Analyzing and optimizing the impact of economic restructuring on Shanghai’s carbon emissions using STIRPAT and NSGA-II

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Abstract

The economic restructuring of cities has a significant impact on their carbon emissions and is an important pathway to low-carbon development. China is the world’s largest carbon emitter, but few studies provide an in-depth analysis of how economic restructuring is affecting carbon emissions at the city level. This study develops a Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model to analyze the impact of economic restructuring on CO2 emissions in Shanghai. The results suggest that Shanghai’s emissions have remained stable post-2007, largely due to the city’s economic restructuring in favor of the tertiary sector: every 1% increase in the tertiary sector’s share of GDP is associated with a 0.76% reduction in CO2 emissions. This study also uses a multi-objective genetic algorithm, specifically the Non-dominated Sorting Genetic Algorithm II (NSGA-II), to optimize economic restructuring of Shanghai with regard to economic and climate objectives. The result suggests that Shanghai should aim to reduce the industrial share of gross output from 49.4% in 2012 to 38.3% in 2020. The main conclusion of the study is that Shanghai and, by extension, other Chinese cities, cannot achieve their climate targets without making meaningful changes to the economy geared towards less carbon-intensive activities.

Keywords: Economic restructuring, Carbon emissions, Low-carbon cities, STIRPAT, NSGA-II, Shanghai, China

1. Introduction

Cities are centers of anthropogenic activities, making them main contributors of greenhouse gas emissions (Satterthwaite, 2010). Cities thus play a critical role in mitigating climate change through the deployment of low-carbon strategies (Broto, 2017; Bulkeley, 2013; Lee & Painter, 2015; Lo, 2014c; Tsolakis & Anthopoulos, 2015; Zhou et al., 2015). Cities are also in perpetual flux, shifting economic priorities and configurations between sectors in Schumpeter’s waves of creative destruction (Boschma, 2015; Tan, Zhang, Lo, Li, & Liu, 2017). As different sectors have different levels of energy consumption and CO2 emissions, economic restructuring may lead to significant change to cities’ overall carbon emissions (Schafer, 2005). For example, in many high-income countries, the shift from an energy-intensive manufacturing economy to a service-oriented economy exerts a downward pressure on CO2 emissions, whereas developing countries are becoming the main emitters of greenhouse gases as their economy moves towards energy-intensive heavy industries (Andreoni & Galmarini, 2016; Atalla & Bean, 2017). The Environmental Kuznets Curve (EKC) can be adapted to describe this inverted U-shaped relationship between economic development and carbon emissions (Kaika & Zervas, 2013; Khan, Zaman, & Zhang, 2016; Tang & Tan, 2015).

Since 1978, China has experienced an unprecedented rate of economic development and industrialization to become the world’s largest manufacturing nation (Wei, 2017). China’s level of industrialization, measured by industrial value added as a percentage of GDP, increased from 36.1% in 1990 to 41.3% in 2011 (Xu & Lin, 2015). The relationship between economic restructuring and carbon emissions has increasingly gained attention in China, following the government’s pledge to peak carbon emissions by 2030 under the Paris Agreement (Mao et al., 2013; Sanwal & Zheng, 2016). Such an ambitious target demonstrates China’s commitment to climate protection, but also presents new challenges in terms of how to achieve this target.

While the importance of renewable energy and energy efficiency in CO2 mitigation is well established in the literature (Lo, 2014b; Lo & Wang, 2013), the role of economic restructuring is more ambiguous and is under-researched, especially at the city level. Several Chinese studies have examined the role of economic restructuring in energy consumption or emissions through decomposition analysis, but with inconclusive results. Some studies have found that economic restructuring has contributed significantly to a rapid rise in energy consumption and carbon emissions in China (Qi, Winchester, Karplus, & Zhang, 2014; Tang & Tan, 2015).

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Table 1: Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$A$</td>
<td>Affluence</td>
</tr>
<tr>
<td>$c_i$</td>
<td>Carbon emissions coefficient of sector $i$</td>
</tr>
<tr>
<td>$Cl_t$</td>
<td>Carbon intensity in year $t$</td>
</tr>
<tr>
<td>$E$</td>
<td>Energy intensity (energy consumption per unit of GDP)</td>
</tr>
<tr>
<td>$e_t$</td>
<td>Error term of the STIRPAT model</td>
</tr>
<tr>
<td>$EKC$</td>
<td>Environmental Kuznets Curve</td>
</tr>
<tr>
<td>$F$</td>
<td>Final demand matrix</td>
</tr>
<tr>
<td>$FDI$</td>
<td>Foreign direct investment</td>
</tr>
<tr>
<td>$GDP_t$</td>
<td>Gross domestic product in year $t$</td>
</tr>
<tr>
<td>$I$</td>
<td>Impact</td>
</tr>
<tr>
<td>$I_t$</td>
<td>CO$_2$ emissions in year $t$</td>
</tr>
<tr>
<td>$IC$</td>
<td>Matrix of import coefficients</td>
</tr>
<tr>
<td>$LMDI$</td>
<td>Logarithmic Mean Divisia Index</td>
</tr>
<tr>
<td>$M$</td>
<td>Government spending in environmental protection</td>
</tr>
<tr>
<td>$Max$</td>
<td>Maximization function</td>
</tr>
<tr>
<td>$Min$</td>
<td>Minimization function</td>
</tr>
<tr>
<td>NSGA-II</td>
<td>Non-dominated Sorting Genetic Algorithm II</td>
</tr>
<tr>
<td>$P$</td>
<td>Population</td>
</tr>
<tr>
<td>STIRPAT</td>
<td>Stochastic Impacts by Regression on Population, Affluence and Technology</td>
</tr>
<tr>
<td>$S^1$</td>
<td>Percentage of the primary sector in GDP</td>
</tr>
<tr>
<td>$S^2$</td>
<td>Percentage of the secondary sector in GDP</td>
</tr>
<tr>
<td>$S^3$</td>
<td>Percentage of the tertiary sector in GDP</td>
</tr>
<tr>
<td>$T$</td>
<td>Technology</td>
</tr>
<tr>
<td>$TC$</td>
<td>Matrix of technical coefficients</td>
</tr>
<tr>
<td>$TCE$</td>
<td>Tons of coal equivalent</td>
</tr>
<tr>
<td>$UM$</td>
<td>Unit matrix</td>
</tr>
<tr>
<td>$v_i$</td>
<td>Industrial added value coefficient for sector $i$</td>
</tr>
<tr>
<td>$X$</td>
<td>Sector output vector</td>
</tr>
<tr>
<td>$x_i$</td>
<td>Economic output of sector $i$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Weighting variable</td>
</tr>
</tbody>
</table>

Tang, Jin, Wang, Wang, & McLellan, 2017). However, other studies have found that economic restructuring may have a negative impact on carbon emissions. Tang, Jin, McLellan, Wang, and Li (2018) used the Logarithmic Mean Divisia Index (LMDI) method to identify economic restructuring as a key reason behind the recent slowing down of coal consumption in China. Li and Wei (2015) found that the impact of economic structure on China’s CO$_2$ emissions has changed from positive to negative in recent years. Other studies have found the impact of economic restructuring on emissions to be relatively small or insignificant (Huang & Wang, 2016; Xu, Fan, & Yu, 2014; Yan & Fang, 2015; Yu & Kong, 2017). These differing conclusions may be related to discrepancies in the studied periods of time, methods, and the dependent variables (e.g., CO$_2$ emissions vs. energy consumption).

A common problem with these national-level analyses, however, is that they mask significant regional disparities in China. China is a very large and diverse country, where some cities have already entered into a phase of deindustrialization while others are still rapidly industrializing (Koo, Hayashi, Weng, & Bi, 2016; Li, Lo, & Wang, 2015; Li, Mu, Zhang, & Gui, 2012). Furthermore, given the increasingly decentralized nature of energy governance in China, a local analysis may be more useful from a policy perspective (Lo, 2014a, 2015). Due to these reasons, a number of regional- and city-level analyses have emerged recently, and they too have reached different conclusions. Wang, Wu, Zhu, and Wei (2013) used an extended STIRPAT model to study energy-related CO$_2$ emissions in Guangdong province and found that economic restructuring has a positive influence on CO$_2$ emissions. Wang, Zhao, Li, Liu, and Liang (2013) conducted an input-output structural decomposition analysis and revealed that economic restructuring is also driving an increase in CO$_2$ emissions in Beijing. Li, Lo, Wang, Zhang, and Xue (2016) found that industrial restructuring in northeast China has a negative impact on energy consumption. Wang et al. (2017) used STIRPAT to uncover that economic restructuring has little impact on CO$_2$ emissions in Xinjiang, northwest China. Li, Liu, and Li (2015) also found industrial restructuring to be the least important factor related to CO$_2$ emissions in Tianjin.

This paper presents the relationship between economic restructuring and carbon emissions in the context of Shanghai. As one of China’s most developed cities, Shanghai plays a leadership role in both economic restructuring and low-carbon development (Yang, Wang, Lo, Wang, & Liu, 2015). It is one of the national low-carbon pilot cities and aims to achieve carbon peaking by 2020, which is ten years prior to the 2030 target for China (Khanna, Fridley, & Hong, 2014). The city has implemented one of the country’s first carbon emission trading schemes, among other policy innovations (Liao, Zhu, & Shi, 2015; Wu, Qian, & Li, 2014). Therefore, the experience of decarbonization in Shanghai can provide important lessons for the rest of China, making it an appropriate choice for this study.

The methods and findings comprise a two-part study that examines the relationship between economic restructuring and carbon emissions in Shanghai. First, the authors extended the STIRPAT model to quantify the impact of economic restructuring on carbon emissions. This is to establish the importance of economic restructuring vis-à-vis other factors such as population, GDP, energy intensity, etc. Second, a multi-objective scenario analysis was conducted, which optimized economic restructuring for both economic and environmental objectives. This analysis is undertaken to determine which path of action would enable Shanghai to achieve low-carbon emissions and at what cost.

The results show that Shanghai cannot achieve its emission reduction targets without making structural changes to the economy geared towards less carbon-intensive activities. These results not only help to provide concrete policy suggestions on economic restructuring in Shanghai, but also have broader implications for other Chinese cities where many are aiming to achieve low-carbon status in the next decade.

The rest of the paper is structured as follows. The methodology and data collection are outlined in Section 2. Section 3 discusses Shanghai’s recent economic and energy development, and levels of energy intensity and CO$_2$ emissions. The results are presented and discussed in Section 4. Section 5 highlights the theoretical and policy implications of the findings.

2. Methodology and data

2.1. Estimating CO$_2$ emissions and carbon intensity

The first step of the study is to calculate CO$_2$ emissions in Shanghai, both at the municipal level and at a more fine-grained sectoral level. This study follows the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006), which outlines the calculation of CO$_2$ emissions from both stationary and mobile fossil-fuel combustion sources. Nine types of fuel that are commonly used in China were included in the calculation: coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, other petroleum products, and natural gas. Electricity was excluded to avoid double counting. Following the classification used in official statistical yearbooks, the study calculated CO$_2$ emissions from six sectors: (1) agriculture, forestry, animal husbandry and fishery; (2) industry; (3) construction; (4) transportation; (5) wholesale, retailing, and catering; and (6) other sectors.

Carbon intensity refers to CO$_2$ emissions per unit of GDP. An efficiency indicator, it reflects the level of low-carbon technological improvement. The equation to calculate carbon intensity is:
CI\_t = \frac{I_t}{GDP_t}

where CI\_t denotes the carbon intensity in year t, I\_t is the emissions in year t, GDP\_t is the gross domestic product in year t.

### 2.2. STIRPAT

The STIRPAT model has emerged as a valuable tool in analyzing the factors shaping energy consumption, carbon emissions, and other types of pollution (Ji & Chen, 2015; McGee, Clement, & Besek, 2015). STIRPAT was developed from the IPAT model proposed by Ehrlich and Holdren (1971) that conceptualizes the relationship between human activities and environmental impact. The classic formula for the IPAT model is:

\[ I = PAT \]

where I is impact, P is population, A is affluence, and T is technology. In other words, the model states that places with high population and wealth levels tend to have a higher environmental impact compared to places that are less wealthy and/or less populous. Additionally, places with a high level of technology and, therefore, more capacity to extract resources, tend to have a higher impact.

Dietz and Rosa (1994) developed a stochastic model to meet statistical testing requirements. The model was named Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) and the formula is:

\[ I = aP^bA^cT^d + e_i \]

where a scales the model, b, c, and d are the exponents of P, A, and T, respectively, and e is the error term. The subscript \( i \) indicates that these quantities vary across observational units. The equation may be converted to natural logarithmic form as follows:

\[ \ln I_i = \ln a + b \ln P_i + c \ln A_i + d \ln T_i + \ln e_i \]

where b, c, and d can be interpreted as the percentage change in environmental impact caused by a 1% change in the corresponding impact factor, when other influence factors remain constant. Other studies have extended the classic STIRPAT model to cover more factors. For example, Wang, Wu et al. (2013) added urbanization level, industrial structure, energy structure, and foreign trade degree to their model. The extended STIRPAT model employed in this study is defined as:

\[ \ln I_i = \ln a + b \ln P_i + c \ln A_i + d_1 \ln S_1 + d_2 \ln S_2 + d_3 \ln S_3 + f \ln E_i + g \ln M_i + k \ln FDI_i + \ln e_i \]

where \( I \) denotes \( CO_2 \) emissions, \( P \) is population, \( A \) is wealth (per capita GDP), \( S_1 \) is the primary sector’s share of GDP, \( S_2 \) is the secondary sector’s share of GDP, \( S_3 \) is the tertiary sector’s share of GDP, \( E \) is energy intensity (energy consumption per unit of GDP), \( M \) is government spending on environmental protection, \( FDI \) is foreign direct investment, and \( b, c, d_1, d_2, d_3, f, g, \) and \( k \) are the coefficients of the respective indicators.

### 2.3. Multi-objective optimization

Multi-objective optimization is a decision-support tool for handling different conflicting objectives (Deb, 2014). Evolutionary algorithms are commonly used to solve multi-objective optimization problems (Konak, Coit, & Smith, 2006). In this study, the authors used MATLAB’s gamultiobj implementation of NSGA-II—one of the best performers among multi-objective optimization algorithms (Deb, Pratap, Agarwal, & Meyarivan, 2002). Fig. 1 summarizes the optimization procedure of NSGA-II. The algorithm begins with the creation of a randomly generated population of solutions \( P_t \) of size \( N \). The solutions are then ranked using non-dominated sorting, and a new population \( Q_t \) is created using individual selection by the tournament method, crossover, and mutation. Then, \( P_t \) and \( Q_t \) are merged into a new composite population \( R_t \) of size \( 2N \), and non-dominated sorting is used to sort the solutions into \( R_t \). Using an elitist strategy, the first \( N \) solutions of \( R_t \) form a new population \( P_{t+1} \). The new population \( Q_{t+1} \) is created from \( P_{t+1} \) using the same recombination operators (i.e., selection, crossover, and mutation). The process is repeated by a pre-determined number of generations.

The objective of the optimization model developed in this study is to maximize economic growth and minimize carbon emissions. Economic growth maximization may be formulated as follows:

![Flowchart of MATLAB's gamultiobj implementation of NSGA-II.](image-url)
Max_{f_i}(x) = \sum^n_{i=1} v_i x_i \tag{6}

where \( x_i \) is the economic output of sector \( i \); \( v_i \) is the industrial value added coefficient for sector \( i \). Formula (6) may be transformed into a minimization problem for ease of solving:

Min_{f_i}(x) = -\max_{f_i}(x) = -\sum^n_{i=1} v_i x_i \tag{7}

The formula for carbon emissions minimization is:

Min_{f_i}(x) = \sum^n_{i=1} c_i x_i \tag{8}

where \( x_i \) denotes the economic output of sector \( i \); \( c_i \) is the \( \text{CO}_2 \) emissions coefficient of sector \( i \), defined as \( \text{CO}_2 \) emissions per 10,000 CNY of output.

Three scenarios were created with different emphasis on economic growth and emissions reduction. First, the “growth-oriented” scenario prioritizes economic growth. The second “low-carbon” scenario prioritizes reduction in \( \text{CO}_2 \) emissions while the third, “balanced” scenario places equal emphasis on economic growth and emissions reduction. These scenarios were achieved by including two weighting variables in the equation:

\[ f = \theta_1 f_1 + \theta_2 f_2 \tag{9} \]

where \( \theta_1 \) and \( \theta_2 \) represent the weight of two target values and \( \theta_1 + \theta_2 = 1 \). The values were set to: \( \theta_1 = 1 \), \( \theta_2 = 0 \) for the growth-oriented scenario, \( \theta_1 = 0 \), \( \theta_2 = 1 \) for the low-carbon scenario, and \( \theta_1 = \theta_2 = 0.5 \) for the balanced scenario.

Five constraints were introduced to the model to enhance the realism of results. They are: (1) general equilibrium constraint, (2) economic growth constraint, (3) carbon emissions constraint, (4) employment constraint, and (5) non-negative constraint. The first constraint on general equilibrium refers to the balancing of the input-output model, whereby the sum of output and import for each sector (i.e., total supply) must be equal to the sum of intermediate consumption from other sectors and the final demand sector (i.e., total demand) (Chen, 2001). In China, input-output tables are compiled every five years; this study used the most recently available, 2012 Shanghai input-output tables as the base. This restriction can be represented mathematically as follows:

\[ F = (UM - TC + IC)X \geq F_{2012} \tag{10} \]

where \( X \) represents the sector output vector, \( UM \) is the unit matrix, \( TC \) is the matrix of technical coefficients, \( IC \) represents the diagonal matrix of import coefficients, and \( F \) is the final demand matrix for each sector.

The second constraint concerns economic growth. The central government has set the target for economic growth from 2016 to 2020 to be above 6.5% annually. As China’s economic hub, Shanghai would be expected to maintain a growth rate of no less than 6.5%. The third constraint is on carbon emissions. China aims to reduce carbon intensity by 40–45% by 2020 compared to its 2005 value. Therefore, a 40% decline is the minimum for Shanghai, which means that, by 2020, Shanghai’s carbon intensity must be below 0.62 ton/10,000 CNY. Assuming Shanghai’s GDP growth will remain at the 7.8% level achieved during the 12th Five-Year Plan, the \( \text{CO}_2 \) emissions limit would be 227.53 million tons. The fourth constraint concerns employment levels. One of the key concerns of the government is to create enough jobs for social security reasons. As such, economic restructuring that may result in a loss of total number of jobs is unlikely to gain acceptance in China. While there is no official target for the number of jobs, the authors observed that from 2006 to 2013 the lowest job growth rate was 1.01%, which was adopted in this study to estimate the minimal number of jobs by 2020. The final constraint is that the variable \( x_i \) cannot be negative. The overall optimization model developed in this study, including the five constraints, is summarized in Fig. 2.

2.4. Data

Data were mainly drawn from government statistical yearbooks. Shanghai’s energy data can be found in the China Energy Statistical Yearbooks (National Bureau of Statistics, 2016). Other statistics for Shanghai including GDP, population, sectoral output, government investments in environment, and foreign direct investment were obtained from the Shanghai Municipal Statistical Yearbooks (Shanghai Municipality Bureau of Statistics, 2016). GDP figures were normalized to the year 2000.

3. Shanghai’s profile

3.1. Economic structure

Shanghai’s economy has developed at a phenomenal rate in the post 1978 reform era. Its GDP increased from 27.3 billion CNY in 1978 to 2496.5 billion CNY in 2015 (Fig. 3). This success has been achieved through dramatic restructuring from a socialist industrial city to a global financial and commerce center, although heavy industries such as shipbuilding, car manufacturing, and steel manufacturing remain an important part of the economy (Wu, 2000). Fig. 3 also shows the declining of the primary sector from 4.03% in 1978 to 0.44% in 2015 and that of the secondary sector from 77.36% to 31.81% over the same period. On the other hand, the contribution of the tertiary sector increased dramatically from 17.61% to 67.75% from 1978 to 2015. In contrast, at the national level, from 1978 to 2015, the relative share of the primary and secondary sectors declined from 27.69% to 8.88% and from 47.71% to 40.93% respectively, while the tertiary sector increased from 24.60% to 50.19%. Therefore, while the general economic restructuring trend of Shanghai is similar to that of China as a whole, Shanghai has been more successful in restructuring itself towards a post-industrial, service-based economy.

![Fig. 2. Optimization model.](image-url)
### 3.2. Energy consumption

Shanghai’s total energy consumption increased from 25.53 million tons of coal equivalent (MTCE) in 1985 to 110.85 MTCE in 2015 (Fig. 4). The average annual increase is 5.15%, which is lower than the national average of 5.99%. This suggests that Shanghai is leading the country in terms of controlling energy consumption. In particular, the growth rate slowed down notably since 2007, with Shanghai recording the first decline in energy consumption in 2014, as depicted by the negative growth rate. Shanghai’s energy consumption is expected to stabilize in the near term.

### 3.3. Energy intensity

Shanghai’s energy intensity (energy consumption per unit of GDP) has decreased consistently (Fig. 5). In 1995, Shanghai’s energy intensity...
was 1.76 TCE/10,000 CNY; in 2014, it was 0.48 TCE/10,000 CNY. However, the pace of this decrease has slowed down in recent years as the economy has become more efficient.

3.4. Carbon emissions

Fig. 6 shows interesting patterns in Shanghai’s CO₂ emissions during the study period. Emissions first rose rapidly from 74.11 million tons in 2000 to 133.45 million tons in 2007, then decreased for two consecutive years during the global financial crisis to a level below 120 million tons. Emissions rebounded sharply in the post-crisis investment boom of 2010, but have remained relatively flat since then, with emission levels of 128.20 million tons in 2014 remaining lower than the 2007 peak. Furthermore, Shanghai’s carbon intensity declined steadily during the study period from 1.55 ton/10,000 CNY in 2000 to 0.67 ton/10,000 CNY in 2014, at a decline of 56.79% (Fig. 7). These results suggest that Shanghai is at the turning point of the EKC and its emissions may be set to follow a long-term downward trend.

From a sectoral perspective, the emissions for different sectors changed substantially. For the household sector, emissions increased from 4.58 million tons in 2000 to 12.65 million tons in 2014, with a corresponding increase in share from 6.17% to 9.90%. Emissions from agriculture, forestry, animal husbandry, and fishery dropped from 1.63 million tons in 2000 to 0.64 million tons in 2014, consistent with the expected decline of farming in an increasingly developed city. The industry sector remains the largest carbon emitter, although its emissions increased slightly from 50.21 million tons in 2000 to 53.12 million tons in 2014. Notably, its share declined from 67.74% in 2010 to 41.56% in 2014 although it remained the largest emitting sector. Emissions from the construction sector rose rapidly from 1.49 million tons in 2000 to 3.07 million tons in 2010, but have since declined steadily to reach 2.34 million tons in 2014, owing to a slowdown in construction activities. The transport sector saw its emissions increase more than three-fold from 12.31 million tons in 2000 to 41.60 million tons in 2014. Its share increased from 16.62% to 32.55% during the same period, making it the second most carbon-polluting sector after the industrial sector. Emissions from the wholesale, retail, and catering sector increased drastically from 1.05 million tons (1.41%) in 2000 to 6.52 million tons (5.10%) in 2014 while emissions from other sectors also increased rapidly from 2.84 million tons (3.84%) in 2000 to 10.93 million tons in 2014 (8.55%).

4. Findings and discussion

4.1. STIRPAT results

The result of the regression analysis of the STIRPAT model outlined in Eq. (5) is:

\[
\ln I = 4.771 + 0.235 (\ln P) + 0.358 (\ln A) - 0.248 (\ln S^2) + 0.180 (\ln S^2) - 0.764 (\ln S^2) - 0.011 (\ln E) + 0.291 (\ln M) + 0.463 (\ln FDI)
\]

(11)

\(\ln S^2\) and \(\ln E\) are significant at 10% significance level; \(\ln P\), \(\ln S^1\), and \(\ln FDI\) at 5% significance level; and \(\ln A\), \(\ln S^2\), and \(\ln M\) at 1% significance level. The coefficient of determination, \(R^2\), is 0.883. Furthermore, the F-statistic reaches the 1% significance level. These results
show that the model can adequately explain Shanghai’s carbon emissions.

Among the variables, population (0.235), per capita GDP (0.358), secondary sector’s share of GDP (0.180), government spending on environmental protection (0.291), and foreign direct investment (0.463) are positively correlated with carbon emissions, whereas the primary and tertiary sector’s share of GDP are negatively correlated (−0.248 and −0.764, respectively). Energy intensity has little correlation with carbon emissions (−0.011). In other words, economic restructuring in favor of the tertiary sector has been not only an important factor but also the only factor contributing to the reduction in Shanghai’s emissions from 2000 to 2014. For every 1% increase in the primary sector’s share of GDP, emissions reduced by 0.25%. This may be the case as agriculture is not only a low carbon-intensive industry but also because agriculture and forestry increase tree cover and raise the carbon sink capacity. On the other hand, for every 1% increase in the secondary sector’s share of GDP, carbon emissions increased by 0.18%. The secondary sector comprises energy-intensive, fossil fuel users. As Shanghai continues to pursue its policy to relocate its heavy industry to make room for the tertiary sector, the GDP share of the secondary industry would continue to decrease. Next, for every 1% increase in the tertiary sector’s share of GDP, emissions reduced by as much as 0.76%, the highest negative coefficient in the model. This suggests that the growth of the tertiary sector, based on modern, knowledge-intensive and service-based, high value-added industries, has been one of the key driving forces in reducing carbon emissions in Shanghai.

Regarding other factors, for every 1% increase in foreign direct investment, carbon emissions increased by 0.46%. This supports the pollution haven hypothesis, which posits that multinationals tend to exploit lax environmental standards in developing countries; thus, an inflow of foreign capital can hurt the local environment (Cole, 2004; Kearsley & Riddel, 2010; Tang & Tan, 2015). As China’s most international city, Shanghai is home to a large number of foreign and multinational corporations. From 2000 to 2014, Shanghai’s annual FDI rose sharply from USD 3.16 billion to USD 18.17 billion, an increase of 475%. Such FDI growth has contributed to the higher energy consumption and carbon emissions of Shanghai.

Furthermore, the model results reveal that every 1% increase in GDP per capita resulted in an increase in emissions of 0.36%. From 2000 to 2014, Shanghai’s per capita GDP increased from 30,000 CNY to 74,700 CNY, an increase of 149%, enhancing both direct and indirect consumption, thereby resulting in increased carbon emissions. Similarly, every 1% increase in population increased carbon emissions by 0.24%. From 2000 to 2014, Shanghai’s population increased from 16 million to 24 million, an increase of 50%. Such population increase results in more production and consumption activities, which, in turn, raises energy consumption and emissions.

Public environmental spending indicates that the importance the government has placed on environmental protection. However, based on the model, every 1% increase in government spending in environmental protection resulted in a 0.29% increase in carbon emissions. There are several explanations for this paradoxical result. First, public spending on environmental protection has multiple objectives beyond reducing carbon emissions. Given growing public concern over air pollution, a large proportion of such spending in recent years has been on the control of SO2 and NOx, although investment in energy efficiency, which should have a positive impact on reducing carbon emissions, is also on the rise (Wong & Karpilus, 2017). In fact, environmental policies such as those focused on pollution control may require enterprises to install new treatment facilities that increase energy consumption and contribute to higher carbon emissions. Second, investment in energy efficiency is typically subject to a rebound effect—the loss of energy savings from energy efficiency improvement due to higher energy demand (Gillingham, Rapson, & Wagner, 2016). A 100% rebound effect means that the potential energy savings from energy efficiency efforts are entirely offset by increasing demand. Studies have found that the rebound effect is particularly strong in China: 74% for the heavy industry sector (Lin & Li, 2014), 74% for the residential electricity sector (Wang, Lu, & Wang, 2014), and 84% for the road freight transport sector (Wang & Lu, 2014). This means that most of the energy efficiency improvement is offset by increased energy consumption in China. The authors’ analysis shows that from 2000 to 2014, Shanghai’s energy intensity decreased by 48.85%, but this improvement in energy efficiency had very little impact on carbon emissions. Third, there is often a time lag between environment-friendly investments and the realization of their benefits (Elsayed & Paton, 2005). In the short term, government spending could increase carbon emissions due to the construction of environmental protection infrastructure and accelerated production by enterprises in anticipation of more stringent environmental regulations. Therefore, long-term and sustained effort is needed in order to achieve a reduction in carbon emissions.

### 4.2. Optimization results

Table 1 summarizes the results of the multi-objective optimization analysis. In the growth-oriented scenario, GDP is estimated to reach 3775 billion CNY in 2020 at an annual growth rate of 8.14%, with CO2 emissions of 174.63 million tons, at an annual growth rate of 5.24%. On the other hand, in the low-carbon scenario, Shanghai’s GDP is estimated to reach 3372 billion CNY in 2020, at an annual growth rate of 6.63%, with CO2 emissions at 155.23 million tons, at an annual growth rate of 3.70%. These results suggest a real trade-off between economic growth and emissions control. This trade-off is addressed by the balanced scenario, whereby GDP is estimated to reach 3503 billion CNY in 2020, at an annual growth rate of 7.14%, and CO2 emissions are estimated to reach 161.95 million tons, at an annual growth rate of 4.25%. Carbon
intensity is expected to decrease from 0.58 ton/10,000 CNY to around 0.46 ton/10,000 CNY in all three scenarios. Fig. 8 shows the optimized economic structure for each of the three scenarios. In all three scenarios, there is a common shift of relative importance from the secondary sector to the tertiary sector. The share of the industry sector declines by more than 10% for all scenarios; the proportion of the construction and transportation sectors also decline, although to a lesser extent. However, all three sectors grow in absolute terms. Based on the optimization model, the dominance of these sectors would be replaced by the wholesale, retail, and catering sector as well as other sectors including telecommunication, finance, business services, and real estate. The primary sector would also undergo a revival, with a slight increase in relative share in all three scenarios. When comparing the low-carbon and growth-oriented scenarios, the main difference is the slower growth in the industry, transportation, and construction sectors in the low-carbon scenario. This implies that realizing the low-carbon scenario depends on more aggressive restructuring of the economy towards low-carbon, tertiary sectors, although at the cost of moderately slower economic growth. The balanced scenario outcome tends to be situated somewhere between the two extremes.

5. Conclusion

City-level analyses of CO₂ emissions are important given the spatial disparities of China and the need to formulate effective local responses to climate change. As a leading metropolis in terms of economic development, Shanghai’s past and future experience in economic restructuring and emissions may be insightful not just for the city itself, but also for the rest of China.

This study shows that Shanghai’s CO₂ emissions have been stable since 2007 mainly due to the shift of economic activities from the secondary industry to the tertiary sector. Other factors such as population, affluence, and technology tend to have a positive or negligible impact on Shanghai’s emissions. The situation of Shanghai can be contrasted with that of Guangdong and Beijing, where emissions are rising in part due to industrialization (Wang, Wu et al., 2013; Wang, Zhao et al., 2013), and that of Tianjin, where emissions are also rising but not due to economic restructuring (Li, Liu et al., 2015). These differences underscore the regional disparities in China and the fact that Shanghai is likely to be among the first cities in China to reap the environmental benefits of deindustrialization.

While economic restructuring has been shown to be an effective way to reduce carbon emissions, adjusting economic activities in favor of the climate may be controversial because of the impact on economic development and job creation. A premature demise or slowdown of the secondary sector may have a significantly negative socioeconomic impact. The optimization analysis shows that the low-carbon scenario has a 1.51% lower annual GDP growth rate than the growth-oriented scenario. When taking both economic growth and emissions reduction into consideration, the balanced scenario developed in this study recommends decreasing the relative proportion of industry by more than 11% and that of the construction sector by 1–2%. The results highlight the need for Shanghai, and by extension other Chinese cities, to pursue

### Table 1

Comparison of the three scenarios.

<table>
<thead>
<tr>
<th></th>
<th>Base year (2012)</th>
<th>Model estimated results for 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Growth-oriented scenario</td>
<td>Low-carbon scenario</td>
</tr>
<tr>
<td>Gross output (billion CNY)</td>
<td>7122.34</td>
<td>12042.10</td>
</tr>
<tr>
<td>GDP (billion CNY)</td>
<td>2018.42</td>
<td>3775.00</td>
</tr>
<tr>
<td>CO₂ emissions (million tons)</td>
<td>116.10</td>
<td>174.63</td>
</tr>
<tr>
<td>Carbon intensity (ton/10,000 CNY)</td>
<td>0.5752</td>
<td>0.4626</td>
</tr>
<tr>
<td>Number of employment (million)</td>
<td>11.16</td>
<td>18.05</td>
</tr>
</tbody>
</table>

Fig. 8. Optimized economic structure for each scenario.
an economic restructuring agenda and to achieve deindustrialization or at least control the growth of the secondary sector.

The main conclusion of the study is that China’s target of climate emission mitigation cannot be achieved solely through technological advancement and more efficient use of energy. Instead, it would be more effective to implement structural changes to the economy geared towards less carbon-intensive activities. It should also be noted that although Shanghai has achieved significant efficiency improvement, this has resulted in almost no emissions reduction due to the high rebound effect.

There are two policy implications of these conclusions. First, additional policy intervention is needed to mitigate the rebound effect. The presence of such rebound effect is linked to a policy failure: while the central government has established a number of policies to mandate improvements in energy efficiency, such as the Ten-Thousand Enterprises Energy Conservation Program, it falls short in controlling absolute energy consumption among energy-intensive enterprises (Lo, Li, & Wang, 2015). There is a need to introduce a maximum limit on energy consumption and avoid the use of energy intensity as a metric. It is also important to implement market-based instruments such as carbon tax or emissions trading, so as to achieve the goal of emissions reduction more flexibly and cost-effectively (Liu, Chen, Zhao, & Zhao, 2015). Second, the government needs to strengthen its economic restructuring policy, as it cannot rely on technological improvements alone to reduce CO2 emissions. In addition to using administrative means to shutdown old industries, the government need to increase investment in research and development (R&D), remove barriers to entry and impediments to competition, and provide a high-quality environment capable of attracting high-tech industries and talents.

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References


