Accepted manuscript
doi: 10.1680/jensu.20.00013

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Accepted manuscript
doi: 10.1680/jensu.20.00013

Submitted: 25 March 2020

Published online in 'accepted manuscript' format: 30 July 2020

Manuscript title: Environmental Regulation and Green Productivity of the Construction Industry in China

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Accepted manuscript
doi: 10.1680/jensu.20.00013

Abstract

There are few studies analyzing whether different types of environmental regulation have differential impacts on the efficiency of the construction industry. Using 2012-2016 panel data from 30 provinces in China, the green total factor productivity (GTFP) of the construction industry is measured with a global Malmquist Luenberger productivity index based on the epsilon measure (EBM-GML) model. Thereafter, a panel Tobit regression model is proposed to explore the relationship between three types of environmental regulation and the GTFP of the construction industry. The results show that: (1) from 2012 to 2016, the GTFP of the Chinese construction industry grew slowly at an average annual rate of 0.14%; (2) both one-phase lagged command-and-control and current phase market-based environmental regulation had a positive linear relationship with GTFP. One-phase lagged voluntary environmental regulation on the other hand, had an inverted U-shaped relationship with GTFP; (3) the three types of environmental regulation can be combined to establish a suitable environmental regulation system. The findings of this study provide guidance for the sustainable development of the construction industry by combining the actions of different types of environmental regulation.

Notation

γ^*	optimal efficiency value
θ	radial efficiency value
ε_x	integrated parameter
w_i	weight
s_i	slack variable
λ	relative importance
X	input vector
x_i	input indicator
Y	output vector
y_i	output indicator
D_0^s	directional distance function
b^t	undesirable output
α	constant term
β	constant term
$\varepsilon_{i,t}$	disturbance term

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1. Introduction

Economic globalization has not only promoted the development of the world economy but has also caused environmental problems in many countries. Indeed, from the perspective of long-term development, economic growth at the cost of environmental pollution is unsustainable (Beck et al., 2011, Millimet and Roy, 2016). The coordination and integration of industrial economic development and environmental protection through environmental regulation has attracted the attention of governments across the world (Gouldson et al., 2009). Environmental regulation (ER) provides an important means for reducing the impact of economic activities on the ecological environment. Governments can use different types of ER to guide enterprises in order to make technological innovations for improving energy efficiency, reducing pollution emissions, increasing green total factor productivity (GTFP), and ultimately realizing sustainable development (Liu et al., 2018). In this context, GTFP is defined as the ratio of the total output of a production system to the actual input of all production factors when considering undesirable output and energy consumption (Wang et al., 2018, Chen et al., 2018).

However, most studies focus on ER's influence on the economy and industry efficiency (Zhang et al., 2018, Zhang et al., 2012). Very few consider the effect of different types of ER on construction industry performance (Xie et al., 2017, Shen et al., 2019). Additionally, while previous studies point out that different ER have different impacts on efficiency (Liu et al., 2018, Ren et al., 2018, Shen et al., 2019), just one has considered the effects on construction industry performance. This study, though, focused only on certain EU regions only (Testa et al., 2011).

Furthermore, since GTFP represents the contribution to industrial growth, its change over time can directly reflect construction industry performance. Different types of ER have either a

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positive (i.e. innovation compensation) or negative (i.e. crowding-out effect) impact on GTFP (Chen et al., 2018). Thus, it is important to explore whether there is a relationship and time lag effect between the implementation of different types of ER and the GTFP.

This study analyzes these two factors in the context of the Chinese construction industry. First, as the world's largest developing country and the second largest economy, China has severe environmental problems from continued economic growth. According to the 2018 BP Statistical Review of World Energy, China is still the world's largest energy consumer and carbon emitter. However, the rapid development of its construction industry has not only consumed vast resources and energy, but has also caused considerable damage to the environment. This has created multiple air, water, solid waste and noise pollution problems (Zhang et al., 2016, Li et al., 2019, Zhang et al., 2019).

Second, to address these issues, the Chinese government has applied different types of ER to regulate the development of the construction industry and promote GTFP. Namely, it has made full use of three types of ER: (a) command-and-control environmental regulation (CER), which requires industry to adopt green technologies to avoid environmental administrative penalties issued by governmental authorities; (b) market-based environmental regulation (MER), which exerts economic pressure to make industry improve its production efficiency and reduce pollutant emissions for cost reasons – pollution charging taxes and environmental protection taxes are some MER examples; and (c) voluntary environmental regulation (VER), which relies on the environmental awareness of citizens to supervise and influence the way industry operates, e.g. from environmental letters and visits (Feng and Chen, 2018, Li and Ramanathan, 2018, Ren et al., 2018). The government requires the construction industry to adopt building materials with low carbon emissions, advanced energy saving, and emission-reduction technologies. These aim to reduce energy consumption and environmental

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pollution in the manufacturing process and promote GTFP (China, 2017).

Hence, this study aims to explore the relationship between different types of ER and GTFP in the Chinese construction industry. Panel data from 30 provinces from 2012 to 2016 are used, with the global Malmquist Luenberger productivity index based on the epsilon measure (EBM-GML) model. This model also considers undesirable outputs when estimating the GTFP. Finally, a Tobit regression model is used to analyze the relationship, impacts and possible time lags between different types of ER and the GTFP.

2. Literature review and hypotheses development

2.1 Environmental regulation and the construction industry

According to externality theory, the pollution discharges of a construction enterprise will bring losses to surrounding enterprises or consumers, and have a negative effect on society and the environment. These are negative externalities and, in environmental economics, ER is the main way to curb those caused by pollution (Arrow, 1969).

However, ER can make the production process easier or more difficult. Sometimes, due to lower energy utilization rates, more environmental pollutants are produced by construction enterprises. When ER is strengthened, construction enterprises are forced to invest more capital in pollution control, thereby crowding out the enterprises' investment in other aspects (Jaffe et al., 1995, Jaffe et al., 2002). Conversely, an appropriate ER can steer technological innovation, help enterprises adopt new methods to improve energy usage, and reduce waste emissions (Porter and van der Linde, 1995, Alpay et al., 2002).

Although previous studies (e.g. Zhang et al. (2012), Zhong et al. (2017), Zhang et al. (2018)) have considered ER as a sole indicator when exploring its impact on the construction industry, there are different types of ER, and each can have different effects. Hence, simply selecting one indicator may not be fully representative. It is necessary to devise an indicator

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system that discriminates according to the type of ER to fully capture the intensity of the regulation and potential impact on GTFP.

Additionally, previous studies have only measured the efficiency (also termed total factor productivity, TFP) of the construction industry. They did not consider the sustainable development dimension of productivity, i.e., they do not measure GTFP. In response, this study considers the different impacts of the three types of ER; takes energy consumption as an input factor and CO_2 emissions as undesirable output; and uses other auxiliary indices to calculate GTFP.

2.2 Environmental regulation and green total factor productivity

The growth rate of TFP and its contribution to output growth is regarded as the main basis for assessing economic development and improvement in economic quality (Lin and Su, 2007). However, TFP does not consider environmental pollution or the loss of resources caused by economic growth. This can bias economic efficiency evaluations and produce misleading policies (Hailu and Veeman, 2000). An improvement proposed by Chung et al. (1997) when measuring the TFP of the Swedish pulp mill, is to use a directional distance function that can treat pollution emissions as undesirable output. With the maturity of technology efficiency, other factors such as pollution emissions, resources, and energy consumption have started to be included in the total factor productivity analysis framework, now called GTFP.

ER is a conventional tool to address the environmental issues arising from economic growth (Wang et al., 2016). The relationship between ER and GTFP is discussed in many studies (e.g. Li and Wu (2017), Wang et al. (2018), Chen et al. (2018)) , but there is still common agreement on how both variables are related − another reason why we need to drill down different types of ER to find clearer answers.

2.2.1 Command-and-control environmental regulation

Faced with increasing emissions of environmental pollutants, many governments formulate emission standards and production technology standards to reduce or eliminate such emissions. This series of policies is often referred to as command-and-control environmental regulation (CER) (Blackman, 2010). When pollutant emissions exceed these standards limits, enterprises face heavy fines or such administrative penalties as forced closure (Yang et al., 2012).

Therefore, some environmental emission standards can prompt industry to find its own low production efficiency. This may lead industry to continuously improve its production processes to reduce pollution, and ultimately improve GTFP, suggesting the hypotheses

H1a: CER has a positive linear relationship with construction industry GTFP.

H1b: CER has a nonlinear relationship with construction industry GTFP.

2.2.2 Market-based environmental regulation

Market-based environmental regulation (MER) tools for control pollution are currently widely accepted by countries worldwide. Similar to CER, MER also have corresponding emission standards, but they are more dependent on other economic tools (Camison, 2010). Under the control of MER, the production options of industry are more flexible, as appropriate investment methods can be chosen to reduce the negative effects of production on the environment (Jacobs et al., 2010).

In summary, MER creates more economic pressure on enterprises by encouraging the transformation of industrial production to a greener one. Thus, two further hypotheses are

H2a: MER has a positive linear relationship with construction industry GTFP.

H2b: MER has a nonlinear relationship with construction industry GTFP.

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2.2.3 Voluntary environmental regulation

Unlike the two types of ER tools mentioned above, voluntary environmental regulation (VER) relies on the environmental awareness and capabilities of citizens to influence the way industry produces (Borck and Coglianese, 2009). When the citizens' environmental awareness is enhanced, they are more inclined to a greener and environmentally friendly lifestyle. Due to changes in market preferences, consumer lifestyles, and the awareness of environmental protection, the industry should move (directly or indirectly) towards greener production methods increasing its GTFP (Vitiea and Lim, 2019).

This provides the final two hypotheses of

H3a: VER has a positive linear relationship with construction industry GTFP.

H3b: VER has a nonlinear relationship with construction industry GTFP.

3. Data and methodology

3.1 Data source

The data for this study covers 30 provinces in China from 2011 to 2016 (with 2011 as the base period). Due to the data from the provinces of Hong Kong, Macau, Taiwan, and Tibet not being available, they were not included in the analysis. Data were mainly drawn from the China's Statistical Yearbook (China, 2012-2017c), China's Statistical Yearbook on Construction (China, 2012-2017d), China's Energy Statistical Yearbook (China, 2012-2017a), China's Environment Yearbook (China, 2012-2017b), China's Statistical Yearbook on Environment (China, 2012-2017e), and relevant annual data concerning Chinese provinces from the website http://data.stats.gov.cn/.

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3.2 Construction industry green total factor productivity

3.2.1 Selection of indicators

The input and output indicators of GTFP are selected from a literature review as follows (references and measurement units from all indicators are summarized later in Table 1):

Input indicators: (1) Labor force: the number of employees is usually selected as the labor force indicator in the construction industry. (2) Capital: denoted here by the total assets of construction enterprises in each region. This indicator is used because of the construction industry’s complex capital structure and the inability to obtain the depreciation rate of the fixed assets in each province. (3) Machinery and equipment: total annual power of machinery and equipment owned by construction enterprises in each region. (4) Energy: under the constraint of limited resources, total energy consumption is a frequent measure of energy input. The terminal energy consumption of the industry is selected here to represent energy input.

Output indicators: (1) Desirable output: Considering the products of the construction industry are mostly buildings, structures, and facilities, it is difficult to summarize their actual volume. Therefore, commonly used output indicators are used, such as gross output value, total profit, gross added value, and area of completed construction. From the perspective of output and profit capacity, the gross output value and total profit of the construction industry are assumed desirable output indicators. (2) Undesirable output: As an unpaid environmental cost, CO_2 is the world's most well-known environmental pollutant, and the CO_2 emissions of the construction industry are therefore used as the undesirable output indicator (Zhang et al., 2018). This indicator is estimated using the United Nations Intergovernmental Panel on Climate Change’s (IPCC) formula (Yin et al., 2015) according to which, the conversion coefficient into CO_2 emissions from the consumption of various common energies is easily estimated.

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3.2.2 Calculation model

A global Malmquist Luenberger (GML) productivity index based on the epsilon measure (EBM) model (EBM-GML) is used to estimate GTFP. Tone and Tsutsui (2010) propose the epsilon-based measure (EBM) model, which integrated the advantages of radial and non-radial models and provides a more accurate measure of decision making unit (DMU) efficiency (Qin et al., 2017, Yang et al., 2018). Oh (2010) constructs the Global Malmquist-Luenberger (GML) productivity index, which overcomes the defects caused by using the geometric average and ensures that linear programming can provide feasible solutions. Thus, the directional distance function is defined based on an EBM model, and the GTFP of the construction industry is calculated by the GML productivity index based on the EBM model.

According to Tone and Tsutsui (2010), it is assumed that there are n decision making units with p inputs and q outputs. The EBM model results in:

$$\gamma^* = \min \theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i s_i}{x_{i0}} \tag{1}$$

$$s.t.\ \theta x_0 - X\lambda - s = 0$$

$$\lambda Y \geq y_0$$

$$\lambda \geq 0,\ s \geq 0$$

where γ^* represents the optimal efficiency value satisfying $0 \leq \gamma^* \leq 1$; θ denotes the radial efficiency value; w_i is the weight of each input indicator satisfying $\sum_{i=1}^{p} w_i = 1 (w_i \geq 0, \forall i)$, $i = 1, \cdots, p$; s_i is a slack variable corresponding to the i-th input indicator; ε_x is the integrated parameter of the radial efficiency value and the non-radial slack variable; and λ represents the relative importance of the reference decision making unit. $X = \{x_{ik}\} \in R^{p\times n}$ is the input vector, $i = 1, \cdots, p$; $Y = \{y_{ik}\} \in R^{q\times n}$ is the output vector, $j = 1, \cdots, q$, with $X > 0, Y > 0$ always.

After building the directional distance function based on the EBM model and according to the GML productivity index constructed by Oh (2010), the simultaneous production technology aims to provide a reference technology set in period *t* for each observed DMU. These can be defined as $P^t(x^t) = \{(y^t, b^t) \mid x^t \text{ can produce } (y^t, b^t)\}$, $t = 1, \cdots, T$, where b^t represents the undesirable output of the DMU in period *t*. The union of all the simultaneous production technology sets constitutes the global production technology set $P^G(x) = P^1(x^1) \cup P^2(x^2) \cup \cdots \cup P^T(x^T)$. Combining the global production possible sets in t and $t+1$ periods, the GML productivity index is:

$$GML_t^{t+1} = \frac{1+D_0^G(x^t, y^t, b^t; y^t, -b^t)}{1+D_0^G(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \tag{2}$$

where the directional distance function is $D_0^s(x^s, y^s, b^s; y^s, b^s)$ $= \max\{\beta : (y^s + \beta y^s, b^s - \beta b^s) \in P^G(xs)\}, s = t, t+1$.

According to Chung et al. (1997), the GML index can be divided into two parts to analyze the causes of productivity changes, namely the efficiency change index (GECH) and the technological progress index (GTCH). A GML index bigger/lower than unity means that productivity has increased/decreased, while GECH and GTCH bigger/lower than unity means efficiency is higher/lower and technology has improved/regressed respectively. Since the GML index is not the GTFP itself but represents its growth rate, assuming that GTFP productivity in period t is unity, the GTFP in period $t+1$ corresponds to the GTFP in t period multiplied by the GML productivity index in period t period, i.e.,

$$GTFP_{t+1} = GTFP_t \times GML_t^{t+1} = GTFP_t \times GECH_t^{t+1} \times GTCH_t^{t+1} \tag{3}$$

3.3 Environmental regulation

3.3.1 Selection of variables

The variables are selected from the ER tools that have regulatory effects on the production behaviors of the construction industry that cause environmental pollution. Then, we select:

- The number of environmental administrative penalty cases for CER.
- The pollution discharge fees levied for MER in China.
- The total number of environmental letters and visits for VER in each region.

Also, the following control variables are used: (1) economic development level as measured by regional Gross Domestic Product (GDP); (2) ownership structure (OSS) as the proportion of state-owned assets of the total assets of regional construction enterprises; and (3) industrial development degree (IDD), as the proportion of construction industry gross output in regional GDP.

3.3.2 Regression model

A panel Tobit regression model is used to explore the relationship between different types of ER and GTFP in the Chinese construction industry. The productivity values calculated by the EBM-GML method always have non-negative values, which require some restricted variables. For the estimation of these variables, ordinary least squares (OLS) methods are not suitable as they are likely to produce biased estimation results (Otero et al., 2012). Therefore, a Tobit model (Tobin, 1958) is used instead. As the data of 30 provinces in China from 2012 to 2016 are used for empirical analysis, the sample data is short in time span but contains many cross section units. Therefore, a random effects panel Tobit model is used to explore the relationship between three types of ER and the GTFP. Model 1 is defined as:

$$GTFP_{i,t} = \alpha_0 + \alpha_1 GTFP_{i,t-1} + \sum_{j=1}^{3} \beta_j ER_{j,i,t} + \beta_4 GDP_{i,t} + \beta_5 OSS_{i,t} + \beta_6 IDP_{i,t} + \varepsilon_{i,t} \qquad Model\ 1$$

where i represents the provinces and t is the year. GTFP's specific value is calculated by EBM-GML with a one-phase lag (1 year). ER_j denotes CER, MER, and VER, j=1,2,3. GDP, OSS, and IDP represent the level of economic development, ownership structure, and industrial development degree respectively. α_0 is the constant term and $\varepsilon_{i,t}$ is the disturbance term.

In order to examine the nonlinear relationships between the three types of ER and GTFP, a quadratic ER term is introduced into Model 1 to produce Model 2 as:

$$GTFP_{i,t} = \alpha_0 + \alpha_1 GTFP_{i,t-1} + \sum_{j=1}^{3} \beta_j ER_{j,i,t} + \sum_{j=1}^{3} \beta_{j+3} ER_{j,i,t}^2 + \beta_7 GDP_{i,t} + \beta_8 OSS_{i,t} + \beta_9 IDP_{i,t} + \varepsilon_{i,t}$$

$Model\ 2$

Both models represent the effects of ER on GTFP over the period of analysis. However, considering that the effect of ER on the construction industry GTFP will take some time to materialize, there will be an inevitable time lag. Consequently, further linear and nonlinear models (Models 3 and 4) are established with one-phase lags in their independent variables. Their control variables are also lagged one phase (year) to avoid a two-way causal relationship with productivity (Rubashkina et al., 2015, Xie et al., 2017).

The selected input and output indicators/variables are summarized in Table 1. The original data are rendered dimensionless by standardization to eliminate dimensional influence.

4. Results

4.1 GTFP of the construction industry

Each input and output indicator are positively correlated at the 1% significance level when subjected to the Pearson correlation test, thereby satisfying the monotonic hypothesis, i.e., when input increases, the output cannot decrease.

Assuming that construction industry GTFP was 1 in 2011; its values from 2012 to 2016 are calculated with the EBM-GML model. The average values of provincial GTFP, GML, and its composition for the construction industry in 2012-2016 are shown in Table 2, with the dynamic changes (trend) shown in Figure 1.

Overall, the average GTFP of the national construction industry in 2012-2016 was greater than one, indicating that, considering environmental factors, productivity was rising. However, the growth rate of GTFP in 2012-2016 was relatively low (average annual rate of 0.14%). Two-thirds of the provinces' construction industry GTFP was increasing. Among these, Sichuan had the highest annual average GTFP and GML index (its GTFP was 1.2412, with an average annual growth rate of 5.26%). However, one-third of the provinces showed a GTFP downward trend, indicating that the industry was in need of extensive development. For example, Inner Mongolia had an average annual GTFP of only 0.6859, the lowest in the whole country, with an average annual reduction of 7.95%. The national efficiency change index was 1.0004, with an increase of 0.04%, and the technological progress index 1.0020 with an increase of 0.2%. This indicates that the improvement in GTFP was mainly due to technological advancement.

The dynamic changes of national GTFP, GML, and composition of the construction industry in 2012-2016 are shown in Figure 2. From the national perspective, the average GTFP was strongly volatile in 2012-2016, with a slight overall increase. The efficiency change and technological progress index were also volatile. The efficiency of the construction industry increased at first and then decreased. Except for 2012 and 2013, the efficiency changes were all below one, which hindered the construction industry's economic growth. Except for 2012 and 2015, the technological progress indices were all increasing.

The dynamic changes in national and regional construction industry GTFP in 2012-2016 are illustrated in Figure 3. This shows that the changes in construction GTFP across the country and in every region were very similar. The Eastern region had the highest GTFP in 2012-2013, but the Western region surpassed the Eastern region since 2014. The Central region GTFP was lower than the national average. Its weak economic foundation resulted in the GTFP in the Central region to rapidly decline under macroeconomic pressure in 2015, exposing a contradictory relationship between the industry's economic growth and ecological environment.

4.2 Regression results

The values of the Pearson correlation coefficients and the variance inflation factors (VIF) indicate a low correlation and multicollinearity between the independent variables, respectively.

We took the 2012-2016 construction industry GTFP in each province as the dependent variable, the three different ER types as independent variables, and GDP, OSS, and IDP as control variables. The random effects panel Tobit model was then used to estimate the relationships between the ERs and GTFP, to analyze their linear and nonlinear relationships and the one-phase lags. The results are shown in Table 3. The Wald $\chi 2$ test, the LR test, and the *r*-values all indicate the suitability of the random effects panel Tobit model. The coefficient of the GTFP lagged one phase is positive and significant at the 99% confidence level. This indicates that GTFP growth had a self-cumulating effect, i.e. an increase in the GTFP in a previous year promoted the GTFP growth in the following year.

For CER, only the one-phase lagged with a linear relationship with GTFP is significantly positive (at the 95% confidence level). Hence, H1a is supported when CER is lagged one phase but H1b is rejected. For MER, only the current phase linear relationship with GTFP is significantly positive (at the 90% confidence level), meaning H2a is supported while H2b is rejected. For VER, only the one-phase lagged quadratic term is significant and negative (at the 90% confidence level). Hence, H3a is rejected, but H3b is supported when VER is lagged one phase.

On the other hand, by comparing the effects of combined and separate ER, CER lagged one phase still has a significant positive linear relationship with construction industry GTFP (at the 90% confidence level). MER in the current phase still has a significant positive linear relationship with construction industry GTFP (at the 90% confidence level). As for VER, the linear and nonlinear relationships are insignificant in current or lagged one phase. Finally, by comparing the regression results of the three types of ER combined with the separate ER, it is found that when the ER work together, the regression coefficient of the CER lagged one phase increases from 0.1145 to 0.1239, and the confidence level increases from 90% to 95%. In addition, the regression coefficient of MER in the current phase increases from 0.1152 to 0.1183.

4.3 Robustness check

In order to validate the models, a robustness test on the estimation results was conducted using a replacement regression model. The panel GEE model was used to replace the panel Tobit model for regression analysis, and the clustering robust standard deviation was also used to estimate the standard deviation. After the panel GEE regression, the coefficients of core variable and significance remained essentially unchanged, meaning the model results above were robust.

5. Conclusions

This study uses 2012-2016 panel data from 30 Chinese provinces to determine the national and regional GTFP of the construction industry. It also analyzes the relationship between three types of ER and their lag effect on the GTFP. The main findings are as follows.

(1) From 0.999 in 2012 to 1.002 in 2016, the national average construction industry GTFP had a slow upward trend, with an average annual growth rate of only 0.14%. One-third of the provinces had a downward trend, indicating that the construction industry in some provinces were still undergoing extensive development. In particular, Inner Mongolia and other provinces with low GTFP need to strengthen the coordination between construction industry development and environmental protection. The improvement in GTFP was mainly due to technological advancement. In the future, the construction industry needs to improve both its technological efficiency and progress, transform its economic growth mode, rationally adjust and upgrade its industrial structure, fully optimize resource allocation, and reach a balanced sustainable development.

(2) There are differences in the impact of different types of ER on GTFP. CER has a positive linear relationship with GTFP but, despite a significant one-year lag effect, the impact of long-term regulation is even more significant. MER and GTFP have a more immediate positive linear relationship. This is the consequence of a faster adjustment due to the openness and dynamics of the market. VER lagged one year and GTFP have an inverted U-shaped relationship, since the public's response to the government or the market requires some time.

(3) The government should combine the three types of ER. Namely, they should implement CER from the perspective of long-term supervision, implement MER from the perspective of short-term supervision, and guide the public to watch corporate environmental behavior in the construction industry (i.e. VER).

The study's main contribution is to outline the practical implications of implementing different types of ER when promoting sustainable development in the construction industry. The study considers undesirable output and energy consumption in the productivity measurement framework for modeling GTFP. Moreover, the separate and combined effects of three types of ER on the GTFP of China's construction industry is examined for the first time. This will be conducive for the government to develop a combination of ER policies that support sustainable development in the construction sector.

This study is limited by the constraints of data accessibility, so that the indicators selected to measure different types of environmental regulation may not be fully representative. It is also limited to China and other similarly placed countries. Therefore, further research may involve collecting and comparing data from other indices and different countries to compare the impact of different types of ER more generally.

Acknowledgements

This research is supported by the National Social Science Fund post-financing projects (No.19FJYB017); Humanity and Social Science Program Foundation of the Ministry of Education of China (No.17YJA790091); List of Key Science and Technology Projects in China's Transportation Industry in 2018-International Science and Technology Cooperation Project (No.2018-GH-006 and No.2019-MS5-100). The sixth author acknowledges the Spanish Ministries of Science, Innovation and Universities for his Ramon y Cajal contract (RYC-2017-22222) co-funded by the European Social Fund.

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Accepted manuscript
doi: 10.1680/jensu.20.00013

Table 1. Summary of input and output indicators of all variables

Category		Indicator/ Variable name	Indicator/Variable description	Unit	Source
Dependent variable (GTFP)	Input indicator	Labor force	Number of employees	CNY 10000	Hu and Liu (2015), Wang et al. (2013), Xu et al. (2016), Gao and Wang (2013), Chen et al. (2016), Nazarko and Chodakowska (2015), Chau et al. (2005), Li and Liu (2010), Zhong et al. (2010)
		Capital	Total assets of construction enterprises	CNY 10000	Wang et al. (2013), Wei and Niu (2013), Xu et al. (2016), Gao and Wang (2013), Zhong et al. (2010)
		Machinery and equipment	Total power of machinery and equipment owned	10000 kw	Wang et al. (2013), Wei and Niu (2013), Xu et al. (2016), Gao and Wang (2013), Chen et al. (2016)
		Energy	Energy consumption of construction	10000 tons	Hu and Liu (2015), Chen et al. (2016)
	Output indicator	Desirable output indicator	Gross output value of construction industry	CNY 10000	Wang et al. (2013), Wei and Niu (2013), Xu et al. (2016), Gao and Wang (2013), Chen et al. (2016)
			Total profits of the construction industry	CNY 10000	Liu et al. (2016), Xu et al. (2016), Chen et al. (2016), Nazarko and Chodakowska (2015)
		Undesirable output indicator	CO_2 emissions	ton	Zhang et al. (2018)
Independent variable		CER	Number of environmental administrative penalty cases	Piece	Li and Ramanathan (2018), Liu et al. (2018)

	MER	Pollution discharge fee	CNY 10 thousand	Feng and Chen (2018), Li and Ramanathan (2018), Ren et al. (2018)
	VER	Total number of environmental letters and visits	Piece	Li and Ramanathan (2018), Feng and Chen (2018)
Control variables	GDP	Regional GDP	CNY 100 million	Li and Ramanathan (2018)
	OSS	Proportion of state-owned assets in total assets of regional construction enterprises	%	Feng and Chen (2018), Chen et al. (2018)
	IDP	Proportion of the gross output value of the regional construction industry in regional GDP	%	Ren et al. (2018), Li and Ramanathan (2018)

Table 2. Average 2012-2016 values of provincial GTFP, GML and their composition

Province	GML	GECH	GTCH	GTFP	Up (U)/Down (D) Trend
Beijing	1.0076	1.0000	1.0076	1.0381	U
Tianjin	0.9839	1.0009	0.9818	0.9398	D
Hebei	1.0040	1.0105	0.9940	1.0629	U
Shanxi	1.0004	1.0122	0.9878	1.0349	U
Inner Mongolia	0.9205	0.9323	0.9858	0.6859	D
Liaoning	0.9037	0.9133	0.9869	0.8524	D
Jilin	0.9706	0.9697	0.9938	0.8490	D
Heilongjiang	0.9782	0.9845	0.9887	0.9714	D
Shanghai	1.0291	1.0152	1.0148	1.0882	U
Jiangsu	1.0227	1.0000	1.0227	1.1071	U
Zhejiang	1.0097	1.0000	1.0097	1.0393	U
Anhui	1.0247	1.0273	1.0011	1.0732	U
Fujian	1.0091	1.0239	0.9882	1.0301	U
Jiangxi	1.0211	1.0000	1.0211	1.1023	U
Shandong	1.0209	1.0172	1.0153	1.1195	U
Henan	1.0275	1.0296	0.9998	1.0724	U
Hubei	1.0489	1.0494	1.0072	1.1825	U
Hunan	0.9724	0.9771	0.9941	0.9036	D
Guangdong	1.0166	0.9739	1.0533	1.0784	U
Guangxi	1.0436	1.0000	1.0436	1.1931	U
Hainan	0.9588	0.9836	0.9772	0.8702	D
Chongqing	1.0315	1.0000	1.0315	1.0827	U
Sichuan	1.0526	1.0219	1.0308	1.2412	U
Guizhou	1.0077	1.0109	0.9967	1.0991	U

Yunnan	1.0183	1.0223	0.9989	1.0967	U
Shaanxi	0.9804	0.9898	0.9931	0.9007	D
Gansu	1.0138	1.0275	0.9892	1.0542	U
Qinghai	0.9720	0.9939	0.9793	0.8943	D
Ningxia	0.9845	1.0078	0.9749	0.9709	D
Xinjiang	1.0079	1.0166	0.9916	1.0828	U
Eastern average	1.0008	0.9949	1.0079	1.0349	U
Central average	0.9960	0.9980	0.9977	0.9861	D
Western average	1.0076	1.0101	0.9984	1.0470	U
Total average	1.0014	1.0004	1.0020	1.0239	U

Table 3. Regression results of three types of ERs combination

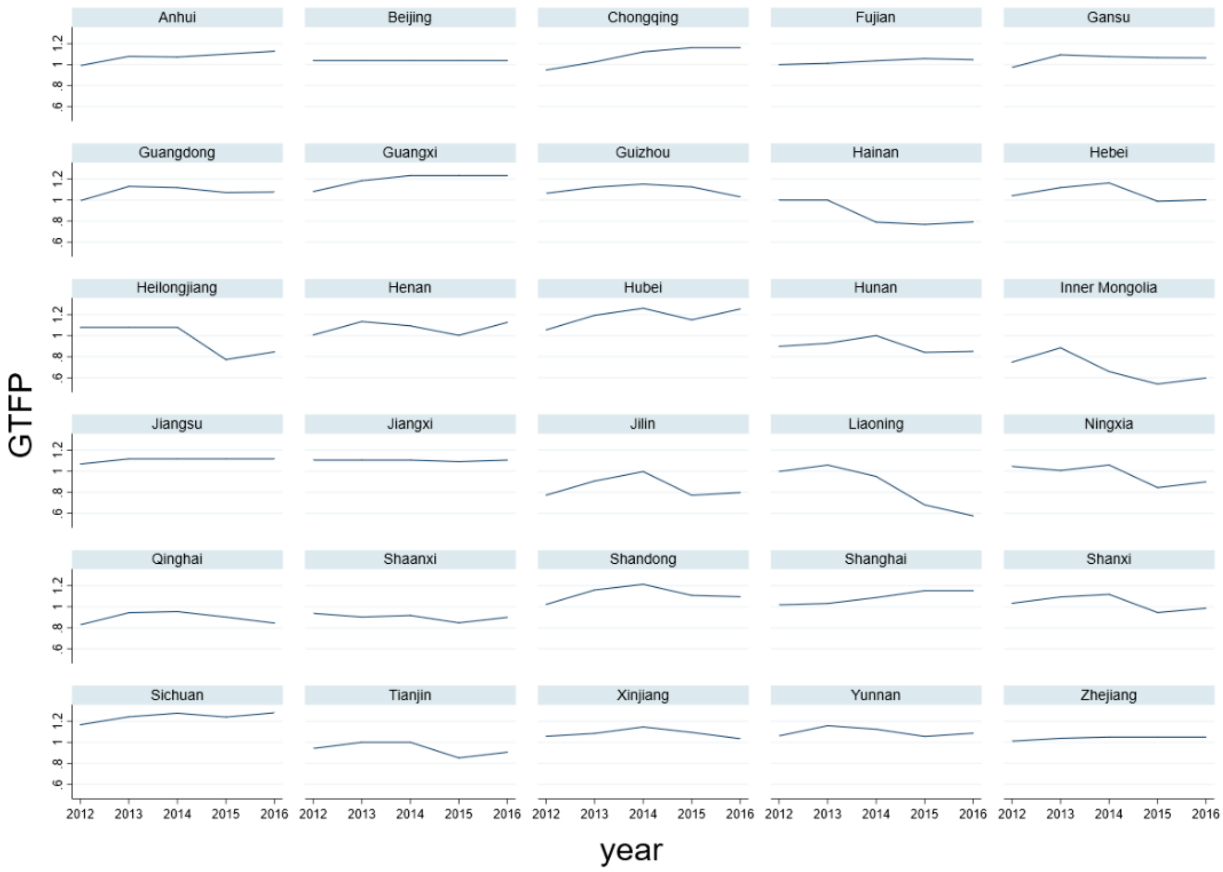
Variable	no lag		one-year lag	
	Model 1	Model 2	Model 3	Model 4
$GTFP_{t-1}$	0.4853***	0.4907***	0.4760***	0.4584***
	(4.94)	(4.86)	(5.2)	(5.05)
CER	0.0587	-0.2059	0.1239**	0.1970
	(1.12)	(-0.79)	(2.11)	(0.86)
CER^2		0.2811		-0.0797
		(1.04)		(-0.33)
MER	0.1183*	0.2472	0.1063	0.1108
	(1.7)	(1.07)	(1.53)	(0.5)
MER^2		-0.1292		-0.0090
		(-0.55)		(-0.04)
VER	0.0155	-0.1117	-0.0114	0.1874
	(0.25)	(-0.74)	(-0.23)	(1.43)
VER^2		0.1604		-0.2560*
		(0.86)		(-1.67)
GDP	0.0252	0.0571	0.0601	0.0277
	(0.35)	(0.55)	(0.92)	(0.33)
OSS	0.1544**	0.1583**	0.2312***	0.2301***
	(2.36)	(2.43)	(3.65)	(3.60)
IDP	0.2600***	0.2925***	0.1429**	0.1265***
	(3.24)	(3.45)	(2.00)	(1.68)
C	0.3632***	0.3544***	0.3818***	0.3877***
	(4.03)	(3.91)	(4.38)	(4.54)
Su	0.0584***	0.0570***	0.0620***	0.0640***
	(4.01)	(3.50)	(4.71)	(4.59)

Se	0.0680***	0.0678***	0.0678***	0.0666***
	(13.62)	(12.9)	(14.31)	(14.08)
r	0.4248	0.4146	0.4555	0.4798
LR test	8.13***	6.04***	9.99***	10.09***
Wald χ^2	104.57***	107.84***	92.95***	97.32***
Log likelihood	167.2559	168.1943	166.2314	167.6217

Note: Number within parentheses represent the z-value. *, **, and *** represent statistically significant at 10%, 5%, and 1% levels, respectively.

Accepted manuscript
doi: 10.1680/jensu.20.00013

Figure 1. Dynamic changes of provincial GTFP of construction industry in 2012-2016



doi: 10.1680/jensu.20.00013

Figure 2. Dynamic changes of national GTFP, GML and its composition of construction industry in 2012-2016

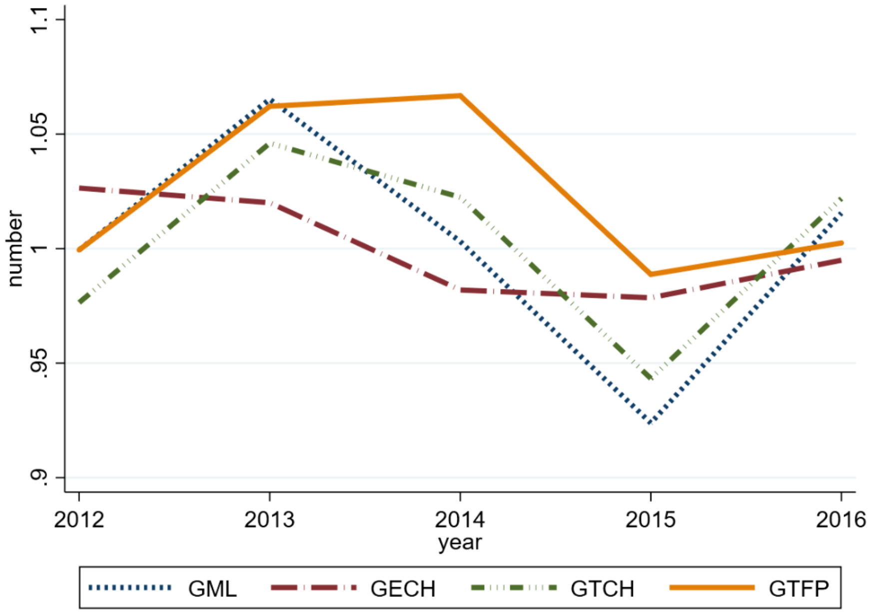


Figure 3. Dynamic changes of national and regional GTFP of construction industry in 2012-2016