Queensland University of Technology
Brisbane Australia

This may be the author's version of a work that was submitted/accepted for publication in the following source:

Zhang, Jingxiao, Cai, Wenyi, Li, Hui, Olanipekun, Ayokunle Olubunmi, & Skitmore, Martin
(2020)
Measuring the capacity utilization of China's regional construction industries considering undesirable output.
Journal of Cleaner Production, *252*, Article number: 119549 1-16.

This file was downloaded from: https://eprints.qut.edu.au/136146/

© Elsevier Ltd

This work is covered by copyright. Unless the document is being made available under a Creative Commons Licence, you must assume that re-use is limited to personal use and that permission from the copyright owner must be obtained for all other uses. If the document is available under a Creative Commons License (or other specified license) then refer to the Licence for details of permitted re-use. It is a condition of access that users recognise and abide by the legal requirements associated with these rights. If you believe that this work infringes copyright please provide details by email to qut.copyright@qut.edu.au

License: Creative Commons: Attribution-Noncommercial-No Derivative Works 2.5

Notice: *Please note that this document may not be the Version of Record (i.e. published version) of the work. Author manuscript versions (as Submitted for peer review or as Accepted for publication after peer review) can be identified by an absence of publisher branding and/or typeset appearance. If there is any doubt, please refer to the published source.*

https://doi.org/10.1016/j.jclepro.2019.119549

Measuring the capacity utilization of China’s regional construction industries considering undesirable output

Abstract

As most industries in developing countries still follow a relatively rough development model, relying on expansionary investment and paying high environmental costs to promote economic growth, they also face the predicament of excess capacity. Conducting capacity utilization (CU) measurement research is the core of dealing with excess capacity. However, most existing research into capacity utilization is concentrated in the manufacturing, coal, and other industries. The quantitative evaluation of the construction industry capacity utilization is very rare, and the environmental impact factors are neglected.

This study aims to develop a capacity utilization measurement index system and use it for the measurement of the construction industry capacity utilization. In doing this, based on the undesirable output perspective, it establishes a capacity utilization measurement index system that considers energy consumption and undesirable output (CO2) for the measurement of construction industry capacity utilization. Two data envelopment analysis-based (DEA-based) difference methods (the “no variable-link difference” and the “adding variable-link difference” methods) are used to measure China’s construction industry capacity utilization between 2011 and 2017.

The findings indicate that using the adding variable-link difference method is more accurate than the no variable-link difference method. It is also shown that the underutilization of capacity in China’s construction industry in 2011–2014 is more serious, but it has improved in the past three years. In addition, with the exception of the Jiangsu and Guangxi provinces, there is underutilization of capacity in the construction industry in other provinces and cities in China.

This study extends the existing knowledge system of capacity utilization, including the evaluation system, measurement, and assessment of capacity utilization, and management implications. Based on the perspective of undesirable outputs, this study lays a foundation for research into the capacity utilization in various industries by considering environmental factors. This study has practical significance for China and other developing countries to establish a nationwide capacity monitoring system.

Keywords：

Construction industry; capacity utilization; difference method; undesirable output

1. Introduction

Currently, the global economy is at a critical stage of development, change, and adjustment. While promoting economic and technological progress and the development of social productive forces, economic globalization is also facing opportunities and challenges. Especially in recent years, the world economy has been in a state of continuous downturn, and the problem of insufficient kinetic energy for world economic growth has been highlighted (Song et al., 2011). Therefore, changing the existing economic development model has become the consensus of all countries in the world. Industrial development is the source of economic growth. Therefore, implementing industrial optimization and promoting technological innovation is the key to break through the bottleneck of current economic development (Zhao and Gu, 2009). Some developed countries have implemented new energy and new technology measures. For example, the United States has implemented a new energy strategy (Wiser et al., 2011) and Japan has formulated such emerging industry strategies as environmentally friendly energy and information (Morozumi et al., 2008). However, for developing countries, due to the lack of new technology development capabilities and the limited ability of traditional industries to update, most industries still follow a relatively rough development model. These industries rely on the expansion of production factors and high environmental costs to obtain the “quantity and speed” of economic growth, while excess capacity is also widespread. For example, excess capacity in such traditional industries as steel, coal, and cement has become one of the major concerns of Chinese government agencies (Zhang et al., 2018b). For India, due to the economic recession, the sluggish market demand has also led to the excess capacity of the industrial and cement industries. Excess capacity has a negative impact on industry competitiveness and the capital market. It not only causes a large amount of idle production capacity and wastes resources, but also undermines the normal order of the market economy and triggers systemic financial risks. Therefore, in order to achieve the high-quality development of the industry and sustainable economic growth, solving the problem of excess capacity has become extremely urgent.

Capacity utilization (CU) is the premise and basis for analyzing excess capacity, which reflects the degree of utilization of production capacity. It is necessary to understand the CU of various industries. For the manufacturing industry, the extent to which installed production equipment produces output at a fixed time can most directly reflect its CU (Yang and Fukuyama, 2018). For the coal industry, the capacity estimated by such factors as equipment progress and resource reserves are considered, and then the ratio of actual coal output to capacity is used to reflect the CU level(Wang et al., 2019). For the construction industry, because the construction products are characterized by single-piece, large size and long cycle (Gao, 2012; Staub-French and Nepal, 2007), the production capacity of the construction industry can’t be fully reflected from the perspective of the quantity of construction products, thus determining the particularity of the CU problem in the construction industry. Combined with the characteristics of the construction industry, according to Yang and Fukuyama (2018) definition of CU, this study measures the production capacity of the construction industry from an economic and environmental perspective, and defines the construction industry CU as the difference between actual output and the maximum potential output that can be produced by human and material resources. Further, with reference to Yang et al. (2018) and Yang and Fukuyama (2018), this paper makes the following determinations of the construction industry's degree of CU: when the actual output is equal to potential output, production capacity is considered to be fully utilized; and when the actual output is less than potential output, there is a problem of underutilization of capacity.

The measurement and assessment of CU is the core of the problem of excess capacity. Under the influence of the resource environment, it is a very important research task to construct a quantitative scientific evaluation standard to measure the CU of the construction industry and reveal the influence of factor changes on CU. However, existing research also has the following shortcomings: Firstly, the existing measurement of CU is mainly concentrated in such traditional industries as manufacturing. Liu (2011) and Song et al. (2016) measure the Chinese manufacturing industry and its sub-sector CU, but there is no attention paid to the construction industry. Due to the rise of the economy in the construction and service industries, Fevolden (2015) and Nightingale and Poll (2000) believe that it is very important to pay attention to their CU issues, while Cadez (2015) only considers the CU of construction management. Secondly, Wang et al. (2019) directly reflect the status of CU through the ratio of actual production to theoretical production. However, this traditional quantitative evaluation is only applicable to such single-output industries as coal and metallurgy, and not to such complex industries as construction (Javed et al., 2018). Moreover, this method can only reveal the fact of excess capacity, unable to analyze the causes of excess capacity, and can't reveal the impact of factor changes on CU (Diane et al., 2002; Roger and Miguel, 1995). Thirdly, as large-scale investments raise the risk of excess capacity, resources and the environment are also severely damaged. Yang et al. (2018) pointed out that it is necessary to incorporate environmental factors into the CU measure. Further, Wang et al. (2019) and Zhang et al. (2018b) only consider the influence of such factors as technology and resources in their CU study, while ignoring environmental factors (such as CO2).

As an important material production source in China, China's construction industry makes a very important contribution to the Chinese economy (Liu et al., 2013). At the same time, the construction industry not only faces the problem of excess capacity, but also has a negative external impact on the environment during the development process (Fu et al., 2014). The industry accounts for approximately 30% of the country's total energy consumption, and its greenhouse gas emissions account for more than 40% of all industries (Hossain and Poon, 2018). Therefore, this study aims to develop a CU measurement index system and use it for the measurement of construction industry CU. Consequently, a construction industry CU index system that takes into account energy consumption and undesirable outputs is developed and used for the measurement of construction industry CU. Specifically, using two DEA-based difference methods, China's construction industry CU between 2011 and 2017 is analyzed, and the specific reasons for the underutilization of capacity are identified.

Additionally, the advantages and disadvantages of the two DEA methods are compared. This study provides a scientific evaluation standard for the construction industry CU, and provides a more scientific basis for formulating policies to improve the regional construction industry CU. The research conclusions also provide a reference for the improvement of CU in other industries. This study extends the existing knowledge system of CU, including the evaluation system, the measurement and assessment of CU, and the management implications. Based on the perspective of undesirable outputs, the study lays a foundation for research into CU in various industries, considering environmental factors. It also provides practical guidance for China and other developing countries to establish a nationwide capacity monitoring system.

The structure of the paper is as follows. Section 2 reviews the literature relating to productivity, energy efficiency, and CU in the construction industry. Section 3 introduces the DEA-based methods, the description of the CU indicators, and CU evaluation index system. Section 4 analyzes the results of an empirical analysis of China's construction industry and regional development layer. Section 5 provides a discussion of the results, with concluding remarks contained in the final section.

2. Literature review

2.1. Productivity in the construction industry

Research into productivity in the construction industry is very expansive, especially that which concerns the factors and trends affecting the industry's productivity. Ge et al. (2010), for instance, find that there are significant regional differences in the impact of the ecological environment. Zhang et al. (2018a) use the Hansen threshold regression model to test the threshold effect of environmental regulation on regional construction industry productivity, and finding that scale efficiency is the most affected. Yan et al. (2017) use the Ghosh model to evaluate the sustainability and the sensitivity of China's regional differences in 2007, finding Beijing and Hebei to be the most and least productive areas respectively. Liao et al. (2012) and Tan et al. (2015) use the Malmquist method to analyze the growth characteristics of China's construction industry productivity and its influencing factors, revealing that technological progress has a major impact on productivity growth.

Researchers have also explored trends in construction industry productivity in China, with Dai and Chen (2010), for instance, finding that the productivity growth rate of the construction industry in 30 provinces and cities in China was relatively low in 1994–2006. Some have also obtained different research results. For example, Lin et al. (2003) find that the productivity of the construction industry in Shanghai and Zhejiang increased significantly during 1999–2000, while the performance of the Guangdong industry with a larger production scale is only moderate. Chancellor and Lu (2016) find that the productivity of China's construction industry increased significantly from 1995 to 2012, with the highest and lowest being in East and North China respectively. Hu and Liu (2018) explore the trends and effectiveness of China's construction industry productivity from 1995 to 2014, also finding that the country's overall productivity is rising, with productivity gains in the eastern region being the most significant. Fan and Yu (2017) also obtain the same results. In short, construction industry productivity is significantly different between China's provinces and cities, with overall productivity increasing.

2.2. Energy efficiency in the construction industry

The rapid expansion of China's construction activities has increased the industry's energy consumption and environmental pollution. Consequently, research has focused on the industry's regional performance, mainly in terms of energy utilization and particularly centering on energy efficiency and conservation potential. For example, Chen et al. (2016) examine regional energy utilization rates and their changing trends, showing energy management and utilization levels to be relatively mature. Based on the circular economy method, Liu and Song (2013) find that the energy recycling rate of China's construction industry had an upward trend during 2006–2010, but the growth rate was slow. Fu and Huang (2010) analyze energy utilization rates in both residential and public buildings at different stages of their life cycle, finding that the rate during construction and use has a greater potential for improvement. Lu et al. (2015) use the Malmquist Productivity Index to measure the industry's energy efficiency in China's provinces and cities during 2005–2012, finding that energy efficiency has much potential for improvement.

To overcome the problem of inefficient energy use in China's construction industry, research has focused on the solutions needed to reduce this and CO2 emissions. Chen et al. (2013), for instance, reveal the best way to reduce energy consumption is by controlling the energy consumption of heating and ventilation. Feng et al. (2014) measure the energy efficiency of China's construction industry from 2004 to 2011, finding that optimizing the energy consumption structure is an effective way to save energy and reduce consumption. Lin and Liu (2015) use the full-factor non-radial directional distance function to estimate the industry's potential of energy saving, revealing that the decline in energy intensity is the main factor reducing carbon dioxide emissions. Du et al. (2017) find that the energy rebound effect of China's construction industry has a fluctuating downward trend, showing that the adoption of appropriate energy tax and energy price reforms can effectively increase the potential to save energy.

To summarize, therefore, there has been a considerable amount of research into the performance of China's regional construction industries in terms of energy utilization and productivity. In contrast, however, the body of knowledge concerning their CU performance is still far from complete.

2.3. Capacity utilization

Chamberlin was the first to propose the concept of excess capacity in his study of productivity under a monopolistic competition structure, pointing out that, when competitors develop to equilibrium, judging where excess capacity occurs can be based on whether output is less than that of a fully competitive manufacturer (Chamberlin, 1933). Subsequently, the academic community has gradually carried out more research into CU and excess capacity. For instance, measuring capacity utilization (CU) can now be divided into direct and indirect methods. Phillips (1963) and Perry (1973) summarize research data from five institutions in the United States, most of which use direct assays to obtain CU by collecting and analyzing corporate data. The most notable feature of the direct measurement method is that it is objective, but the true extent of the enterprise data affects the accuracy of the CU measurement results. In addition, this method also requires a great deal of manpower and resources to conduct long-term investigations covering a large number of enterprises. As a result, direct measurement has not been widely adopted, and scholars usually prefer more objective and indirect measurement methods.

Indirect measurement includes the peak, function, and DEA methods. The former is often used for exploring CU problems. For instance, Cassels (1937) and Morrison (1985) employ the peak method to reflect the CU of the automotive industry, while Klein (1960) uses it for calculating the CU of cyclical fluctuations in actual output. For the function method, Klein and Preston (1967) use it to estimate capacity output to obtain manufacturing industry CU. Meanwhile, Charnes et al. (1978) use DEA to construct the production frontier and measure its CU based on the fixed capital of the production unit; Färe et al. (1989, 1994) extend this to obtain the CU of each variable input directly by estimation. Subsequently, some scholars use the DEA method in the CU study of fishing vessels to identify the reasons for the inefficiency of the fishery economy (Lindebo et al., 2007; Tsitsika et al., 2008).

Other studies examine CU from the perspective of the economic output capabilities of different industries. Zhang et al. (2009), for example, find that the use of collaborative optimization of off-site CU strategies can effectively improve the interests of airlines. Karagiannis (2015) measures the CU of a sample of Greek public hospitals, revealing that the underutilization of caregivers and doctors has led to an excess capacity in the hospitals. Yang and Fukuyama (2018), based on the generalized CU index, find significant regional differences in China’s production potential. Liu (2011) argues that the impact of consumer demand will increase China’s manufacturing CU, while strong consumer demand is the basis for large-scale investment. Song et al. (2016) measure the CU of 12 sub-sectors in China’s manufacturing industry through such factors as fixed assets, manpower, and energy consumption, finding that excess capacity in the coal, oil, and nuclear fuel industries is the most serious. Zhang et al. (2018b) estimate the Chinese coal CU from 1990 to 2014 by considering such factors as technology, capital, manpower, and time, finding that the decoupling effect of coal CU and China's economic growth is related to the decoupling index. Similarly, Wang et al. (2019) measure the capacity of the coal industry through such factors as equipment advancement and resource reserves, and reflects the CU by the ratio of actual coal production to estimated capacity. However, despite this extensive research activity into CU, it is mainly focused on the manufacturing industry, with no concern for the construction industry.

2.4. Gaps in the knowledge

In summary, the existing research mainly has the following limitations: (1) it mainly assesses the performance of the construction industry from the aspects of productivity and energy efficiency, and research into the measurement of the construction industry's CU is lacking; (2) an evaluation index system with multi-input and output is not used to measure CU, and the influence of undesirable output is not known-causing large differences in the measurement results; and (3) traditional quantitative evaluations, such as by the ratio method, can only reveal the reality of excess capacity-it is unable to comprehensively analyze the causes of excess capacity, and can't reveal the impact of factor changes on CU. In response, this study addresses this gap in knowledge by: (1) establishing a multi-input and multi-output construction industry CU evaluation index system that considers undesirable output and energy consumption, and improves the accuracy of the CU measurement results; (2) utilizing two DEA model-based methods to measure the CU of China's construction industry between 2011 and 2017, determine the degree of CU, and compare the advantages and disadvantages of the two methods; and (3) identifying and analyzing the specific causes of underutilization of capacity through factor decomposition of CU, and suggesting targeted management implication.

3. Methodology

Both the "no variable-link difference" and the "adding variable-link difference" methods are used to measure China's construction industry capacity utilization (CU). Both are based on the DEA model, which characterizes the degree of utilization of the industry by estimating the difference between the industry's potential and actual output. The adding variable-link difference method increases the link between the variable input and undesirable output, to reflect the industry's actual production process more realistically. In order to judge and analyze the utilization status of each decision-making unit (DMU), the evaluation criteria of the CU indicator are specified. 2011–2017 panel data is used in the analysis, obtained from national, local, and industry statistical yearbooks (NBS, 2012–2018; NBSMEP, 2012–2018) available at http://cyfd.cnki.com.cn/. To enhance the generalizability of study, the panel data comprises of 30 provinces and cities, as listed in Table 3.

3.1. Method I: the no variable-link difference method

Yang and Fukuyama (2018) propose a differential method based on the DEA model and apply it to the measurement of the CU of China's manufacturing industry. On the basis of Yang et al.'s (2018) research, this paper improves the model, by assuming there are H decision-making units DMU $(H = 1, \dots, h\,)$, with the variable inputs $v = (v_1, \dots, v_N) \in R_N^+$, fixed inputs $f = (f_1, \dots, f_P) \in R_p^+$, desirable outputs $d = (d_1, \dots, d_M) \in R_M^+$, and undesirable outputs $u = (u_1, \dots, u_I) \in R_I^+$ set to establish the Production Possibility Sets:

$$\{(v, f, d, u) | (v, f) can\ produce\ (d, u)\} \tag{1}$$

This reflects the consumption of certain variable inputs and fixed inputs in the actual production process, which can produce both desirable and undesirable outputs. According to Shephard's (1974) joint weak disposability (JWD) attributes, the desirable and undesirable outputs are treated as:

$$\text{JWD: } (v, f, d, u) \in T\ and\ 1 \geq \varphi \geq 0 \rightarrow\ (v, f, \varphi d, \varphi u) \in T \tag{2}$$

where φ represents the abatement factors, which means that while the undesirable outputs are reduced, the desirable outputs are also reduced. Referring to Kuosmanen's (2005) study, the limitation of the common expansion factor in the hypothesis is relaxed, allowing the expansion factor φ to be varied in the different DMUs. Let $v_{nj}, f_{pj}, u_{lj}, d_{mj}$ be the observed variables of the DMU_j, under the assumption that the variable returns to scale (VRS; the DEA production possibility set can be expressed as

$$\mathrm{T}_1 = \left\{ (v, f, d, u) | \begin{array}{c} v_n \geq \sum_{j=1}^{J} v_{nj} \lambda_{j,}\ \forall n; \\ f_p \geq \sum_{j=1}^{J} f_{pj} \lambda_{j,}\ \forall p; \\ d_m \leq \sum_{j=1}^{J} \varphi_j^h d_{mj} \lambda_{j,}\ \forall m; \\ u_i = \sum_{j=1}^{J} \varphi_j^h u_{ij} \lambda_{j,}\ \forall i; \\ \sum_{j=1}^{J} \lambda_j = 1;\ \lambda \geq 0; 1 \geq \varphi_j^h \geq 0,\ \forall h \forall j \end{array} \right\} \tag{3}$$

Furthermore, based on Chung et al. (1997), the direction vector is set to $g = \left(g^a, g^b\right)$. This shows that, under the production technology T condition, the direction vector g is used to reduce the undesirable outputs while increasing desirable outputs, thereby improving the production status. The direction distance function of DMU_j is expressed as

$$\theta_0(v_0, f_0, d_0, u_0; g) = max\{\beta | (v_0, f_0, d_0 + \beta g^b, u_0 - \beta g^a; g) \in \hat{T}, \beta\ free\}$$

$$= max \left\{ \beta | \begin{array}{c} v_{n0} \geq \sum_{j=1}^{J} v_{nj}\, \lambda_{j,}\ \forall n; \\ f_{po} \geq \sum_{j=1}^{J} f_{pj}\, \lambda_{j,}\ \forall p; \\ d_{m0} + \beta g_m^b \leq \sum_{j=1}^{J} \varphi_j^h d_{mj}\, \lambda_{j,} \forall m; \\ u_{i0} - \beta g_i^a = \sum_{j=1}^{J} \varphi_j^h\, u_{ij} \lambda_{j,} \forall i; \\ \sum_{j=1}^{J} \lambda_j = 1;\ \lambda \geq 0; 1 \geq\ \varphi_j^k \geq 0,\ \forall k \forall j;\ \beta\ free \end{array} \right\} \tag{4}$$

The above nonlinear programming is transformed into a linear programming by introducing a linear rule of $s_j^h = \varphi_j^h \lambda_j \geq 0\ (\forall h \forall j)$, $r_j^h = \left(1-\varphi_j^h\right)\lambda_j = \lambda_j - s_j^h\ (\forall h \forall j)$, $r_j^h \geq 0,\ \lambda_j = \sum_{h=1}^{H}\left(r_j^h + s_j^h\right) \geq 0$, $\sum_{j=1}^{J}\lambda_j = \sum_{j=1}^{J}\sum_{h=1}^{H}\left(r_j^h + s_j^h\right) = 1$. Under the condition that the variable inputs are certain (restricted), the directional output distance function can be expressed as

$$\theta_0(v_0, f_0, d_0, u_0; g)$$

$$= max\left\{\beta \middle| \begin{array}{c} v_{n0} \geq \sum_{j=1}^{J} v_{nj} \sum_{h=1}^{H}\left(r_j^h + s_j^h\right)\ .\forall n; \\ f_{p0} \geq \sum_{j=1}^{J} f_{pj} \sum_{h=1}^{H}\left(r_j^h + s_j^h\right)\ ,\ \forall p; \\ d_{m0} + \beta g_m^b \leq \sum_{j=1}^{J} d_{mj} \sum_{h=1}^{H} s_j^h\ ,\ \forall m\ ; \\ u_{i0} - \beta g_i^a = \sum_{j=1}^{J} u_{ij} \sum_{h=1}^{H} s_j^h,\ \forall i \\ \sum_{j=1}^{J}\sum_{h=1}^{H}\left(r_j^h + s_j^h\right) = 1;\ r_j^h + s_j^h \geq 0;\ \forall h \forall j; \\ \sum_{j=1}^{J}\sum_{h=1}^{H} s_j^h \leq 1\ , r_j^h \geq 0\ , \forall h \forall j; s_j^h \geq 0,\ \forall h \forall j, \beta\ free \end{array}\right\} \tag{5}$$

Similarly, in line with Fare et al. (1989, 1994) and Kirkley et al. (2002), the constraints on variable inputs are removed, allowing them to change freely. Under the condition that the variable inputs are unrestricted, the directional output distance function can be expressed as

$$\widehat{\theta_0}(v_0, f_0, d_0, u_0; g) = max\left\{\beta \middle| \left(v_0, f_0, d_0 + \beta g^b, u_0 - \beta g^a; g\right) \in \hat{T}, \beta\ free\right\}$$

$$= max\left\{\beta \middle| \begin{array}{c} \delta_h^v v_{n0} \geq \sum_{j=1}^{J} v_{nj}\left(r_j^h + s_j^h\right), \forall n;\ ; \\ f_{p0} \geq \sum_{j=1}^{J} f_{pj} \sum_{h=1}^{H}\left(r_j^h + s_j^h\right)\ , \forall p; \\ d_{m0} + \beta g_m^b \leq \sum_{j=1}^{J} d_{mj} \sum_{h=1}^{H} s_j^h\ ,\ \forall m; \\ u_{i0} - \beta g_i^a = \sum_{j=1}^{J} u_{ij} s_j^h,\ \forall i; \\ \sum_{j=1}^{J}\sum_{h=1}^{H}\left(r_j^h + s_j^h\right) = 1; r_j^h + s_j^h \geq 0;\ \forall h \forall j,\ \delta_n^v \geq 0, \forall n; \\ \sum_{j=1}^{J}\sum_{h=1}^{H} s_j^h \leq 1\ , r_j^h \geq 0\ , \forall h \forall j; s_j^h \geq 0, \forall h \forall j, \beta\ free \end{array}\right\} \tag{6}$$

Of these, δ_h^v represents the degree of change in variable inputs when the potential desirable outputs reach a maximum. Use * to indicate the optimal solution sought, according to the original variable inputs (v_{no}), the corrected optimal variable inputs (indicated by v_{no}^*) can be calculated by

$$v_{no}^* = v_{no} * \delta_n^{v*} \tag{7}$$

$\theta_0(v_0, f_0, d_0, u_0; g)$ represents the actual production capacity of the construction industry when variable inputs are limited. $\widehat{\theta_0}(v_0, f_0, d_0, u_0; g)$ represents the maximum potential production capacity of the construction industry when variable inputs are unlimited, with

$$CU = \widehat{\theta_0} - \theta_0 \tag{8}$$

3.2. Method II: adding variable-link difference method

In the actual production process, the undesirable output of the construction industry is mainly derived from its energy consumption. Therefore, in order to better treat the actual production situation and improve the accuracy of the CU measurement, this study links the variable inputs directly related to the undesirable outputs in the model.

Also consider variable inputs *v*, fixed inputs *f*, expected outputs *d*, and undesired outputs *u* and Shephard's (1974) Joint Weak Dispositionability (JWD) attributes. Based on formula (4), the variable inputs $v_h^u(h = 1, \ldots H)$ directly related to the undesirable outputs $u_h^v(h = 1, \ldots H)$ are linked. Referring to the study of Chung et al. (1997), the direction vector $g = (g^a, g^b)$ is introduced, and the direction distance function of the adding variable link DMU_j is

$$D_0(v_0^u, u_0^v, v_0, f_0, d_0; g) = max\left\{\beta \middle| \begin{matrix} v_{h0}^u \geq \sum_{j=1}^J \partial_j^k v_{hj}^u \lambda_{j,} \forall h; \\ u_{h0}^v - \beta g_k^a = \sum_{j=1}^J \partial_j^k u_{hj}^v \lambda_{j,} \forall h; \\ v_{n0} \geq \sum_{j=1}^J v_{nj} \lambda_{j,} \ \forall n; \\ f_{p0} \geq \sum_{j=1}^J f_{pj} \lambda_{j,} \ \forall p; \\ d_{m0} + \beta g_m^b \leq \sum_{j=1}^J d_{mj} \lambda_{j,} \forall m; \\ \sum_{j=1}^J \lambda_j = 1; \ \lambda \geq 0; \ \partial_j^k \geq 1, \ \forall k \forall j; \beta \ free \end{matrix} \right\} \tag{9}$$

where $\lambda = (\lambda_1, \ \ldots, \ \lambda_j)$ is a vector of intensity variables and ∂_j^k is an amplification factor that enables the link between v_h^u and u_h^v. Following the advice of Kuosmanen (2005), ∂_j^k is allowed to change in different DMUs. Introducing the linear rules $r_j^h = \frac{1}{H} \partial_j^h \lambda_j \ (\forall h \forall j)$, $s_j^h = (\lambda_j/H) - \frac{1}{H} \partial_j^h \lambda_j = (\lambda_j/H) - r_j^h \ (\forall h \forall j)$, $\sum_{H=1}^h s_j^h = \lambda_j - \sum_{H=1}^h r_j^h, \lambda_j = \sum_{H=1}^h (r_j^h + s_j^h) \geq 0$, under the condition that the variable inputs are certain (restricted), the linear directional output distance function can be expressed as

$$D_0(v_0^u, u_0^v, v_0, f_0, d_0; g) = max\left\{\beta \middle| \begin{matrix} v_{h0}^u \geq H \sum_{j=1}^J v_{hj}^u r_j^h \ , \forall h; \\ u_{h0}^v - \beta g_h^a = H \sum_{j=1}^J u_{hj}^v r_j^h, \ \forall h; \\ v_{n0} \geq \sum_{j=1}^J v_{nj} \sum_{h=1}^H \left(r_j^h + s_j^h\right) \ \forall n; \\ f_{p0} \geq \sum_{j=1}^J f_{pj} \sum_{h=1}^H \left(r_j^h + s_j^h\right), \forall p; \\ d_{m0} + \beta g_m^b \leq \sum_{j=1}^J d_{mj} \sum_{h=1}^H \left(r_j^h + s_j^h\right), \ \forall m; \\ \sum_{j=1}^J \sum_{h=1}^H \left(r_j^h + s_j^h\right) = 1; \ r_j^h + s_j^h \geq 0; \ \forall h \forall j; \\ r_j^h \geq 0 \ , \forall h \forall j; \ s_j^h \leq 0 \ , \forall h \forall j, \beta \ free \end{matrix} \right\} \tag{10}$$

Now release the constraints of variable inputs under the condition that the variable inputs are unrestricted, the directional output distance function can be expressed as

$$\widehat{D_0}(v_0^u, u_0^v, f_0, v_0, d_0; g) = max\{\beta|\left(v_0^u, u_0^v - \beta g^a, f_0, v_0, d_0 + \beta g^b; g\right) \in \hat{T}, \beta\ free\}$$

$$= max\left\{\beta| \begin{array}{c} \delta_h^{vu} v_{h0}^u \geq H \sum_{j=1}^J v_{hj}^u r_j^h, \forall h; \\ u_{h0}^v - \beta g_h^a = H \sum_{j=1}^J u_{hj}^v r_j^h, \ \forall h; \\ f_{p0} \geq \sum_{j=1}^J f_{pj} \sum_{h=1}^H \left(r_j^h + s_j^h\right), \forall p; \\ \delta_n^v v_{n0} \geq \sum_{j=1}^J v_{nj} \sum_{h=1}^H \left(r_j^h + s_j^h\right) \ \forall n; \\ d_{m0} + \beta g_m^b \leq \sum_{j=1}^J d_{mj} \sum_{h=1}^H \left(r_j^h + s_j^h\right), \ \forall m; \\ \sum_{j=1}^J \sum_{h=1}^H \left(r_j^h + s_j^h\right) = 1; r_j^h + s_j^h \geq 0; \ \forall h \forall j \\ r_j^h \geq 0; \ \forall h \forall j; \ s_j^h \leq 0, \forall h \forall j; \ \delta_h^{vu} \geq 0, \forall h; \ \delta_n^v \geq 0, \forall n; \ \beta\ free \end{array} \right\} \quad (11)$$

where $\delta_h^{vu}$and δ_n^v represent the correction coefficients of the linked variable inputs and the variable inputs respectively. Use * to indicate the optimal solution sought, according to the link variable inputs and variable inputs (v_{h0}^u, v_{no}), the corrected optimal link variable inputs and variable inputs (indicated byv_{ho}^{u*}, v_{no}^*) can be obtained by

$$\begin{cases} v_{ho}^{u*} = v_{ho}^u * \delta_h^{vu*} \\ v_{no}^* = v_{no} * \delta_n^{v*} \end{cases} \quad (12)$$

Similarly, in the adding variable-link difference method, combined with the definition of CU in the construction industry, the CU indicator is defined as the difference between $\widehat{D_0}$ and D_0, i.e.,

$$CU = \widehat{D_0} - D_0 \quad (13)$$

3.3. Criteria of the CU indicator

CU = 0 means that the evaluated DMU can take advantage of the current fixed inputs to produce the maximum amount of output. On the other hand, CU > 0 indicates that the assessed DMU is experiencing underutilization of capacity, including production and excess capacity, in which the fixed input is not fully utilized and the production potential is not fully explored. A DMU with excess capacity indicates it is overused for fixed input.

According to the model, $\widehat{\theta_0} \geq \theta_0$, and in line with Yang and Fukuyama (2018), we define CU> 0, $\delta_h^{vu} \geq 1$ (∀h) and $\delta_n^v \geq 1$ (∀n) at the same time, indicating there is excess capacity in the corresponding DMU (Kirkley et al., 2002; Yang and Fukuyama, 2018).For an ineffective DMU without excess capacity, the formula (8) in the case of Method I can be rewritten as

$$\widehat{\theta_0} = CU + \theta_0 \quad (14)$$

where CU=0 means that the current DMU is facing a technical low problem, and CU>0 indicates that the current DMU has both underutilization of capacity and low technical problems.

3.4. Data and variables

As mentioned previously, a multi-input and multi-output construction industry CU evaluation index system that considers carbon dioxide emissions is proposed. This consists of four parts: fixed input, variable input, desirable output, and undesirable output. Table 1 summarizes the existing input and output variables. For the input, the variables mostly involve fixed assets, manpower, materials, and energy, while the output variables are mostly the total output value of the construction industry, profits, and construction land. Very few studies consider CO2 as undesirable output. The input variables are further divided into fixed variable inputs, while the output variable is further divided into desirable and undesirable output, all of which form the construction industry CU evaluation index system (from the perspective of CO2 being an undesirable output), as shown in Table 2.

4. Empirical results

4.1. Analysis of China's overall construction industry

Taking the adding variable-link difference method as an example, the D0ˆ,D0 of each province/city are estimated by the model, and the capacity utilization (CU) value is obtained according to eqn (13). Based on this, the CU status is judged in combination with the criteria of CU indicator. As shown in Table 2 in the Appendix, the average 2011–2017 China construction industry CU using the adding variable-link is 0.3833. This indicates that the industry has not fully utilized its production capacity, and thus there is a greater room for improvement in its CU. Fig. 1 shows the average CU trend over the study period. It is divided into two phases. In the first phase (2011–2014), the average CU value increased from 0.2346 to 0.4881, indicating a decrease in the CU use of its variable input to engender capacity production output. In the second phase (2015–2017), the average CU value dropped from 0.4178 to 0.3684, indicating an increase in CU, but still with potential for improvement.

Table 3 in the Appendix shows the 2011–2017 CU for various provinces and cities. Fig. 2 provides a visual illustration, which fully reflects the changes experienced. It can be seen that the Jiangsu and Guangxi provinces CU were zero over the study period, indicating that the production potential in the two provinces was fully utilized, and there was no shortage of CU. However, the average CU in the other 28 provinces and cities was greater than zero. This indicates an underutilization of capacity. In addition, because they encompass most of China's geographical land space, it is likely that the majority of the country's regional construction industries have an underutilized capacity. Therefore, for those with underutilized capacity, optimizing the variable input allocation activities should effectively improve their overall CU level. For instance, as shown in Fig. 2, Hainan's 2011–2012 CU was zero, indicating a fully utilized variable input for capacity production during the period. However, the CU became positive from 2013, indicating that its level of construction industry CU declined since 2013.

Table 3 in the Appendix gives the ranking of the average 2011–2017 CU of the provinces and cities; the last Figure in Fig. 2 also clearly reflects the distribution of the CU averages. This shows that three provinces have a relatively high average CU (>0.5). Of these, Hubei has the highest average CU of 0.6504, followed by Zhejiang (0.6229), both indicating an underutilization of capacity. Meanwhile, Jiangsu, Guangxi, and Inner Mongolia have an average CU of less than 0.2, indicating the full utilization of their CU per variable inputs.

4.2. Analysis of China's regional development

With the continuous deepening of the economic restructuring of China's construction industry, the provincial and city CUs have experienced some dynamic changes. At the same time, the construction industries in each region compete with each other and develop closely (Wells, 1984). To provide a more systematic and comprehensive display of the overall development of the regional construction industries, regional CU differences are analyzed using the adding variable-link difference method. In doing this, the country is divided into eight regions in line with their geographical and economic characteristics as shown in Table 3(Wang and Wei, 2014). This shows the average 2011–2017 CU in each region. The regions with a higher average CU include the central Yangtze River area, northeast China, indicating a relative underutilization of their production capacity. The average CU in southwest China and the coastal areas of east China is low, indicating that these regions have more fully utilized capacity per variable inputs. In other regions, including the coastal areas of south China, the central Yellow River area, northwest China, and the coastal areas of north China, the average CU is greater than 0.35, indicating that the production potential in these regions has not been fully exploited, and there is much scope for improvement.

Fig. 3 provides a visual illustration of the average CU in each region. Based on the inputs and outputs, each region has different degrees of excess capacity. Although the excess capacity in southwest China is not high, it also needs to be corrected. The excess capacity in the central Yangtze River area is the most serious, and requires urgent intervention and timely control. In addition to the higher construction industry utilization in Guangxi, southwest China, and Jiangsu in the coastal areas of east China, provinces and cities in other regions have different levels of CU improvement potential. In particular, production in Hubei in the central part of the Yangtze River, Zhejiang in the coastal areas of east China, Tianjin in the coastal areas of north China, and Jilin in northeast China need urgent improvement.

When the CU value is measured by the adding variable-link difference method, the correction coefficient (indicated by $\delta nv*$ and $\delta hvu*$) of each input variable can be obtained. Combined with the criteria of the CU indicator, the current status of CU can be determined. According to the original variable input data (indicated by vn,vhu), the corrected optimal input (indicated by $vn*$,$vhu*$) can be estimated by eqn (12). This present study takes Hubei, Tianjin, and Zhejiang as examples to explore the feasible ways of improving CU. The annual optimal variable input, index correction factor, and raw input data in the Hubei construction industry are shown in Table 4 in the Appendix. Based on the annual values of $\delta kvu*$ and $\delta kv*$, combined with the defined criteria of the CU indicators, there is no excess capacity in Hubei. Using the decomposition of eqn (13), the reason for Hubei's underutilized capacity is technical inefficiency and underutilization of fixed inputs to generate CU. The revised optimal variable input shows that the revised number of employed people, total assets, and total power of the machines and equipment have increased significantly. This means that if Hubei's construction industry increases its corresponding human, material, and financial resources within a certain range, it may be able to exploit its production potential fully. In addition, Table 4 in the Appendix also shows that, compared with actual annual energy input, the revised optimal energy input in Hubei has been reduced by different degrees. This indicates that the energy consumption and carbon emissions in the Hubei construction industry needs to be reduced to exploit its CU fully.

Similarly, in the case of the Tianjin construction industry (Table 5 in Appendix), combined with the defined criteria of the CU indicators, there is no excess capacity. The revised number of employed people in the construction industry there has grown significantly, which means that Tianjin needs to increase its CU by increasing the corresponding amount of construction industry personnel.

In the case of the Zhejiang construction industry (Table 6 in Appendix), there is excess CU, indicating an overuse of fixed input. The result of the revised optimal variable input value only means that the Zhejiang construction industry is facing excess capacity problems and does not represent the ideal value of the input variables. By way of suggestion to the provinces with excess capacity, the Chinese government needs to strengthen its supply-side structural reforms, take corresponding measures to limit excessive investment, and use such fixed inputs as land to reduce the industry's excess capacity.

5. Discussion

This study measures China's construction industry capacity utilization (CU) using two DEA methods. The first (Method I) is the no variable-link difference method (CU value estimated by Method I, shown in Table 7 of the Appendix), and the second (Method II) is the adding variable-link difference method. Compared with Method I, Method II increases the link between variable inputs and undesirable outputs, and further clarifies the source of undesirable outputs. Based on the 2011–2017 annual CU in each province and city, the differences between Methods I and II are analyzed as shown in the nuclear density graph in Fig. 4.

The CU is either equal, or close to, zero-indicating that the DMUs are fully utilizing the current variable input to produce the corresponding output. Fig. 4 shows that, between 2011 and 2012, the proportion of provinces and cities that used Method II to make full use of the current variable input to produce the corresponding output is higher than Method I, while the methods are juxtaposed beyond 2013. Still, between 2011 and 2017, the maximum CU value measured using Method I was greater than Method II. Furthermore, the CU distribution of the Method II measure is more concentrated than with Method I. Between 2011 and 2017, the peak of the CU distribution curve obtained by Method II is on the left side of the peak of the CU distribution curve obtained by Method I, which indicates that the overall CU obtained by Method II is smaller than by Method I.

Considering the relationship between partial variable input and undesirable output, the underutilization of capacity situation is more optimistic, indicating a smaller deviation between potential output and actual output. Yang et al. (2018) had similar findings in their study of the measurement of China's manufacturing industry CU. This is due to the increase in constraint conditions in the process of identifying the optimal output of linear programming based on DEA. Method II establishes a link between undesirable output and energy consumption, which adds constraints to obtaining the optimal solution by linear programming, and reduces the potential output measurement results. In the actual production process in the construction industry, undesirable output often occurs from one or more inputs. Establishing the link between undesirable output and variable input can more accurately reflect the actual production process and improve the accuracy and rationality of CU measurement.

Furthermore, it is found that the temporal changes in China's construction industry average CU are divided into two phases. The first (2011–2014) shows an increase in CU value, indicating that the problem of underutilization of capacity in the construction industry is more serious. In the second phase (2015–2017), the CU value decreased, indicating the problem had improved in the past three years. In addition, there are significant regional differences in CU, which may be explained by the July 2014 Ministry of Housing and Urban-Rural Development issuing its Several Opinions on Promoting the Development and Reform in the Construction Industry. This reform promoted the establishment of a national construction market system, aimed at eliminating market barriers, opening up markets, enabling competition in an orderly manner, and enhancing the industry's CU. In addition, the difference in production levels is an important cause of regional CU differences. There are two reasons for the inefficiency of the DMU capacity: technical limitations and the underutilization of capacity. However, there is a large regional difference in the industry's productivity levels in China (Chen et al., 2018; Zhang et al., 2018a), which has the effect of exacerbating regional CU differences.

Based on the analysis results, the following recommendations are proposed for China's construction industry.

(1) The adoption of policies conserving building energy, and improvement in the incentive mechanisms for low carbon development. It has been established that

the application of energy-saving technologies can promote the improvement in building construction technology (Li and Feng, 2018). Therefore, areas in the industry with underutilized capacity can improve their CU using new environmental protection materials and advanced green energy-saving technologies.

(2) The introduction a talent introduction strategy. Pan et al. (2019) and Song (2017), for example, found that deepening the reform of the talent management system and adopting a technology introduction strategy could effectively enhance the progress of the industry. Strengthening policy guidance to help improve the utilization of capacity areas can attract more highly skilled talents to the industry, help optimize the labor structure, and fully exploit the production potential of regional construction industries.

(3) Optimize the industry business model. Ran et al. (2012), for example, found that the effective use of fixed assets greatly encourages an increase in the industry’s added value. Therefore, breaking through the single business model of engineering construction services, organically combining engineering construction with capital management, and broadening capital channels should help optimize resource allocation and enhance industry CU.

(4) Establish a competitive mechanism for low-carbon development in the industry. CO2 emissions are an important reason for restricting the further improvement of the industry (Lin and Liu, 2015), and their reduction provides a viable means of increasing the industry’s CU. Establishing a competitive mechanism for low-carbon development will help stimulate innovation in green building technologies and have a positive effect on the industry’s sustainable development (Meng et al., 2018).

6. Conclusion

Industrial optimization is the key to unlock the bottleneck of current economic development. However, for many developing countries, due to their lack of technological innovation, industry still follows a relatively rough development model. The large-scale investment expansion in many industries has led to excess capacity and the increasingly severe problems of high energy consumption and severe pollution, which have seriously hindered the sustainable development of the economy. It can be seen that under the premise of resource and environmental constraints, mastering the status quo of industrial CU is an important prerequisite for coping with excess capacity and realizing the high-quality development of the national economy.

Based on the perspective of undesirable outputs, this paper establishes a construction industry CU indicator system considering energy consumption and undesirable output for the first time, and measures the construction industry CU, which provides a scientific basis for the formulation of development policy for managing regional construction industry CU. Using two DEA-based difference methods and 2011–2017 China panel data, the study extends the existing knowledge system of CU including the evaluation system, and the measurement and assessment of CU. In addition, the study provides a reference for CU research in various industries considering environmental factors, and has practical significance for establishing a nationwide CU monitoring system for China and other developing countries. The study mainly draws the following conclusions:

(1) CU measurement using the adding variable-link difference method is more accurate than the no variable-link difference method. The adding variable-link difference method more accurately reflects the actual production process and helps improve the accuracy and rationality of the measurement process.
(2) At an average CU of 0.3833, the capacity of China’s construction industry between 2011 and 2014 was underutilized due to an inappropriate variable input allocation, but improved thereafter.
(3) With the exception of Jiangsu and Guangxi, the Chinese construction industries in different provinces and cities are facing the problem of underutilization of capacity.
(4) Similarly, regional construction industries have different CU. The Yangtze River and the Northeast China regions are facing the more serious problem of underutilization of capacity compared with Southwest China.

Based on these conclusions, it is suggested that more effective policy measures are needed to improve construction industry CU, as this will go a long way towards stemming the industry’s high-energy emissions. Also needed is a nationwide monitoring system of the industry’s CU, as this will enable the timely determination of regional CU and allow the targeted adoption of corresponding policy measures of great significance for the improvement of the industry’s utilization levels. In addition, the inappropriate allocation of variable inputs is the main reason for underutilized capacity, and therefore an optimized variable input allocation will provide an improvement. Moreover, considering the large regional differences in construction industry CU, there is a need for such policy support as developing talents, technology, and capital channels. Future research is also needed to examine the impact of different management policies.

Declaration of competing interest

The authors declare no conflict of interest for the order and cooperation.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (No. 71301013); 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); Shaanxi Social Science Fund (No.2017S004 and No. 2016ZB017); Shaanxi Province Social Sciences Major Theoretical and Practical Research Fund (No.2019Z191 and No.2017Z028); Xi’an Social Science Fund (No.18J139); Xi’an Construction Science and Technology Planning Project (No. SJW201705, No.SZJJ201915 and No. SZJJ201916); Xi’an Science Technology Bureau Fund (No.201805070RK1SF4(6)); Shaanxi Universities Second Batch of Youth Outstanding Talents Support Projects(No.[2018]111); Shaanxi Province Higher Education Teaching Reform Project (No.17BZ017); Education Funding of Master of Engineering Management in China (No. 2017-ZX-004); Shaanxi Province Civil Engineering "first-class professional" project(No.300103292804 and No. 300103282803); Special Fund for Graduate Student Education Reform of Central College, Chang’an University (No.300103190413, No.300103190018, No. 300103190943, No.300111002005, No.300103187091 No. 310623176201, No.310623176702, No.310628176702 and No.310628161406); Fundamental Research for Education Reform of Central College, Chang’an University (No.300104292305, No.300104292304, No.300104292308, No. 300103292806, No. 300104282301, No. 300104282318, No. 300104282323, No.310623172904, No. 310623171003 and No. 310623171633); Fundamental Research for Funds for the Central Universities (Humanities and Social Sciences), Chang’an University (No.300102239616); Fundamental Research for Funds for the Central Universities, Chang’an University (No. 300102238201).

Appendix A. Supplementary data

The supplementary data found in this article can be found online at https//doi.org/10.1016/j.jclepro.2019.119549.

References

Bian, Y., Liang, N., Xu, H., 2015. Efficiency evaluation of Chinese regional industrial systems with undesirable factors using a two-stage slacks-based measure approach. J. Clean Prod. 87. https://doi.org/10.1016/j.jclepro.2014.10.055

Cadez, I., 2015. Application of the manufacturing costs/construction time-method and the capacity utilization-method for the determination of general costs at claim requests according to VOB/B. Bautechnik 92(3), 201-206. https://doi.org/10.1002/bate.201400102

Cassels, J.M., 1937. Excess capacity and monopolistic competition. https://doi.org/10.2307/1884835

Chamberlin, E., 1933. The Theory of Monopolistic Competition. Cambridge Harvard University Press. https://doi.org/10.1108/eb002637

Chancellor, W., Lu, W.S., 2016. A regional and provincial productivity analysis of the Chinese construction industry: 1995 to 2012. Journal of Construction Engineering and Management 142(11). https://doi.org/10.1061/(asce)co.1943-7862.0001177

Charnes, A., Cooper W W, E., R., 1978. Measuring efficiency of decision making units. European Journal of Operational Research 2, 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, X.H., Ma, Y.L., Zhang, G.F., Liu, B., 2013. Modeling method of Building Energy Consumption & Conservation, in: Tanabe, H. (Ed.) Automatic Control and Mechatronic Engineering Ii. Trans Tech Publications Ltd, Durnten-Zurich, pp. 716. https://doi.org/10.4028/www.scientific.net/AMM.415.716

Chen, Y., Liu, B.S., Shen, Y.H., Wang, X.Q., 2016. The energy efficiency of China's regional construction industry based on the three-stage DEA model and the DEA-DA model. KSCE Journal of Civil Engineering 20(1), 34-47. https://doi.org/ 10.1007/s12205-015-0553-3

Chen, Y., Liu, B.S., Shen, Y.H., Wang, X.Q., 2018. Spatial analysis of change trend and influencing factors of total factor productivity in China's regional construction industry. Applied Economics 50(25), 2824-2843. https://doi.org/10.1080/00036846.2017.1409421

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: A directional distance function approach.. Journal of Environmental Management 51(3). https://doi.org/10.1006/jema.1997.0146

Dai, Y., Chen, C., 2010. Technical efficiency in China's construction industry and its influencing factors. China Soft Science (1), 87-95. https://doi.org/10.3969/j.issn.1002-9753.2010.01.010

Diane, P., Dupont, R., Grafton, Q., Kirkley, J., 2002. Capacity utilization measures and excess capacity in multi-product privatized fisheries. Resource and Energy Economics 24(3), 193-210. https://doi.org/ 10.1016/S0928-7655(01)00050-1

Du, J., Chen, Y., Huang, Y., 2018. A modified Malmquist-Luenberger productivity index: Assessing environmental productivity performance in China. Eur. J. Oper. Res. (Netherlands) 269(1), 171-187. https://doi.org/10.1016/j.ejor.2017.01.006

Du, Q., Li, Y., Bai, L.B., 2017. The energy rebound effect for the construction industry: Empirical evidence from China. Sustainability 9(5), 11. https://doi.org/10.3390/su9050803

Fan, J., Yu, X., 2017. Total factor productivity growth of China's construction industry: A stochastic frontier approach. BIM application and offsite construction. Proceedings of the 2016 International Conference on Construction and Real-Estate Management (ICCREM), 292-300.

Fare, R., Grosskopf, S., E, K., 1989. Measuring plant capacity, utilization, and technical change: a nonparametric approach. Int Econ Rev 30(3), 655-666. https://doi.org/10.2307/2526781

Fare, R., Grosskopf, S., Lovell, C.A.K., 1994. Production Frontiers. Cambridge University Press. https://doi.org/10.2307/2235033

Feng, B., Wang, X., Llu, B., 2014. Provincial variation in energy efficiency across China's construction industry with carbon emission considered. Resources Science 36(6), 1256-1266.

Feng, C., Wang, M., 2017. The economy-wide energy efficiency in China's regional building industry. Energy 141, 1869-1879. https://doi.org/10.1016/j.energy.2017.11.114

Fevolden, A.M., 2015. New perspectives on capacity utilization: from moving assembly lines to computer-based control systems. Int. J. Innov. Technol. Manag. (Singapore) 12(4), 1550014 (1550013 pp.)-1550014 (1550013 pp.). https://doi.org/10.1142/s0219877015500145

Fu, F., Ma, L.W., Li, Z., Polenske, K.R., 2014. The implications of China's investment-driven economy on its energy consumption and carbon emissions. Energy Conv. Manag. 85, 573-580. https://doi.org/10.1016/j.enconman.2014.05.046

Fu, J., Huang, J., 2010. Preliminary analysis on potential development of construction business with low-carbon economy in cold regions based on the full life-cycle theory: A case study on Changchun City. Resources Science 32(3), 499-504. https://doi.org/10.1097/ICO.0b013e3182000add

Gao, X.J., 2012. The Life Cycle Routes for the Green Residential Buildings in China's Low-carbon City Background, in: Pan, W., Ren, J.X., Li, Y.G. (Eds.), Renewable and Sustainable Energy, Pts 1-7. Trans Tech Publications Ltd, Stafa-Zurich, pp. 1387-1390. https://doi.org/10.4028/www.scientific.net/AMR.347-353.1387

Ge, Z.-b., Zhang, J.-b., Li, D.-z., Zhang, X., 2010. Eco-efficiency evaluation of construction industry in China: A data envelopment analysis approach. Journal of Qingdao Technological University 31(5), 95-100.

Hossain, M.U., Poon, C.S., 2018. Global warming potential and energy consumption of temporary works in building construction: A case study in Hong Kong. Building and Environment 142, 171-179. https://doi.org/10.1016/j.buildenv.2018.06.026

Hu, X.C., Liu, C.L., 2018. Measuring efficiency, effectiveness and overall performance in the Chinese construction industry. Engineering Construction and Architectural Management 25(6), 780-797. https://doi.org/10.1108/ecam-06-2016-0131

Huang, J., Yang, X., Cheng, G., Wang, S., 2014. A comprehensive eco-efficiency model and dynamics of regional eco-efficiency in China. J. Clean Prod. 67, 228-238. https://doi.org/10.1016/j.jclepro.2013.12.003

Huo, T., Ren, H., Cai, W., Feng, W., Tang, M., Zhou, N., 2018. The total-factor energy productivity growth of China's construction industry: evidence from the regional level. Natural Hazards 92(3), 1593-1616. https://doi.org/10.1007/s11069-018-3269-0

Javed, A.A., Wei, P., Le, C., Wenting, Z., 2018. A systemic exploration of drivers for and constraints on construction productivity enhancement. Built Environ. Proj. Asset Manag. (UK) 8(3), 239-252. https://doi.org/10.1108/bepam-10-2017-0099

Karagiannis, R., 2015. A system-of-equations two-stage DEA approach for explaining capacity utilization and technical efficiency. Ann. Oper. Res. 227(1), 25-43. https://doi.org/10.1007/s10479-013-1367-7

Kirkley, K., Morrison P. C., Squires, D., 2002. Capacity and capacity utilization in com- mon-pool resource industries. Environ Resour Econ 22, 71-97. https://doi.org/10.1023/a:1015511232039

Klein, L.R., Preston, R.S., 1967. Some new results in the measurement of capacity utilization. American Economic Review 3, 34-58. https://doi.rg/ 10.1007/BF01316537

Klein, R., 1960. Some theoretical issues in the measurement of capacity. Econometrica 28(2). https://doi.org/10.2307/1907721

Kuosmanen, T., 2005. Weak disposability in nonparametric production with undesirable outputs. Am J Agric Econ 87(4), 1077-1082.https://doi.org/ 10.2307/3697791

Li, Q., Song, Y., 2012. Productivity Growth in Chinese Construction Industry Considering Solid Wastes Generation, in: Chen, W.Z., Xu, X.P., Dai, P.Q., Chen, Y.L. (Eds.), Advanced Manufacturing Technology, Pts 1-4. pp. 3316-3319. https://doi.org/10.4028/www.scientific.net/AMR.472-475.3316

Li, Y., Feng, Q., 2018. General green building energy efficiency. Applied Mechanics and Materials 878, 236-242. https://doi.org/10.4028/www.scientific.net/AMM.878.236

Liao, L.H., Li, X.D., Huo, C.T., Chen, Q., 2012. Empirical Research on Production Efficiency of Construction Industry in Central China Based on DEA. China Architecture & Building Press, Beijing. https://doi.org/10.14181/j.cnki.1002-851x.2011.12.001

Lin, B.Q., Liu, H.X., 2015. CO2 mitigation potential in China's building construction industry: A comparison of energy performance. Building and Environment 94, 239-251. https://doi.org/10.1016/j.buildenv.2015.08.013

Lin, C., Wang, Y., Wu, Y., 2003. Application of DEA method in evaluating ranking-Research on the productive efficiency ranking of Guangdong's construction industry in China. Journal of Jinan University 24(1), 26-30. https://doi.org/10.3969/j.issn.1000-9965.2003.01.006

Lindebo, E., Hoff, A., Vestergaard, N., 2007. Revenue-based capacity utilisation measures and decomposition: The case of Danish North Sea trawlers. Eur. J. Oper. Res. (Netherlands) 180(1), 215-227. https://doi.org/10.1016/j.ejor.2006.03.050

Liu, L., 2011. Capacity utilization, investment and consumer demand: Evidence from 28 manufacturing industries using PVAR. 2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC 2011), 5475-5478. https://doi.org/10.1109/aimsec.2011.6009812

Liu, S.G., Song, X.D., 2013. Efficiency Evaluation on Construction Industrial Circular Economy based on Improved DEA Model, in: Tan, D.Y. (Ed.) Proceedings Of The 2013 International Conference On Advanced ICT and Education. Atlantis Press, Paris, pp. 838-843. https://doi.org/10.2991/icaicte.2013.167

Liu, Y.S., Zhao, X.F., Liao, Y.P., 2013. Market Structure, Ownership Structure, and Performance of China's Construction Industry. Journal of Construction Engineering and Management 139(7), 852-857. https://doi.org/10.1061/(asce)co.1943-7862.0000656

Lu, J., Zhang, R., Hu, K., 2015. Analysis of low carbon behavior efficiency in China's construction industry. Engineering Journal of Wuhan University 48(6), 809-813. https://doi.org/10.14188/j.1671-8844.2015-06-013

Meng, Y.Z., Ling, T.C., Mo, K.H., 2018. Recycling of wastes for value-added applications in concrete blocks: An overview. Resources Conservation And Recycling 138, 298-312. https://doi.org/10.1016/j.resconrec.2018.07.029

Morozumi, S., Nakama, H., Inoue, N., 2008. Demonstration projects for grid-connection issues in Japan. Elektrotech. Inf.tech. (Austria) 125(12), 426-431. https://doi.org/10.1007/s00502-008-0594-0

Morrison, C.J., 1985. Primal and dual capacity utilization: An application to productivity measurement in the U.S. automobile industry. Journal of Business & Economics Statistics 10, 312-324. https://doi.org/ 10.1080/07350015.1985.10509463

NBS, 2012-2018. China Statistical Yearbook—2012-2018, Chinese statistics. China Statistics Press.

NBSMEP, 2012-2018. China Energy Statistical Yearbook—2012-2018. China Statistics Press.

Nightingale, P., Poll, R., 2000. Innovation in Services: The Dynamics of Control Systems in Investment Banking, in: Metcalfe, J.S., Miles, I. (Eds.), Innovation Systems in the Service Economy: Measurement and Case Study Analysis. Springer US, Boston, MA, pp. 247-269. https://doi.org/10.1007/978-1-4615-4425-8_12

Pan, W., Chen, L., Zhan, W.T., 2019. PESTEL Analysis of construction productivity enhancement strategies: A case study of three economies. J. Manage. Eng. 35(1), 15. https://doi.org/10.1061/(asce)me.1943-5479.0000662

Perry, G.L., 1973. Capacity in Manufacturing. Brookings Papers on Economic Activity 4, 701-742. https://doi.org/10.2307/2534205

Phillips, A., 1963. An appraisal of measures of capacity. American Economic Review 53, 275-292. https://www.jstor.org/stable/1823871

Ran, L., Zhai, F., Wang, H., Wang, W., 2012. Analysis of added value increasing resulted from production factors in Chinese construction industry. Journal of Harbin Institute of Technology 44(5), 111-115.

Roger, B., Miguel, K., 1995. Are financial variables inputs in delivered production functions? Revista de Análisis Económico(RAE) 10(1), 22-27.

Shephard, R.W., 1974. Indirect Production Functions. Mathematical systems in eco- nomics 10. Meisenheim am Glad: Anton Hain. https://doi.org/10.2307/3438928

Song, D., 2017. Entering new era and establishing new prosperity. Bulletin of the Chinese Academy of Sciences 32(3), 228-232. https://doi.org/10.16418/j.issn.1000-3045.2017.03.002

Song, M.L., Wang, S.H., Yu, H.Y., Yang, L., Wu, J., 2011. To reduce energy consumption and to maintain rapid economic growth: Analysis of the condition in China based on expended IPAT model. Renew. Sust. Energ. Rev. 15(9), 5129-5134. https://doi.org/10.1016/j.rser.2011.07.043

Song, Y., Shuang, Y., Jin-gui, J., 2016. The research of capacity utilization measurement on manufacturing industry in China. 2016 International Conference on Management Science and Engineering (ICMSE), 160-166. https://doi.org/10.1109/icmse.2016.8365434

Staub-French, S., Nepal, M.P., 2007. Reasoning about component similarity in building product models from the construction perspective. Autom. Constr. (Netherlands) 17(1), 11-21. https://doi.org/10.1016/j.autcon.2007.02.013

Tan, D., Wang, G., Cao, D., 2015. Growth characteristics and impacting factors of the total factor productivity in the construction industry. Journal of Tongji University. Natural Science 43(12), 1901-1907. https://doi.org/10.11908/j.issn.0253-374x.2015.12.021

Tsitsika, E.V., Maravelias, C.D., Wattage, P., Haralabous, J., 2008. Fishing capacity and capacity utilization of purse seiners using data envelopment analysis. Fisheries Science 74(4), 730-735. https://doi.org/10.1111/j.1444-2906.2008.01583.x

Wang, K., Wei, Y.M., 2014. China's regional industrial energy efficiency and carbon emissions abatement costs. Applied Energy 130, 617-631. https://doi.org/10.1016/j.apenergy.2014.03.010

Wang, X.F., Chen, L., Liu, C.G., Zhang, Y.Q., Li, K., 2019. Optimal production efficiency of Chinese coal enterprises under the background of de-capacity Investigation on the data of coal enterprises in Shandong Province. J. Clean Prod. 227, 355-365. https://doi.org/10.1016/j.jclepro.2019.04.191

Wells, J., 1984. The construction industry in the context of development: a new perspective. Habitat International 8（3/4), 9-28. https://doi.org/10.1016/0197-3975(84)90040-7

Wiser, R., Barbose, G., Holt, E., 2011. Supporting solar power in renewables portfolio standards: Experience from the United States. Energy Policy 39(7), 3894-3905. https://doi.org/10.1016/j.enpol.2010.11.025

Xue, X., Wu, H., Zhang, X., Dai, J., Su, C., 2015. Measuring energy consumption efficiency of the construction industry: the case of China. J. Clean Prod. 107, 509-515. https://doi.org/10.1016/j.jclepro.2014.04.082

Yan, J.N., Zhao, T., Lin, T., Li, Y.J., 2017. Investigating multi-regional cross-industrial linkage based on sustainability assessment and sensitivity analysis: A case of construction industry in China. J. Clean Prod. 142, 2911-2924. https://doi.org/10.1016/j.jclepro.2016.10.179

Yang, G.-l., Fukuyama, H., Song, Y.-y., 2018. Estimating capacity utilization of Chinese Manufacturing Industries. Socio-Economic Planning Sciences. https://doi.org/10.1016/j.omega.2017.05.003

Yang, G.L., Fukuyama, H., 2018. Measuring the Chinese regional production potential using a generalized capacity utilization indicator. Omega-International Journal of Management Science 76, 112-127. https://doi.org/10.1016/j.seps.2018.10.004

Zhang, H., Minghua, H.U., Chen, S., 2009. Collaborative optimization of capacity utilization and flow assignment in airport terminal area. Journal of Southwest Jiaotong University 44(1), 128-134. https://doi.org/10.1016/S1874-8651(10)60073-7

Zhang, J.X., Li, H., Xia, B., Skitmore, M., 2018. Impact of environment regulation on the efficiency of regional construction industry: A 3-stage Data Envelopment Analysis (DEA). J. Clean Prod. 200, 770-780. https://doi.org/10.1016/j.jclepro.2018.07.189

Zhang, N., Choi, Y., 2013. Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis. The Social Science Journal 50(2). https://doi.org/10.1016/j.soscij.2013.01.003

Zhang, Y.F., Nie, R., Shi, R.Y., Zhang, M., 2018. Measuring the capacity utilization of the coal sector and its decoupling with economic growth in China's supply-side reform. Resources Conservation And Recycling 129, 314-325. https://doi.org/10.1016/j.resconrec.2016.09.022

Zhao, L.F., Gu, Q.L., 2009. Globalization and industrial upgrading: A case of China apparel industry. Publishing House Electronics Industry, Beijing.

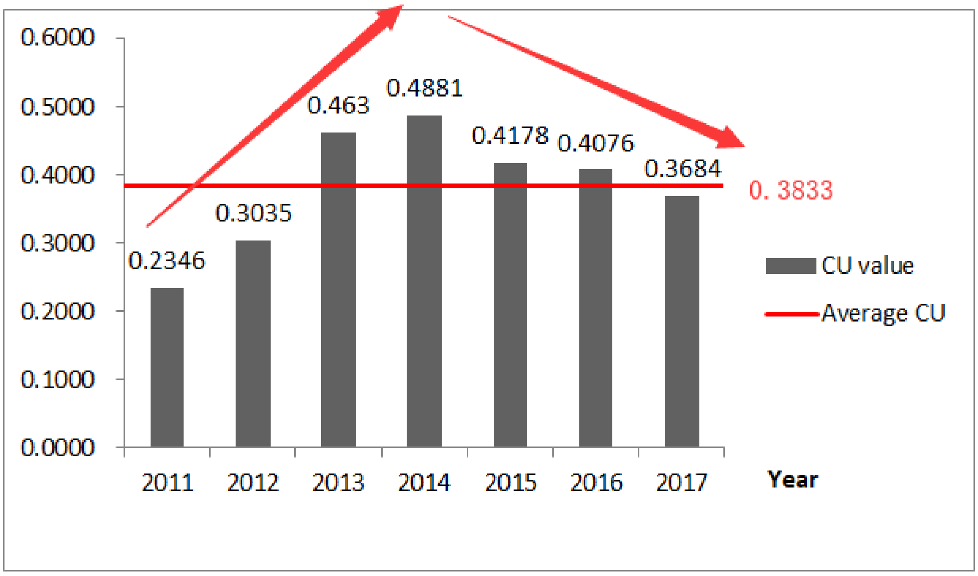
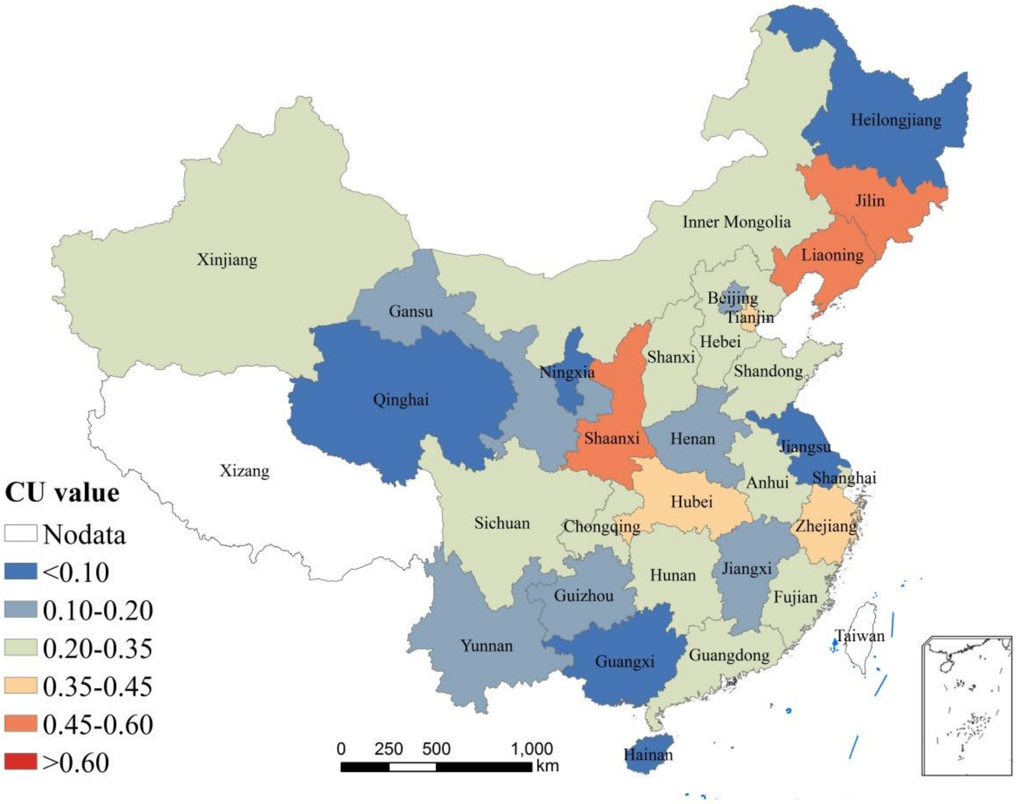
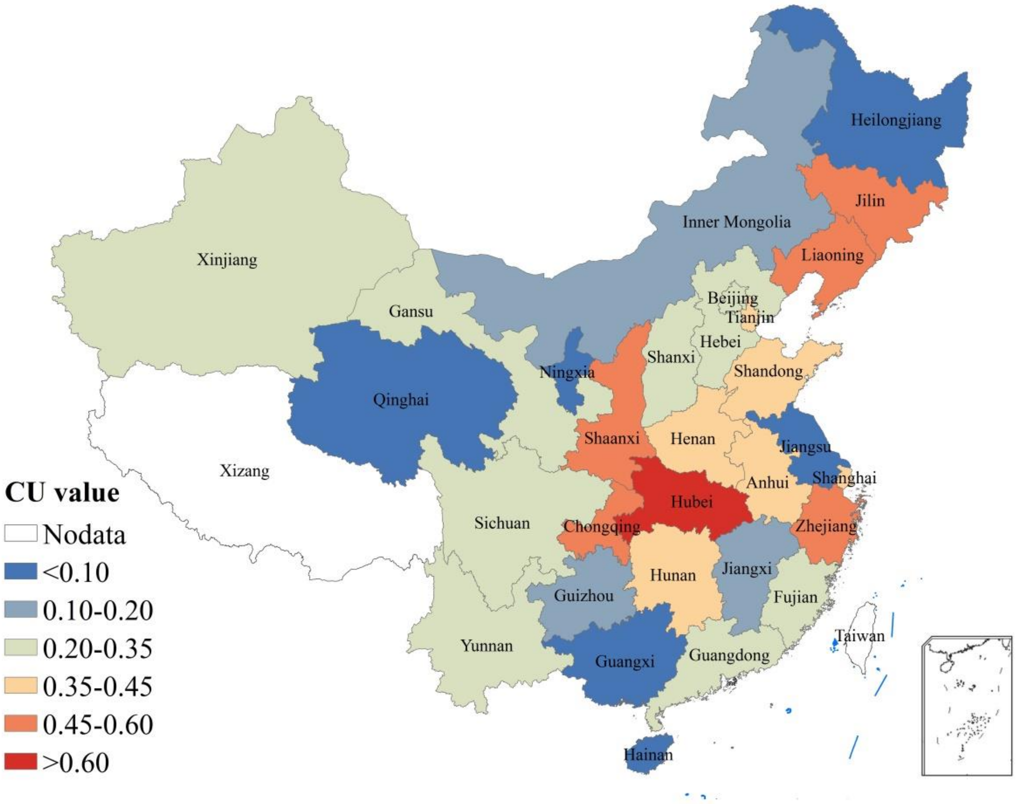


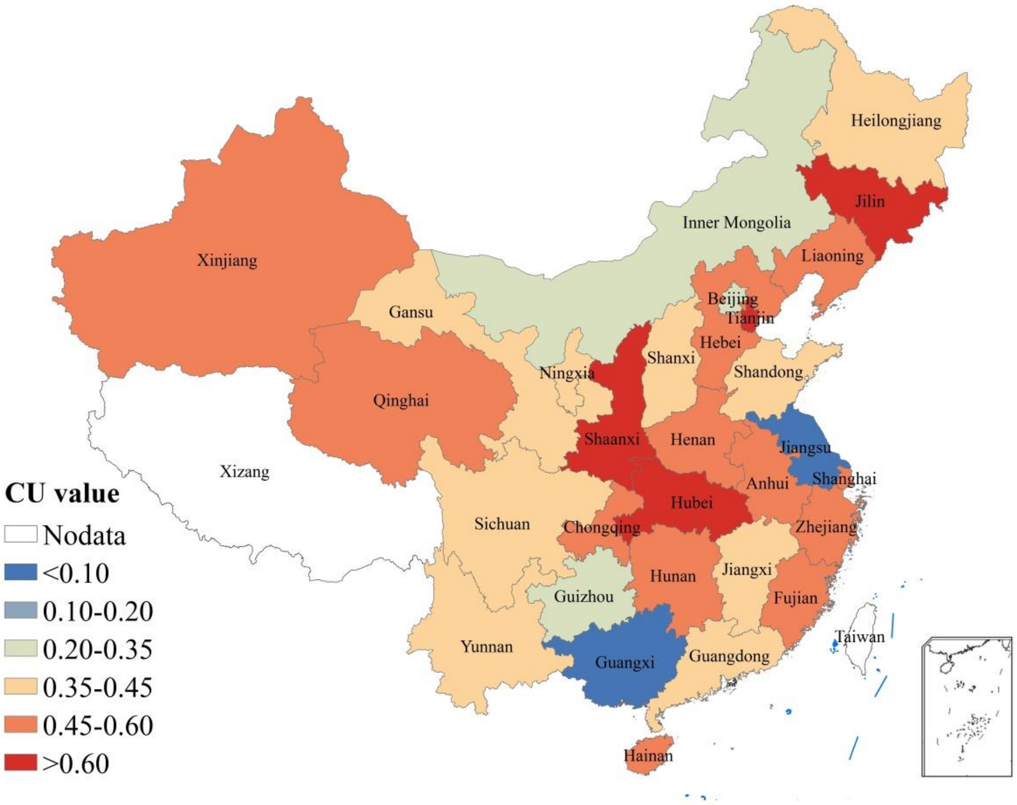
Figure 1. 2011-2017 average construction industry CUs


Heilongjiang
Jilin
Inner Mongolia
Liaoning
Xinjiang
Beijing
Tianjin
Gansu
Hebei
Shanxi
Ningxia
Shandong
Qinghai
Shaanxi
Henan
Jiangsu
Xizang
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Taiwan
Yunnan
Guangxi
Guangdong
Hainan
CU value
Nodata
<0.10
0.10-0.20
0.20-0.35
0.35-0.45
0.45-0.60
>0.60
0 250 500 1,000 km

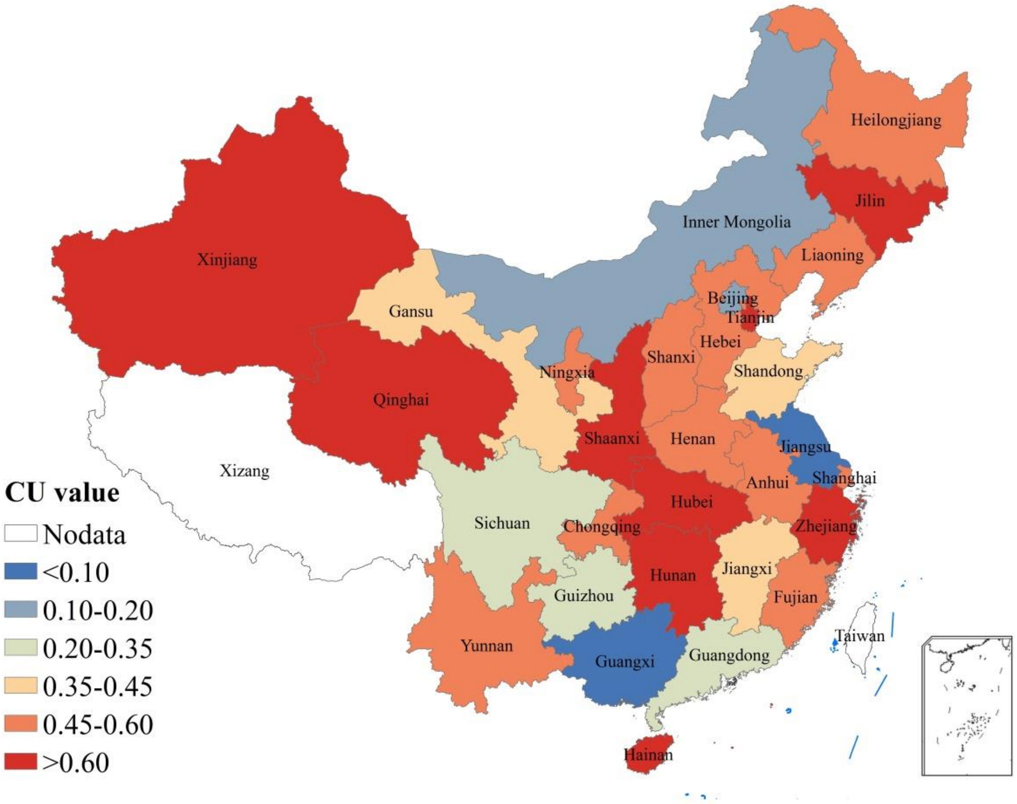
(2011)


Heilongjiang
Jilin
Inner Mongolia
Liaoning
Xinjiang
Beijing
Tianjin
Gansu
Hebei
Shanxi
Ningxia
Shandong
Qinghai
Shaanxi
Henan
Jiangsu
Xizang
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Taiwan
Yunnan
Guangxi
Guangdong
Hainan
CU value
Nodata
<0.10
0.10-0.20
0.20-0.35
0.35-0.45
0.45-0.60
>0.60

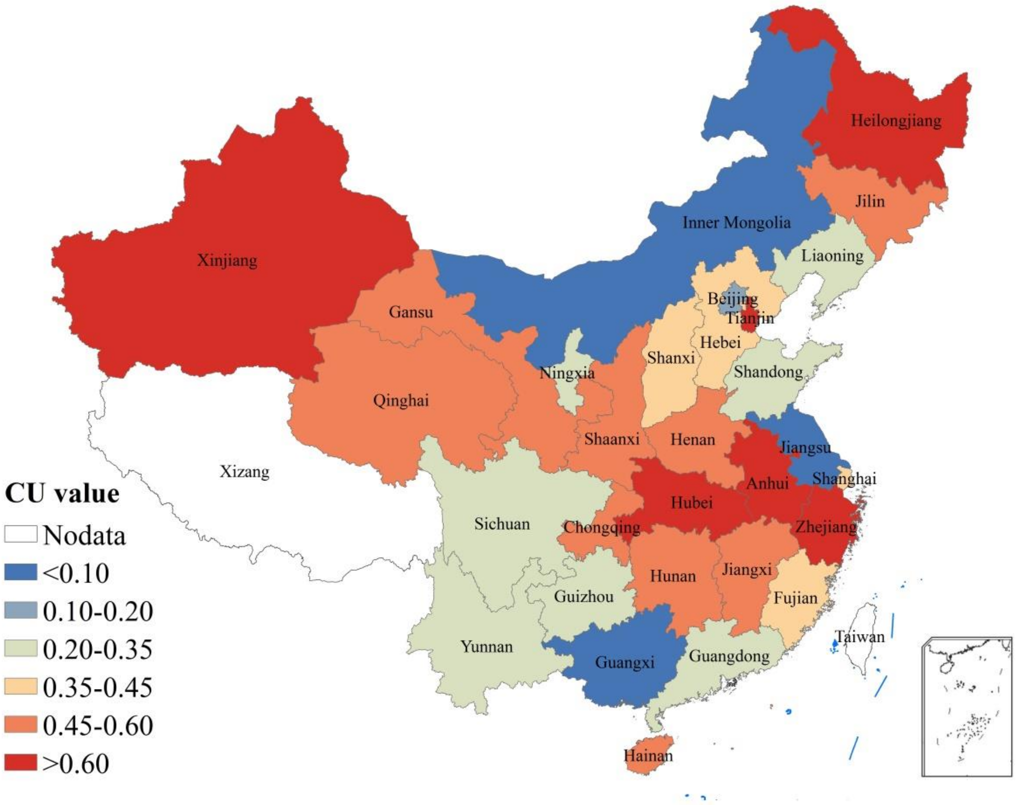
(2012)


Heilongjiang
Jilin
Inner Mongolia
Liaoning
Xinjiang
Gansu
Beijing
Tianjin
Hebei
Shanxi
Shandong
Ningxia
Qinghai
Shaanxi
Henan
Jiangsu
Xizang
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Taiwan
Yunnan
Guangxi
Guangdong
Hainan
CU value
Nodata
<0.10
0.10-0.20
0.20-0.35
0.35-0.45
0.45-0.60
>0.60

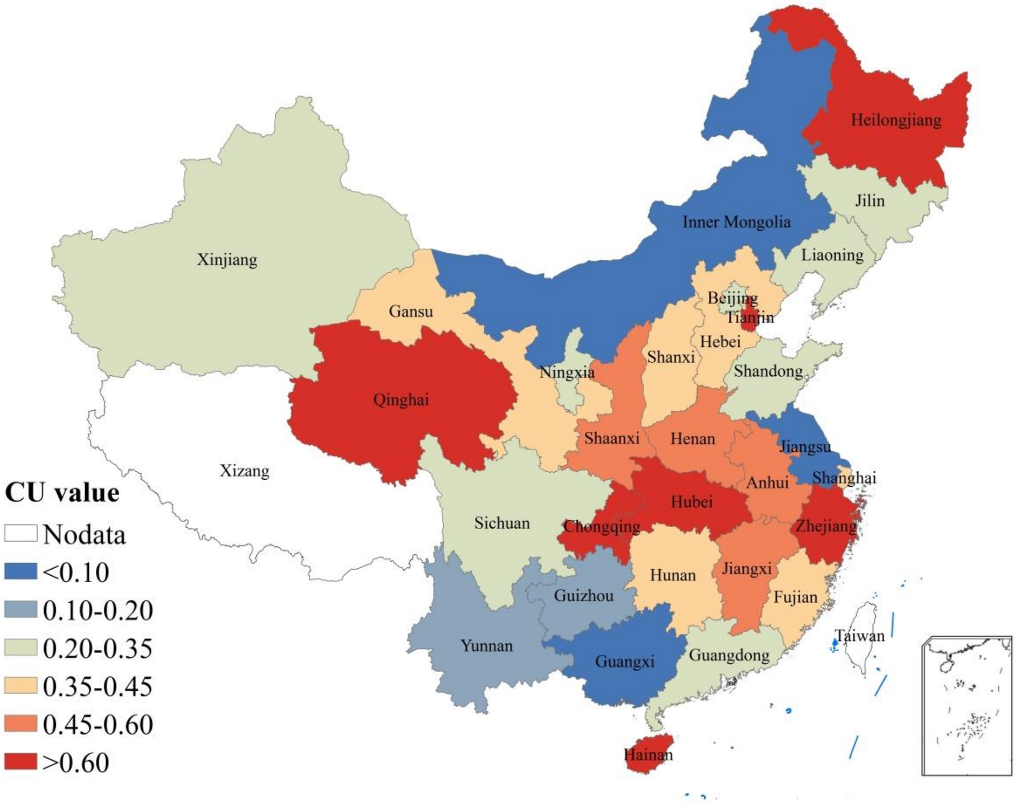
(2013)


Heilongjiang
Jilin
Inner Mongolia
Liaoning
Xinjiang
Gansu
Beijing
Tianjin
Hebei
Shanxi
Shandong
Ningxia
Qinghai
Shaanxi
Henan
Jiangsu
Xizang
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Taiwan
Yunnan
Guangxi
Guangdong
Hainan
CU value
Nodata
<0.10
0.10-0.20
0.20-0.35
0.35-0.45
0.45-0.60
>0.60

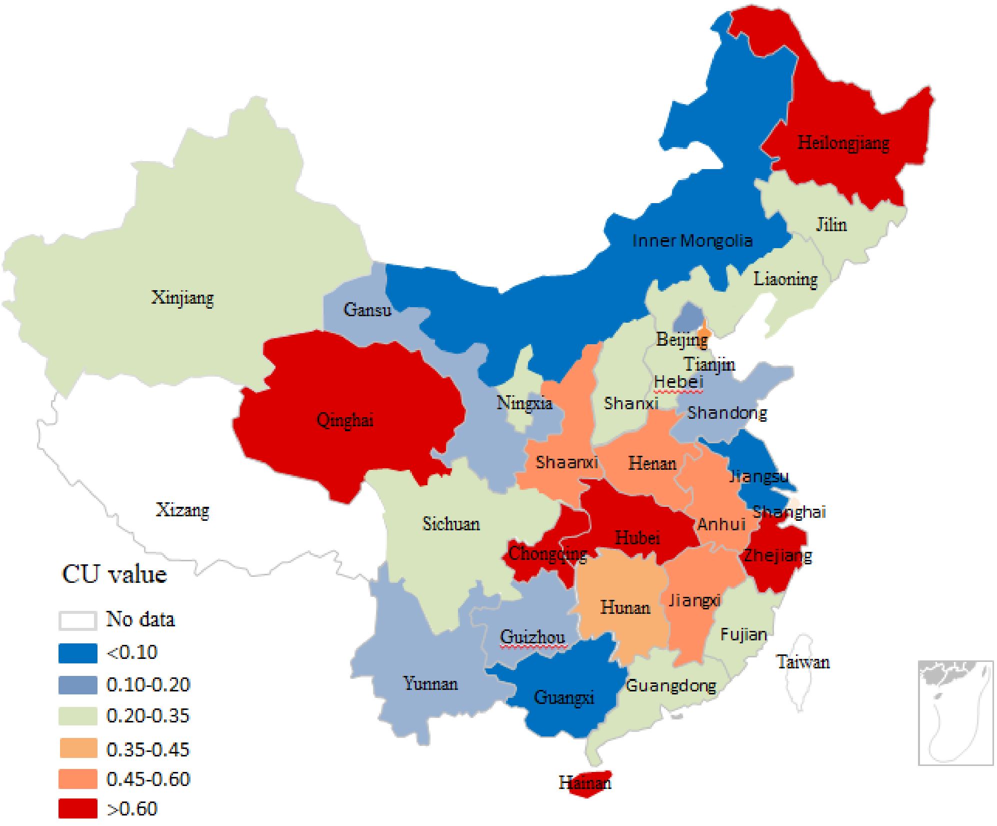
(2014)


Heilongjiang
Jilin
Inner Mongolia
Liaoning
Xinjiang
Gansu
Beijing
Tianjin
Hebei
Shanxi
Ningxia
Shandong
Qinghai
Shaanxi
Henan
Jiangsu
Xizang
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Taiwan
Yunnan
Guangxi
Guangdong
Hainan
CU value
Nodata
<0.10
0.10-0.20
0.20-0.35
0.35-0.45
0.45-0.60
>0.60

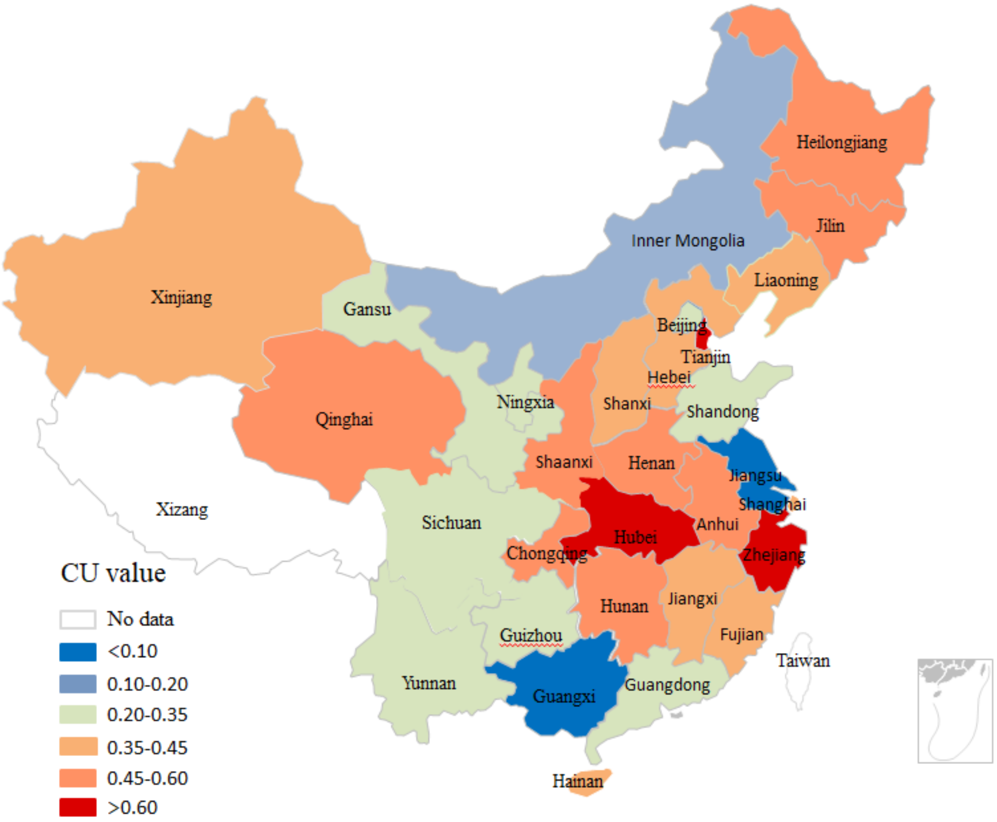
(2015)


Heilongjiang
Jilin
Inner Mongolia
Liaoning
Xinjiang
Gansu
Beijing
Tianjin
Hebei
Shanxi
Ningxia
Shandong
Qinghai
Shaanxi
Henan
Jiangsu
Xizang
Anhui
Shanghai
Hubei
Sichuan
Chongqing
Zhejiang
Hunan
Jiangxi
Guizhou
Fujian
Taiwan
Yunnan
Guangxi
Guangdong
Hainan
CU value
Nodata
<0.10
0.10-0.20
0.20-0.35
0.35-0.45
0.45-0.60
>0.60

(2016)



(2017)



(CU average during 2011-2017)

Figure 2. 2011-2017 provincial and city construction industry CU and average CU distribution

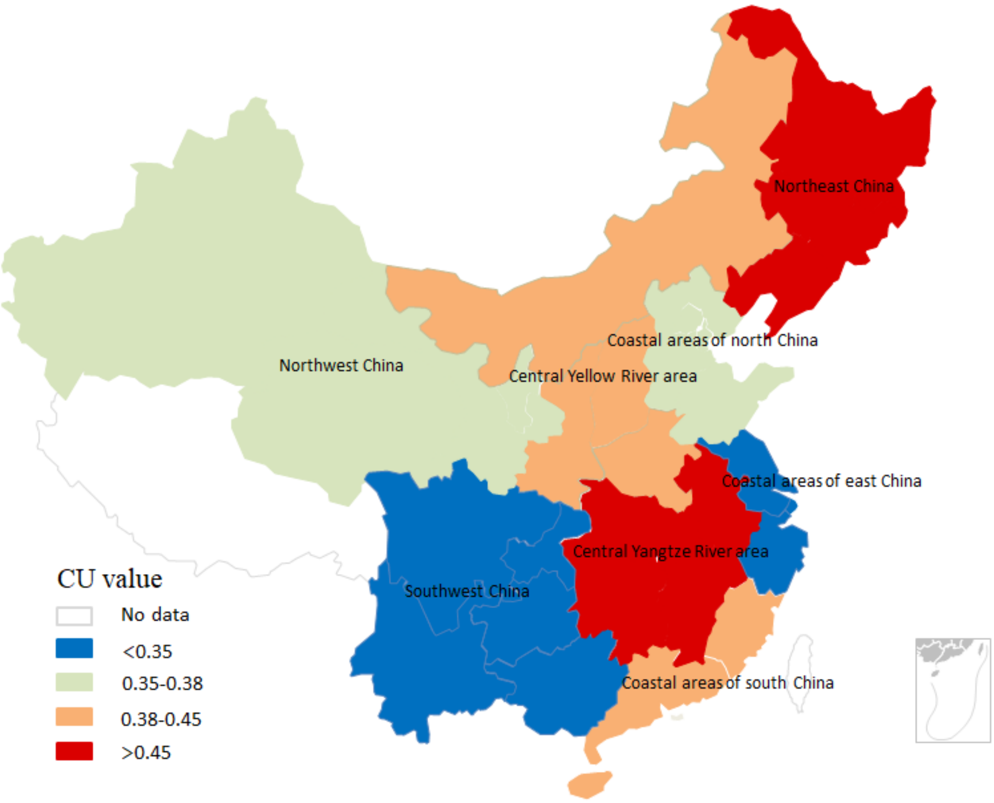
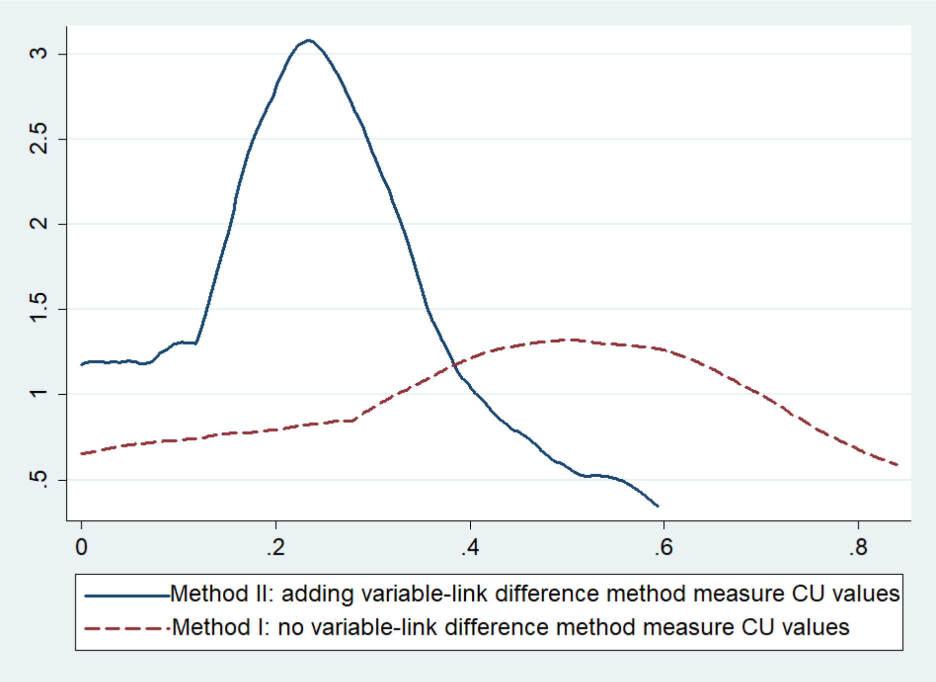
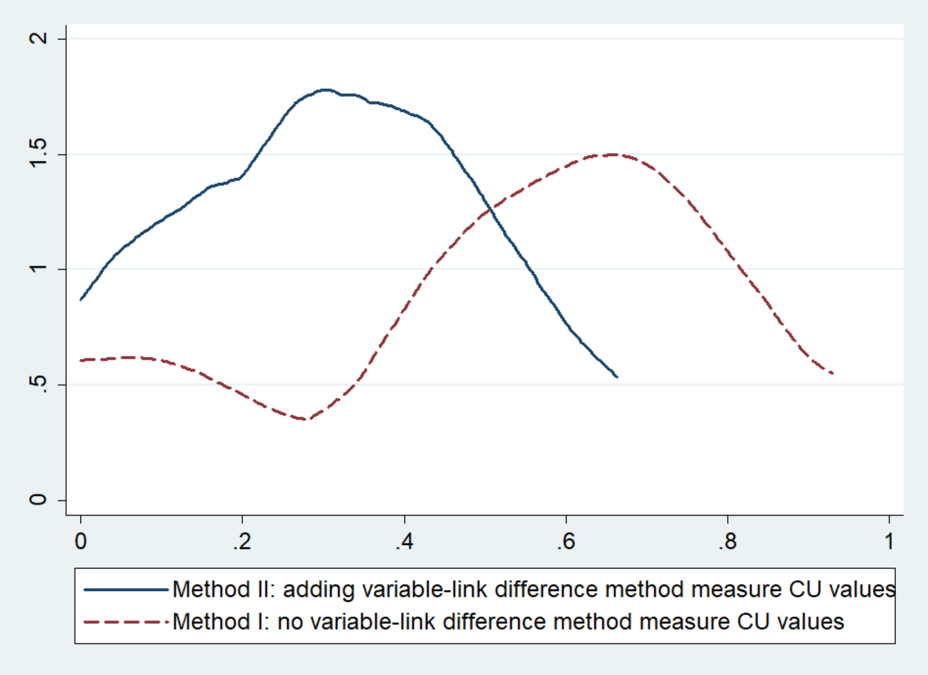


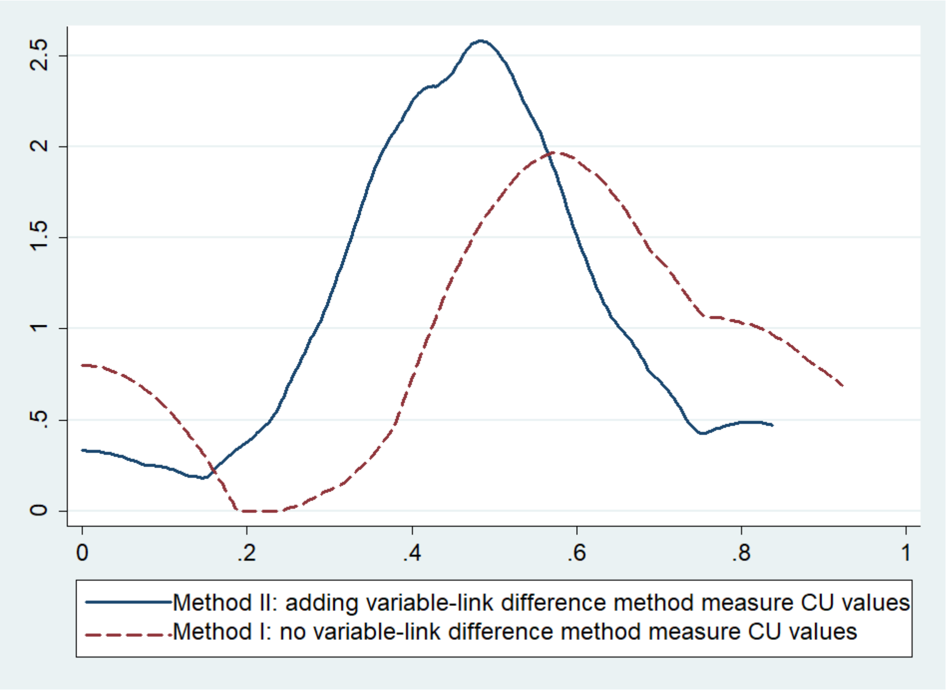
Figure 3. 2011-2017 average CU distribution in eight regions


3
2.5
2
1.5
1
.5
0
.2
.4
.6
.8
Method II: adding variable-link difference method measure CU values
Method I: no variable-link difference method measure CU values

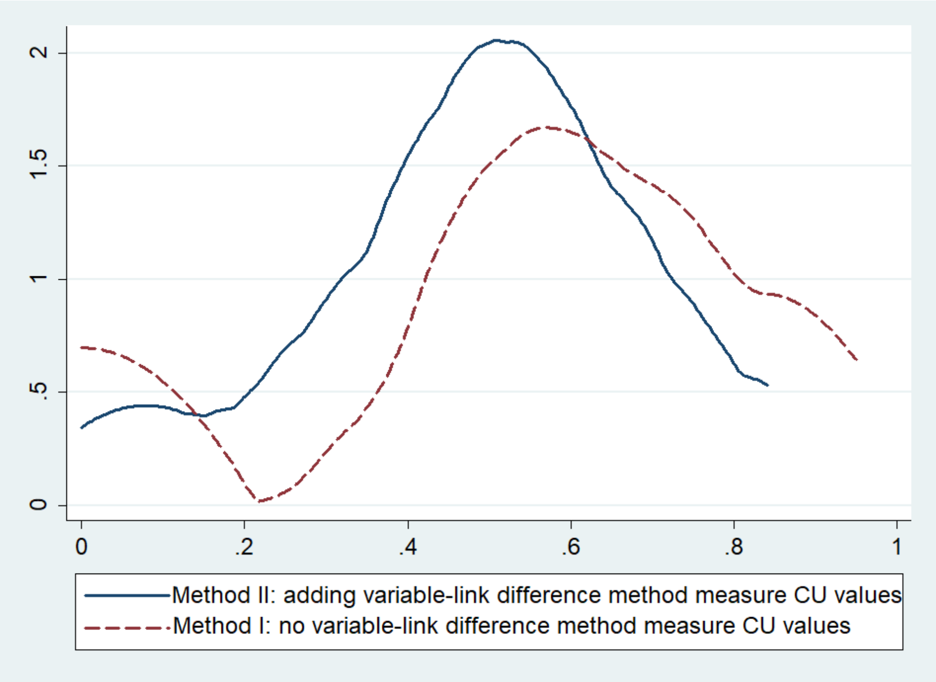
(2011)


2
1.5
1
.5
0
0
.2
.4
.6
.8
1
Method II: adding variable-link difference method measure CU values
Method I: no variable-link difference method measure CU values

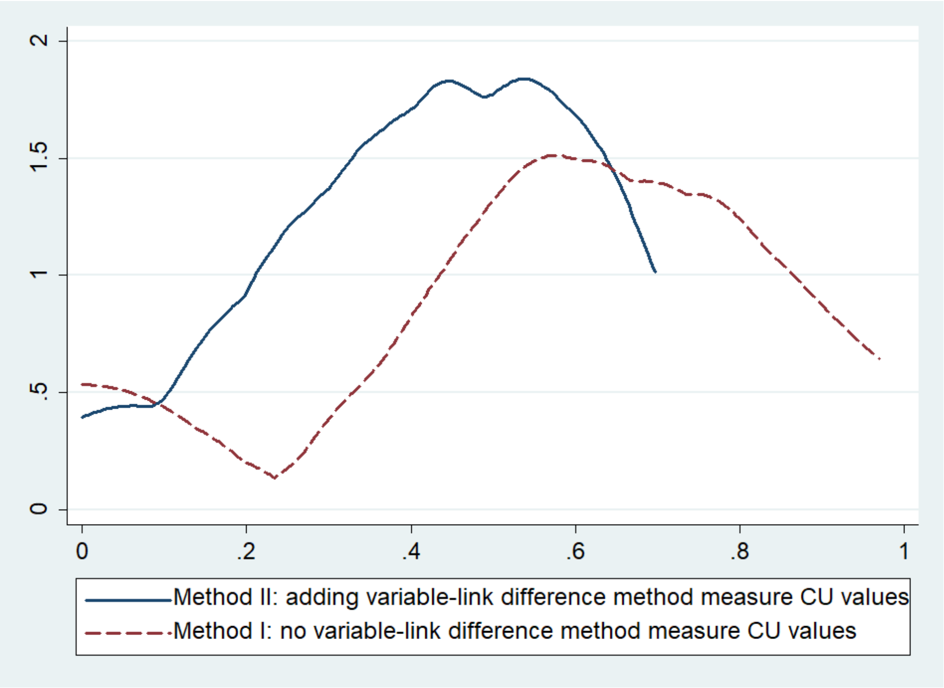
(2012)


0
.5
1
1.5
2
2.5
0
.2
.4
.6
.8
1
Method II: adding variable-link difference method measure CU values
Method I: no variable-link difference method measure CU values

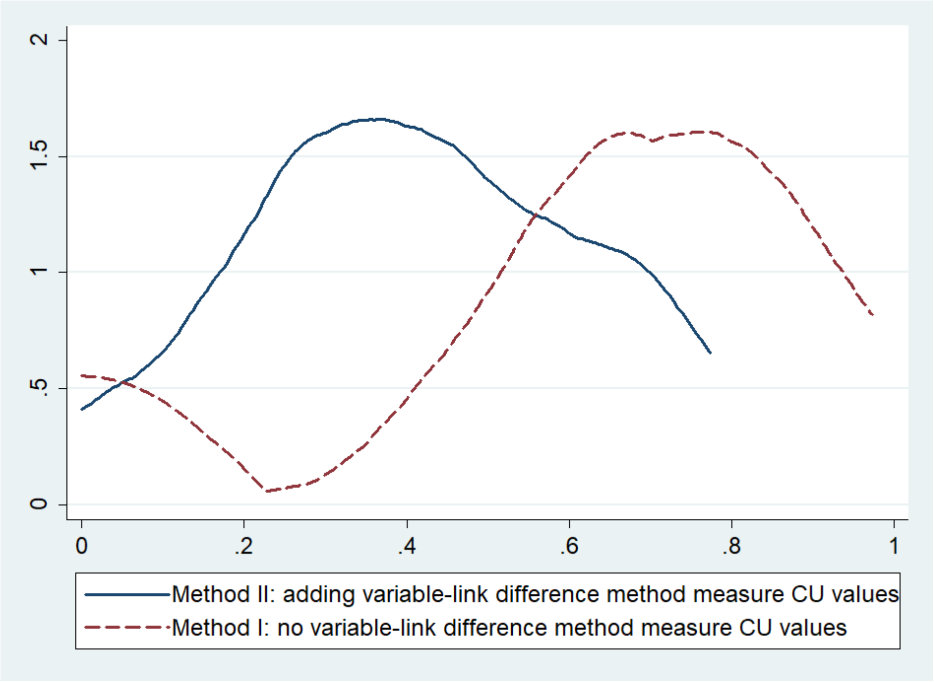
(2013)


0
.5
1
1.5
2
0
.2
.4
.6
.8
1
Method II: adding variable-link difference method measure CU values
Method I: no variable-link difference method measure CU values

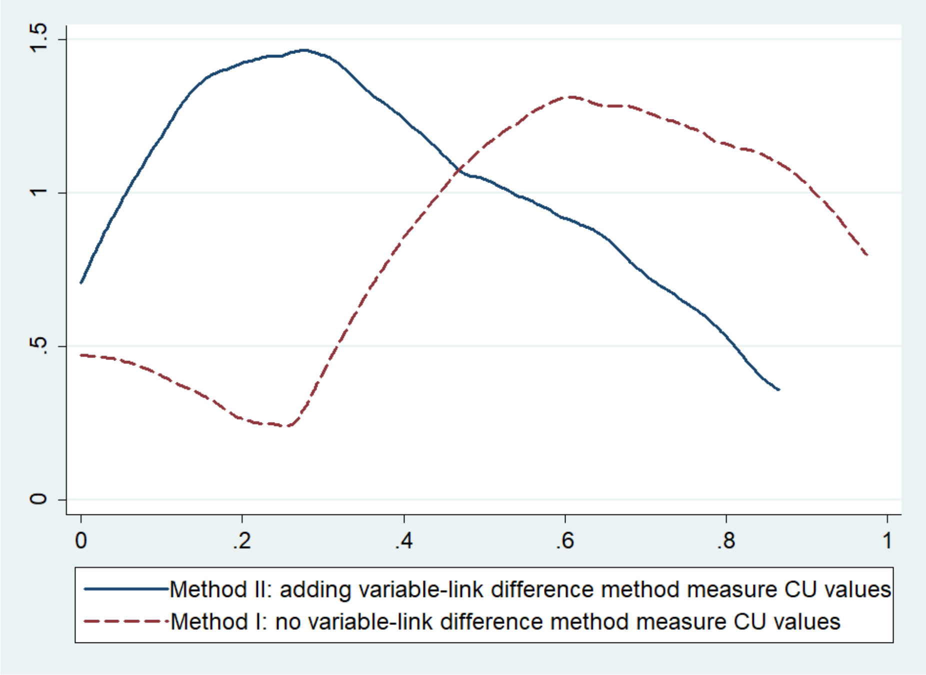
(2014)


0
.5
1
1.5
2
0
.2
.4
.6
.8
1
Method II: adding variable-link difference method measure CU values
Method I: no variable-link difference method measure CU values

(2015)


0
.5
1
1.5
2
0
.2
.4
.6
.8
1
Method II: adding variable-link difference method measure CU values
Method I: no variable-link difference method measure CU values

(2016)



(2017)

Figure 4. Comparison of the adding variable-link difference method and no variable-link difference method in measuring CU

Table 1.

Input and output variables of Chinese regions obtained from the literature review

Reference	DMUs	Major issues addressed	Variables	
			Inputs	Outputs
(Zhang et al., 2018)	Chinese provinces and cities	The impact of environmental regulation on regional construction efficiency	(1) Energy consumption of the construction industry, (2) number of engaged persons, (3) total wages of construction workers, (4) total assets of the construction industry, (5) total power of machinery and equipment	(1) Engineering settlement profits, (2) floor space of buildings under construction, (3) gross output value of construction, (4) total profits of the construction industry, (5) co$_2$ emissions
(Yang and Fukuyama, 2018)	Chinese regions	Chinese regional production potential	(1) Built-up area, (2) total number of employees, (3) capital stock, (4)energy consumption, (5) total water usage	(1) Industrial solid wastes produced, (2) industrial waste gas emissions, (3) industrial wastewater discharge, (4) urban green area, (5) gross domestic product
(Xue et al., 2015)	Chinese regions	Energy consumption productivity change of the construction industry	(1) Coal consumption, (2) electricity consumption	(1) Industrial value added.
(Huo et al., 2018)	Chinese regions	Energy productivity of construction industry	(1) Labor force, (2) total assets of construction enterprises, (3) total capacity of machinery and equipment owned, (4) energy	(1) Gross output value in construction industry, (2) the floor space of buildings under construction.
(Chancellor and Lu, 2016)	Chinese regions	Estimate construction productivity and efficiency	(1) Number of construction workers and staff at year-end, (2) paid up total capital (3) total assets, (4) total power of machinery and equipment owned.	(1) Total floor space of buildings completed (2) total output value of construction.
(Feng and Wang, 2017)	Chinese regions	Energy efficiency of China's Regional building industry	(1) Labor force, (2) capital, (3) energy consumption	(1) Industrial output (2) CO_2 emissions.
(Li and Song, 2012)	Chinese regions	The productivity growth of the construction industry	(1) Labor force, (2) asset of construction enterprises,	(1) The value added to the construction industry, (2) total solid waste in construction industry.

(Bian et al., 2015)	Chinese regions	The efficiency of Chinese regional industrial systems	(1) Fixed assets, (2) labor (3) energy consumption, (4) industrial pollution abatement investment	(1) GDP, (2) COD (chemical oxygen demand), (3) SO_2 emissions, (4) ammonia nitrogen, (5) output value of products made from comprehensive utilization of industrial waste
(Du et al., 2018)	Chinese regions	Environmental Productivity Performance in China	(1) Energy consumption, (2) labor force,(3) fixed investment	(1) GDP, (2) SO_2 emissions,(3) industrial waste water, (4) CO_2 emissions, (5) industrial dust
(Zhang and Choi, 2013)	Chinese regions	Environmental energy efficiency of China's regional economies	(1) Capital, (2) labor input, (3) energy consumption	(1) GDP, (2) SO_2 emissions, (3) COD, (4) CO_2 emissions
(Huang et al., 2014)	Chinese regions	Regional eco-efficiency in China	(1) Capital, (2) labor input, (3) Land input, (4) energy.	(1) GDP, (2) environmental pollutants

Table 2.

Identified input and output variables

Variables	Types	Units	Reference
f_1 = Construction land	Fixed input	km^2	(Yang and Fukuyama, 2018)
v_1 =Number of staff and workers in construction enterprises	Variable input	10,000 persons	(Xue et al., 2015), (Huo et al., 2018), (Chancellor and Lu, 2016), (Feng and Wang, 2017), and (Li and Song, 2012)
v_2=Assets of construction enterprises	Variable input	CNY 100 million	(Zhang, J.X. et al., 2018), (Huo et al., 2018), and (Chancellor and Lu, 2016)
v_3 =Total power of machinery and equipment owned by construction enterprises	Variable input	10,000 kw	(Huo et al., 2018) and (Chancellor and Lu, 2016)
v_1^u =Terminal energy consumption of the construction industry	Linked variable input	10,000 tons	(Feng and Wang, 2017), (Bian et al., 2015), and (Du et al., 2018)
u_1^v =CO_2 emissions from the construction industry	Linked undesirable output	10,000 tons	(Feng and Wang, 2017), (Du et al., 2018), and (Zhang and Choi, 2013)
d_1 = Total output value of construction enterprises	Desirable output	CNY 100 million	(Zhang, J.X. et al., 2018) and (Huo et al., 2018)
d_2 = Total profits of construction enterprises	Desirable output	CNY 100 million	(Zhang, J.X. et al., 2018) and (Li and Song, 2012)

Notes:

f_1 = Construction land. This is the land provided for various construction works. It includes not only urban and rural residential and public facilities land, but also land used for manufacturing and mining, energy, transportation, water conservancy, communications, and other infrastructure development purposes.

v_1 = Number of staff and workers in construction enterprises. This is the total number of registered personnel in the construction industry at the end of each year, which comprises both administrative staff and construction workers. The total number of employees is from state-owned, collective capital investment, Hong Kong-, Macao, and Taiwanese-investment, and foreign-investment enterprises.

v_2 = Assets of construction enterprises. This includes fixed assets in the construction industry, as well as current assets and ongoing construction projects, and is the sum of the construction industry’s assets, including the state-owned, collective capital investment, Hong Kong, Macao, and Taiwanese-investment, and foreign-investment enterprises. The corresponding data are from the China Statistical Yearbook (NBS, 2012-2018).

v_3 = Total power of machinery and equipment owned by construction enterprises. This is the sum of the power in the construction industry's own production and transportation equipment, and construction machinery–reflecting the technical equipment in the construction industry.

v_1^u = Terminal energy consumption of the construction industry. This is the amount of energy consumed in the construction industry after deducting the consumption and loss of secondary energy for processing.

$u_1^v =$ CO_2 emissions from the construction industry. CO_2 emissions, as an unpaid environmental cost, is an indicator of undesirable output. The basic formula for calculating the emissions from the construction industry's energy consumption is $CO_2 = \sum_{i=1}^{n} Ei \times NCVi \times CEFi \times COFi \times (44/12)$, which is derived from the IPCC issued by the country Greenhouse Gas IPCC Guidelines. Of these, the terminal consumption of the i^{th} energy source and the average low-level calorific value of the i^{th} energy source are represented by Ei and NCVi, respectively, the carbon emission factor and the carbon oxidation rate are represented by CEFi and COFi, respectively, with a carbon conversion coefficient of 44/12. The CO_2 emissions of each energy source can be calculated as shown in Appendix Table 4.

$d_1 =$ Total output value of the construction enterprises. This refers to the sum of the value of civil engineering and building construction architectural decoration, construction, and installation work of China's construction industry. It is also the sum of the construction industry products that provide services and production over a certain period, reflecting the total economic income of the industry.

Table 3. 2011-2017 average regional construction industry CU

No.	Regional division	Provinces	Average CU							Average	
			2011	2012	2013	2014	2015	2016	2017	Value	Rank
1	Coastal areas of north China	Tianjin, Shandong, Hebei, Beijing	0.2600	0.3614	0.4856	0.4751	0.3765	0.3791	0.2886	0.3752	6
2	Northeast China	Heilongjiang, Jilin, Liaoning	0.3721	0.3846	0.6085	0.6308	0.4688	0.4384	0.4319	0.4764	2
3	Northwest China	Ningxia, Gansu, Xinjiang, Qinghai	0.1285	0.1448	0.4508	0.5554	0.5274	0.4464	0.3869	0.3772	5
4	Central Yangtze River area	Hubei, Jiangxi, Anhui, Hunan	0.2899	0.4010	0.5774	0.6394	0.5702	0.5291	0.5322	0.5056	1
5	Central Yellow River area	Henan, Inner Mongolia, Shaanxi, Shanxi	0.2736	0.3579	0.4520	0.4736	0.3822	0.3916	0.3300	0.3801	4
6	Coastal areas of east China	Zhejiang, Jiangsu, Shanghai	0.2245	0.3187	0.3553	0.3688	0.3487	0.3960	0.4004	0.3446	7
7	Southwest China	Sichuan, Yunnan, Guangxi, Guizhou, Chongqing	0.1864	0.2556	0.3389	0.3295	0.2765	0.2683	0.2244	0.2685	8
8	Coastal areas of south China	Hainan, Guangdong, Fujian	0.1696	0.2192	0.4804	0.4742	0.4248	0.4666	0.4276	0.3803	3