Energy Policy 128 (2019) 276–283

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Have China's provinces achieved their targets of energy intensity reduction? Reassessment based on nighttime lighting data

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ARTICLE INFO

Keywords:
Energy intensity
Nighttime lighting data
GDP growth rate
Target responsibility system

ABSTRACT

Energy intensity has been a major assessment indicator in the design of energy saving policies, and it is one of the eight binding indicators of the target responsibility system for officials' performance evaluation in the 11th Five-Year Plan in China. However, the accuracy of measurement of energy intensity depends to a large extent on the reliability of GDP data. This paper revises the GDP growth rate with nighttime lighting data and recalculates the rate of energy intensity reduction for each province during the 11th Five-Year Plan in China. Our results show that the GDP growth rate of some provinces has been exaggerated. Further, although the energy intensity of all provinces showed a significant downward trend during the 11th Five-Year Plan, some provinces failed to meet the target of energy intensity reduction. These results suggest that when designing energy conservation policies, cross-evaluation indicators should be included to improve the effective implementation of policies.

1. Introduction

Energy efficiency, usually measured as energy consumption per unit of GDP, or energy intensity, is a measure that can simultaneously address the contradiction between economic growth and emission reduction. While energy efficiency can lead to negative costs, policy intervention is needed due to factors such as a high discount rate, that prevent the adoption of energy efficiency measures (Shi, 2015, 2014).

China, the world's largest energy consumer, has made tremendous efforts to reduce energy intensity by setting clear energy conservation and emission reduction targets. This has been done for several reasons. The rapid growth of China's economy has been accompanied by a sharp increase in energy consumption. On the one hand, this increase has caused serious environmental problems such as high CO_2 emission and pollution. On the other hand, it has also led to an increasing dependence on imported energy sources such as oil and natural gas. To reduce energy consumption, pollution, and CO_2 emission, China has had a numerical management system since 2006. In 2006, for the first time, China set a binding target of reducing energy intensity by 20% in its 11th Five-Year-Plan (FYP, 2006–2010) period (Li et al., 2016). The national target was allocated among the provinces and this was the first time that an energy-saving target was included in the performance evaluation system for local bureaucrats. Administrative enforcement was put into place by the end of 2005 as part of the 11th FYP in China. The top-down target-based responsibility scheme ensures that local officials are tied to satisfying higher-level mandates for career advancement. The reduction of energy intensity has positive effect on the probability of local official promotion (Zheng et al., 2014). The implementation of the energy intensity reduction policies in the 11th FYP has helped reverse the increasing trend of energy intensity in China (Song and Zheng, 2012). This policy was carried through the 12th FYP (2011–2015) and the target was further set at 16% by 2015, compared with 2011 (Li et al., 2016).

Despite the energy intensity target have been officially assessed as achieved, China's continuous growth of energy consumption casts a question on the reliability of the assessment. According to the Notice of the National Development and Reform Commission No. 09 (NDRC, 2011) in 2011 and No. 27 (NDRC, 2016) in 2016, during the 11th FYP and 12th FYP periods, all provinces have achieved and even exceeded their energy intensity reduction targets. However, the total energy

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https://doi.org/10.1016/j.enpol.2019.01.014
Received 27 September 2018; Received in revised form 3 January 2019; Accepted 7 January 2019

consumption is still increasing significantly due to a substantial growth of the Chinese economy. This seems uncontrolled growth motivates the Chinese government to further launched the Total Energy Consumption Control policy during the 12th FYP (Sun, 2018; Wang et al., 2014).

Among the numerous academic assessments of whether the energy intensity target has been achieved (Li et al., 2016; Yuan et al., 2016), few have considered whether the measurement of GDP data is accurate. For a long time, the authenticity and accuracy of China's GDP data have been a subject of controversy (Hsu, 2017; Shi, 2011). Some scholars believe that official GDP data seriously overestimate the economic growth rate (Maddison, 1998; Rawski, 2001; Young, 2003). Other scholars acknowledge that China's official statistical system has many shortcomings and deficiencies; yet, they consider China's GDP data to be credible overall (Holz, 2014, 2006; Xu, 2010, 2009). The most of these literature based on official statistics and found that local government basically met the energy conservation policy targets (Lin and Du, 2014; Lin and Tan, 2017; Song and Zheng, 2012).

The past few years have shown that China's GDP data have likely been inflated. One of the most obvious examples is that the sum of local GDP persistently far exceeds the national GDP. In 2012, 2013, and 2014, the total GDP of the provinces exceeded the national GDP by 11%, 10.8%, and 7.5%, respectively (see Fig. 1). Media also frequently uncovered the facts about the manipulation of GDP data. In 2017 and 2018, local governments, such as Liaoning, Inner Mongolia, and Tianjin, actively acknowledged the existence of fraud in past GDP data.[1] Overestimated GDP data provides a false picture of good economic performance and achieving the target of energy intensity reduction. These double dividends encourage local governments to manipulate their GDP data.

The intentional manipulation of GDP data will distort the energy intensity indicators and thus undermine the function of China's energy intensity numeric management system.[2] One reason underlying the introduction of further total energy consumption control policy is that the growth of energy consumption, although justifiable by the energy intensity performance with inflated GDP, has gone beyond the central government's tolerance level. Therefore, accurate measure of GDP will have an important impact on assessing energy intensity policies in China. Given that China is the world's largest consumer of energy, such a policy change in China will affect the global energy sector and emission levels.

By using nighttime light data to revise official GDP statistics, we reassess the energy intensity changes for China's provinces during the 11th FYP period. Following Henderson et al. (2012), this paper uses satellite nighttime lighting data to revise the GDP growth rate. On this basis, the present study more accurately measures the energy intensity changes of each province and reassesses the performance of the policy objectives. The time period for this study is limited to 2006–2010, China's 11th FYP period, because the central government has set a clear energy intensity constraint index for local governments based on the value at the end of 2005. The analysis can give us a clearer understanding of the performance of energy intensity policies after considering the accuracy of GDP growth data. Although our study period was limited by the nighttime light data, which is only available until 2013, the findings are still highly relevant and valuable (Chen et al., 2018; Li et al., 2019; Song and Zheng, 2012), because the Chinese government applied similar indicator assessment system in both the 11th FYP (2006–2010) and 12th FYP (2011–2015) periods. At the same time, existing studies (Wallace, 2016) have found that GDP misreporting is a long-term phenomenon in China, and it is still widespread after 2010. Therefore, the research findings in this paper still have practical implications after 2010.

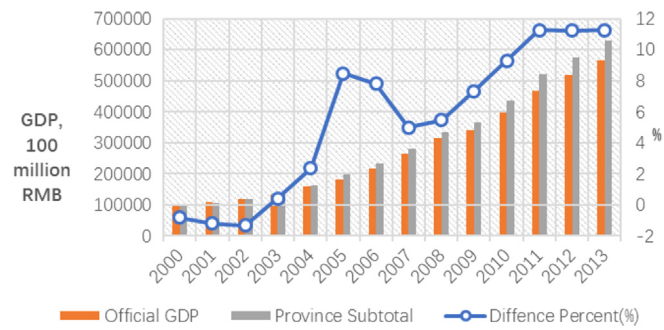

Fig. 1. Difference between National and Province GDP.
Source: National Bureau of Statistics

The major contribution of this paper is offering an alternative and independent measurement of energy intensity indicators based on the revised GDP data. Our results find that the reduction in energy intensity has been overestimated due to distorted GDP data. This alternative and more accurate assessment of provincial energy intensity performance can be applied to municipal and other lower levels of governments and thus help China to improve the implementation of energy conservation policy. Given the dominant role of China in global energy consumption and associated emissions, this study is also of great value to the global community. Additionally, this study also sheds light on the growing literature on data manipulation of government. Official data manipulation in China mainly focused on output due to economic performance driving promotion incentives for local officials (Kung and Chen, 2011; Wallace, 2016). Our paper shows that including energy-saving target in the performance evaluation system add a further motivate for local government to inflate GDP growth rate. Local government could get a double dividend, i.e. good economic performance and achieving the target of energy intensity reduction, by manipulating data.

The rest of the paper is as follows: The next section reviews the literature, Section 3 reports the methodology and the data, Section 4 reports our estimation of energy intensity changes in China's 11th FYP period for each province, and the final section concludes the paper and discusses policy implications.

2. Literature review

Given that the Chinese government has set a mandatory target of energy intensity reduction, energy intensity has been extensively investigated in the recent literature. Zhang et al. (2011) used three different estimates of energy saving during the period 2006–2009 to illustrate how policies and measures are implemented at the provincial level to meet the energy intensity target of the 11th FYP by using Shanxi province as an example. By comparing the differences between the value-added method and the production output method, Li et al. (2016) demonstrated that the national target of energy intensity reduction cannot be fully disaggregated to local governments, sectors, and enterprises without omissions. Based on a preliminary decomposition model, Yue et al. (2016) proposed a method to further decompose provincial energy intensity targets to prefecture level by using Henna province as a case study. Li and Lin (2015) used an improved DEA method which combines the super-efficiency and sequential DEA models to avoid “discriminating power problem” and “technical regress” and estimate the energy efficiency improvement potential in

[1] https://www.reuters.com/article/us-china-economy-data/another-chinese-city-admits-fake-economic-data-idUSKBN1F60I1.

[2] While this paper focuses on the manipulation of GDP data instead of energy consumption data, we do not intend to deny that energy consumption data could also be manipulated. However, the propose of this paper is to demonstrate the applicability of, and insights form a well-established methodology that has not been applied to studying China energy intensity control before. Some studies showed that energy consumption is less plagued by problems of manipulation (Henderson et al., 2012), which has also been supported by the divergence between the GDP growth and electricity production (Wallace, 2016).

China's provinces. Huang et al. (2017) used spatial panel methods to investigate the driving forces of the change in China's energy intensity. They found that the impact of technological progress on energy intensity is partly through the spatial spillover effect.

With the popularization of CO2 intensity, many studies have focused on emission reduction targets, a concept that is closely linked to energy intensity due to China's fossil fuel dominant energy mix. Yang et al. (2018) examined whether China can achieve its carbon intensity reduction target of 40–45% by 2020 from the 2005 level; they suggested that China needs additional mitigation efforts to achieve the Copenhagen commitment using a dynamic panel data model. Through a dynamic simulation analysis based on LINGO programming, Xu et al. (2013) performed a comprehensive evaluation of carbon and energy intensity targets, with a focus on their interactions; they suggested that carbon intensity and energy intensity in China can be reduced by 43% and 46%, respectively, by the year 2020, compared with the 2005 levels. Duan et al. (2018) developed a stochastic energy-economy-environment integrated model to assess China's energy and climate targets in 2030 by considering of the nexus among different targets. Xian et al. (2018) found that the nationwide 18% intensity reduction target in the 13th FYP (2016–2020) is not feasible in the power sector through either improving technical efficiency or upgrading technology for electricity generation and carbon abatement in either the short- or medium-term, in which meta-technology approach is applied to identify technological heterogeneity.

Although each of these intensity indicators has two determinant factors, the existing literature on energy intensity and carbon intensity largely ignores various scenarios of the denominator the economic growth. This is understandable, as the energy and climate researchers are less familiar with possible issues in the economic growth data. However, existing research shows that many governments deliberately manipulate official statistics for specific purposes. For example, Italy and Greece have deliberately understated their budget deficits to meet the economic conditions of joining the European Union (Barber and Hope, 2010). Michalski and Stoltz (2013) found that countries' balance of payments data do not always conform to the law of statistical distribution and, thus, inferred that the government may make strategic data false reports under certain conditions. Kerner et al. (2014) revealed that, some countries, in addition to cover up a bad economic situation, have deliberately lowered per capita national income to obtain preferential loans from the World Bank.

Economic growth data in China is more vulnerable to manipulation than other countries because of its close link with performance evaluation for local governments and their leaders (Shi, 2011). The study of China's official data manipulation problem is mainly related to the top-down official assessment system (Edin, 1998). Kung and Chen (2011) found that, between 1958 and 1960, local officials falsely reported food production to meet their superior goals. This resulted in the excessive food levy and serious difficulties for the national economy. Wallace (2016) explored promotion-oriented data fraud through the difference between the official GDP growth rate and the electricity consumption growth rate. The results showed that during the change of government officials, the gap of the growth rate between GDP and power is larger than in other periods; this further indicates that the possibility of data fraud at this time is also greater. At the city level, discontinuous breakpoints occurred when the air pollution concentration was at the critical point of the blue sky standard (Chen et al., 2012; Ghanem and Zhang, 2014). The government may use fraud data to meet the air quality assessment standards of higher levels of government.

GDP is essentially a measure of human economic activity, and this statistic is not always perfect, especially in developing countries. In China, as mentioned above, data manipulation is a major challenge to official GDP statistics. The nighttime lighting data have been used widely as an alternative to official statistics data for the measurement of GDP for the following reasons. Firstly, nighttime lighting reflects human economic activity (Croft, 1978). Numerous studies have shown that the brightness value and the change rate of nighttime light are highly correlated with the level and change rate of GDP, respectively (Doll et al., 2006; Elvidge et al., 1997; Sutton and Costanza, 2002). Secondly, even nighttime light is not a perfect measurement indicator of economic activity, its measurement error is mainly caused by satellite technology but is not related to measurement error of government GDP statistics. Therefore, the nighttime lighting data allow us to produce a better measurement of GDP than the official statistics by combining the GDP statistics and the nighttime light data (Browning and Crossley, 2009; Henderson et al., 2012; Pinkovskiy and Sala-I-Martin, 2016).

Initial researches focused on examining whether nighttime lighting from satellite observations is significantly correlated with GDP (Doll et al., 2006; Elvidge et al., 1997; Sutton and Costanza, 2002). Based on the significant correlation between satellite lighting data and economic growth, subsequent researches have further compensated for the lack of official statistics by using satellite lighting information. The groundbreaking study by Henderson et al. (2012) modified the GDP growth rates of some countries with lower statistical quality by combining satellite lighting data with official statistics. Chen and Nordhaus (2015) also showed that satellite lighting data can be used to improve the quality of socioeconomic statistical data in less-developed countries. Michalopoulos and Papaioannou (2014) used satellite lights to measure the economic development level of closely adjacent areas on both sides of the borders of African countries. Xu et al. (2015) used satellite lighting data to measure China's actual economic growth rate and find that there is a possibility that local governments will exaggerate GDP data. Fan et al. (2016) used satellite lighting data to measure the actual impact of political connections on economic growth in various regions of China.

Unlike their popular application in measuring regional economic activities, nighttime lighting data are only occasionally applied in energy studies. Doll and Pachauri (2010) applied nighttime lighting data and spatially explicit population datasets to investigate electricity access between 1990 and 2000. Letu et al. (2010) proposed a methodology to estimate electric power consumption by using a stable light image. The limit of application of the nighttime lighting data in the energy sector is because such data cannot actually reflect total energy consumption, as transport lights determined by urban design distort the satellite image. Furthermore, although nighttime lighting data have been applied to measure either GDP or energy consumption, no study has to date considered both simultaneously in the context of energy intensity.

In general, although the existing literature contains detailed studies on energy intensity issues, they usually don't consider the impact of economic growth data distortion on the accuracy of energy intensity. Because both are important assessment indicators for local government, they are also faced with similar data distortion problems. To fill this research gap, this paper reassess the energy intensity changes for China's provinces during the 11th FYP period by using revised GDP growth rate. Following Henderson et al. (2012), the GDP growth rate was revised by applying the nighttime lighting data. Using different GDP growth rate will lead to different energy intensity change rates because the energy intensity is defined as energy consumption per unit of GDP, which means that as long as GDP grows faster than energy consumption, energy intensity will continue to decline (Li et al., 2016; Sun, 2018).

It is worth highlighting that we used satellite lighting data instead of electricity consumption, rail freight, and other indicators, mainly because they are derived from the official statistical system and, thus, may have the same measurement bias. In relation to this, Holz (2014), for example, provided examples of manipulation of electricity consumption statistics. In addition, some statistical indicators, represented by electricity consumption, will also change their statistical scope over time. For example, the significant decrease in electricity consumption in 1998 is mainly due to the change in statistical scope during 1997–1998, rather than to actual power consumption reduction. The collection of satellite lighting data is independent of official statistics, thereby avoiding such problems.

3. Research design

3.1. Data sources

3.1.1. Nighttime lighting data

Global nighttime lighting data were originally collected by the US Defense Meteorological Satellite Project. Since 1992, the National Geographic Data Center of the National Oceanic and Atmospheric Administration of the United States has processed and revealed a variety of global nighttime lighting data. Most of the existing research used stable light data for analysis-this eliminates strong natural light, such as moonlight, aurora, forest flares, and cloudy days, and ultimately includes the light produced by human activities, such as the light from cities and towns. The data observation period is 20:30–22:00 local time in the evening, and the observation range is from 180° east longitude to 180° west longitude and from 65° south latitude to 75° north latitude. Each grid area is observed for 30 s. Each grid is assigned an observed luminance value in the range of 0–63. The brightness of either a country or a region is the sum of all grid brightness values within it. For detailed discussion of the nighttime lighting data, please refer to Henderson et al. (2012).

Like Henderson et al. (2012), the present study also selects stable light data and uses ArcGIS software to project the global administrative division map and satellite lighting data image to obtain China's provincial lighting brightness value total data for 2005–2010. Finally, the light density per square kilometer of each province is calculated. Following the same methodology, prefectural and county level data can be obtained, thus enabling to apply our analysis to lower levels of government.

3.1.2. Other data

The energy data of each province used in this paper mainly includes the energy intensity (energyinten) and the energy consumption (energycons) taken from the *China Statistical Yearbook* and the *China Energy Statistics Yearbook*. Some studies have indicated that industrial structure, economic activity agglomeration, and other factors will affect the relationship between lighting and economic activities (Pinkovskiy and Sala-I-Martin, 2016). Therefore, we also use some variables as control variables; these include the ratio of the value added of the secondary (GDP2), tertiary industries (GDP3) to GDP, and urbanization rate (urban). These data come from the *China Statistical Yearbook*. Descriptive statistics for all variables are given in Table 1.

3.2. Methodology

3.2.1. Estimation of GDP growth rate based on nighttime lighting data

First, we need to test the correlation between satellite lighting and official GDP data. On this basis, we can combine the information contained in the two datasets to more accurately measure the GDP growth rate in each province of China. As seen from the representative provinces in Table 2, the more economically developed the region, the lower is the proportion of the grid with no brightness value and the higher is the proportion of the grid with a higher brightness value (>10).

The above findings provide visual evidence for the correlation between satellite lighting and economic growth. However, to provide data prerequisites for subsequent calculations, it is necessary to accurately measure the correlation between the two data series. Thus, we further develop our empirical analysis by using the following regression equations:

$$y_{i,t} = c + \beta l_{i,t} + \eta_i + \mu_t + \varepsilon_{it} \tag{1}$$

where y is the official GDP growth rate, l is the growth rate of the light density value (sum of brightness value/province area); β reflects the degree of correlation between the two data series; η_i and μ_t are province fixed effects and time fixed effects, respectively; i represents province; and t represents time.

As shown in Henderson et al. (2012), the basic framework is as follows. Assume that the following conditions are true:

$$y_i = \beta l_i + \varepsilon_i \tag{a1}$$

$$l_i = \gamma y_i^* + \varepsilon_{l,i} \tag{a2}$$

$$y_i = \Phi y_i^* + \varepsilon_{y,i} \tag{a3}$$

$$E(\varepsilon_{l,i}) = E(\varepsilon_{y,i}) = 0 \tag{a4}$$

$$E(\varepsilon_{l,i}\varepsilon_{y,i}) = 0 \tag{a5}$$

Among them, y^* is the true GDP growth rate, and y is the official GDP growth rate. At this point, we can get a predicted value $\hat{y}_i^*$ for y^*.

$$\hat{y}_i^* = \lambda y_i + (1-\lambda)\beta l_i \tag{2}$$

where $\lambda < 1$, and we can obtain λ that minimizes the prediction error,

$$\lambda = (\theta - \rho^2)/(1-\rho^2) \tag{3}$$

$$\theta = \sigma^2_{y_i^*}/Var(y_i) \tag{4}$$

ρ is the correlation coefficient between y and l. By assuming the value of θ, the corresponding λ and $\hat{y}_i^*$ can be obtained. Under the assumption that (a1)–(a5) is established, it can be proved that $\hat{y}_i^*$ as the prediction of y^* is more accurate than that of y and l. The θ is actually a judgment on the accuracy of official statistics, and its value is also based on certain objective criteria. As can be seen from Eq. (3), λ actually is a function of θ and is weight to the official GDP growth rate in Eq. (2). We follow the method of Henderson et al. (2012), which gives China the corresponding λ value based on the World Bank (2002) assessment of statistical capacity and quality in countries.

3.2.2. Assessment changes in energy intensity

The existing energy intensity measurement mainly uses the energy consumption of per unit GDP, and its composition is as follows:

$$\text{Energy Intensity(EI)} = \text{Energy Consumption(EC)}/\text{GDP}$$

According to this formula, the change rate of energy intensity is as follows,

$$\frac{\Delta EI}{EI} = \frac{\Delta\left(\frac{EC}{GDP}\right)}{\frac{EC}{GDP}} = \frac{GDP^*\Delta EC - EC^*\Delta GDP}{GDP^2} {}^* \frac{GDP}{EC} = \frac{\Delta EC}{EC} - \frac{\Delta GDP}{GDP}$$

$$\text{i.e. ,}(\Delta\text{Energy Intensity, \%}) = (\Delta\text{Energy Consumption, \%}) - (\Delta\text{GDP, \%}) \tag{5}$$

that is, the rate of change in energy intensity is the difference between the growth rate of energy consumption and GDP growth rate. Therefore, given the growth rate of energy consumption, different measures of GDP growth rate will lead to different rates of change in

Table 1
Variables and their statistical description.

Variables	Number	Mean	Standard deviation	Minimum	Maximum
dndensity	186	7.99	11.63	0.02	67.66
GDP	186	8593.17	7327.39	248.8	36,053.2
GDP2	186	47.42	8.21	23.5	61.5
GDP3	186	40.2	8.04	28.6	75.5
urban	186	47.89	15.02	20.85	89.3
energyinten	60	1.45	0.72	0.582	4.14
energycons	180	10,874.56	7043.94	822	34,808

Table 2
Average satellite lighting for representative provinces: 1992–2012.

Provinces		Jiangsu	Shandong	Hebei	Jiangxi	Yunnan
Distribution of brightness values	0	17.91%	18.36%	50.76%	84.03%	89.28%
	1–10	58.89%	65.10%	38.23%	13.26%	8.77%
	11–20	10.20%	8.36%	6.56%	1.47%	1.08%
	21–62	12.96%	7.90%	4.28%	1.15%	0.85%
	63	0.07%	0.28%	0.23%	0.15%	0.02%
Average brightness value		10.34672	8.08837	4.826542	1.311646	0.958047
GDP per capita (2012)		68,347	51,768	36,584	28,800	22,195

energy intensity. While changes in energy intensity are affected by many factors based on its definition, all changes will be reflected by changes of the energy consumption or GDP, and these will be included in the ΔEnergy Consumption and ΔGDP.

4. Results and discussion

4.1. Correlation between nighttime lighting and GDP growth rate

As mentioned above, we first need to accurately measure the correlation between nighttime lighting and economic growth. On this basis, we will revise the GDP growth rate and then re-calculate the energy intensity of each province. The regression equation used is (1), and the results are shown in Table 3.

In Table 3, we first use the pooled method to run a regression in columns 1–2. We find that the change in light density is closely related to the GDP growth rate, and the coefficient is close to 0.5. The two-way fixed effect regression of columns 3–4 shows that the correlation between satellite lighting and the GDP growth rate is significantly reduced after controlling for provincial and time fixed effects. However, the coefficients themselves remain significant. Because we mainly focus on the energy intensity changes of the 11th FYP at the end of 2005 compared with the end of 2010. And as the short sample interval, abnormal shock has some impact on the stability relationship. Thus columns 5–6 investigate the relationship between long-term lighting and GDP changes in 2005–2010 using the difference between the end of the period and the beginning of the period. This long different result again demonstrates that the two sets of data are highly correlated. For every 1% increase in the nighttime light density, the GDP increased by approximately 0.5%. After adding the control variables, the results did not change significantly. Overall, the results in Table 3 indicate a significant correlation between China's nighttime lighting density changes and the GDP growth rate. This finding is consistent with the literature (Xu et al., 2015). Given the significant relationship between the nighttime lighting density change and the GDP growth rate, following Henderson et al. (2012), we revise the official GDP growth rate and recalculate the energy intensity of each province.

4.2. Reassessment of energy intensity change during the 11th FYP

4.2.1. Revised GDP growth rate

First, we need to obtain the GDP growth rate used in the official assessment of the change in energy intensity. It is not clear which statistical indicator of economic growth rate is used by the central government to evaluate the achievement of the 11th FYP of each province. This task involves long-term inter-temporal comparison between the end of 2005 and the end of 2010. Further, China's Statistical Yearbook does not provide the GDP data of provinces with long-term constant price. Therefore, we adopt other methods for calculation. Specifically, based on the energy intensity calculation formula described above, this economic growth rate can be obtained by calculating the difference between the rate of change in energy consumption and the rate of change in energy intensity. The results are shown in Table 4.

Based on formula (2), the key point is to determine the reasonable β and λ and give appropriate weights to the official GDP growth rate and the nighttime lighting growth rate in order to revise the economic growth rate. Because we are trying to measure the long-term economic growth and energy intensity changes during the 11th FYP period, we use the results of long-term differential regression in Table 3. Therefore, the value of β is assumed to be 0.5. Moreover, China is a developing country with a relatively stable statistical system (World Bank, 2002). Accordingly, Henderson et al. (2012) assigned an official data weight of 0.85 for such countries. And we also set a value of 0.85 for λ. Thus, we have obtained a revised economic growth rate, which is presented in the last column of Table 4. The comparison between the two GDP growth rates shows that the official GDP growth rate of most provinces

Table 3
Satellite lighting and GDP growth rate.

	Pooled	Pooled	FE	FE	Long difference	Long difference
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lnGDP	lnGDP	lnGDP	lnGDP	lnGDP	lnGDP
lndndensity	0.483***	0.498***	0.103***	0.0587*	0.515***	0.531***
	(0.0337)	(0.0500)	(0.0359)	(0.0305)	(0.0946)	(0.105)
GDP2		0.0328***		0.0158***		−0.0423
		(0.0113)		(0.00331)		(0.0638)
GDP3		0.00285		0.0103**		−0.0734
		(0.0134)		(0.00396)		(0.0787)
urban		−0.00938		0.0105***		0.124**
		(0.00663)		(0.00317)		(0.0571)
Constant	8.073***	6.836***	8.270***	6.701***	7.588***	7.004***
	(0.0659)	(0.865)	(0.0353)	(0.325)	(0.157)	(0.371)
Observations	186	186	186	186	31	31
R-squared	0.528	0.599	0.961	0.974	0.505	0.610

Notes: The value in parentheses below the coefficient is the standard error.
*** indicates significance at the 1% level.
** indicates significance at the 5% level, and.
* indicates significance at the 10% level.

Table 4
Energy consumption and economic growth rate in the 11th FYP.

Province	Energy consumption growth rate (%)	Official energy intensity change rate (%)	Official GDP growth rate (%)	Revised GDP growth rate (%)
Beijing	25.93	− 26.59	52.52	48.09
Tianjin	66.92	− 21.00	87.92	79.81
Hebei	38.79	− 20.11	58.90	56.94
Shanxi	31.83	− 22.66	54.49	51.26
Inner Mongolia	74.01	− 22.62	96.63	92.95
Liaoning	53.90	− 20.01	73.91	69.02
Jilin	56.10	− 22.04	78.14	74.97
Heilongjiang	39.55	− 20.79	60.34	59.99
Shanghai	36.18	− 20.00	56.18	50.44
Jiangsu	50.13	− 20.45	70.58	67.61
Zhejiang	40.17	− 20.01	60.18	58.25
Anhui	49.19	− 20.36	69.55	68.97
Fujian	59.71	− 16.45	76.16	74.16
Jiangxi	48.27	− 20.04	68.31	66.56
Shandong	44.06	− 22.09	66.15	62.20
Henan	46.59	− 20.12	66.71	62.99
Hubei	50.15	− 21.67	71.82	69.61
Hunan	53.26	− 20.43	73.69	69.89
Guangdong	50.15	− 16.42	66.57	60.95
Guangxi	62.65	− 15.22	77.87	77.34
Hainan	65.23	− 12.14	77.37	75.11
Chongqing	58.93	− 20.95	79.88	74.36
Sichuan	51.42	− 20.31	71.73	70.38
Guizhou	44.92	− 20.06	64.98	62.78
Yunnan	43.99	− 17.41	61.40	63.21
Shaanxi	59.43	− 20.25	79.68	78.21
Gansu	35.61	− 20.26	55.87	58.52
Qinghai	53.76	− 17.04	70.80	70.98
Ningxia	45.15	− 20.09	65.24	66.30

Notes: The data come from the **China Statistical Yearbook** and the **China Energy Statistics Yearbook**. In addition, due to the lack of data on energy consumption in Tibet and Xinjiang, which did not participate in energy intensity assessment, the analysis here does not include the above two provinces.

is overestimated and Tianjin and Liaoning have the two largest gaps, which indirectly confirms the news reports of GDP fraud and suggest that our results are credible.

4.2.2. Reassessment of the change in energy intensity

Based on the revised GDP growth rate, we reassess the changes in energy intensity during the 11th FYP period. Specifically, as shown in Fig. 2(a), the energy intensity reduction in 10 of the provinces, including Tianjin, Inner Mongolia, and Liaoning, are significantly overestimated. The revised energy intensity change value is significantly different (more than 3%) from the targets set by the 11th FYP and the energy intensity reduction calculated using the official GDP data. On average, this group of 10 provinces differ from the 11th FYP target by 4.5%.

In Fig. 2(b), the overestimates of energy intensity reductions in Hebei, Shanxi, and other provinces are relatively low (more than 1%), and the average difference between revised energy intensity change and targets of the 11th FYP is 1.9%. Further, the nine provinces in Fig. 2(c), including Beijing and Anhui, have basically completed the established policy objectives of energy intensity reduction, and the average reduction rate of energy intensity is higher than the target of the 11th FYP.

It should be further noted that the revised energy intensity reduction of Gansu and Yunnan are significantly higher than their official statistics in Fig. 2(c). This is likely because some provinces that have overshoot their targets may underreport their performance to make future efforts easier. The literature has shown that some provinces adjusted their energy intensity upward by the end of 2005 to reduce the difficulty of completing the target of the 11th FYP (Ma and Zheng, 2018). Following the same logic, provinces that significantly exceed their required targets will also have incentives and the ability to adjust their energy intensity upward at the end of 2010, i.e. understating the reduction in energy intensity during the 11th FYP (2006–2010), to make it easier to meet the policy targets of the subsequent 12th FYP (2011–2015). Since Gansu and Yunnan have significantly exceeded their policy targets, these two provinces may underreport the reduction in energy intensity.

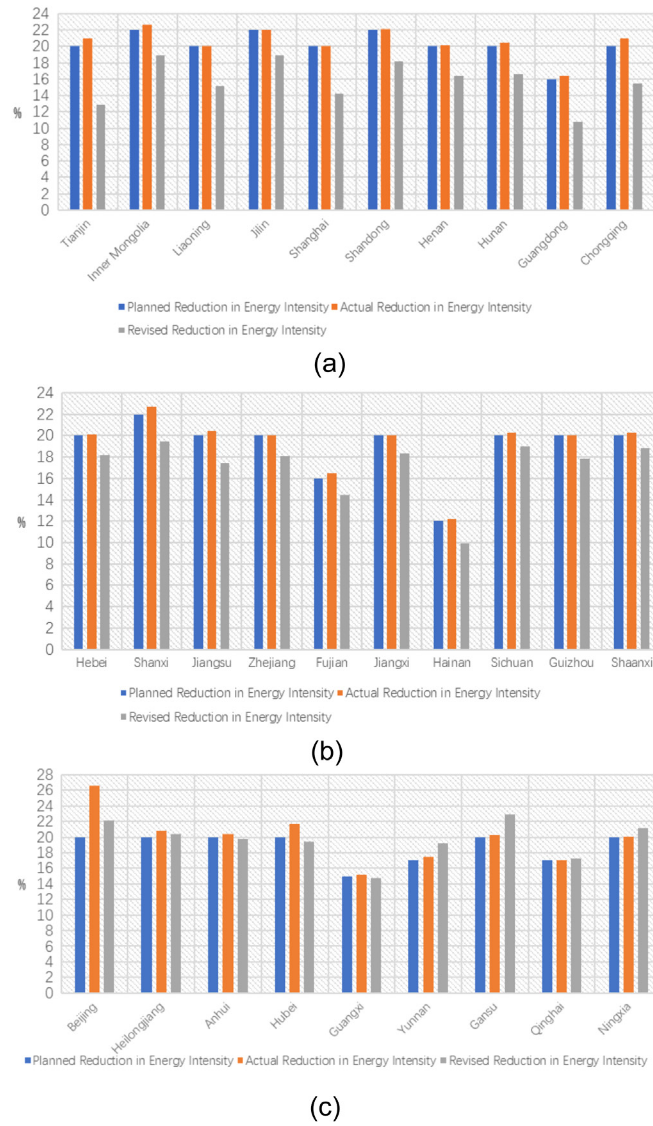

Fig. 2. **(a)** Energy Intensity Change Rate: Significantly Overestimated Area. **(b)** Energy Intensity Change Rate: Moderately Overestimated Area. **(c)** Energy Intensity Change Rate: Almost Met Area.

Overall, according to the original statistics, all provinces have either met or exceeded the policy targets of energy intensity reduction during the 11th FYP period. However, after revising the GDP growth rate, although the energy intensity of each province has decreased significantly, some provinces have not achieved their policy target. If an energy intensity change rate exceeding the planned target of 2% or more is taken as the threshold, approximately half of the provinces cannot achieve the policy target. The gaps in Tianjin and Liaoning are particularly large. This indicates that the false high value economic growth data also interferes with the realization of energy intensity.

5. Conclusions and policy implications

Energy efficiency may partially resolve the conflict between economic growth and increase in energy consumption and associated emission. To control rapid rising energy consumption pollutions and emission during China's economic growth, the Chinese central government has included energy intensity targets into its performance evaluation for its provinces and their leaders. While this policy effort has pushed energy efficiency improvement in China, its actual performance is undermined by the evidenced manipulation of GDP data, the denominator of the energy intensity indicator. Accurate assessment of the energy intensity performance can help China to improve the energy intensity policy. However, there is no study in the literature that introduce one alternative assessment of GDP data to reassess the Chinese provinces' energy intensity performance.

This article uses nighttime lighting data to revise the GDP growth rate and reassess energy intensity performance of Chinese provinces. This study reaches the following conclusions: First, the GDP growth rate contains certain errors, and there is significant overestimation in some provinces. Second, after correcting the GDP growth rate, the energy intensity of most provinces still shows a marked decline. Third, the revised GDP growth rate indicates that approximately half of the provinces failed to achieve the target of energy intensity reduction in China's 11th FYP. The findings in this study differ from those in previous studies (Lin and Du, 2014; Song and Zheng, 2012), and thus offer new insights regarding the energy intensity control policy. Existing research generally suggested that provinces basically met the energy conservation policy targets based on official statistics. Our results imply that the reduction in energy intensity will be overestimated if GDP distortions are not considered. This will interfere with the smooth implementation of energy conservation policy and undermine the effectiveness of such policy.

The above conclusions have certain realistic policy implications on how to reduce energy consumption and promote low carbon growth:

First, in the design of a multi-assessment system, it is necessary to prepare for undesirable reactions from local governments to ensure that relevant policies are effectively implemented. Fortunately, because the central government's evaluation for local governments no longer simply emphasizes the economic growth and now considers indicators such as resource consumption and ecological benefits, local governments are now less interested in manipulating GDP data than they were previously. However, energy intensity assessment alone can still incentivize local governments to inflate GDP data.

Second, in the design of future energy conservation and emission reduction policies, multiple assessment indicators should be included to monitor the effective implementation of policy objectives. Although the highly simplified single policy target design is easy to observe, it encounters interference and insufficient accuracy during implementation. When selecting the indicators of energy-saving assessment, the proportion of indicators directly provided by lower-level governments should be reduced to avoid manipulation. Mordent technologies that can provide verification of GDP data, such as nighttime lighting data, could be used to identify potential data manipulation.

Lastly, and more dramatically, administrative policies to achieve energy consumption reduction should be replaced by well-established alternative instruments, such as minimum energy efficiency performance standards, which can be applied to major energy consuming appliances, electric motors, vehicles, and buildings (Shi, 2015) and the emerging national emission trading scheme.

The shortcomings of this paper are mainly that there is a lack of analysis of factors that affect the difference completion degree of energy policy targets among provinces. This is also an important issue worthy of further investigation in future research. The related vintage in data is another shortcoming which could be overcome in the future when more updated satellite lighting data become available.

Acknowledgements

This work was supported by the National Social Science Fund of China on “Study of Measurement of Statistical Misreporting and Correction Mechanism: Based on Incentive of Local Government” (Grant no. 17BJL070), Humanity and Social Science Youth Foundation of Ministry of Education of China on “GDP Misreporting and Formation Mechanism under Official Evaluation: Study Based on Satellite Light Data” (Grant no. 16YJC790136), National Natural Science Foundation of China on “Modelling Industrial Capacity Cut under a Cap and Trade Mechanism and Policy Issues: A case study of coal sector” (Grant no. 71828401), the Major Projects of the National Social Science Fund of China on “Supply-side Structural Reform and New Developing Impetus” (Grant No. 16ZDA006), the Major Projects of the National Social Science Fund of China on “Institutional Dividend of the Transformation of Government Functions” (Grant no. 18ZDA113), and National Social Science Fund of China on “Energy Consumption and Efficiency in New Urbanization Process” (Grant no. 15BTJ021).

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