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How Does Target-Based Performance Evaluation Affect the Accuracy of Energy-Saving Data: Evidence From China

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Energy intensity measured by energy consumption per unit of GDP has always been the main assessment indicator for the design of energy-saving policies, but its accuracy is highly dependent on the reliability of GDP data. This paper finds that the indicator accuracy is improving after the central government has included energy intensity into the performance appraisal system for local officials. This means that the energy-saving target-based performance evaluation has restrained the data misrepresentation behavior of local officials. Further mechanism analysis shows that the pressure of energy saving restricts the development of the industrial sector, which weakens the ability of local governments to manipulate GDP data, thus improving the accuracy of energy intensity statistics. These findings provide some insightful references for China's future green development and policy design.

Keywords: target-based performance evaluation, data accuracy, energy intensity, green development, policy design

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INTRODUCTION

Energy intensity, calculated by energy consumption per unit of GDP, is an important measure of energy efficiency. This indicator takes both the economic growth and policy objectives of energy saving into account, which is widely used for public policy and academic research (Zhang et al., 2011; Shi, 2014). China, the world's largest energy consumer, has taken a series of measures to achieve the goal of reducing energy intensity, thus promoting green development. Among them, the 11th (2006–2010) and the 12th (2011–2015) Five-Year Plan (FYP) put forward a binding target of energy intensity reduction (Song and Zheng, 2012; Li H. et al., 2016). Moreover, the national target was allocated to the provincial level, and the energy-saving target was for the first time to be incorporated into the performance evaluation system for the local officials (Zhang et al., 2019). The political system in China is centralized, and thus, the local government is responsible for national policies (Xiong, 2018; Lo, 2020). The top–down target-based responsibility system ensures that the local officials are tied to satisfying the required mandates for career concerns as the energy intensity reduction has positive effects on the promotion probability (Zheng et al., 2014; Chen et al., 2018).

The previous studies comprehensively analyzed the influencing factors of China's energy intensity from the aspects of technological progress, industrial structure adjustment, and policy regulation (Zhang et al., 2020). However, most studies ignored that the calculation accuracy of energy intensity basically depends on data reliability. For a long time, there has been a dispute about authenticity and accuracy of local government GDP data. For example, at the end of 2015, the Xinhua News Agency reported that data manipulation of GDP was rampant in Northeast China. Moreover, in 2017 and 2018, some local governments, such as Liaoning, Inner Mongolia, and Tianjin, admitted that there was fraud in the past GDP data, which reduced the historical economic growth significantly. Some scholars also believe that the official GDP data seriously overestimate the economic growth rate (Rawski, 2001; Young, 2003). In view of this, the data accuracy of energy intensity is doubtful. Zhang et al. (2019) demonstrated that the energy intensity of most provinces in China was overestimated during 2006–2010 after correcting the GDP growth rate.

As mentioned above, to achieve the policy goals of energy saving, the central government included energy intensity into the performance evaluation for local officials during the 11th and the 12th FYP, requiring the local government to meet corresponding targets of energy intensity reduction. So, on the one hand, it is obvious that the overestimation of GDP data cannot only provide excellent economic growth performance but also make it easier to achieve the goals of energy intensity reduction (Lo, 2014; Lo, 2020). This provides a higher incentive for local governments to falsely report economic growth data, which may further weaken the data accuracy. However, on the other hand, energy consumption is highly correlated with GDP growth in the short term, and it is relatively difficult to manipulate energy consumption data (Wallace, 2016). If GDP statistics are blindly improved without corresponding increase in energy consumption, it will raise a question and then increase the risk of false data being found (Rawski, 2001). From this point of view, the central government includes the energy intensity indicators into the performance evaluation for local officials, which may inhibit the GDP misrepresentation and improve the accuracy of energy-saving data. Therefore, the impact of target-based performance evaluation on the energy data accuracy is an effort worth studying. Moreover, in the era of big data, the utilization of information technologies may provide opportunities to strengthen the supervision of behaviors of the central government, thus helping to promote statistical data accuracy.

Based on the study of Henderson et al. (2012), this paper firstly corrects the GDP growth rate by using nighttime lighting data and then calculates the change rate of energy intensity more accurately on this basis. The accuracy of energy intensity is represented by the difference between the revised change rate in energy intensity and the official change rate. Finally, it is analyzed whether the target-based assessment enlarges or narrates the above gap, that is, it weakens or improves the accuracy of energy-saving data. Our research suggests that official data do generally overstate the decline in energy intensity across regions, thanks to widespread GDP misreporting. Further study on the effect of energy conservation policies shows that the inclusion of energy intensity in the performance appraisal system for local officials improves the data accuracy. Specifically, the main mechanism is the decline of the industrial share in economic output.

Our paper contributes to the literature in the following two aspects. First, although previous studies have pointed out that energy-efficiency policy is an important factor affecting China's energy intensity, they have not taken into account that policy design may also affect the energy data quality. Our findings provide direct evidence of how energy-efficiency target-based performance evaluation policies affect the energy data accuracy. Second, the study sheds light on a growing body of literature on government data manipulation. Previous studies have found that government target assessment can affect the quality of statistical data (Chen et al., 2012; Ghanem and Zhang, 2014; Wallace, 2016), but our results reveal that the statistical data quality has improved.

This paper is organized as follows. *Literature Review* reviews the related research. *Estimation Strategy* introduces the research methods, variable construction, and data source. Specifically, we recalculate the change rate in energy intensity to infer the official statistical data accuracy by using the nighttime lighting data. *Main Results* mainly empirically discusses the impact of target-based performance evaluation on the accuracy of energy-saving data. Finally, *Conclusion and Policy Implications* concludes this article.

LITERATURE REVIEW

The existing studies comprehensively analyze the influencing factors of China's energy intensity change from various aspects. For example, Zhang et al. (2020) found that better access to credit can improve energy efficiency measured by energy intensity. Xue and Wang (2021) demonstrated that mitigation of financial pressure makes a significant contribution to the energy intensity reduction. Lin and Zhu (2021) confirmed the new-type urbanization or human-centered urbanization has a positive effect on energy intensity. Overall, energy intensity is an important indicator for evaluating the performance of local officials. Especially since the 11th FYP, this indicator has been included in the performance evaluation for local officials. However, most of the studies measure energy intensity using the official data without considering data reliability.

Since data misreporting is nothing new, several studies have shown that many governments deliberately manipulate official statistics for specific purposes (Li P. et al., 2016). For example, in order to meet the economic conditions of joining the EU, Italy and Greece have deliberately understated their budget deficits (Barber and hope, 2010). Michalski and Stoltz (2013) found that the balance of payments data sometimes does not conform to the statistical distribution law and thus inferred that the government might make strategic data misrepresentation. The opposite data manipulation also exists, and not only for the bad economic situation. Kerner et al. (2014) revealed that some countries would deliberately lower their per capita national income in order to obtain concessional loans from the World Bank. Research on China's official data manipulation is mainly related to the top–down official assessment system (Edin, 1998). Kung and Chen (2011) found that, during 1958–1960, local officials falsely reported grain output to cater to the goals of their superiors, resulting in excessive grain purchase and serious difficulties in the national economy. Chen et al. (2012) and Ghanem and Zhang (2014) analyzed the air pollution data at the city level and revealed that there is a discontinuous breakpoint when the air pollution concentration is at the critical point of the "blue sky" standard, which indicates that the local government may satisfy the air quality assessment standard through data fraud. Wallace (2016) measured the promotion-oriented data fraud by the difference between the official GDP growth rate and the electricity consumption growth rate and found that the gap is larger than that in other periods during the change of government officials.

Given that the Chinese central government has set a series of mandatory targets for energy conservation and environmental protection, many studies also have focused on the issues on the target-based responsibility scheme. For example, Lo (2014) proved that the energy conservation target responsibility system has been constrained by problems including weak targets and lack of reliable local energy statistics. Li H. et al. (2016) highlighted that the national energy intensity target cannot be fully disaggregated without omissions. Chen et al. (2018) estimated how local officials respond to an emission reduction target–based performance evaluation system and found that the performance evaluation system leads to the decrease in SO_2 emission with the decline of cost of GDP growth rate. Lo (2020) examined the key aspects and limitation of the energy conservation target responsibility system in China.

In general, although the existing literature has done a more detailed study on energy intensity, few literature works discuss whether the target-based performance evaluation of local government improves or worsens the quality of energy-saving statistics. In this paper, the distortion of energy intensity statistical index caused by the false report of the GDP data is eliminated by using nighttime lighting data. Based on this, the impact of the assessment of energy conservation policies on the accuracy of energy data during the 11th and the 12th FYP is discussed, thus making up for the deficiencies of the existing research.

ESTIMATION STRATEGY

Estimation Framework

The main objective of our empirical analysis is to test the effect of energy intensity reduction regulation on data accuracy. The time and spatial variation of the reduction target of the 11th and the 12th FYP since 2006 provides an opportunity to implement the difference in difference (DID) method. Specifically, before 2006, namely, the first year of the 11th FYP, the regulation stringency of energy intensity reduction ratio was almost uniform across the provinces. However, some provinces face a stringent energy intensity reduction mandate assigned by the central government. Thus, the DID estimation compares the provincial data accuracy of energy intensity before and after 2006 with more stringent targets relative to lax targets. The DID estimation specification is set as follows (Beck et al., 2010; Li P. et al., 2016; Chen et al., 2018; Shi and Xu, 2018):

$$gap_{i,t} = c + \beta target_{i,t} * post + \gamma controls_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t}, \quad (1)$$

where $gap_{i,t}$ is the difference in the revised ratio of energy intensity change and official data in province i at year t. We use this indicator to represent data distortion, and a higher value means lower accuracy of official energy intensity data. $target_{i,t}$ is the planned reduction ratio of energy intensity, namely, the target assessment ratio required by the central government. The higher planned reduction rate of energy intensity means that the local government faces greater assessment pressure. That is, the assessment intensity of energy conservation (*target*) will be greater. As 2006 is the beginning year of the 11th FYP, *post* takes a value of one if $t \geq 2006$ or otherwise 0.

$Controls_{i,t}$ denotes control variables, including some provincial economic indicators and the characteristics of the provincial party secretary and governor. Specifically, provincial economic indicators mainly refer to the percentage of second industry (*Second*), the percentage of third industry (*Third*), the proportion of fixed investment to GDP (*Invest*), the proportion of total consumption sales to GDP (*Consume*), and the total value of foreign trade (*Foreign*). Furthermore, as the personal characteristics and behavior of local officials will have a significant impact on the economic development of the jurisdiction, we further control the characteristics of provincial officials, mainly including age, gender, the experience of serving in the central government, the experience of serving in his hometown or not, the term of office, and the quadratic term of age to control the possible non-linear relationship. δ_i and μ_t are the province fixed effect and year fixed effect, respectively. $\varepsilon_{i,t}$ is the error term, and c is the constant.

The positive value of β means the higher requirement of energy intensity reduction will lead to the worse accuracy of energy intensity. That is, faced with the assessment pressure, local governments tend to distort the statistical indicators. In contrast, the negative value of β means the higher requirement results in the higher data accuracy. In other words, in view of the great impact of the central target assessment on a local official's career, the incorporation of energy-saving indicators into the assessment system may inhibit the fraudulent behavior of local officials.

Variable Construction

As mentioned, the difference in the revised energy intensity change rate and official data is the explained variable in our paper. However, this indicator cannot be obtained directly. The energy intensity indicator is usually measured by energy consumption per unit of GDP. Especially, energy consumption data involve the specific performance in terms of power grid companies and other units, which does not interfere with the GDP pursuit of local officials, and thus, there is limited room and motivation for manipulation. Therefore, it is usually recognized that energy consumption data are more real and exact as it is relatively difficult to manipulate energy consumption data (Wallace, 2016). However, the past evidence shows the GDP data in China have likely been manipulated (Xu et al., 2015). To calculate this indictor, our basic idea is to revise the GDP growth rate with nighttime lighting intensity and then measure data accuracy of energy intensity by using the revised GDP growth rate. The specific setting and calculation are described in detail as follows.

TABLE 1 | Relationship between satellite lighting and the GDP growth rate.

	(1) Lngdp	(2) Lngdp
Lnlight	0.427***	0.267**
	(4.31)	(2.12)
Constant	8.049***	7.774***
	(43.91)	(49.94)
Year fixed effect	No	Yes
Province fixed effect	No	Yes
Observations	290	290
R-squared	0.350	0.992

Note:
***p < 0.01.
**p < 0.05.
*p < 0.1.***, **, * denote significance at 1%, 5% and 10%, respectively. The t-statistics are reported in parentheses and clustered at the provincial level.*

Estimating GDP Growth Rate Based on Nighttime Lighting Intensity

To revise the GDP growth rate based on nighttime lighting intensity, we first need to accurately measure the correlation between nighttime lighting intensity and economic growth. Thus, we have the following regression specification:

$$y_{i,t} = c + \alpha l_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t}, \tag{2}$$

where $y_{i,t}$ is the logarithm of official GDP in province i at year t with 2000 as the base year. $l_{i,t}$ is the logarithmic value of nighttime lighting intensity. α captures the relationship between real GDP and light intensity as well as the relationship between the official GDP growth rate and the light density growth rate. ω_i, μ_t, and $\varepsilon_{i,t}$ are the province fixed effect, the year fixed effect, and the error term, respectively.

Based on Henderson et al. (2012), we estimate the growth rate of real GDP with the following ideas. We assume that the statistical relationship among the real GDP growth rate, official GDP growth rate, and light intensity growth rate satisfies the following conditions:

$$y_i = \beta l_i + \varepsilon_i, \tag{3}$$

$$l_i = \gamma y_i^* + \varepsilon_{l,i}, \tag{4}$$

$$y_i = \varnothing y_i^* + \varepsilon_{y,i}, \tag{5}$$

$$E(\varepsilon_{l,i}) = E(\varepsilon_{y,i}) = 0, \tag{6}$$

$$E(\varepsilon_{l,i}\varepsilon_{y,l}) = 0, \tag{7}$$

where y^* represents the real GDP growth rate, y is the official GDP growth rate, l is the nighttime lighting intensity growth rate, β reflects the degree of correlation, and i represents the province. Then, we have the following equations:

$$\hat{y}_i^* = \lambda y_i + (1-\lambda)\beta l_i, \tag{8}$$

$$\lambda = \frac{\theta - \rho^2}{1-\rho^2}, \tag{9}$$

$$\theta = \frac{\sigma^2_{y_i^*}}{var(y_i)}. \tag{10}$$

The correlation coefficient between $y$and l is ρ, and the predicted value of $\hat{y}_i^*$is more accurate than that of y_i. Among them, λ describes the accuracy of official statistics. In the following analysis, based on the World Bank (2002) evaluation of China's statistical capacity and quality, we give a more objective value of λ.

Based on the method mentioned above, we empirically test the relationship between GDP and nighttime lighting intensity. **Table 1** shows the regression results from **Eq. 2**. The results show that there is a significant positive relationship between nighttime lighting intensity and GDP, which is very close to the result of Henderson et al. (2012). They found that the correlation coefficient was about 0.28.

Furthermore, to correct the GDP growth rate, we need to assign an appropriate value to **Eq. 8**, that is, to determine the respective weight of the official GDP growth rate and the nighttime lighting intensity growth rate. Based on the findings in **Table 1**, we choose the results in column (2) with $\beta = 0.267$. According to the research of the World Bank (2002), China is a developing country with a relatively sound statistical system and better statistical quality. Henderson et al. (2012) assigned the official data weight of such countries to be 0.85. We also use this value, and thus, λ is set as 0.85. Therefore, we can calculate the revised GDP growth rate. That is, $cogdpgrow = 0.85 * GDP + 0.267 * 0.15 * lggrow$, where $cogdpgrow$ is the revised GDP growth rate, GDP is the official GDP growth rate, and $lggrow$ is the growth rate of nighttime lighting intensity.

Measuring Data Accuracy of Energy Intensity

The energy intensity indicator is usually measured by energy consumption diving GDP. Thus, the change rate of energy intensity is equal to the difference between the change rate of energy consumption and the GDP growth rate. Given the unchanged energy consumption growth rate, different measures on the GDP growth rate will lead to different change rates of energy intensity. This paper applies the difference in the

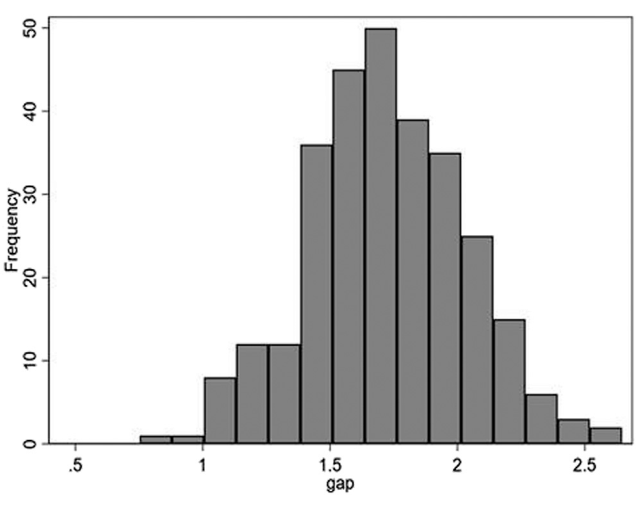

FIGURE 1 | Distribution of data accuracy of energy intensity (gap).

TABLE 2 | Descriptive statistics.

Variable	Definition	Mean	SD	OBS
Lngdp	Gross domestic product	8.655	0.967	290
Lnlight	Nighttime light density	1.418	1.338	290
lnEc	Change rate of energy consumption	9.387	5.528	290
Gap	Data accuracy of energy intensity reduction ratio	1.717	0.310	290
Target	Planned reduction rate of energy intensity	18.65	2.568	290
Actualtarget	Actual reduction rate of energy intensity	19.11	2.967	290
Second	Percentage of second industry	47.03	7.879	290
Third	Percentage of third industry	40.48	8.027	290
Invest	Proportion of fixed investment to GDP	55.79	16.48	290
Consume	Proportion of total consumption sales to GDP	0.344	0.0470	290
Foreign	Total value of foreign trade	14.46	1.733	290
sz_gender	Gender of the province's governor	0.972	0.164	290
sz_center	Governor's experience of working in the central government	0.324	0.469	290
sz_home	Governor serving in home or not	0.334	0.473	290
sz_term	Governor's term of office	3.097	1.887	290
sz_age	Governor's age	57.39	3.898	290
sj_gender	Provincial party secretary's gender	0.990	0.101	290
sj_center	Provincial party secretary's experience of working in the central government	0.590	0.493	290
sj_home	Provincial party secretary serving in home or not	0.110	0.314	290
sj_term	Office term of provincial party secretary	3.376	2.127	290
sj_age	Age of provincial party secretary	58.86	4.209	290

revised ratio of energy intensity change and official data to measure the data accuracy (*gap*). The higher value always means lower data accuracy of energy intensity due to false statistical data issued by the local officials.

Based on the revised GDP growth rate, we also calculate the change rate of energy intensity with a constant rate of energy consumption. Then, the difference between the revised and the official energy intensity change rates can be obtained, namely, the degree of data distortion (*gap*). As mentioned, this indicator is applied to measure the data accuracy of energy intensity. **Figure 1** shows the distribution frequency of these data. We find that the value of *gap*is always greater than 0. Combined with **Table 2**, the average value and standard deviation of the gap in the sample are 1.717 and 0.31, which indicates the overestimated energy intensity reduction from 2003 to 2012.

Data Source

Our sample contains 29 provinces, cities, and autonomous regions over 2003 to 2012 in China. Though the sample period is limited to 2012 as the nighttime light data are not available since then, the empirical findings are still valuable and relevant (Li P. et al., 2016; Chen et al., 2018; Jia et al., 2021) because the indicator assessment applied by the central government in the 11th and the 12th FYP is rather similar. Due to data limitation, Xinjiang, Tibet, Taiwan, Hong Kong, and Macao are not included in this paper. The original data of global nighttime lighting intensity come from the US Defense Meteorological Satellite Project (DMSP-OLS), which includes global nighttime lighting images from 1992 to 2012 obtained by several satellites. The saturation value of the pixel gray value (DN value) is 63, with the problem that the DN value obtained by different sensors in the same year is different. Especially, the existing raw data of satellite nighttime lighting face the problems of discontinuity and saturation (Donaldson and Storeygard, 2016). Therefore, we use the lighting image correction method including inter-calibration and intra-annual composition based on the invariant target area to correct the original lighting image data and get the provincial lighting intensity value (*light*) from 2003 to 2012 (Liu et al., 2012), which can more reasonably reflect the regional economic development differences. This method is widely used in the literature to correct the long time series nighttime lighting image data (Henderson et al., 2012; Wu et al., 2013; Jia et al., 2021).

Provincial energy data mainly include the change rate of energy consumption index (*lnEc*), the planned rate of energy intensity reduction (*target*), and the actual reduction rate of energy intensity (*actualtarget*). The data are mainly from China Statistical Yearbook, China Energy Statistical Yearbook. Other provincial economic indicators are all derived from China Statistical Yearbook. In addition, we have manually collected the personal information of provincial officials (secretary of the provincial party committee and governor) from government websites and Baidu Encyclopedia. The descriptive statistics are shown in **Table 2**.

MAIN RESULTS

This section mainly analyzes the impact of energy-saving policy target assessment on the accuracy of energy statistics. In addition to baseline estimates, we also conduct a series of robust tests, including a parallel trend test, a placebo test, and replacement of the explained variable. Furthermore, we also study the regional heterogeneity and verify the influence mechanism.

Baseline Estimation

Table 3 reports the main results of the effect of target assessment on the data accuracy of energy intensity from **Eq. 1**. Only

TABLE 3 | Baseline estimates.

	(1) Gap	(2) Gap	(3) Gap	(4) Gap
target×post	−0.027**	−0.025**	−0.029**	−0.027**
—	(−2.10)	(−2.18)	(−2.40)	(−2.17)
Second	—	0.012	0.013	0.006
—	—	(0.92)	(1.18)	(0.47)
Third	—	0.023	0.020	0.017
—	—	(1.63)	(1.52)	(1.20)
Investment	—	0.011***	0.009***	0.008**
—	—	(4.06)	(3.53)	(2.65)
Consume	—	−1.675	−1.416	−1.150
—	—	(−1.39)	(−1.16)	(−0.86)
Foreign	—	0.091	0.069	0.039
—	—	(0.96)	(0.85)	(0.42)
Constant	1.506***	−1.045	−3.990	−1.047
—	(30.83)	(−0.71)	(−0.76)	(−0.22)
Provincial party secretary characteristics	No	No	Yes	Yes
Governor characteristics	No	No	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Year* regional fixed effect	No	No	No	Yes
Observations	290	290	290	290
R-squared	0.384	0.499	0.552	0.592

Note:
***p < *0.1.*
**p < *0.05.*
*p < *0.01.***, **, * denote significance at 1%, 5% and 10%, respectively. The t-statistics are reported in parentheses and clustered at the provincial level.*

province and year fixed effects are included in the first column, and the estimated results show that the assessment policy significantly improves the data accuracy. This means that the energy conservation assessment started in 2006 has a significant constraint or regulation effect on the behavior of local governments, making them less prone to fraud in energy intensity data statistics.

Provincial economic characteristics are introduced as control variables in column (2). We find that the provinces with a higher proportion of fixed asset investment to GDP have lower data accuracy of energy intensity. In column (3), the personal characteristics of provincial officials are controlled, and the results are still robust. In addition, in order to control the influence of time-varying unobservable factors at the regional level on the dependent variable, the interaction term of year and regional fixed effects in eastern, central, and western regions is further added in column (4), and the results are highly consistent with the findings in columns (1)–(3).

As shown in **Table 3**, the estimation coefficient between the target assessment intensity and the energy intensity data accuracy is always statistically significantly negative. This shows that the energy-saving target-based performance evaluation since 2006 has led to a significant improvement in data accuracy. In an economic sense, if energy intensity target assessment intensity changes by a standard deviation, the degree of data distortion will decrease by about 13.7% (0.137 = 0.027*8.71/1.72) according to the regression coefficient in column (4).

Robustness Checks

To further verify our results are robust, we report a series of robustness checks, including a parallel trend test, a placebo test, and replacement of the explained variable.

Parallel Trend Test

A necessary condition for supporting our identification is that provinces with different target assessment have similar time trends on the outcomes before and after treatment. This means that the differences of assessment requirements faced by different provinces before 2006 will not affect the accuracy of the previous data. Thus, we use the event study approach (Chen et al., 2018). The estimation specification is as follows:

$$gap_{i,t} = c + \sum_{t=2004}^{t=212} \beta_t * target_{i,t} * yeardummy_t + \gamma controls_{i,t} + \delta_i + \mu_t + \varepsilon_{i,t}, \tag{11}$$

where $yeardummy_t$ is the dummy variable taking a value of one if $t = year$ or 0 otherwise. β_t captures the difference in outcomes between different provinces before and after treatment. As shown in **Figure 2**, the regression coefficients before 2006 are not significant, which indicates that there is no significant difference in data accuracy among provinces before treatment. Therefore, it is reasonable and feasible to use the DID method to test the impact of target assessment on the accuracy of energy intensity statistics. Further analysis of the

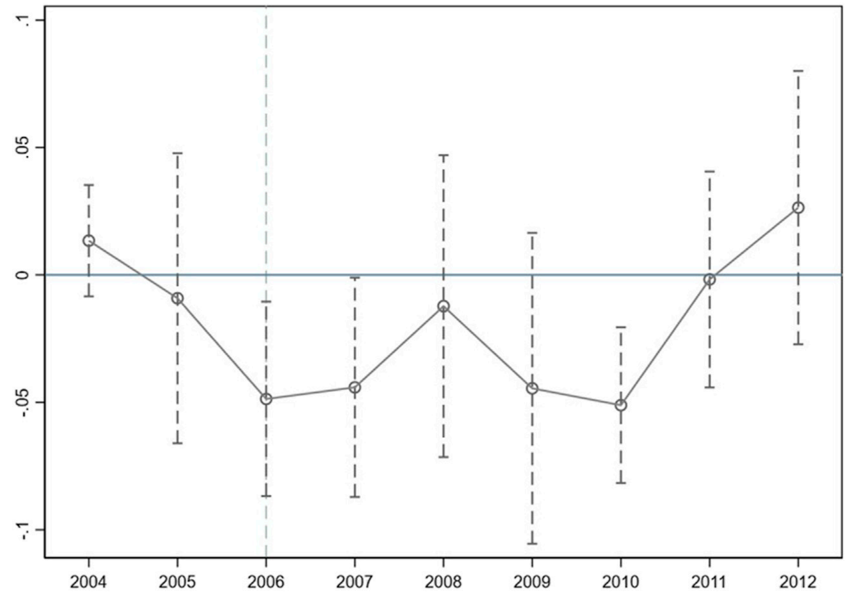

FIGURE 2 | Parallel trend test.

TABLE 4 | Placebo test.

	(1) Gap	(2) Gap	(3) Gap
target×pre	0.024	0.019	0.013
—	(1.28)	(1.04)	(0.70)
Provincial economic indicators	No	Yes	Yes
Provincial party secretary characteristics	No	No	Yes
Governor characteristics	No	No	Yes
Year fixed effect	No	Yes	Yes
Province fixed effect	No	Yes	Yes
Observations	290	290	290
R-squared	0.374	0.490	0.539

Note:
***p < 0.01.
**p < 0.05.
*p < 0.1.***, **, * denote significance at 1%, 5% and 10%, respectively. The t-statistics are reported in parentheses and clustered at the provincial level.

dynamic policy impact shows that the coefficient of the first evaluation year is negative, which indicates that the policy has a positive impact on data accuracy. The estimates are negative and stale until 2011. Particularly, the estimates in 2010 are the most prominent in both the numerical and the statistical sense, which is completely consistent with time when the local government submitted the final energy intensity assessment document to the central government in the 11th FYP. This has also deepened our understanding of the policy operation mechanism.

Placebo Test

To further verify the reliability, we set the policy time for the implementation of the 11th FYP in 2005. Assuming that the energy intensity assessment is only implemented in 2005, we conduct regression analysis again and assign *pre* = 1 if *year* = 2005or 0 otherwise. In other words, if the accuracy improvement in energy intensity statistics is really caused by target assessment, the estimate should not be significant. According to the results in **Table 4**, the estimated coefficient is not significant, so the influence of other unobservable potential factors on the previous findings can be excluded.

Replacement of the Explained Variable

To avoid one-sided understanding of the assessment indicators, we replace the core explanatory variable in **Table 5**. The planned reduction rate of energy intensity is replaced by the actual reduction rate. According to the regression results, we find that the coefficient is slightly smaller, but still statistically significantly negative. In an economic sense, the actual reduction rate of energy intensity is reduced by one standard deviation, and the data accuracy is improved by about 10%. Therefore, after changing the explanatory variables, the results still show that the higher requirements of energy-saving assessment will result in higher statistical accuracy of energy data.

Regional Heterogeneity

Considering that economic development and policy orientation differ greatly in different regions, we divide all provinces into eastern, central, and western regions to investigate the heterogeneous impacts[1]. Columns (1)–(3) in **Table 6**, respectively, report the comparative results by controlling provincial economic variables, official characteristics, province fixed effect, and year fixed effect. Generally speaking, the

[1]According to the common division methods, the eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes Guangxi, Inner Mongolia, Shaanxi, Gansu, Qinghai, Ningxia, Sichuan, Chongqing, Yunnan, and Guizhou.

TABLE 5 | Replacement of the explained variable.

	(1) Gap	(2) Gap	(3) Gap	(4) Gap
actualtarget×post	−0.023**	−0.020*	−0.022**	−0.019*
—	(−2.36)	(−2.00)	(−2.11)	(−1.77)
Provincial economic indicators	No	Yes	Yes	Yes
Provincial party secretary characteristics	No	No	Yes	Yes
Governor characteristics	No	No	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Year* regional fixed effect	No	No	No	Yes
Observations	290	290	290	290
R-squared	0.383	0.497	0.549	0.588

Note:
***p < 0.01.
**p < 0.05.
*p < 0.1.***, **, * denote significance at 1%, 5% and 10%, respectively. The t-statistics are reported in parentheses and clustered at the provincial level.*

TABLE 6 | Regional heterogeneity.

	(1) East Gap	(2) Central Gap	(3) West Gap
target×post	−0.032***	−0.153*	0.003
—	(−3.94)	(−1.95)	(0.20)
Provincial economic indicators	Yes	Yes	Yes
Provincial party secretary characteristics	Yes	Yes	Yes
Governor characteristics	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes
Observations	110	80	100
R-squared	0.852	0.671	0.645

Note:
***p < 0.01.
**p < 0.05.
*p < 0.1.***, **, * denote significance at 1%, 5% and 10%, respectively. The t-statistics are reported in parentheses and clustered at the provincial level.*

eastern and central provinces are stronger than the western provinces in both economic strength and political game ability, which may lead to the heterogeneity in the response of assessment policy. The analysis results show that the accuracy of energy intensity data is significantly improved in both eastern and central regions. The relationship between energy target assessment and data distortion is positive, but not significant in the western region. This means that local governments with greater economic power and political influence will weigh the potential risks and benefit more carefully when faced with appraisal pressure and reduce the tendency to falsify data.

Mechanisms

We hope to better understand the specific mechanism how this policy effect can be achieved. Since the re-estimation of the change rate of energy intensity is mainly based on different estimates of the economic growth rate, we actually need to find the influence channels on the misreporting of economic growth rate. Chen et al. (2019) found that the local government mainly distorts statistical data by adjusting the industrial output on the output side and reduces statistical accuracy by adjusting the investment data on the expenditure side. Therefore, energy-saving assessment may also affect the economic growth rate through industrial output and fixed asset investment, finally influencing the accuracy of energy intensity data. Later, we will analyze the impact mechanism of energy intensity assessment on data accuracy from the perspective of industrial output and fixed asset investment.

Industrial Output

Energy-saving assessment encourages local governments to adjust industrial output, thus affecting the accuracy of energy intensity data. To test this mechanism, this paper takes the proportion of industrial output to GDP as the explained variable. The corresponding regression results are reported in columns (1) and (2) of **Table 7**. The results show that the target assessment of energy intensity reduces the proportion of industrial output, which reduces the potential possibility of false reporting of output data and improves the accuracy of energy data.

Fixed Asset Investment

Energy-saving assessment may encourage local governments to adjust fixed asset investment, thus affecting the data accuracy of energy intensity. Similarly, this paper takes the proportion of fixed asset investment to GDP as the explained variable. As shown in columns (3) and (4) of **Table 7**, there is a negative relationship between energy intensity assessment and fixed asset investment, but it is not statistically significant.

Overall, we find that the energy-saving target assessment policy is mainly to reduce the proportion of local industrial output to improve the accuracy of statistical data. It also has a certain impact on investment, but it is not significant.

CONCLUSION AND POLICY IMPLICATIONS

Although energy intensity has always been the main measurement for the energy-saving policy design, its accuracy is affected by the false report of the GDP data. At the same time, few literature works discuss whether it will weaken or improve the

TABLE 7 | Mechanisms.

	(1) Industry	(2) Industry	(3) Invest	(4) Invest
target×post	−0.448**	−0.425**	−0.335	−0.269
—	(−2.59)	(−2.61)	(−0.68)	(−0.72)
Provincial party secretary characteristics	No	Yes	No	Yes
Governor characteristics	No	Yes	No	Yes
Provincial economic indicators	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Province fixed effect	Yes	Yes	Yes	Yes
Observations	290	290	290	290
R-squared	0.395	0.444	0.762	0.824

Note:
***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.***, **, * denote significance at 1%, 5% and 10%, respectively. The t-statistics are reported in parentheses and clustered at the provincial level.

data accuracy when energy intensity is included in the performance appraisal system for the local government. The understanding of this issue affects how the government designs effective energy conservation and emission reduction policies to achieve the important strategic goal of green development.

This paper analyzes the impact of energy-saving target assessment on data accuracy by using satellite lighting data to re-calculate energy intensity. We find that, after controlling the impact of false report of the economic growth rate, the official data generally overestimate the decline rate of energy intensity. Furthermore, data accuracy has significantly improved after the central government included the energy intensity reduction target in the performance appraisal for local governments. The higher assessment requirements faced by local governments will lead to the improvement of data accuracy. The reason for the above phenomenon is that the pressure of energy saving has inhibited the development of the industrial sector. As the output data of the industrial sector contain a large amount of moisture, energy-saving target assessment weakens the ability of local governments to manipulate GDP data and improves the accuracy of energy intensity indicators.

The above conclusions have some practical policy implications on how to effectively reduce energy consumption and promote green development in China.

First, although the simplified single policy objective is easy to observe, it is vulnerable to be impacted by external interference in practice, resulting in insufficient accuracy. This study finds that the accuracy of energy-saving data is improved when facing the task of economic growth and energy-saving target assessment at the same time. Therefore, in future policy design for energy conservation and emission reduction, we should try to include cross multiple assessment indicators, so as to promote the effective implementation of policy objectives. Moreover, setting a concrete target-based responsibility system for energy saving or environmental policies may have positive effects. In the information age, how to use big data technology and machine learning methods to supervise the behavior of local officials and improve the performance of energy saving is also needed to be further discussed.

Second, it is found that the introduction of energy-saving index into local government performance assessment significantly improves the data accuracy. Though the fulfillment degree of policy objectives is reduced on the surface, it still contains positive factors such as the reduction of data fraud. Therefore, in the performance evaluation of energy saving, some appropriate flexibility is needed and the tolerance can be given if the energy saving does not perform as well as expected. This will provide reasonable incentives for local governments to take the initiative to reduce data distortions and thus to increase their real efforts to achieve energy conservation, emission reduction, and green development goals.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, and further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

PZ, SL, and RH conceptualized the idea and wrote the original draft. PZ, TY, SL, and RH performed the methodology. TY ran the software and curated the data. SL and RH supervised the work and reviewed and edited the paper. All authors have read and agreed to the published version of the article.

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