17, 18], and so on. These models difficultly avoid multiple linear correlations and easily show the phenomenon of 'spurious regression'. Meanwhile, these models are short of considering nonstationarity and dynamics in time series.

The cointegration theory puts forward a new idea for the establishment of relationships between nonstationary time series. Apergis and Payne [19] examined the determinants of renewable energy consumption per capita in seven Central American countries and found that a long-run cointegrated relationship exists between renewable energy consumption per capita, real GDP per capita, CO₂ emissions per capita, real coal prices, and real oil prices. Rahman et al. [20] examine the empirical cointegration, long and short run dynamics, and causal relationships between carbon emissions, energy consumption, and industrial growth in Bangladesh over the period of 1972–2011. Abid [21] investigated empirically the causal relationship between economic growth and CO₂ emissions in Tunisia by combining a cointegrated model specification with EKC hypothesis. However, few attentions were paid on the prediction of CO₂ emission using the cointegration theory. In this paper, the cointegration theory

is applied to establish prediction models of CO₂ emissions for energy consumption, in order to evaluate the potential challenges faced by China low-carbon development. The cointegration theory, created in 1980s by Engle and Granger [22], has been widely applied in many research fields, such as renewable energy, electric power, and stock markets [23–25]. The increasing application of cointegration approach is partly due to avoiding spurious regression and higher prediction accuracy compared to other time series regression models. The objectives of the paper are as follows: firstly, based on the statistical data of China from 1953 to 2016, we calculate the CO₂ emissions for energy consumption from 1953 to 2016 by method provided by IPCC. Secondly, we establish the models of long-term prediction. Finally, according to the forecasting results, we analyze the change trend of carbon emissions and carbon intensity in China from 2017 to 2030 and provide relative policy countermeasures.

2. Methodology and Data

2.1. Cointegration Theory. Cointegration theory is an econometric analysis method to deal with nonstationary data. It explores the long-term equilibrium relationship among nonstationary variables, also called cointegration relationship. The cointegration theory combines the short-term dynamic model with long-term equilibrium model, which provides a new method for the nonstationary time series data.

For a random vector $x_t = (x_{1t} \ x_{2t} \ x_{3t} \ \dots \ x_{Nt})^T$, if it is a time series with autoregressive moving average (ARMA) after differencing d times instead of $d-1$ times, we believe that it has d order integration, denoted $x_t \sim I(d)$. Engle and Granger describe the definition of cointegration as follows. If the random vector x_t meets the condition, i.e., $a^T x_t \sim I(d-b)$, where $a(a \neq 0)$ is a $N \times 1$ vector, b is a constant, $b > 0$, there exists cointegration relationship among the time series x_t , denoted $x_t \sim CI(d, b)$. Thus, a is called the cointegrating vector. In the paper, we adopt cointegration theory to judge whether there exists a cointegration relationship among nonstationary series data firstly and estimate the cointegrated parameters based on the existence of cointegration relationship. If a time series has cointegrated relationship, there exists a long-term equilibrium relationship among them [26].

2.2. Data Description and Variables Selection. In this paper, to implement empirically the long-term forecast of CO₂ emissions, we require the historical data on carbon emission and influential variables in China during 1953–2016. The calculation of carbon emission for energy consumption is based on the method provided by "IPCC National Greenhouse Gas Emission Inventory Guideline" [27]. The paper adopted (1) to calculate the carbon emission for energy consumption in China:

$$CE = \sum_{i=1}^n E_i F_i \quad (1)$$

where i is the type of energy, $i=1, 2, 3$, which represents coal, oil, and natural gas, respectively; E_i refers to the i -th

TABLE 1: The values of factors for measuring the CO₂ emission peak in China.

Item	2015	2020	2030	2040
Per capita GDP (Yuan)	\$8183	\$10000	\$20000	
Urbanization level (%)	56	60	68	72
Energy intensity (tce.10 ⁻⁴ Yuan)	0.62	0.53		0.114
Energy consumption(billion ton)	4.0	4.8	6.0	

Sources: the following contents in the paper.

energy consumption, which was sourced from China Energy Statistical Yearbook [28] and calculated by standard coal; F_i refers to carbon emission factors of energy consumption [27] which are given with 0.7559, 0.5860, and 0.4483 for coal, oil, and natural gas, respectively. The data for influential forces was obtained from China Statistical Yearbook [29] and China Energy Statistical Yearbook [28]. There are many impact factors on CO₂ emissions according to the existing researches [9, 30, 31]. The theoretical framework of STIRPAT [32] is referred to in the paper. Under the framework of STIRPAT, per capita GDP usually is proxied by per capita affluence, energy intensity represents the level of environmentally damaging technology, and urbanization level is also considered as influential factors [31]. To explore the impact of energy consumption on carbon emissions compared to the other variables, we select the energy consumption as independent variables instead of population, because more studies focus on the relationship between energy consumption and carbon emissions [6]. Therefore, this paper chooses per capita GDP (PG), urbanization level (UL), energy intensity (EI), and total energy consumption (TE) as influencing factors to study their impacts on CO₂ emissions (CE). Forecasting the four factors in the future period is necessary to measure carbon emissions for energy consumption in future China, meanwhile combined with national development planning and routing arrangement. The values of factors for measuring the CO₂ emission peak in China are shown in Table 1.

2.2.1. Per Capita GDP. The per capita GDP, characterizing the level of regional economic development, is measured by the ratio of Gross Domestic Product (GDP) at constant price in 2016 and the total population. In 2016, per capita GDP in China is RMB 53,800, around \$8,680. According to Chinese government work report (2012), the per capita income of urban and rural residents in 2020 will double compared to that in 2010. That is to say, per capita GDP in 2020 will exceed \$10,000, which means that China will enter into the ranks of middle income countries. Tracking the development path of mainly developed countries [33], we find that there is 10-13 years needed to realize the double of per capita GDP from \$10,000 to \$20,000. For America, the process experienced 10 years (1978-1988); Britain 13 years (1983-1996); however, Japan only 9 years (1982-1991). In the paper, it is reasonable to set goal of 10 years (2020-2030) needed to realize per capita GDP \$20,000 in China.

2.2.2. Urbanization Level. The urbanization level, deemed as a paramount indicator of urban modernization, is measured

mainly by single indicator such as population ratio, i.e., the percentage share of the urban population in the total population. Urbanization strategy has ever been an important aspect of world economic and social development. Since 1995, China has entered the stage of urbanization rapid development by over 30%. From 2002 to 2016, proportion of urban population has increased with an average 1.4% annually and reached 57.35% in 2016. According to the report “*Blue Book of Macroeconomy*” published by Chinese Academy of Social Sciences [34], China’s urbanization rate will reach up to 57.67% in 2020, almost 68% in 2030. Meanwhile, the China’s urbanization process will transform from accelerating growth to slow growth in 2030.

2.2.3. Energy Intensity. Energy intensity is obtained from energy consumption of per unit of GDP. According to ‘People’s Republic of China National Economic and Social Development Plan in the Thirteen Five-Year Period (2016-2020)’, energy consumption of per unit of GDP will fall by 15%, from 0.62 tce/10⁴ yuan in 2015 to 0.53 tce/10⁴ yuan in 2020. In 2016, energy intensity is 0.59 tce/10⁴ yuan, which is nearly 1.8 times that of the world average. According to the change trend of energy intensity in countries, we presumed that China’s energy intensity will be decreasing gradually and achieve the world average of energy intensity, i.e., 0.332 tce/10⁴ yuan in 2025. According to ‘*World Energy Outlook 2015*’ issued by International Energy Agency (IEA), China energy intensity will decrease in 2040 by 85% relative to 2014.

2.2.4. Total Energy Consumption. The total energy consumption is accounting by translating primary energy consumption, i.e., coal, natural gas, crude oil, hydropower, nuclear power, and wind power into standard coal (standard coal equivalent, SCE). In 2016, China’s consumption of primary energy has reached 4.36 billion tce. Meanwhile, the proportion of coal consumption is 62%, that is, higher than global average level of 30.1%, and the share of nonfossil energy is only 13.5%. According to ‘*Action Plan for Energy Development Strategy (2014-2020)*’, by 2020 the total amount of energy consumption will be controlled at about 4.8 billion tce. According to prediction results of Energy Research Institute in China State Development and Reform Commission, the total amount of energy consumption will reach 6.0 billion tce in 2030 and 7.7 billion tce in 2050. Meanwhile, the share of nonfossil energy is set goal as 15% in 2020 and 20% in 2030.

2.3. Modelling Framework. To effectively eliminate fluctuation and heteroscedasticity of time series data, it should make

FIGURE 1: Modelling framework of CO₂ emissions for energy consumption.

logarithm transformation firstly to CO₂ emissions for energy consumption and its influencing factors. The logarithm transformation of the above five variables is represented by LNCE, LNUL, LNEI, LNPG, and LNTE. To test if there exists cointegration relationship between the variables, the unit root test is introduced to verify the same order single integration among logarithmic sequences in Section 3.2.1. The long-term equilibrium model is established based on the cointegration relationship between the variables in Section 3.2.2. The fitting test of cointegration model is implemented in Section 3.2.3. Finally, long-term forecast of total CO₂ emissions during 2017-2030 is done based on established cointegration model in Section 3.3. The specific modelling process is shown in Figure 1. Eviews (version 6.0) software is implemented in the study to finish the work.

3. Results and Analysis

3.1. The Change Trend of CO₂ Emissions for Energy Consumption in China. Based on the method provided by IPCC, the results indicate that CO₂ emissions for energy consumption in China have increased rapidly during 1953-2016, from 0.1378 billion tons CO₂ (1953) to 9.1116 billion tons CO₂ (2016) (Figure 2). Meanwhile, the annual growth rate of GDP attained 8.056% (GDP calculated by 2016 constant price), which shows that China has a relatively high rate of economic development with CO₂ emissions increase. Furthermore, the carbon intensity dropped from 1.6720 kg/yuan to 1.2245 kg/yuan, which indicates that annual descending rate of the carbon intensity reached to 0.4965%. However, the carbon intensity in 2010 is over 2.93 times higher than that of the world average. Thus, the reduction task of CO₂ emissions is very serious in order to attain the target of CO₂ reduction proposed by China government in the international community. In this context, it is extremely urgent to predict the development trend of CO₂ emissions in the future in order to provide some crucial CO₂ emissions reduction policy recommendations to the policy makers.

FIGURE 2: Time series analysis of CO₂ emissions for energy consumption in China during 1953-2016.

FIGURE 3: Times histories of level value.

3.2. Establishment of Long-Term Equilibrium Model

3.2.1. ADF Stationary Test. To establish long-term equilibrium model, the stationary test and cointegration test must be done. In this paper, Augmented Dickey Fuller (ADF) unit root test is utilized to determine whether there is a cointegration relationship between the variables [35].

From Figure 3, lnCE, lnEI, lnPG, lnTE, and lnUL show the nonstationary characteristics with rising or declining trends. Therefore, lnCE, lnEI, lnPG, lnTE, and lnUL are the nonstationary variables. Figure 4 shows that in dlnCE, dlnEI, dlnPG, dlnTE, and dlnUL, which represent the first-differenced variables, the similar change period exists with the characteristics of white noise. This is called the typical feature of cointegration relationship.

The result of the ADF test presented in Table 2 suggests that lnCE, lnEI, lnPG, lnTE, and dlnUL are 1-order single sequence after the first-order difference, meeting the condition of cointegration test.

3.2.2. Cointegration Test. To determine a long-term equilibrium relationship among variables, the paper adopts Johansen test method based on vector autoregression,

TABLE 2: The ADF test result for the series.

Item	Variable	Test Type	Statistics of ADF	P value	Confidence threshold of 1%	Confidence threshold of 5%	Confidence threshold of 10%	Results
The level item	lnCE	(C, T,6)	-3.127378	0.1100	-4.127338	-3.490662	-3.173943	Non-stationary
	lnTE	(C, T,6)	-2.983204	0.1459	-4.127338	-3.490662	-3.173943	Non-stationary
	lnPG	(C, T,2)	-1.717557	0.7315	-4.115684	-3.485218	-3.170793	Non-stationary
	lnUL	(C, T,5)	-2.024651	0.5757	-4.124265	-3.489228	-3.173114	Non-stationary
	lnEI	(C, T,1)	-3.340095	0.0694	-4.113017	-3.483970	-3.170071	Non-stationary
First-order differential term	dlnCE*	(C, N, 1)	-4.554732	0.0005	-3.542097	-2.910019	-2.592645	stationary
	dlnTE*	(C, N, 1)	-4.523070	0.0005	-3.542097	-2.910019	-2.592645	stationary
	dlnPG*	(C, N, 1)	-5.613558	0.0000	-3.542097	-2.910019	-2.592645	stationary
	dlnUL*	(C, N, 2)	-3.676089	0.0069	-3.544063	-2.910860	-2.593090	stationary
	dlnEI**	(C, N, 1)	-3.172484	0.0265	-3.542097	-2.910019	-2.592645	stationary

Note: C denotes including the intercept, T denotes including trend items, N denotes not including trend items, the digital denotes lag interval, $P=0.001$, * denotes the variables are steady at 1% significance level, and ** denotes the variables are steady at 5% significance level.

TABLE 3: Optimal lag orders of VAR (vector autoregression) model.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	233.1427	NA	3.88e-10	-7.480088	-7.307066	-7.412279
1	721.8201	881.2216	9.73e-17	-22.68263	-21.64449	-22.27577
2	788.4342	109.2033	2.53e-17	-24.04702	-22.14378*	-23.30112
3	832.7521	65.38710*	1.40e-17*	-24.68040*	-21.91204	-23.59545*

Note: * indicates lag order selected by the criterion.

FIGURE 4: Times histories of first difference value.

introduced by *Johansen and Juselius* [36]. Its basic idea is testing cointegration relationship by likelihood ratio method based on Trace statistics and Max-Eigen statistics of error correction model (ECM). The Johansen test assumes that the normal variables are independent identically distribution in vector autoregression (VAR). Therefore, the residual of VAR should be taken a diagnostic test firstly. The appropriate lag order K must be ascertained by Akaike information criterion (AIC), Schwarz information criterion (SC), sequential modified LR test statistic (LR), final prediction error (FPE), and Hannan-Quinn information criterion (HQ). As

is shown in Table 3, the lag order is set as 3 by most criterions.

According to the Trace statistics in Table 4(a), the first and the second eigenvalues are greater than the critical values at the 5% level. Simultaneously, the first eigenvalue in Max-Eigen statistics is also greater than the critical values at the 5% level (Table 4(b)). That is to say, there exists cointegration relationship among $\ln CE$, $\ln TE$, $\ln PG$, $\ln UL$, and $\ln EI$ according to the results of Trace statistics and Max-Eigen statistics. At last, the standardized cointegrating equation is obtained (Table 5), which can be written as follows:

$$\ln CE = 0.7701 \ln TE + 0.2616 \ln PG - 0.3842 \ln UL + 0.0558 \ln EI + 6.2597 \quad (2)$$

Table 6 shows the unit root test results on residual series in (2) by the ADF test method, which indicates that the residual series is stationary.

In (2), the coefficients of elasticity reveal that the variables statistically have significant impact on the CO_2 emission. 1% increase in total energy consumption (TE), per capita GDP (PG), and energy intensity (EI) will result in increase of CO_2 emissions by 0.7701%, 0.2616%, and 0.0558%, respectively. Hence, the sum elasticity of the three variables is 1.0874%, which indicates the three factors are contributed to considerably increase the CO_2 emissions. However, the urbanization level negatively affects CO_2 emissions with the elastic coefficient of -0.3842%.

TABLE 4

(a) Results of Johansen cointegration test (Trace)

the null hypothesis: the number of cointegrating vectors	Eigenvalues	Trace Statistics	threshold value of confidence 5%	P values	Test results
None	0.690327	120.2196	69.81889	0.0000	decline
maximum 1	0.376680	48.71311	47.85613	0.0414*	accept
maximum 2	0.173818	19.87870	29.79707	0.4311	decline
maximum 3	0.115112	8.231362	15.49471	0.4410	decline
maximum 4	0.012567	0.771439	3.841466	0.3798	decline

Note: $P=0.001$; * denotes acceptance of the original hypothesis at the 5% level of significance.

(b) Results of Johansen cointegration test (Max-Eigen)

the null hypothesis: the number of cointegrating vectors	Eigenvalues	Max-Eigen Statistics	threshold value of confidence 5%	P values	Test results
None	0.690327	71.50651	33.87687	0.0000	accept
maximum 1	0.376680	28.83441	27.58434	0.0344*	decline
maximum 2	0.173818	11.64733	21.13162	0.5827	decline
maximum 3	0.115112	7.459923	14.26460	0.4363	decline
maximum 4	0.012567	0.771439	3.841466	0.3798	decline

Note: $P=0.001$; * denotes acceptance of the original hypothesis at the 5% level of significance.

TABLE 5: Normalized cointegrating coefficients.

lnCE	lnTE	lnPG	lnUL	lnEI	C
1.000000	-0.770072 (0.08348)	-0.261565 (0.12829)	0.384231 (0.09409)	-0.055820 (0.10764)	-6.259733

Note: the data in brackets is asymptotic standard error.

TABLE 6: Unit root test results on residual series.

Statistics of ADF	Confidence threshold of 1%	Confidence threshold of 5%	Confidence threshold of 10%	P value
-7.178756	-2.609324	-1.947119	-1.612867	0.0000

3.2.3. The Fitting Test of Cointegration Model. To develop the cointegration model for forecasting the CO₂ emissions in China up to 2030, the fitting test is needed by inputting the historical data of the variables, including TE, PG, UL, EI, and CE, into (2) during 1953–2016. From Figure 5, during 1953–1957, the deviations between actual lnCE and fitting lnCE are slightly larger than other years with its relative error reaching about 1 %, up to 1.0745%. After 1957, the fitting curve almost coincides with its actual curve with relative errors less than 0.3574%. In summary, the established cointegration model has great fitting accuracy adapting to the long-term forecast on CO₂ emissions.

3.3. Long-Term Forecast Results. According to “the 13th Five-Year Plan for National Economic and Social Development in China (2016–2020)”, by 2020, the urbanization level, GDP, the population, and per capita GDP will reach 60%,

FIGURE 5: Fitting test of long-term equilibrium relationship model.

FIGURE 6: The trends of carbon emissions for energy consumption and GDP (2017-2030).

TABLE 7: The values of carbon intensity and energy intensity in 2005, 2015, 2020, and 2030.

	Carbon intensity (kgCO ₂ /yuan)	Energy intensity (kgce/yuan)
2005	2.130	0.930
2015	1.311	0.616
2020	1.062	0.524
2030	0.806	0.396

957.3 hundred billion yuan, 1.42 billion, and 67415 yuan (calculating by 2016 constant price). Meanwhile, the Plan that has set the value of the energy intensity (i.e., energy consumption per unit of GDP) will decline 15% in 2020 relative to 2015. We forecast the CO₂ emissions for energy consumption during 2017-2030 based on (2). Meanwhile, the development tendency of GDP and CO₂ emissions for energy consumption during 2017-2030 are shown in Figure 6. In Figure 6, the forecast results provide a dynamic window for CO₂ emissions for energy consumption of China in future time series. According to the forecast results, China would bear great pressure of CO₂ emissions for energy consumption of 14.4853 billion tCO₂ by 2030, which is nearly 1.59 times that of 2016 and nearly 105 times that of 1953. And carbon emissions and GDP maintain almost same rate of growth. Obviously, the conflict between the economic development and environmental protection will become more and more tense and China needs to make greater efforts for reduction credits.

From Table 7, the predictive values of carbon intensity (i.e., CO₂ emissions per unit of GDP) will drop from 1.311 kgCO₂/yuan by 2015 to 1.062 kgCO₂/yuan by 2020, decreased by 18.9% during this period, which is nearly consistent with the binding target of the Plan, i.e., 15%. Especially, the reduction of carbon intensity in 2020 will account for 49.86% that of 2005, which meets the requirements announced by Chinese government in Copenhagen conference in 2009. Meanwhile, Table 7 shows the different values of energy intensity in 2005, 2015, 2020, and 2030. The decline rate of carbon intensity would be greater than that of energy

intensity from 2005 to 2015, however nearly equal from 2015 to 2020. This fully exhibits that the decrease of energy intensity greatly promotes carbon reduction in the studied period.

4. Discussion

The cointegration approach precedes to establish the relationships between nonstationary time series in the previous studies and effectively avoids spurious regression, higher prediction, and accuracy compared to other time series regression models. Our study confirms that not only does a long-term cointegration nexus among energy intensity, per capita GDP, total energy consumption, urbanization level, and carbon emissions for energy consumption in China exist, but also it has great fitting accuracy adapting to the long-term forecast on CO₂ emissions. It is worthwhile to bring forward that the cointegration model is fit for the long-term forecast on CO₂ emissions with great fitting accuracy and forecast precision.

In the paper, the cointegration model is applied to reveal the influential mechanisms and influential degrees of energy intensity, per capita GDP, urbanization level, and total energy consumption on carbon emissions for energy consumption. According to the study results, carbon emissions associated with rapid energy consumption will show a clipping upward trend during the studied period. In the influential factors, the urbanization level is contributed to carbon reduction to some extent. However, the mitigating effect of urbanization level on carbon pollution cannot offset the accumulative positive effect of the other three factors, i.e., energy intensity, per capita GDP, and total energy consumption. Thus, it may infer that urbanization has offered new opportunities to government for mitigating the carbon pollution. Meanwhile, though the predicting result of carbon intensity in 2020 meets the set goal announced by China government in Copenhagen, sustainable economic growth in China offers important information to further improve carbon emission reductions and preventing global warming. In addition to the factors considered in the paper, several aspects such as consumption patterns, regulatory measures, and technological innovations are likely to affect this future prospects of CO₂ emission. Therefore, we will consider more influential factors to effectively evaluate the development tendency of CO₂ emissions for energy consumption. In addition, our study computes CO₂ emissions at the country level from macroperspective and focuses on the time series analysis, which is lack of spatial econometrics analysis and not incorporating spatial spillover effects due to provincial heterogeneity in emission forecasting. [11]. The contents will be studied in the next step.

5. Conclusions

In this paper, cointegration approach is adopted to forecast the change trend of CO₂ emissions for energy consumption in China from 2017 to 2030. Firstly, IPCC method is applied to analyze quantitatively the change trend of CO₂ emissions for energy consumption from 1953 to 2016. Secondly, we establish

cointegration model to conduct the long-term prediction including four influential factors, i.e., per capita GDP, urbanization level, energy intensity, and total energy consumption. Finally, we analyze the change trend of carbon intensity and energy intensity. Based on the current studies, the following conclusions are drawn. Based on continuous increase of carbon emissions resulting from energy consumption during 1953–2016, China has an urgent need of carbon reduction confronting a great pressure from international community. Reduction of carbon intensity in 2020 maybe attains the goals announced by Chinese government in 2009, and, relative to a business-as-usual (2016), carbon emissions for energy consumption attain 14.4853 billion tCO₂ by 2030, which is nearly 1.59 times that of 2016. The results suggest that, under connotation development of urbanization, it is very important for the policymakers in China to formulate the more effective measures to mitigate the CO₂ emissions and reach the peak of the CO₂ emissions as soon as possible in China.

The findings of the study deserve special attention from policy makers, particularly those in developing nations where rapid urbanization and industrialization are arising. The special attention should be paid to connotation development of urbanization, including energy policy, environmental protection policy, and so on. The policymakers may mainly consider reducing energy intensities and formulating stricter environmental regulations as follows: first of all, optimizing the composition of energy consumption and improving the energy efficiency; secondly, promoting green technologies and building low-carbon industrial system; finally, constructing stricter Air Act and collecting discharge licenses. In addition, we need to estimate expected costs of emission reductions and expected benefits from preventing global warming.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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