China's provincial energy-related carbon emissions-economy nexus: A two-stage framework based on decoupling analysis and panel vector autoregression

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Abstract
China is transforming the growth model and speeding up industrial structural improvement and upgrading now and in the coming years, which means the slowdown of economic growth and more serious environmental costs in economic and social development would be the “New Normal.” As the world's largest energy consumer and carbon-emitting country, China’s emissions reduction commitments are crucial to global greenhouse gas emissions mitigation, so there is a profusion of research focused on China's economy-environment nexus. Among which, the dynamic relationship of carbon emission and economic growth and its evolution combined the national, regional, provincial data have not been discussed thoroughly. This paper analyses the elasticity of economic performance of carbon emissions based on 30 Chinese provincial data from 2000 to 2016; furthermore, a panel vector autoregressive model is constructed to discuss the interactions of variables within environmental economic system. It is concluded that China is experiencing a turning point from weak decoupling to strong decoupling in recent years, and its economic performance of carbon emissions has been gradually improved with larger disparities among provinces though. Regression result confirms the role of the energy mix on carbon emissions, and it also indicates that the impact of most factors influencing that have been discussed in previous studies may not be direct, prominent, and for long term.

KEYWORDS
carbon emissions, China, decoupling, energy economics, turning point
1 | INTRODUCTION

In the light of the global warming, greenhouse gas emissions have received increasing attention from the public. State parties have taken various measures and made great efforts to control greenhouse gas emissions and to prevent dangerous anthropogenic interference with the climate system. However, many challenges still exist in reducing global greenhouse emissions and achieving sustainable economic and environmental development. On one hand, due to the attribute of air as a common good, achieving the goals requires the concerted understanding and action of international community; otherwise, the effect is limited. On the other hand, greenhouse gases such as carbon dioxide emissions are often considered as negative externalities of economic activity. Therefore, environmental goals and economic goals are often contradictory, with the former the higher priority in the policymaking usually. For example, the United States announced its withdrawal from the Paris Agreement because of underlining the U.S. economy and employment. So, it is necessary to obtain global consensus on emission reduction and to clarify each country’s specific responsibility it should take in the joint participation and action of all state parties to mitigate global warming, before which a comprehensive assessment of economy-environment nexus is needed.

China is currently the world’s largest energy consumer and carbon emitter. Although a series of effective measures have been implemented domestically, problems still exist in China’s carbon emission reduction practice. For example, the scale of the national carbon emissions trading market launched in December 2017 is small and far below market expectations. Extensive growth way in the last decade which relies on resource consumption and investment is difficult to be continued. Chinese economy has now passed into a new stage (“New Normal”), in which the economic growth mode has changed greatly from pursuing of rapid economic growth to moderate but more sustainable growth. Change in domestic production structure and consumption patterns has affected both the drivers of China’s carbon emission growth and the global climate change mitigation. In this context, governments are paying increasing attention to how to transform the growth mode from driven by a single factor to relying on the total factor growth; researches are increasingly focused on China’s low-carbon economy and sustainable development issues, among which the environmental and economic relations are the most widely studied for its practical guidance.

This paper mainly analyzes China’s provincial energy-related carbon emissions-economy nexus by adopting the decoupling coefficient, and we contribute to the literature by combining static decoupling analysis and dynamic vector autoregressive method to comprehensively assess the relationship between China’s carbon emissions and economic variables. On one hand, China’s emission reduction practice is still in its infancy, most of decisions are still based on some basic indexes. For example, carbon intensity is the most important index in the central government’s assessment system for local governments. While as a change rate index, economic elasticity of carbon emissions is more practical and instructive. On the other hand, comprehensive analysis containing both evaluation energy-economy-environmental relationship and the analysis of dynamic influencing factors continues to be lacking. Methodologically, most existing studies fail to achieve this goal. For example, researches on environmental economics or ecological economics are usually focused either the production process or the production technology; thus, it usually does not reach the decision recommendations, while some policy guidance studies which evaluate green economy or low-carbon economy may suffer from subjectivity and ambiguities, in addition to conceptual issues. Therefore, an improved framework is needed.

2 | LITERATURE

Previous studies on Energy-economy-environment (3E) are mainly composed of two major issues, that is, energy-economy-environmental relationship and the endogenous interactions (or factors influencing) among them. Relationships in 3E system can be roughly classified into three categories. The first group goes to study the Kuznets relationship based on regression or other econometric tools. Human impact population affluence technology (IPAT) and stochastic impacts by regression on population, affluence, and technology framework (STIRPAT) are the most widely used method currently. Wang et al. explored the impact of urbanization on energy consumption and CO2 emissions with consideration of provincial differences. He et al. analyzed panel data from 1995 to 2013 of China to examine the influence of urbanization on CO2 emission at different development levels. They found that three regions showed an inverted U relationship between urbanization and CO2 emission in the major regions of China besides the effects of urbanization vary significantly across the regions. Wang et al. explored the income/urbanization and disaggregated industrial carbon dioxide emissions nexus, using panel data together with semiparametric panel fixed-effects regression. Yu et al. combined energy analysis and an IPAT equation to create an integrated framework for evaluation of sustainable development of Liaoning province in China and uncovering the driving forces. Meanwhile, econometrics tools such as regression analysis, cointegration test, and causality analysis are widely used in the study of environmental and economic issues.

The second group is about assessment of energy-economy-environmental performance, including index assessment and efficiency evaluation. The data envelopment analysis (DEA) which is based on mathematical programming is
usually used to evaluate the efficiency performance. As its advantage at dealing with measuring the relative efficiency of decision making units with multiple inputs and outputs, DEA has been widely adopted to evaluate the energy, environmental, and carbon emission efficiency.38-41 Although DEA-based assessment method could overcome the subjectivity exists in the index evaluation method, the static efficiency evaluation method fails to provide specific factors of trend change; the Malmquist productivity index based on the DEA method makes up for this deficiency.32-35

The third group is based on environment-economy elasticity to analyze the decoupling status of regional or industry level. Decoupling refers to two variables change at different speed, the Organization for Economic Co-operation and Development (OECD) defined decoupling as breaking the link between “environmental bads” and “economic goods.”36 Tapio37 modified the decoupling evaluation model and divided them into eight categories according to the degree of decoupling. Armed with this framework, many scholars have studied the environment-economy decoupling status at the national level.38-41 As for decoupling in china, most studies have been focused on regional, provincial, and sector levels. At regional level, Zhang and Da42 analyzed the decoupling relationship between carbon emissions and economic growth in China from 1996 to 2010, most years during their study period saw the relative decoupling effect between carbon emissions and economic growth. Wang and Yang43 constructed an expanded decomposition model for decoupling elasticity and analyzed the delinking indicators in Beijing-Tianjin-Hebei economic band. At provincial level, Wang et al44 studied energy-related carbon emission from electricity sector in Shandong province. Wang et al45 conducted research on decoupling relationship between economic growth and carbon emission of transportation in Jiangsu province and found an obvious characteristic of weak decoupling-expansive negative decoupling-weak decoupling in Jiangsu. At sector level, Wang et al46 used the improved Tapio model to estimate the decoupling elasticity between the development of China’s transportation industry and carbon emissions. Luo et al47 investigated the decoupling of carbon dioxide emissions from agricultural economic growth from 1997 to 2014. Jiang et al48 combined decoupling and decomposition econometric techniques to quantify both the decoupling effects and the driving power of carbon emissions in China’s six major sectors.

As for factors influencing of carbon emissions, the factor decomposition method has been extensively applied to study changes in carbon dioxide emissions and energy consumption.49-52 There are typically two types of decomposition approaches: index decomposition analysis (IDA) and structural decomposition analysis (SDA). Wang et al53 reviewed studies published in 2010-2015 and compared the two techniques from the methodological and application viewpoints. IDA method is built on the index number theory, and it only uses the department's aggregate data. Therefore, it is under a relatively low demand for data, because of this advantage, it is the most widely used decomposition method. Xu et al54 adopted IDA to decompose the factors that influence carbon emissions of six Chinese industrial sectors. Wang and Feng55 employed the logarithmic mean Divisia index (LMDI) method to explore the salient factors driving the changes in energy consumption in China’s nonferrous metal industry from 2000 to 2014 in China. Mi et al5 used SDA method to analyze the impact of population, carbon emissions intensities, consumption patterns, production structure, and per capita consumption on China’s carbon emission changes during 2005-2012. Mi et al6 adopted MRIO-based decomposition to investigate the determinants of changes in China’s export embodied emissions. Su et al56 investigated the drivers of carbon emission changes in Singapore using structural decomposition analysis. SDA decomposition can not only include both direct and indirect carbon emissions of energy consumption but also examine the indirect influence of variable changes on other regions and departments. However, because of its dependence on input-output tables, analytical results from SDA tend to have time lag.

The vector autoregressive model (VAR) proposed by Sim could overcome shortcomings of IDA and SDA by carrying out empirical analysis based on continuous and longer time series data, which can not only explain the relationship among variables but also provide dynamic analysis and prediction.57 It is usually employed to capture the dynamic impacts of the influencing factors among variables. Xu and Lin58 analyzed the influencing factors of the changes in carbon dioxide emissions in China’s transport sector during 1980-2012 with VAR model. Abbasi and Riaz59 explored the influence of Pakistan’s economic and financial development on carbon emissions in an augmented VAR framework. Chevallier60 reviewed and considered the nonlinear adjustment between industrial production and carbon prices in the EU 27 based on threshold vector error correction and Markov-switching VAR models. Li and Su61 adopted the VAR model to examine the dynamic effect of renewable energy consumption on carbon dioxide emissions in the United States from 1990 to 2015.

As a classical method of econometrics, VAR is relatively less applied in the environment-economic area mainly because the model usually needs long time series, and many environment-economic data cannot satisfy the condition of stability. Panel vector autoregressive model (PVAR) proposed by Holtz-Eakin et al62 which combines the traditional VAR approach and panel-data approach, relaxes the stability assumptions and can be estimated under steady state with relatively short time series data. Antonakakis et al63 examined interactions among oil dependence variables, economic growth, and several political institutional variables in 76 countries over the period 1980-2012. Lin and Zhu64 used the interprovincial panel data of China from 2000 to 2015 to analyze the dynamic relationship among the
urbanization, industrial structure, energy consumption, and carbon intensity. They found urbanization and upgrading of industrial structure have a larger contribution rate to the deviation in energy and carbon intensity. Ouyang and Li studied the endogenous relationships among financial development, energy consumption, and economic growth in China over the period 1996Q1-2015Q4. Lei et al. developed an indicator to assess low-carbon economy in China and further employed a panel vector autoregression approach to find out the role of economic variables in determining the low-carbon economic growth. Their results showed that adjusting industrial structure and reducing the coal energy share are the two most effective approaches to improve low-carbon economy in both the short run and the long run.

A lot of work has been done in previous papers, but there are two major deficiencies in current studies about 3E system. On one hand, much of the research on decoupling only use integrated data, or data from some individual years, while decoupling or delinking might be time-being phenomena, and results from individual years, regions, or sectors often fail to reflect real decoupling status. Therefore, it is necessary to strengthen the reliability of the results from a longer time series and multilevel of research objective. On the other hand, most of the comprehensive analysis containing both environment-economic nexus and influence factors are usually based on decoupling and IDA or SDA. While result from these two methods is both based on data from two periods (which is closer to static analysis), thus it fails to well reflect the evolution of factors influencing and other dynamic characteristics. Considering these deficiencies, we combine static decoupling analysis and dynamic PVAR method to comprehensively assess the relationship between China's carbon emissions and economic variables. Furthermore, we adopt the latest Chinese provincial data to conduct qualitative and quantitative analysis at provincial, regional, and national levels. These efforts make our assessment of China's decoupling state more typical and reliable in terms of the country's reality.

3 | METHODS

3.1 | Compiling carbon emissions inventories for 30 provinces in China

We calculate the carbon emissions from 8 kinds fossil fuels (coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, and natural gas) combustion of each province based on IPCC guidelines for national greenhouse gas inventories, the calculation formula is

\[
CE = \sum_{i=1}^{n} E_i \cdot EF_i \cdot NCP_i, \tag{1}
\]

where \(EF_i\) represents the carbon emissions coefficient of the \(i\)-th energy source, we adopt IPCC default value. \(NCP_i\) represents the net heating value of the \(i\)-th energy source, and \(E_i\) is total energy consumption of different fossil fuel \(i\).

3.2 | Decoupling model

Decoupling theory proposed by the Organization for Economic Cooperation and Development (OECD) is to describe the relationship between economic growth and resource consumption or environmental pollution. Tapio

\begin{equation}
\end{equation}

FIGURE 1  The degrees of coupling and decoupling. As far as the degree of decoupling is concerned, D > C > N; and the smaller the number is, the higher the degree of decoupling will be. For example, when comparing the degree of decoupling, D1 > D3 > N1 > N3. As decoupling coefficient is calculated based on two years’ data, \(e\) in this paper refers to period \(t-1\) to \(t\)
further develops the theory and redefines the division of decoupling status. The formula is as follows:

\[ e = \frac{\% \Delta C}{\% \Delta GDP} = \frac{(\Delta C/C)}{(\Delta GDP/GDP)} \quad (2) \]

In Equation (2), \( e \) is the decoupling elasticity coefficient, \( \Delta C \) denotes the carbon emission increment, \( C \) is the carbon emissions of the current year, and \( \Delta GDP \) is the GDP increment. Decoupling (coupling) in this paper is defined based on \( e \) valued in Equation (2), and the judging framework is shown in Figure 1. The value of \( e \) is complex because absolute value and plus or minus simultaneously affect the meaning of this coefficient. It is to be noted that the specific value of \( e \) in a year or two cannot fully explain the decoupling status. Only a continual state can indicate more reliable results of linkage between economy and carbon emissions. Similarly, results from the aggregate data at national level may not describe the whole picture without considering regional disparity. Both temporal and spatial features should be considered, so we use the panel data and combine the results of quantitative analysis and qualitative analysis to study China’s decoupling status. The economic elasticity of carbon emissions is used for quantitative analysis; meanwhile, degree of decoupling and continuity of state are adopted for the main reference for qualitative analysis.

3.3 The panel vector autoregressive model

VAR takes the form of multiple simultaneous equations, and the endogenous variables in each equation to form a regression with the lagged values of all endogenous variables. Holtz-Eakin et al. combine the VAR model and panel-data approach to introduce the panel VAR model. A \( k \)-variate panel VAR of order \( p \) without considering the exogenous covariates could be specified as follow:

\[ Y_{it} = A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + \cdots + A_p Y_{i,t-p} + \mu_i + \nu_i + \epsilon_{i,t} \]
\[ i \in \{1, 2, \ldots, N\}, t \in \{1, 2, \ldots, T\} \]

where \( N \) is numbers of cross section, and \( T \) is the time serious. \( Y_{i,t} \) is a \((1 \times k)\) vector of dependent variables; the \((k \times k)\) matrix \( A_1, A_2, \ldots, A_p \) is parameter to be estimated; \( \mu_i \) is \((1 \times k)\) vector of dependent variable-specific panel fixed-effects; and \( \nu_i \) and \( \epsilon_{i,t} \) are \((1 \times k)\) vectors of dependent variable-specific time effect and individual effect at time \( t \). Generalized moment estimators (GMM) are known
to be consistent, asymptotically normal, and efficient, and it relaxes the requirements for statistical distribution characteristics of sample data, so we use it to estimate the PVAR model.

3.4 | Variable description and database

All data come from China Statistical Yearbook (2000-2017) and China Energy Statistics Yearbook (2000-2017). Table 1 gives the statistical description of all variables this paper used. It should be noted that there are some inconsistent data in China Energy Statistics Yearbook, in dealing with that we choose the newest revised version.

GDP is transformed into 2000 price with GDP deflator of each province. Carbon intensity (CI) is calculated as the carbon emissions (CE) divided by real GDP. Urbanization (URB) is the share of urban population to total population. Because there are no URB data in 1999, 2001-2004, we adopt results of Ref.68,69 to replace the missing data. As coal is the most important energy in China, the proportion of coal consumption in total energy consumption is calculated as energy mix (EM). Note that we did not adjust for the abnormal values (EM bigger than 1) appeared in some individual provinces such as Sanxi and Inner Mongolia for two major reasons: (a) EM is a virtual viable, a larger EM value means an energy structure more dependence on primary energy, which makes sense in theory, and (b) the database we adopt is the most authoritative which available to public, and it would be difficult to find other sources to supplement it and meanwhile arbitrary to strip out these data. Industry structure (IS) in this paper is defined in Equation (4), where $Y$ and $Y_i$ represent the total output and output of sector $i$, respectively, and $L$ and $L_i$ represent the number of employment for the whole industry and sector $i$, respectively. The value of IS should be 0 in a balanced economy, and a bigger value means a more crowded (worse) industry structure.

$$IS = \sum_{i=1}^{n} \frac{Y_i}{Y} \left( \frac{Y_i/L_i}{Y/L} \right).$$

4 | RESULTS

4.1 | Improved performance of energy-related carbon emissions in China

China has pledged to lower carbon dioxide emissions per unit of GDP by 60-65 percent from the 2005 level by 2030 at the 2015 climate conference in Paris.70 Based on the panel data since 21st century, we can infer that it is very likely for Chinese government to achieve this goal. As shown in Figure 2A, China's carbon intensity is declining at an average rate of 3.7% during 2000-2016. Before 2006, the change rate is slow (average 1.6%) and the gap between regions is relatively large, while carbon intensity decreased significantly after 2006 (average 5%) with less regional disparities (which start to increase around 2012). The Chinese government announced in early 2018 that its carbon intensity decreased by 46.1% from 2005 to 2017 (2017 is down 5% from 2016, while specific data of energy and industrial activities in 2017 were not published; based on this data, our calculation is 46.5%, which is basically in accordance with the official announcement), and has achieved its 2020 emission reduction target ahead of schedule.71 As far as the commitment in 2030, in

![FIGURE 2](image-url) Evolution of China’s environmental and economic relations. A, Evolution of China's carbon intensity. The central and east are above the national average, while the northwest is relatively worse. B, Evolution of China’s decoupling elasticity coefficient. Areas among the dotted lines (0.8) mean the weak decoupling. The value of elasticity coefficient does not necessarily correspond to the decoupling status, but in the regional and national level in our study they are corresponding to each other, and a smaller value means higher the degree of decoupling.
a lowest scenario (1.6%), carbon emissions per unit of GDP will decrease more than 65%.

Decoupling coefficient explains the relationship between carbon emissions and economic growth from mutual impact in changing process. Figure 2B shows China has been in a weak decoupling state from 2000 to 2016 as a whole; that is, both carbon emissions and economic aggregates are on the rise, with the growth rate of the former lower than the latter. From the changing trends, elasticity shows a general declining trend, indicating that the degree of decoupling in China is strengthening. Regional decoupling states are consistent with that of the national level; six regions are generally in weak decoupling status in the research period with the degree of decoupling strengthening, but spatial variation has increased since 2012. 2012 is a very important year, and China was in an unstable state of weak negative decoupling before 2012 with elasticity fluctuates significantly. However, after 2012, e value is much smaller and shows little fluctuation, indicating that the overall decoupling state in China has improved since 2012; a strong decoupling state even appeared in 2012-2013 (e = −0.04675). Meanwhile, it is shown in Figure 2B that 2002, 2006, and 2008 are the other three years showing a change in the trend. We can subdivide the decoupling state of China into specific phases, which needs to be further integrated with provincial and regional results.

4.2 Three stage of economy-emissions nexus in provincial level

Combined with the quantitative analysis and qualitative analysis of national, regional, and provincial levels, we subdivide China’s environment-economy development into three stages. Figure 3 describes that China’s environmental economic relationship has gone from good to bad, and then to good, with increasing provincial disparities. Generally, affluent regions (such as the North and the East) and provinces and cities with preferential policies (such as Beijing, Chongqing, Tianjin, and Shanghai) are superior to other regions and provinces in terms of the degree of decoupling. It reflects the huge differences between China’s regions and their development stage and growth model: Developed regions and provinces have shown a lower carbon development due to the accumulation of capital and technology at the early stage, while developing areas, because of the late start and poor level of industrialization and urbanization, are undertaking industrial transfer (especially those resource consumption and labor-intensive industries) from the developed area. Environmental economic relations are still deteriorating.

2000-2005 is the first stage, in which most regions and the nation as whole transition from weak decoupling to expansive coupling, so we define this period as recession stage. Reform of state-owned enterprises in the 1990s activated industrial production; but limited by technology and management level, the growth rate of energy consumption and carbon emissions is usually faster than that of economic development in this stage. The second stage covers 2006 to 2011, it can be observed that all regions in this stage are almost represented by weak decoupling, and we can call it the stability (of weak decoupling) stage, in which Chinese government attaches more importance to the environment and climate issues, and energy consumption (Energy conservation and environmental protection have been formally incorporated into the 11th Five-Year Plan (2006-2010), which mainly focused on energy consumption per unit of GDP and emissions of major pollutants). We define the 2012-2016 as the optimization (of weak decoupling) stage. Strong decoupling was demonstrated in many provinces, but heavy-industrialized and energy-intensive provinces such as Shanxi, Inner Mongolia, Liaoning, Heilongjiang, and Xinjiang show signs of negative decoupling. Therefore, it should be noted that although China as a whole is at the stage of decoupling optimization during
2012–2016, the disparity in each region and province at this stage was more apparent.

4.3 | Panel vector autoregression results

The dynamic relationship and interactions between carbon emissions and its factors influencing, that is, GDP, carbon intensity (CI), energy mix (EM), industry structure (IS), and urbanization process (URB) are analyzed by constructing a provincial PVAR model. Pretests (Tables 2 and 3) are conducted to make sure our data meet the conditions of the model, logarithmic form of variables are taken into PVAR to increase the smoothness of data. Furthermore, determining the optimal lag length is a very important step before estimating the model because a too long lag will lead to an increase in the estimated parameters and loss degrees of freedom, while a too short one may not be able to capture the dynamic behaviors among variables. Depending on the lag order selection results in Table 4, we then establish a 3-period lag PVAR (6) model.

Table 5 gives the GMM estimation result of the PVAR model. First, only the energy mix shows a direct negative correlation with carbon emissions. GDP and industry structure have a positive and urbanization has a negative impact on carbon emissions; however, the impact of GDP, IS, and URB on the carbon emissions is not significant at 10% level. Second, on the effects of other variables, we focus on the first column of the regression results of IS, and first-period lag of GDP has a negative impact on the industrial structure, but the second-period lag has a positive and more pronounced effect on IS. Generally speaking, it can be considered that GDP and IS are positively correlated, indicating that China's economic development is not balanced, and accompanied with the process of industrial agglomeration. In addition, first-period lag of URB has a positive impact on IS, while second lag and third lag have a negative impact, indicating that the level of China's urbanization is relatively low, accompanied by industrial aggregation process in early stage; while it improves subsequently, the industry structure will become more and more balanced.

4.4 | Three conclusions from impulse-response analysis

4.4.1 | Green economy in China

China has shown the possibility of long-term development of a low-carbon economy. One standard shock from GDP will generate a short-term increase in carbon emissions, but the impact will change from positive to negative since the fourth period after the shock (Figure 4), indicating that economic growth in the short term will increase carbon emissions, but in the long term, economic growth and environmental improvement are
not contradictory. The results also confirm the possibility of the strong decoupling trend between carbon emissions and economic growth in the future of China we discussed above. As for URB, there is a weak negative effect on the CE before the 5th period. That turned positive from the 6th period and the influence was strengthened. It shows that urbanization has a long-term positive impact on carbon emissions.

### 4.4.2 The most important factor influencing

Balance of industrial structure is the most important factor affecting carbon emissions, and industrial aggregation (worse industrial structure) will result in an increase in carbon emissions (Figure 5). The influence of CE mainly came from CE itself at an early stage, and the proportion of contribution declined gradually, reaching 9.5% in the 10th period. The contribution rate of IS on the deviation of carbon emission maintains a gradual upward trend. From the 5th forecast period, it becomes the most contributing factor to the CE fluctuations. Then, the contribution rate continues to rise and reaches 85.3% in the 10th period. However, the contribution rate of other variables to carbon emission fluctuations is generally small, among which, the contribution rate of EM rises from the first period, peak in the fourth period (4.8%), and then decline to 1.1% in the 10th period. The contribution rate of GDP on EM has been continuously enhanced and reached 2.5% in the 10th period. Contribution of URB is very limited (0.3%).

### 4.4.3 Indirect influence

During the past decade, China’s growing carbon emissions were accompanied by a reduction in carbon intensity, an optimization of energy consumption structure and an increasing rate of urbanization. We can find in Figure 4 that the impact of CI and EM on carbon emissions is negative, which is inconsistent with our cognition, as the increase in primary energy consumption tends to result in more carbon emissions. On one

| Lag | AIC     | BIC     | HQIC    |
|-----|---------|---------|---------|
| 1   | −17.2189| −15.2465| −16.4415|
| 2   | −17.8999| −16.7714| −16.9417|
| 3   | −19.7003| −16.7714| −18.5393|

AIC (Akaike information criterion), BIC (Bayesian information criterion), and HQIC (Hannan and Quinn information criterion criteria) are used to determine the optimal lag length. When the maximum lag order is >4, the variance matrix is asymmetric or highly singular, so the max lag is set to 3.

*Optimal lag order selected.

| Dependent variables |
|---------------------|
| CE     | GDP     | CI      | IS      | EM      | URB         |
| L1-CE   | 1.0673*** | 0.2278  | 0.2348  | −0.2702 | 0.1819  | 0.0186 |
| L2-CE   | −0.3993  | −0.0667 | −0.2416 | 0.2090  | −0.1290 | 0.0082 |
| L3-CE   | 0.1685   | 0.0268  | 0.3182  | −0.0024 | 0.0044  | 0.0056 |
| L1-GDP  | 0.3581   | 0.7974***| 0.1981  | −0.4512 | −0.0471 | −0.0715 |
| L2-GDP  | −0.1417  | 0.0615  | −0.5901 | 0.7494* | 0.0014  | 0.0476 |
| L3-GDP  | −0.1708  | −0.0838 | −0.3183 | −0.3461 | 0.0236  | 0.0009 |
| L1-CI   | −0.0643  | −0.3661 | 0.8482***| −0.0362 | −0.1231*| −0.0029 |
| L2-CI   | 0.1438   | 0.2920  | 0.0614  | 0.0166  | 0.1735**| 0.0036 |
| L3-CI   | −0.1208  | 0.0065  | −0.1135 | −0.0098 | −0.0746*| 0.0015 |
| L1-IS   | 0.2883   | 0.0689  | 0.2355  | 0.7954  | −0.5132 | 0.0704 |
| L2-IS   | 0.0931   | −0.0738 | 0.2332  | 0.3458  | 0.0217  | 0.0280 |
| L3-IS   | 0.1207   | −0.0186 | 0.1672  | 0.1376  | 0.0066  | 0.0143 |
| L1-ES   | −0.3514* | −0.0573 | −0.5188 | 0.0523  | 0.7397***| 0.0133 |
| L2-ES   | −0.0229  | 0.0379  | −0.0526 | −0.1868 | −0.0837 | 0.0024 |
| L3-ES   | 0.2204*  | 0.0156  | 0.2586  | 0.0243  | 0.1211  | −0.0058 |
| L1-URB  | −0.3076  | 0.3598  | −1.6547 | 1.4740* | 0.0076  | 1.0124***|
| L2-URB  | −0.7651  | −0.8477 | 0.7067  | −1.6419 | −0.1460 | −0.2047 |
| L3-URB  | 0.2791   | 0.3914  | −0.3353 | −0.0124 | −0.0015 | −0.0627 |

*P < 0.1, **P < 0.05, ***P < 0.01.
hand, results from PVAR are based on past time series data; it can only show that China's carbon emission growth in the past was accompanied by the decrease in carbon intensity and the increase in the proportion of primary energy consumption, which reflects correlation not causality. On the other hand, the influence of EM and CI on carbon emissions may be conducted through other variables (such as industrial structure) in the economic system; thus, the influences may be complicated.
5 | DISCUSSION

We have discussed that it is virtually certain for China to achieve its carbon intensity target. Here, we focus on another commitment, that is, peaking carbon dioxide emissions around 2030. First, in national level, the coefficient (\(e\)) is stabilized at 0.1–0.2 and will be turned into negative, indicating the decoupling degree is continuing to strengthen. Second, in regional level, southwest and north have shown continuous strong decoupling, which means they have reached a stable peak of carbon emissions; central is turning from weak decoupling to strong decoupling either. Third, in provincial level (Figure 2B), strong decoupling has appeared at seven provinces in 2012 that number grows to 14 in 2016. The gap between provinces will gradually narrow due to interregional flow of production factors as well as the push of regional economic strategy. More and more provinces will change into strong decoupling; the environmental and economic relations will continue to improve. It is very likely for China to peak carbon dioxide emissions in 2030.

There are two main sources of uncertainties in the estimation of China’s carbon emissions. The first comes from the energy statistics, specifically, from the inconsistent between national energy consumption data and provincial ones, which leads to national aggregated data may not equal the sum of provincial data. This gap can be explained by different statistical caliber or standards, misuse of units for separate provinces, etc. The second and more important source of uncertainties is that from the conflicting estimates of emission factors. We have followed the most widely used IPCC default values overestimated China’s CO2 emissions, emission factors from different sources can differ by up to 40%. China’s carbon emissions are on a turning point now and in the next decade; further studies compiling greenhouse gas emission inventories at the industry and the city level are needed.

Analysis of influence factors of carbon emission is usually based on index decomposition analysis or structural decomposition analysis, which obtains the contribution rate of each factor adopting data from two periods. But the results are not statistically reliable for lacking the support of longer time series data. We study this issue based on provincial panel data in the framework of variable autoregressive, which can not only explain the relationship among variables but also provide dynamic analysis and prediction. It is, to a certain extent, make up for the deficiency and has methodological significance. But our results only confirm the direct correlation between energy mix and carbon emissions, this needs to be viewed dialectically: On one hand, industry structure is considered as the most important factor in the economic environmental system, while the conclusion is not consolidated for not within the confidence interval (Figure 4). It is nevertheless of significance to provide a perspective and a possible conclusion. On the other hand, previous studies that adopt factor decomposition theory give deterministic impact of each factor, but the impact may be not be direct, prominent, and for long term. With the implementation of reform and opening-up policy, China has experienced a rapid economic growth and undergone huge changes in social development and environment. Some of them are trend (eg, GDP and URB) and some are volatile (eg, IS). Just because these changes are so huge and rapidly changing, it is hardly to say that there is much stable correlation between the variables, not to mention the interactions.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

AUTHOR CONTRIBUTIONS

Pan W.L. designed the study. Pan W coordinated and supervised the project. Shan Liu, Sang-Bing Tsai, Cheng Hu, and Hai-Ting Tu revised and edited the paper. All authors participated in the writing of the manuscript.

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