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Authors: Jingxiao Zhang[1], Yuhuan Zhang[1], Simon P. Philbin[2], Pablo Ballesteros-Pérez[3], You Ouyang[1], Jiawei Cheng[1]

Affiliations: [1]School of Economics and Management, Chang'an University, Shaanxi Xian, P.R. China, 710061. [2]Nathu Puri Institute for Engineering and Enterprise, London South Bank University, 103 Borough Road, London SE1 0AA, United Kingdom. [3]Dpto. de Ingeniería Mecánica y Diseño Industrial, Escuela Superior de Ingeniería. Universidad de Cádiz, Cádiz, Spain.

Corresponding author: Jingxiao Zhang, School of Economics and Management, Chang'an University, Shaanxi Xian, P.R. China, 710061. Tel.: +86-159-2973-987

E-mail: zhangjingxiao@chd.edu.cn

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Abstract

The determination of whether market size can influence industrial agglomeration or selection is an important topic in economic development. To analyse the differential economic development of the construction industry under different market sizes, this research analyses the employment density of China's provinces and their Total factor productivity (TFP). It also analyses whether the difference in the provinces' productivity are explained by their agglomeration and selection effects. First, a DEA-Malmquist model is used to calculate the TFP of each construction industry sub-sector. Then, a nested model is used to measure the influence of the selection and the agglomeration effects on the TFP at different market sizes of the construction industry. Results evidence that there are significant differences in the construction productivity at different sub-sectors in different regions of China. These differences are mainly the consequence of the agglomeration effect, rather than the selection effect. Findings of this study suggest that the Chinese construction industry should optimise its structure in different provinces to achieve a balanced growth at different market sizes.

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Notation

Ei	energy terminal consumption
NCVi	energy average low calorific value
CEFi	energy carbon emission coefficient
COFi	energy carbon oxidation rate (%)
S_t	the production technology level in time period (t)
X_t	the input in time period (t)
Y_t	the output in time period (t)
M_c^t	the Malmquist TFP index
$d_c^t(X_t, Y_t)$	the ratio between the maximum possible output and the actual output of (X_t, Y_t) when the production technology in time period t is taken as a reference.
TFP	total factor productivity
q^0	the amount of standardized goods (usually agricultural products) consumed,
Ω	differentiation industrial goods collection
q^k	the consumption quantity of the kth differential industrial product
α	parameters and greater than zero
Γ	parameters and greater than zero
H	parameters and greater than zero
h	the manufacturer's marginal cost
P_j	average price of industrial products for consumption in region j
$p_{ij}(h)$	the selling price of a product with a marginal cost of h in region i to a single

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	consumer in region j
$q_{ij}(h)$	the demand for a single consumer of region j for the manufacturer's product with a marginal cost h of region i
S_i	the selection effect
A_i	the agglomeration effect
D_i	the dilation effect

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1. Introduction

The study of industrial agglomeration for different market sizes has been attracting recent research attention (Guo et al. 2020). Industrial agglomeration refers to the highly intensive clustering of a number of different types of enterprises producing a certain product within a certain region, as well as the upstream and downstream enterprises and related service industries supporting these enterprises. There is a tendency to attribute the production advantages of large cities to the impact of an agglomerated economy. Industrial agglomeration on a certain scale is conducive to the flow of human capital, knowledge and information spillover and infrastructure sharing. Related industries that are aggregated in a region, can improve their resource allocation efficiency, reduce production costs and obtain greater economic profits through the division of labour and cooperation among enterprises (Accetturo et al. 2018; Duranton and Puga 2003).

Similarly, according to studies on the industrial productivity of diverse market sizes, the selection effect also seems to condition the development of certain regions (Accetturo et al. 2018; Baldwin and Okubo 2006; Ding and Niu 2019; Yu et al. 2019). Selection effect refers to the survival of the fittest mechanism formed in the fierce competition environment -- in order to avoid fierce competition, low efficiency and low productivity enterprises will shift from a larger market to a smaller market. This means that the enterprises that can survive in a larger market are those with higher efficiency and productivity, which will drive the productivity up in larger markets. Hence, the agglomeration and selection phenomena can endogenously lead to substantial productivity differences between large-scale and small-scale market regions

doi: 10.1680/jensu.20.00012

(Baldwin and Okubo 2006; Ding and Niu 2019; Yu et al. 2019).

However, when analysing industrial agglomeration and selection, previous research has usually focused on the traditional and services industries, ignoring the construction industry (Chen et al. 2020; Guo et al. 2020; Wu et al. 2020). This is mainly because industrial agglomeration and selection are usually long-term processes, whereas construction projects create most of the time one-time non-repeatable outputs. Therefore, many scholars believe that the agglomeration or selection effects found in the traditional and services industries should not be expected in the construction industry (Lee 2008). Yet, as an important contributor to most national economies, the construction industry is characterized by labour-intensive, technology-intensive, and industrial linkages. These are some reasons why the construction industry should indeed be suitable for agglomeration (Zhao et al. 2017). At the same time, under the dual constraint of resources and environment, all countries require that the construction industry reduces its negative impact on the environment while maintaining economic growth (Zhang et al. 2020). But this is undoubtedly a challenge. The improvement of a country's Total factor productivity (TFP) is an important manifestation of an industry's sustainable development (Chen et al. 2017; Zhang et al. 2020). This is normally manifested as an improvement of resource utilization efficiency and a reduction of energy consumption (Young et al. 2009). Hence, taking advantage of the agglomeration and/or selection effects on TFP of the construction industry at different market sizes could help national policy makers to meet this challenge. This would also allow a more efficient equilibrium between economic growth and environmental protection, particularly at sub-national (e.g. provincial or sub-sector)

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level whose study has also been neglected (Chia et al. 2012; Crawford and Vogl 2006; Nazarko and Chodakowska 2015; Park 2006; Zhang et al. 2017).

The focus of this research will be on the Chinese economy, but the research methods are equally applicable to other countries. The objective of this research is to measure the specific impact of the selection and agglomeration effects on productivity changes in various sub-sectors of the construction industry and at different market sizes. These aspects are expected to help improve the current structure of the industry and achieve a long-term and more sustainable economic development (Jiang and Yuan 2017).

2. Literature review

2.1 Market size

Market Size mainly refers to the overall size of the target industry, which may include the output and output value of the industry within a specified period. It is mainly divided according to the results of the survey on population size, people's demand, age distribution and regional wealth. Badinger (2007) pointed out that the size of a domestic market can be estimated from the national market by the population and area of that region. Similarly, Ding and Niu (2019) that the employment density of provinces in China is a suitable indicator for measuring the size of the market. They also suggested that this indicator can be applied to the analysis of the selection effect of the manufacturing industry. Hence, for the measurement of macro-market sizes (i.e. national and provincial) commonly used indicators are area, employment density, population and population density. This study has chosen the employment population density of provincial regions as the benchmark of market size. In the case of micro-scale measurements (e.g. companies and enterprises), indicators such as the number of employees can be used instead.

2.2 Construction industry productivity

Chau and Walker (1988) were the first to propose a method to estimate the total factor productivity (TFP) of the construction industry from varied statistical data such as construction costs and price indices. Later, Kapelko and Abbott (2017) analysed the extent of productive changes in the construction industry by means of a two-sided index with DEA (data envelopment analysis). More recently, Zhan et al. (2018) chose capital, labour input and time as the calculation indices and proposed an improved calculation model of the TFP.

By reviewing the existing literature, it can be seen that productive power has been frequently adopted as an indicator of the TFP in the construction industry (e.g. Chau and Walker 1988; Chen et al. 2017; Zhi et al. 2003). This study will also adopt the TFP and discuss the current state of productive power in the Chinese construction industry. Measurement of the TFP include parametric and non-parametric estimation methods (Melfou et al. 2009; Tsolas 2011; Xiang-qian and Li 2016; Xue et al. 2008). Calculation indices can be varied, though. In this study, a DEA-Malmquist Productivity Index will be to measure the TFP. The Malmquist index model is usually combined with DEA static analysis to better understand an industry's efficiency evolution over time. That is, unlike other models, it allows a dynamic analysis of the production efficiency.

doi: 10.1680/jensu.20.00012

2.3 Selection effect and agglomeration effect

Baldwin and Okubo (2005) analysed the spatial selection effect of heterogeneous enterprises and concluded that large areas are attractive for high productivity enterprises. Combes et al. (2012) proposed a nested model whose results showed that the selection effect could not explain the difference in spatial productivity. Furthermore, Accetturo et al. (2018) applied the empirical method of Combes et al. to Japanese and Italian manufacturing enterprises and found that there also was little evidence that urban size could result in a selection effect. However, Ding and Niu (2019) analysed Chinese manufacturing enterprises and found that the existence of a selection effect was obvious.

From a broader literature review it can be seen that the current research on the selection and agglomeration effects is mainly focused on the enterprise level (e.g. Gonzalez-Val and Marcen 2019; Lu et al. 2019; Yu et al. 2019). That is, recent analyses do not involve the segmentation of industries. Hence, our study will report the TFP of the construction industry under different scales in different provinces. To do so we will adopt a nested model similar to the one proposed by Combes et al. (2012) (the CDGPR model). This model will allow us to discriminate the productivity impact of selection effect and the agglomeration effect separately.

3. Research method

3.1 Calculation model

The objective of this study is to verify whether the selection effect and the agglomeration effect really influence the productivity of different market segments (sizes) in the Chinese

Accepted manuscript
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construction industry. First, we will establish an indicator system for calculating the TFP of the construction industry through the analysis of previous literature. Second, we will use the DEA-Malmquist Productivity Index method to measure the TFP of the construction industry as a whole and the TFP of four subsectors (segments). This approach does not involve to construct production functions and avoids some subjective and endogenous problems that have been previously attributed to other DEA methods (Zhang et al. 2018). Finally, the CDGPR nested model will be used again to analyse the influence and reasons of different market sizes on productivity changes under China's current construction industrial structure. More specifics of DEA-Malmquist model and the nested model can be found in Annex A.

3.2 Indicator selection

According to the *Industrial Classification of National Economic Activities* issued by China's National Bureau of Statistic in 2017 (NBS 2017), there are four types of sectors in China's construction industry: (1) housing construction, (2) civil engineering, (3) construction and installation, and (4) building decoration and other construction industries. These sub-industries or sub-sectors are coded as 47, 48, 49 and 50, respectively. More precisely, we resort here to a series of input-output indicators. The input indicators are capital and labour (Chancellor and Lu 2016; Hu and Liu 2018; Ye et al. 2019). Capital is expressed by the net value of fixed assets of construction enterprises, and labour is expressed by the average employment of the construction (sub) industry. The output indicators are the total profit generated by the construction industry (Kapelko and Abbott 2017; Zhang et al. 2018), its total value added (Chancellor and Lu 2016; Ye et al. 2019), the total output value of the construction industry

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(Dan et al. 2015), and the carbon dioxide (CO2) emissions as an undesired output (Yeh et al. 2010; Zhang and Choi 2013).

3.3 Source of data

3.3.1 Market size data

In a study of market size, it can be found that the proportion of population in China's rural areas is quite high. Yet, during the decade of 2008-2017, China's urbanization rate rose from 46.99% to 58.52%. Hence, in this case the employment density may be a better indicator of provincial market size compared to the population of that province. Particularly, the provincial employment density equals the number of employed people in the province divided by its total area (Ding and Niu 2019).

When analysing the scale of the Chinese construction industry market, the data selected in this investigation includes 30 provincial-level units. Among them there four municipalities (Shanghai, Beijing, Chongqing, and Tianjin), four autonomous regions (Ningxia, Guangxi, Inner Mongolia, and Xinjiang) and 22 provinces (the rest). Due to restrictions on the sources of data on energy emissions in Tibet, this study does not include it. Similarly, data analysis does not include Taiwan, Hong Kong and Macau either as it is currently not possible to obtain reliable data from these regions.

From the *China Statistical Yearbook* (2009-2018) (National Bureau of Statictics 2001-2018) and the *Statistical Yearbooks* (2009-2018) of 30 provincial-level units (China 2009-2018; China 2001-2018; China 2009-2018), provinces' data such as total resident population, employment and land area were collected and analysed.

3.3.2 TFP indicator data for the construction industry

The indicators for estimating the TFP of the construction industry were obtained for each sub-sector of the construction industry from: the net value of fixed assets, the average employment, the total output value, the value-added, and the total profits. These data are all available in the *China Statistical Yearbook* (2009-2018) and the *Statistical Yearbooks of China's Provinces* (2009-2018) referenced above.

For calculating the CO_2 emissions in the construction industry we resorted to equation (1). This is the official formula for estimating CO_2 emissions of any industry from its energy consumption proposed by the Intergovernmental Panel on Climate Change (IPCC) in its Guidelines for National greenhouse gas Inventories (IPCC 2006):

$$CO_2 = \sum_{i=1}^{n} Ei \times NCVi \times CEFi \times COFi \times \left(\frac{44}{12}\right) \quad (1)$$

Where Ei represents energy terminal consumption, $NCVi$ represents energy average low calorific value, $CEFi$ represents energy carbon emission coefficient, $COFi$ represents energy carbon oxidation rate (%), and $\frac{44}{12}$ represents the ratio of the relative molecular mass of carbon dioxide to the relative atomic mass of carbon. The conversion tables for some common types of energy and carbon dioxide emissions can be found in Table B-1 in Annex B. The calculated carbon dioxide results are listed in Table B-2 of Annex B.

4. Empirical results

4.1 TFP of the sub-sectors of the Chinese construction industry

The calculation results of the market size of each province can be found in Table B-3 (Annex

doi: 10.1680/jensu.20.00012

B). The total factor productivity (TFP) for each province was determined according to the provincial standard of size (see Table B-3). A summary of the average and dispersion values of the input indices and TFP values for each construction sub-sector are shown in Table 1. The detailed TFP values for each segment of the construction industry in each province can be found in Table B-4 of the Annex B.

In Table 1, those provinces with employment population density above the median are considered large provinces, otherwise they are considered small provinces. The TFP is calculated by every segment's mean of TFP for 10 years.

4.2 Results of nested models

After comparing productivity of provinces which are above and below the average employment density values, the calculation results of the nested models are shown in Tables 2 and 3 for the four sub-sectors of the Chinese construction industry.

Table 2 shows the regression parameter values and the coefficient of determination (R^2) of three regression models combining the (independent) variables: selection effect (S), agglomeration effect (A), and dilation effect (D). Dilation effect is an index that reflects the income of enterprises with different productivity in the agglomeration economies. The first and second columns show the results of the first regression model when only the selection effect is considered. The second model (columns 3 to 5) combines both the selection and agglomeration variables. The third model makes use of the three independent variables (S, A and D). On observing which models reach higher R^2 values with the maximum number of statistically significant independent variables we can understand which explanatory variables are the most

doi: 10.1680/jensu.20.00012

representative.

These are the major interpretations from Table 2:

(1) When TFP among provinces of different sizes is explained by the selection effect alone (S), the explanatory power of this models relatively high. In column (1) of Table 2, the S regression coefficients of the four construction industries are positive and most of them statistically significant, ranging from 0.0951 to 0.4424. This result shows that the number of enterprises eliminated in large-scale provinces varies between 9.51% to 44.24% (more than in small-scale provinces).

Additionally, the four R^2 values remains between 0.4608 and 0.9106. This indicates that when the agglomeration effect in an economy is neglected, the selection effect alone can only account for 46% to 91% of the productivity variability among provinces of different sizes. In the average case of all construction industries, the calculation results suggest that the province has eliminated 32.95% companies more than the small provinces. This selection effect accounts for 55.49% of the discrepancy in productive forces among provinces of different sizes.

(2) On including the agglomeration effect, the selection effect regression parameter values of all sub-industries are lower. That is, the values in column (3) are substantially lower than those of column (1). Yet, results suggest that the agglomeration effect does exist in the construction industry as a whole and at provincial level. This is because most regression values of the parameter A in column (4) (except for the housing building industry) are significant and greater than 0.1067. This also indicates that the productivity growth of large-scale provinces is

mainly due to the combined effect of selection and agglomeration.

Moreover, the explanatory power (R^2 values) of the combination of agglomeration effect and selection effect is very high and much greater considering both effects than just the selection effect (values in column (5) >> values in column (2)).

(3) Signs in columns (6)-(9) of Table 2 indicates signs of either expansion (+) or contraction (-) in the construction industry. If the estimated modulus of D (i.e. dilation effect value) is close to 1, this means that construction enterprises with different production capacity benefit similarly in agglomeration economies. If the estimated value of D is greater than 1, it means that the enterprises with high productivity will secure more income in an agglomeration economy. In the results of this research, the D values of various sub-sectors and the overall construction industry are significant and clearly below 1. This means that among the four sub-sectors, the enterprises with lower productivity are more profitable in an agglomeration economy. Also, in this scenario the selection effect does not exist. This as the S regression parameter values of most sub-sectors are negative and not significant. Hence, in view of these industry differences, the consolidation of all construction industry segments does not provide evidence for the selection effect. However, calculation results in column (7) do provide evidence that the enterprise benefits from the agglomeration effect. Except for decoration and other construction industries sub-sector, the A values and the overall construction industry are both positive and significant. This means that the average productivity of large-scale provinces in the industry has increased by more than 15.64% compared to small-scale provinces.

Finally, the R^2 values of the third model (column (9)) are certainly very high. However,

doi: 10.1680/jensu.20.00012

as the selection effect variable is hardly significant, it seems appropriate to propose other models excluding this variable. This justifies the existence of Table 3.

Results in Table 3 suggest that by neglecting the selection effect we undervalue the agglomeration effect (values of column (3) in Table 3 < values of column (7) in Table 2). Hence, if the selection effect exists but it is ignored, this may entail important calculation errors regarding the effect of the agglomeration in an economy. Therefore, in the analysis of the production rate of the construction industry, considering both the agglomeration effect and the selection effect is a pre-requisite.

Similarly, with the exception of building decoration and other construction industries (code 50), the D parameter values of the other three sub-sectors are substantially increased by ignoring the selection effect (values in column (4) in Table 3 > values in column (8) of Table 2). This means the influence of the dilation effect is significantly overestimated.

Hence, neglecting the selection effect substantially lowers the models' representativeness. This can also be observed by comparing the values of column (2) of Table 2 with those of column (2) of Table 3. The selection effect alone explains 55.49% of the productivity difference between different market sizes of provinces, while the agglomeration effect alone explains for 77.57%. Then, despite in the four construction industry sub-sectors (segments), the agglomeration effect has a stronger explanatory power than the selection effect, a comparison of column (9) of Table 2 with column (5) of Table 3 shows that the addition of the selection effect significantly improves the model fitness (higher R^2 values).

Accepted manuscript
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4.3 Kernel density estimation

According to the TFP calculation results of the large and small provinces, it is possible to draw a nuclear density distribution map of each sub-sector (segment) of China's construction industry (see Figure 1). The solid line represents the large-scale provinces and the dotted lines represent the small-scale provinces. It can be observed that the small-scale provincial enterprises in the four sub-sectors have experienced a “left tailing” phenomenon. This indicates that the proportion of low-productivity enterprises is higher in larger provinces. In each large-scale province, there is a clear “right shift” phenomenon, and the low-productivity enterprises’ right shift is larger than that of high-productivity enterprises. This phenomenon indicates that the high productivity of large-scale provincial construction enterprises is more affected by the agglomeration effect. In this scenario, low-productivity enterprises are more profitable from the agglomeration economy than high-productivity enterprises. Also, it can be found in Figure 1 that in the Chinese market, whether in large-scale or small-scale provinces, all segments of the construction industry are dominated by high-productivity enterprises.

5. Conclusions

This research has analysed the productivity differences in several Chinese construction industry sub-sectors under different market scales. The results of the study are significant for the long-term progress of the construction industry as it may allow optimising its economic and industrial structure. The main conclusions are as follows:

(a) There are significant agglomeration effects in various sub-sectors of China's

doi: 10.1680/jensu.20.00012

construction industry. Without considering the selection effect, only the agglomeration effect can explain the difference in the TFP between large-scale provinces vs small-scale provinces. However, if the contribution of the selection effect is omitted, important estimation errors appear.

(b) The combination of both the selection effect and the agglomeration effect has a good explanatory power (R^2 values around 90%) for the change of construction industry productivity.

(c) When considering the selection effect, the agglomeration effect and the dilation effect simultaneously, the model has the strongest explanatory power (R^2 values > 95%).

The major result of these regression analyses is that governments should strongly encourage the concentration of construction enterprises in a region. This provides hard empirical proof for the governments to formulate policy plans and for construction companies to formulate business strategies which could ultimately affect the future development of the construction industry. High consumption and high pollution problems have been the main obstacles restricting the sustainable development of the construction industry for a long time. Governments should actively take measures to eliminate cross-provincial trade barriers, expand the market scale of the construction industry, and increase the productivity. Government needs to make reasonable use of agglomeration effects and selection effects to increase the productivity of the construction industry, reduce resource consumption in the production process, and ultimately achieve the sustainable development of the industry. For construction companies, higher productivity means lower costs and higher profits. Companies should

doi: 10.1680/jensu.20.00012

choose provinces with a larger market for production and operation activities. They should also make the most of the advantages brought about by the agglomeration effect (such as technology, capital, and talents). These actions will allow continuous improvement of productivity, improve resource utilisation, reduce production costs and reduce pollution problems. All these outcomes will allow meeting the Sustainable Development Goals set for the industry in many countries.

Hence, findings from this study can influence the future industrial and economic development of China and other parts of the world. However, each country's economic development status is different, and different countries have different standards for the classification of their construction industry segments. Analysing other countries, though, is left for future research.

Annex A

A-1 DEA-Malmquist model

The Malmquist index was assumed to be the production technology level in time period (t) at S_t. The input in time period (t) was represented by X_t and the output by Y_t. Similarly, X_{t+1} and Y_{t+1} represent the input and output at t+1, respectively. Therefore, the following set represents the production process:

$$S_t = \{(X_t, Y_t) : X_t \to Y_t\} \tag{1}$$

Where, S_t represents the set of production possibilities, while production technology frontier refers to the subset of the maximum output that can be obtained with a certain input. When the technology in time period t is selected as a reference, the Malmquist TFP index based on output

doi: 10.1680/jensu.20.00012

can be expressed as follows:

$$M_c^t = \frac{d_c^t(X_{(t+1)}, Y_{(t+1)})}{d_c^t(X_t, Y_t)} \tag{2}$$

Where, $d_c^t(X_t, Y_t)$ represents the ratio between the maximum possible output and the actual output of (X_t, Y_t) when the production technology in time period t is taken as a reference. $d_c^t(X_{(t+1)}, Y_{(t+1)})$ represents the ratio between the maximum possible output and the actual output of $X_{(t+1)}$, $Y_{(t+1)}$, when the production technology in time period t+1 is taken as a reference.

$$\text{TFP} = \text{Techch} \times \text{Effch} = \text{Techch} \times \text{Sech} \times \text{Pech} \tag{3}$$

In order to overcome the arbitrariness of the production technical reference items, the change in TFP is represented by calculating the mean value of M_c^t and M_c^{t+1}. Techch and Effch can be further decomposed under the assumption of constant return to scale. These two index changes represent the sources of TFP growth, respectively. According to Banker et al. (Banker et al, 1996) for the scale of the same conditions of the loose, the technical efficiency indicators can be further decomposed into pure technical efficiency and scale efficiency. Therefore, TFP can be expressed as follows:

A-2 A nested model of selection and agglomeration

This research study adopts the nested model proposed by Combes et al. (2012) in order to calculate the selection effect and agglomeration effect of market size of different provinces on TFP for the construction industry segments in China. The specific principle of the model is as follows:

doi: 10.1680/jensu.20.00012

Assuming that there are I regions and N_i that represent the population in region i, then the utility function of a single consumer is:

$$\mathrm{U} = q^0 + \alpha \int_{k \in \Omega} q^k dk - \frac{1}{2} \gamma \int_{k \in \Omega} (qk)^2 dk - \frac{1}{2} \eta \left(\int_{k \in \Omega} q^k dk \right)^2 \tag{4}$$

Where q^0 represents the amount of standardized goods (usually agricultural products) consumed, Ω represent differentiation industrial goods collection, q^k represents the consumption quantity of the kth differential industrial product. α, γ and η are parameters and greater than zero, and it means that consumers prefer industrial products to standardized products when the greater the α is or the smaller the η is. The larger the γ, the greater the difference between the differentiated industrial products. Also, the consumer utility function is maximised under budget constraints.

Assuming that the scale of production of standardized commodities is constant, one unit of labour produces one unit of standardized goods, and there is no cost for trade between standardized commodity areas. If the price of standardized goods is one, the wages of workers are one, and the market of differentiated industrial products is a monopolistic competition. Each industrial product manufacturer can produce differentiated products after paying the s unit sunk cost. The production of one unit product requires the use of h unit labour, the marginal cost of the manufacturer is h, the marginal cost of each manufacturer is different, and the marginal cost of manufacturers in all regions is subject to the probability density function g (h), whose cumulative density function is G (h). If the manufacturer's marginal cost h is higher than $\bar{h}$, then the product demand is 0, and the manufacturer exits the market. Therefore, the industrial product collection in the economic equilibrium is:

doi: 10.1680/jensu.20.00012

$$\bar{\Omega} = \{k \in \Omega \big| h \ll \bar{h}\}\,. \tag{5}$$

Then, there is a trade cost for inter-regional trade in industrial products. The trade cost is "iceberg-style" cost, and only one unit can be reached when T unit products are shipped to another region. For consumers, all differentiated industrial products are symmetrical, where the demand for a single consumer of region j for the manufacturer's product with a marginal cost h of region i is:

$$\begin{aligned} q_{ij}(h) &= \frac{1}{\gamma + \eta\omega_i}\left(\alpha + \frac{\eta}{\gamma}\omega_i p_j\right) - \frac{1}{\gamma} p_{ij}(h) = \frac{1}{\gamma}\left(P_j + \frac{\gamma(\alpha - P_j)}{\gamma + \eta\omega_i} - p_{ij}(h)\right) \\ &= \frac{1}{\gamma}\left[\bar{h}_j - p_{ij}(h)\right] \end{aligned} \tag{6}$$

Manufacturers entering the market need to pay the sunk cost of S units, so the manufacturer's expected profit is S. It can be assumed that $\tilde{F}(\emptyset)$ is a potential logarithmic productivity cumulative density function measured without considering the size of the province:

$$F_i(\emptyset) = \max\left\{0, \frac{\tilde{F}(\emptyset - A_i) - S_i}{1 - S_i}\right\} \tag{7}$$

Among them, S_i represents the proportion of manufacturers in i province who have withdrawn due to insufficient production capacity after entering the market. Further, the cumulative density function of the large-scale province j can be obtained by the cumulative density function of the small-scale province i.

Assuming that there are both large market i and small market j in the economic market, the actual enterprise logarithmic productivity distribution function after the large market area i is affected by the selection effect S_i, the agglomeration effect A_i and the dilation effect D_i is:

$$F_i(\emptyset) = \max\left\{ 0, \frac{\tilde{F}\left(\frac{\emptyset - A_i}{D_i}\right) - S_i}{1 - S_i} \right\} \tag{8}$$

The actual enterprise logarithmic productivity distribution function after the small market area j is affected by the selection effect, the agglomeration effect and the dilation effect is:

$$F_j(\emptyset) = \max\left\{ 0, \frac{\tilde{F}\left(\frac{\emptyset - A_j}{D_j}\right) - S_j}{1 - S_j} \right\} \tag{9}$$

The parameters that need to be calculated are as follows: A = $A_i - DA_j$, $D = D_i/D_j$, S = $(S_i - S_j)/(1 - S_j)$. This research study adopts the estimation methods provided by Combes et al. (2012) to calculate A, D and S. The parameter standard error is estimated by the bootstrap method.

Annex B

Table B-1. Reference factors for various energy standard coal and carbon emissions

Energy	Heat value (KJ/kg)	Carbon emission factor (kg/106KJ)	Carbon oxidation rate	CO_2 emissions (kg)
Coal (1kg)	20,908	25.8	0.910	1.800
Coke (1kg)	28,435	29.2	0.928	2.285
Crude oil (1kg)	41,816	20.0	0.979	3.002
Gasoline (1kg)	43,070	18.9	0.980	2.956
Kerosene (1kg)	43,070	19.6	0.986	3.052
Diesel oil (1kg)	43,070	20.2	0.982	3.102

Fuel oil (1kg)	41,816	21.1	0.985	3.187
Natural gas (1m^3)	38,931	15.3	0.990	2.162
Liquefied petroleum gas (1kg)	50,179	17.2	0.980	3.101

Note: The above data in the table is derived from the *General Rules for the Calculation of Comprehensive Energy Consumption* (GB/T 2589-2008) and the *Guidelines for the Compilation of Provincial Greenhouse Gas Inventories* (NDRC [2011] No. 1041). The density of natural gas is generally in the range of 0.7 kg/m^3 to 0.75 kg/m^3. This research assumes 0.75 kg/m^3.

Table B-2. Carbon dioxide emission from construction industry in Chinese provinces from 2008 to 2017 (tons)

province \ year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Shanghai	629.98	672.76	737.81	689.12	673.80	611.26	545.44	546.62	543.36	580.22
Tianjin	728.79	685.06	850.38	979.84	1038.57	1057.42	1097.05	1179.01	1297.15	1242.87
Beijing	363.26	513.63	548.05	468.29	404.62	324.71	341.03	342.04	328.92	344.70
Jiangsu	297.66	356.66	409.96	423.76	388.54	457.23	480.50	225.92	233.56	176.42
Shandong	721.58	864.36	931.82	1024.46	860.13	866.37	912.14	886.11	899.49	891.77
Henan	103.11	185.85	290.01	363.80	382.81	493.64	364.76	836.15	918.41	1333.04
Zhejiang	1092.06	1214.12	1433.97	1491.52	1497.97	1669.58	1707.78	1772.35	1733.03	1772.71
Anhui	347.87	365.52	415.27	490.28	541.24	706.27	756.45	821.45	876.95	957.96
Guangdong	466.70	537.11	581.90	615.89	634.97	655.23	669.26	562.49	667.59	668.45
Chongqing	291.18	300.69	366.24	401.99	450.71	485.88	495.29	507.49	521.50	538.29
Hubei	877.86	1126.87	1366.89	1517.96	1487.88	1603.42	1635.66	1663.55	885.26	905.36
Hebei	315.07	330.69	383.35	424.18	434.74	374.72	340.29	655.03	665.01	659.31
Hunan	498.87	660.83	781.45	874.71	966.60	1084.00	1210.44	1311.38	1380.97	1355.19
Fujian	444.57	474.01	506.92	540.14	419.00	668.90	687.57	698.75	726.90	791.06
Liaoning	568.13	649.66	744.22	788.36	624.92	623.62	401.76	268.02	230.91	269.77
Jiangxi	76.78	84.39	96.16	110.21	106.92	169.47	181.94	187.00	195.98	221.36
Guizhou	197.92	225.64	240.65	224.77	236.13	347.16	436.33	394.57	488.78	481.54
Guangxi	108.45	114.03	34.27	38.09	44.46	15.16	18.37	44.17	20.23	22.13

Hainan	46.63	62.37	80.77	94.70	101.57	113.11	126.30	134.25	136.82	146.18
Sichuan	466.44	517.08	571.06	589.32	545.25	409.16	422.78	494.35	885.01	960.86
Shanxi	412.81	493.24	492.61	480.83	496.61	587.64	509.62	520.16	557.67	619.99
Shaanxi	715.16	473.83	650.97	666.96	723.31	684.01	647.88	573.71	329.98	345.23
Jilin	290.02	322.38	383.17	392.89	390.09	649.28	648.48	625.89	611.06	523.40
Yunnan	421.11	489.85	569.78	666.92	671.92	670.26	646.82	673.49	711.25	737.16
Ningxia	115.57	145.41	163.60	170.73	200.20	197.16	222.38	197.42	196.21	192.00
Heilongjiang	27.59	29.67	34.50	54.90	64.62	77.74	82.60	86.87	89.69	102.03
Gansu	245.39	255.00	285.90	286.12	313.76	287.31	284.28	269.52	335.92	327.28
Inner Mongolia	645.94	702.79	1187.00	923.95	937.75	860.69	821.50	650.35	756.11	786.12
Xinjiang	211.43	212.52	211.16	238.68	252.37	337.05	339.54	358.26	357.52	357.52
Qinghai	69.96	76.89	85.45	100.41	106.98	111.20	117.45	148.11	164.63	186.33

Table B-3. Characteristics of market size in China's provinces

Province	Area （$10000km^2$）	Population （Million）	Employed Population （Million）	Population Density	Employment Density
Shanghai	0.6300	2347.5000	1226.2200	3726.1905	1946.3810
Tianjin	1.1300	1412.6000	803.8200	1250.0885	711.3451
Beijing	1.6800	2046.3000	1113.8500	1218.0357	663.0060
Jiangsu	10.2600	7916.3000	4749.3200	771.5692	462.8967
Shandong	15.3800	9711.9000	6495.3300	631.4629	422.3231
Henan	16.7000	9453.5000	6334.8000	566.0778	379.3293
Zhejiang	10.2000	5466.7000	3679.2400	535.9510	360.7098
Anhui	18.0000	10594.8000	6009.7700	588.6000	333.8761
Guangdong	13.9700	6088.7000	4195.0200	435.8411	300.2878
Chongqing	18.7700	7287.8000	4046.1200	388.2685	215.5631
Hubei	12.1300	3767.0000	2509.4700	310.5523	206.8813

Hebei	8.2300	2954.8000	1628.3600	359.0279	197.8566
Hunan	18.5900	5795.0000	3611.5000	311.7267	194.2711
Fujian	21.1800	6649.3000	3965.0900	313.9424	187.2092
Liaoning	14.5900	4371.3000	2365.8400	299.6093	162.1549
Jiangxi	16.7000	4513.0000	2552.8100	270.2395	152.8629
Guizhou	3.4000	890.3000	478.9100	261.8529	140.8559
Guangxi	23.6000	4760.1000	2833.5000	201.6992	120.0636
Hainan	15.6300	3594.2000	1786.1300	229.9552	114.2758
Sichuan	17.6000	3524.0000	1882.6100	200.2273	106.9665
Shanxi	20.5600	3765.6000	2063.4000	183.1518	100.3599
Shaanxi	48.1400	8150.9000	4801.1400	169.3166	99.7329
Jilin	18.7400	2742.6000	1391.7400	146.3501	74.2657
Yunnan	38.3300	4672.1000	2572.4500	121.8915	67.1132
Ningxia	6.6400	650.3000	345.8300	97.9367	52.0828
Heilongjiang	45.4400	2581.7000	1508.9500	56.8156	33.2075
Gansu	45.4800	3822.0000	1293.8600	84.0369	28.4490
Inner Mongolia	118.3000	2490.9000	1324.0900	21.0558	11.1926
Xinjiang	166.0000	2268.2000	999.8800	13.6639	6.0234
Qinghai	72.2300	575.5000	312.7200	7.9676	4.3295
Tibet	122.8000	312.1000	206.7200	2.5415	1.6834
Mid-value	17.6000	3767.0000	2063.4000	270.2395	152.8629
Mean value	31.0010	4360.5484	2551.2416	444.3757	253.4695
standard error	38.1072	2743.5839	1775.8468	672.1017	357.1880

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Table B-4. Total Factor Productivity (TFP) of Construction Industry Segments in all Provinces of China from 2008 to 2017

Province	Name of Subdivision Industry	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Shanghai	Housing Construction	0.4081	0.4800	0.4378	0.5331	0.4663	0.4879	0.2911	0.3711	0.2648	0.4687
Tianjin		0.2865	0.3458	0.3159	0.2823	0.2848	0.3748	0.1168	0.1994	0.0597	0.2242
Beijing		0.4404	1.0000	0.7277	1.0000	0.7908	1.0000	1.0000	0.6857	1.0000	1.0000
Jiangsu		1.0000	0.7659	0.6279	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shandong		0.5561	0.5688	0.5343	0.5735	0.6037	0.7527	0.3144	0.5486	0.2519	0.6375
Henan		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang		0.3983	0.4971	0.4831	0.5953	0.5205	0.4987	0.2141	0.2959	0.1572	0.4325
Anhui		0.3677	0.4837	0.4419	0.6837	0.5160	0.5160	0.1579	0.2922	0.1275	0.4455
Guangdong		0.5063	0.6477	0.5966	1.0000	0.7800	0.8606	0.3876	0.7378	0.3298	0.7133
Chongqing		0.5086	0.7201	0.5980	0.7368	0.6186	0.7429	0.3732	0.7474	0.3128	0.8436
Hubei		0.3200	0.3929	0.4142	0.4515	0.4181	0.5140	0.1847	0.3385	0.2929	0.5789
Hebei		0.4074	0.4612	0.4656	0.5929	0.5170	0.5662	0.3476	0.2542	0.1323	0.3422
Hunan		0.4714	0.4471	0.4189	0.3891	0.3728	0.4932	0.1263	0.2383	0.1128	0.3908
Fujian		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.2277	1.0000	0.2027	1.0000
Liaoning		0.0914	0.5359	0.5222	0.1130	0.6030	0.6522	0.4567	0.4945	0.2645	0.4667
Jiangxi		0.5595	0.6459	0.5266	0.7736	0.7733	0.7032	0.5783	0.5500	0.3984	0.5784
Guizhou		0.1294	0.1590	0.1793	0.2177	0.2128	0.2653	0.0642	0.1571	0.0851	0.4002
Guangxi		0.2095	0.4369	0.5732	1.0000	0.6929	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan		0.3868	0.3481	0.2345	0.2722	0.3321	0.3842	0.1043	0.2206	0.0842	0.3832
Sichuan		0.3635	0.4650	0.4169	0.5923	0.5722	0.6716	0.4106	0.3913	0.1793	0.3652
Shanxi		0.1585	0.2429	0.2814	0.2424	0.2323	0.2287	0.0905	0.1025	0.0791	0.2453
Shaanxi		1.0000	0.4792	0.3820	0.4759	0.3593	0.5565	0.1676	0.3173	0.2569	0.5252

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Jilin		0.2398	0.6799	0.5576	0.7157	0.5875	0.3901	1.0000	1.0000	1.0000	0.4648
Yunnan		0.2380	0.3224	0.3975	0.3779	0.3110	0.4355	0.1469	0.2480	0.1324	0.3718
Ningxia		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0955	0.1806	0.1007	0.3872
Heilongjiang		1.0000	1.0000	1.0000	1.0000	1.0000	0.8549	0.5613	0.4427	0.2992	0.4281
Gansu		0.2397	0.2804	0.3483	0.3097	0.3505	0.4201	0.1531	0.2453	0.1128	0.4267
Inner Mongolia		0.5880	1.0000	1.0000	1.0000	1.0000	1.0000	0.0960	0.2651	0.1246	0.3977
Xinjiang		0.2664	0.3610	0.3810	0.3847	0.4279	0.4530	0.1276	1.0000	0.0916	0.5118
Qinghai		0.5513	0.0599	0.2917	0.5093	0.2593	0.1777	0.0503	0.0885	0.0317	0.1394
Shanghai	Civil Engineering Construction	0.3749	0.4447	0.4094	0.3658	0.4596	0.4399	0.2346	0.3730	0.4819	0.4553
Tianjin		0.2718	0.2819	0.2652	0.2459	0.3515	0.4086	0.0944	0.1711	0.1278	0.1571
Beijing		0.3360	0.5516	0.5303	0.4505	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangsu		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shandong		0.5206	0.5074	0.5199	0.4303	0.6891	1.0000	0.2140	0.5233	0.5496	0.6699
Henan		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang		0.3675	0.4564	0.4407	0.3832	0.6135	0.5668	0.2101	0.3652	0.4213	0.3824
Anhui		0.3985	0.5291	0.5376	0.4689	0.6183	0.7890	0.1497	0.3335	0.3707	0.4431
Guangdong		0.4624	0.5561	0.5400	0.3886	0.7016	0.8124	0.2649	0.6558	0.6058	0.5509
Chongqing		0.4658	0.6446	0.5666	0.4960	0.6057	0.8047	0.2585	0.6450	0.6045	0.6114
Hubei		0.3136	0.3648	0.3416	0.3367	0.4416	0.4972	0.1329	0.2926	0.4728	0.4285
Hebei		0.4300	0.4754	0.4446	0.3640	0.4933	0.4697	0.2211	0.2411	0.2354	0.2453
Hunan		0.4310	0.3520	0.3255	0.2956	0.4163	0.5469	0.0912	0.1965	0.2364	0.2853
Fujian		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.1502	1.0000	1.0000	1.0000
Liaoning		0.4898	0.4547	0.4673	0.0665	0.5582	0.5891	0.2886	0.4626	0.4349	0.3326
Jiangxi		0.5269	0.5704	0.5541	0.5526	0.6397	0.5969	0.3608	0.5308	0.4909	0.6580
Guizhou		0.0985	0.0686	0.0858	0.0637	0.0751	0.3397	0.0473	0.1372	0.1775	0.4100
Guangxi		0.1903	0.2680	0.8487	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Hainan		0.3190	0.2675	0.1716	0.2178	0.3850	0.4177	0.0770	0.1815	0.1917	0.3043
Sichuan		0.3221	0.4059	0.4072	0.3990	0.5143	0.5481	0.2588	0.3466	0.2847	0.2556
Shanxi		1.0000	0.2108	0.2778	0.2614	0.3974	0.3950	0.1339	0.3531	0.2816	0.2997
Shaanxi		1.0000	0.4376	0.2279	0.3817	0.3670	0.4333	0.1639	0.2933	0.4674	0.4409
Jilin		0.2168	0.2297	0.4088	0.5567	0.6066	0.4340	1.0000	1.0000	1.0000	0.3438
Yunnan		0.2361	0.2770	0.2386	0.0932	0.3888	0.4037	0.0927	0.1856	0.3454	0.3071
Ningxia		0.5827	1.0000	1.0000	1.0000	1.0000	0.5232	0.0834	0.1509	0.3096	0.3037
Heilongjiang		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.1737	0.2655	0.2951	0.2215
Gansu		0.2132	0.2273	0.2860	0.2585	0.4230	0.4510	0.1640	0.3060	0.3633	0.4026
Inner Mongolia		0.7529	1.0000	1.0000	1.0000	1.0000	1.0000	0.1382	0.3104	0.2835	0.5272
Xinjiang		0.2080	0.2736	0.2965	0.2713	0.4528	0.4511	0.0911	0.3481	0.2419	0.4577
Qinghai		0.0170	0.3253	0.2486	0.2055	0.3813	0.4660	0.0930	0.2189	0.2807	0.3148
Shanghai	Construction and Installation	0.3034	0.3657	0.3276	0.1726	0.3243	0.3478	0.3994	0.3552	0.4832	0.5576
Tianjin		0.1179	0.1830	0.1483	0.0801	0.1511	0.2133	0.2229	0.1460	0.1059	0.2396
Beijing		0.2191	0.4690	0.4716	0.2659	0.6251	0.7473	0.6688	0.5364	1.0000	1.0000
Jiangsu		1.0000	0.6716	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shandong		0.3641	0.3654	0.3878	0.2177	0.5413	0.7247	0.7116	0.5872	0.5347	0.6089
Henan		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang		0.4061	0.5023	0.5179	0.2610	0.5283	0.5349	0.5605	0.4281	0.4812	0.5708
Anhui		0.3279	0.4495	0.4906	0.3603	0.4715	0.5190	0.5778	0.4862	0.4139	0.5757
Guangdong		0.3583	0.4662	0.4497	0.2392	0.5426	0.6875	0.6737	0.6781	0.6254	0.6750
Chongqing		0.3414	0.6348	0.6452	0.3487	0.3991	0.5384	0.6695	1.0000	0.7238	1.0000
Hubei		0.1720	0.2804	0.2724	0.1578	0.6822	0.4073	0.3078	0.3305	0.5369	0.6102
Hebei		0.3982	0.4174	0.4556	0.2166	0.5090	0.5793	0.5400	0.3937	0.4327	0.5946
Hunan		0.2823	0.2591	0.2219	0.1121	0.2184	0.2911	0.2875	0.2329	0.2148	0.3887
Fujian		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Liaoning		0.3200	0.3538	0.3518	0.0217	0.4716	0.5648	0.5391	0.4508	0.4782	0.4600
Jiangxi		0.4868	0.4027	0.5424	0.2985	0.6617	0.5645	0.6318	0.4987	0.6338	0.5768
Guizhou		0.1296	0.1887	0.1956	0.1428	0.1741	0.1993	0.1621	0.1709	0.1685	0.4439
Guangxi		0.1155	0.0284	1.0000	1.0000	0.7529	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan		0.1787	0.1896	0.1081	0.0760	0.1817	0.2200	0.2446	0.2196	0.1682	0.3667
Sichuan		0.2051	0.2822	0.3023	0.1840	0.4321	0.5420	0.4980	0.3620	0.3284	0.3758
Shanxi		0.1093	0.1908	0.2211	0.1104	0.2350	0.2582	0.1940	0.2474	0.2488	0.3675
Shaanxi		1.0000	0.2953	0.1932	0.2288	0.2737	0.3616	0.3348	0.2812	0.6377	1.0000
Jilin		0.1116	0.2343	0.1963	0.1646	1.0000	0.2441	1.0000	1.0000	1.0000	0.4599
Yunnan		0.0940	0.2636	0.1476	0.0638	0.2117	0.2366	0.3615	0.2709	0.2817	0.3508
Ningxia		0.3520	1.0000	1.0000	1.0000	1.0000	1.0000	0.4045	0.1817	0.1705	0.3815
Heilongjiang		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.5538	0.3779	0.6442	0.5242
Gansu		0.1172	0.1017	0.2191	0.0879	0.2268	0.0000	0.1121	0.1700	0.1627	0.2738
Inner Mongolia		0.3384	0.4600	0.6819	0.4593	1.0000	0.3838	0.3133	0.3643	0.3701	1.0000
Xinjiang		0.1060	0.1829	1.0000	0.0933	0.2198	0.2094	0.2634	0.2675	0.2127	0.4597
Qinghai		0.0000	0.1187	0.1764	0.0000	0.1160	0.2002	0.0852	0.1776	0.2521	0.3155
Shanghai	Building Decoration and Other Construction Industry	0.5626	0.4948	0.5211	0.2701	0.4545	0.4703	0.3657	0.4047	0.5272	0.7339
Tianjin		0.1409	0.2091	0.2004	0.1598	0.2215	0.4001	0.1748	0.2764	0.2321	0.2514
Beijing		1.0000	1.0000	1.0000	0.2834	0.6747	1.0000	0.6357	0.4373	1.0000	1.0000
Jiangsu		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shandong		0.5092	0.5289	0.5819	0.3797	0.7126	1.0000	1.0000	0.8152	0.6165	0.5437
Henan		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Zhejiang		0.3653	0.4865	0.5088	0.6712	0.6205	0.5620	0.4110	0.3821	0.5063	0.6214
Anhui		0.3830	0.5166	0.5435	1.0000	0.6427	0.6546	0.4720	0.4100	0.4326	0.4921
Guangdong		0.4415	0.5125	0.5347	0.2472	0.6478	0.7323	0.6428	0.8404	0.6522	0.7707
Chongqing		0.2082	0.3138	0.4530	0.2581	0.3867	0.5503	1.0000	1.0000	0.4848	1.0000

Hubei		0.1294	0.1056	0.2724	0.1581	0.5833	0.4262	0.2635	0.3661	0.5741	0.7741
Hebei		0.4682	0.5529	0.4720	0.2739	0.5707	0.5646	0.4629	0.3662	0.5496	0.5657
Hunan		0.3387	0.2442	0.2795	0.1810	0.3055	0.5238	0.2374	0.2600	0.3254	0.4298
Fujian		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Liaoning		1.0000	0.3647	0.4442	0.0298	0.5297	0.5657	0.4764	0.4045	0.5063	0.5509
Jiangxi		0.5678	0.6357	0.6063	0.3108	0.6567	0.5828	0.5378	0.4472	0.5947	0.6787
Guizhou		0.0000	0.0764	0.1600	0.4837	0.3672	0.3918	0.2016	0.2057	0.2701	0.4638
Guangxi		0.2595	0.3245	0.7438	1.0000	0.8462	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan		0.2072	0.1648	0.1352	0.1589	0.2633	0.4435	0.2186	0.2733	0.3024	0.3903
Sichuan		0.2319	0.3104	0.3528	0.2178	0.4844	0.5535	0.4169	0.3292	0.3871	0.4432
Shanxi		0.2324	0.2580	0.3069	0.2183	0.2754	0.4288	0.2023	0.1332	0.2810	0.3499
Shaanxi		1.0000	0.1341	0.0173	1.0000	1.0000	0.5126	0.3799	0.2494	0.5509	0.6504
Jilin		1.0000	1.0000	1.0000	0.6591	1.0000	0.4365	1.0000	1.0000	1.0000	0.4117
Yunnan		0.1034	0.1320	0.1263	0.1494	0.1962	0.3015	0.1956	0.2504	0.3295	0.4690
Ningxia		0.8742	1.0000	1.0000	1.0000	1.0000	0.0000	0.2729	0.2227	0.2964	0.4018
Heilongjiang		1.0000	1.0000	1.0000	1.0000	1.0000	0.6770	1.0000	0.4805	1.0000	0.5551
Gansu		0.0787	0.2504	0.1942	0.0781	0.4787	0.0000	0.1199	0.2542	0.3599	0.4947
Inner Mongolia		1.0000	1.0000	1.0000	1.0000	0.5043	1.0000	1.0000	0.5648	0.4591	0.5219
Xinjiang		0.1118	0.1596	0.2135	0.1243	0.2585	0.2780	0.1519	0.3909	0.2705	0.4084
Qinghai		0.0100	0.0179	0.0323	0.0339	0.5474	0.2903	0.0899	0.1040	0.1443	0.0001
Shanghai	Overall Construction Industry	0.5197	0.5351	0.5294	0.5345	0.5358	0.5488	0.4449	0.4063	0.5171	0.5392
Tianjin		0.2595	0.2996	0.2769	0.2486	0.2918	0.3919	0.1847	0.1813	0.1127	0.1888
Beijing		0.4702	0.6160	0.6919	1.0000	1.0000	1.0000	1.0000	0.7704	1.0000	1.0000
Jiangsu		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shandong		0.6968	0.6205	0.6218	0.6088	0.6368	0.7513	0.5605	0.6229	0.5072	0.6085
Henan		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Zhejiang		1.0000	1.0000	1.0000	1.0000	0.5865	0.6028	0.4837	0.5012	0.4125	0.5057
Anhui		0.4169	0.5364	0.5371	0.5671	0.5463	0.5770	0.3564	0.3232	0.3160	0.4568
Guangdong		0.5448	0.6503	0.6347	0.3963	0.7258	0.7634	0.5732	0.6882	0.5965	0.6127
Chongqing		0.6355	1.0000	1.0000	0.8853	0.7026	0.7615	0.6787	1.0000	1.0000	1.0000
Hubei		0.3164	0.3707	0.3786	0.3685	0.4904	0.5249	0.2847	0.3315	0.5045	0.5589
Hebei		0.4617	0.5521	0.5734	0.7538	0.6030	0.7177	0.5738	0.3485	0.3087	0.4132
Hunan		0.6125	0.5187	0.4721	0.4415	0.4757	0.5532	0.3112	0.3154	0.3269	0.4761
Fujian		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Liaoning		0.3679	0.5226	0.5743	0.0941	0.6237	0.6860	0.5778	0.4997	0.4507	0.3940
Jiangxi		0.6632	0.6455	0.6164	0.7648	0.7125	0.6671	0.6632	0.7343	0.6127	0.5760
Guizhou		0.1469	0.1357	0.1615	0.1849	0.1997	0.3053	0.1194	0.1550	0.1630	0.3823
Guangxi		0.2527	0.4088	1.0000	1.0000	0.6552	1.0000	1.0000	1.0000	1.0000	1.0000
Hainan		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Sichuan		0.4006	0.4889	0.4766	0.5860	0.5917	0.6292	0.5218	0.4679	0.3415	0.4184
Shanxi		0.1755	0.2324	0.2890	0.2450	0.3168	0.3562	0.2098	0.5417	0.2129	0.2957
Shaanxi		1.0000	0.4534	0.2810	0.3909	0.3470	0.5019	0.3088	0.2938	0.4591	0.4776
Jilin		0.2347	0.5602	0.5078	0.5667	0.5782	0.4663	1.0000	1.0000	1.0000	0.4515
Yunnan		0.2856	0.3094	1.0000	0.2772	0.3306	0.3911	0.2939	0.2591	0.3015	0.4264
Ningxia		1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.3719	0.2196	0.2578	0.4427
Heilongjiang		1.0000	1.0000	1.0000	1.0000	1.0000	0.7783	0.5632	0.4046	0.4430	0.3576
Gansu		0.4370	0.2959	0.3461	0.3491	0.3973	0.5010	0.3443	0.3469	0.3373	0.5103
Inner Mongolia		0.7487	1.0000	1.0000	1.0000	0.4933	1.0000	0.5109	0.2750	0.3925	0.5165
Xinjiang		0.3810	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.2733	0.4920
Qinghai		0.2094	0.2734	0.2497	0.2564	0.2627	0.3452	0.1482	0.1351	0.1588	0.2509

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References

Accetturo, A., Di Giacinto, V., Micucci, G., and Pagnini, M. (2018). "Geography, productivity, and trade: Does selection explain why some locations are more productive than others?" *Journal of Regional Science*, 58(5), 949-979.

Badinger, H. (2007). "Market size, trade, competition and productivity: evidence from OECD manufacturing industries." *Applied Economics*, 39(17), 2143-2157.

Baldwin, R., and Okubo, T. (2005). "Heterogeneous Firms, Agglomeration and Economic Geography: Spatial Selection and Sorting." *NBER Working Paper*.

Baldwin, R. E., and Okubo, T. (2006). "Heterogeneous firms, agglomeration and economic geography: spatial selection and sorting." *Journal of Economic Geography*, 6(3), 323-346.

Chancellor, W., and Lu, W. (2016). "A Regional and Provincial Productivity Analysis of the Chinese Construction Industry: 1995 to 2012." *Journal of Construction Engineering and Management*, 142(11), 1-9.

Chau, K. W., and Walker, A. (1988). "The measurement of total factor productivity of the Hong Kong construction industry." *Construction Management and Economics*, 6(3), 209-224.

Chen, C., Sun, Y., Lan, Q., and Jiang, F. (2020). "Impacts of industrial agglomeration on pollution and ecological efficiency-A spatial econometric analysis based on a big panel dataset of China's 259 cities." *J. Clean Prod.*, 258.

Chen, Y., Liu, B., Shen, Y., and Wang, X. (2017). "Spatial analysis of change trend and influencing factors of total factor productivity in China's regional construction industry."

doi: 10.1680/jensu.20.00012

Applied Economics, 50(25), 1-20.

Chia, F. C., Skitmore, M., Runeson, G., and Bridge, A. (2012). "An analysis of construction productivity in Malaysia." *Construction Management and Economics*, 30, 1055–1069.

China, B. M. B. o. S. o. t. P. R. (2009-2018). "Statistical Yearbook of Beijing(2009-2018)." C. S. Press, ed.Beijing, P.R. China.

China, S. M. B. o. S. o. t. P. R. (2001-2018). "Statistical Yearbook of Shaanxi (2001-2018)." C. S. Press, ed.Beijing, P.R. China.

China, T. M. B. o. S. o. t. P. R. (2009-2018). "Statistical Yearbook of Tianjin(2009-2018)." C. S. Press, ed.Beijing, P.R. China.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D., and Roux, S. (2012). "The Productivity Advantages of Large Cities: Distinguishing Agglomeration From Firm Selection." *Econometrica*, 80(6), 2543-2594.

Crawford, P., and Vogl, B. (2006). "Measuring productivity in the construction industry." *Building Research & Information*, 34(3), 208-219.

Dan, T., Guangbin, W., and Dongping, C. (2015). "Growth characteristics and influencing factors of total factor productivity in construction industry." *Journal of Tongji University(Natural Science)*, 43, 1901-1907.

Ding, C., and Niu, Y. (2019). "Market size, competition, and firm productivity for manufacturing in China." *Regional Science and Urban Economics*, 74, 81-98.

Duranton, G., and Puga, D. (2003). "Micro-foundations fo Urban Agglomeration Economies." *NBER Working Paper*.

doi: 10.1680/jensu.20.00012

Gonzalez-Val, R., and Marcen, M. (2019). "Agglomeration Economies in Small Cities and Business: The Impact of the Great Recession in Aragon (Spain)." *Sustainability*, 11(14).

Guo, Y., Tong, L., and Mei, L. (2020). "The effect of industrial agglomeration on green development efficiency in Northeast China since the revitalization." *J. Clean Prod.*, 258.

Guo, Y. H., Tong, L. J., and Mei, L. (2020). "The effect of industrial agglomeration on green development efficiency in Northeast China since the revitalization." *J. Clean Prod.*, 258, 13.

Hu, X., and Liu, C. (2018). "Measuring efficiency, effectiveness and overall performance in the Chinese construction industry." *Engineering, Construction and Architectural Management*, 25(6), 780-797.

IPCC (2006). "Guidelines for national greenhouse gas inventories."

Jiang, D., and Yuan, Y. (2017). "The Empirical Analysis of the Impact of Technical Innovation on Manufacturing Upgrading-Based on Subdivision Industry of China." *Proceedings of the Eleventh International Conference on Management Science and Engineering Management*, 274-285.

Kapelko, M., and Abbott, M. (2017). "Productivity Growth and Business Cycles: Case Study of the Spanish Construction Industry." *Journal of Construction Engineering and Management*, 143(5), 05016026(05016021-05016011).

Lee, H. (2008). "Agglomeration and growth." *The Korean Economic Review*, 24(2), 425-457.

Lu, Y., Wang, J., and Zhu, L. (2019). "Place-Based Policies. Creation, and Agglomeration Economies: Evidence from China's Economic Zone Program." *American Economic*

doi: 10.1680/jensu.20.00012

Journal-Economic Policy, 11(3), 325-360.

Melfou, K., Theocharopoulos, A., and Papanagiotou, E. (2009). "Assessing productivity change with SFA in the sheep sector of Greece." *Operational Research*, 9(3), 281-292.

National Bureau of Statictics, P. s. R. o. C. (2001-2018). "China Statistical Yearbook." China Statistics Press, Beijing.

Nazarko, J., and Chodakowska, E. (2015). "Measuring Productivity of Construction Industry in Europe with Data Envelopment Analysis." *Procedia Engineering*, 122, 204-212.

NBS, N. B. o. S. o. t. P. R. C. (2017). "Industrial classification for national economic activities." C. S. Press, ed.Beijing, P.R. China.

Park, H.-S. (2006). "Conceptual Framework of Construction Productivity Estimation." *Construction Management*, Vol. 10.

Tsolas, I. E. (2011). "Modelling profitability and effectiveness of Greek-listed construction firms: an integrated DEA and ratio analysis." *Construction Management and Economics*, 29(8), 795-807.

Wu, J., Ge, Z., Han, S., Xing, L., Zhu, M., Zhang, J., and Liu, J. (2020). "Impacts of agricultural industrial agglomeration on China's agricultural energy efficiency: A spatial econometrics analysis." *J. Clean Prod.*, 260.

Xiang-qian, L., and Li, H. (2016). "A Study of Provincial TFP Including Education and Health Human Capital——Based on SFA and DEA." *Economic Survey* 33.

Xue, X., Shen, Q., Wang, Y., and Lu, J. (2008). "Measuring the Productivity of the Construction Industry in China by Using DEA-Based Malmquist Productivity Indices."

Journal of Construction Engineering and Management 143, 64-71.

Ye, G., Wang, Y., Zhang, Y., Wang, L., Xie, H., Fu, Y., and Zuo, J. (2019). "Impact of Migrant Workers on Total Factor Productivity in Chinese Construction Industry." *Sustainability*, 11(3), 1-18.

Yeh, T.-l., Chen, T.-y., and Lai, P.-y. (2010). "A comparative study of energy utilization efficiency between Taiwan and China." *Energy Policy*, 38(5), 2386-2394.

Young, A., Perry, C., Manson, R., and Happold, a. B. (2009). "Briefing: Energy efficiency in buildings." *Proceedings of the Institution of Civil Engineers*, 162(ES3), 127-132.

Yu, H., Zhou, L., and Shen, T. (2019). "Location selection and spatial effects of agglomeration economy in manufacturing enterprises." *Geographical Research*, 38(2), 273-284.

Zhan, W., Pan, W., Javed, A. A., and Chau, K. W. (2018). "Correlation Analysis of Key Influencing Factors to the Total Factor Productivity of the Hong Kong Construction Industry." *Proceedings of the 21st International Symposium on Advancement of Construction Management and Real Estate*, 565-575.

Zhang, D., Nasir, H., and Haas, C. T. (2017). "Development of an Internal Benchmarking and Metrics Model for Industrial Construction Enterprises for Productivity Improvement." *Canadian Journal of Civil Engineering*, 1-46.

Zhang, J., Li, H., Xia, B., and 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.

Zhang, J. X., Cai, W. Y., Li, H., Olanipekun, A. O., and Skitmore, M. (2020). "Measuring the

doi: 10.1680/jensu.20.00012

capacity utilization of China's regional construction industries considering undesirable output." *J. Clean Prod.*, 252, 16.

Zhang, N., and Choi, Y. (2013). "Environmental energy efficiency of China's regional economies: A non-oriented slacks-based measure analysis." *The Social Science Journal*, 50(2), 225-234.

Zhao, Z.-Y., Tang, C., Zhang, X., and Skitmore, M. (2017). "Agglomeration and Competitive Position of Contractors in the International Construction Sector." *Journal of Construction Engineering and Management*, 143(6), 04017004.

Zhi, M., Hua, G. B., Wang, S. Q., and Ofori, G. (2003). "Total factor productivity growth accounting in the construction industry of Singapore." *Construction Management and Economics*.

doi: 10.1680/jensu.20.00012

Table 1. Input indices and TFP values of China's construction industry sub-sectors

Segment industry code		Net fixed assets (10,000 yuan)	Number of employed people (10,000 people)	Value added (10,000 yuan)	CO_2 emissions (10,000 tons)	Total profit (10,000 yuan)	Gross output value (10,000 yuan)	Large-scale province TFP	Small-scale province TFP
47	Mean	1,419,581	94.92	5,786,868	313.46	4,129,584	25583966.68	0.57	0.46
	Std. Dev.	1,559,319	123.64	7,596,779	248.74	13,525,582	34350516.34	0.23	0.21
48	Mean	1,374,083	31.81	2,410,565	159.85	532,233.	13397864.53	0.56	0.44
	Std. Dev.	1,838,210	36.88	2,299,080	127.98	578,787	16964754.16	0.24	0.20
49	Mean	256,393	8.29	536,730	32.61	138,616	2837029.37	0.55	0.41
	Std. Dev.	237,644	9.15	581,465	24.56	181,813	2760447.11	0.25	0.22
50	Mean	218,377	8.15	509,457	22.81	103,151	2734181.64	0.60	0.47
	Std. Dev.	639,749	12.40	1,435,567	21.57	152,873	8653275.85	0.24	0.26
All	Mean	3,289,562	144.11	2,310,905	533.67	1,831,651	48590783.12	0.65	0.57
	Std. Dev.	3,480,011	168.38	4,579,327	380.30	2,004,455	54131849.73	0.23	0.23

Table 2. Correlation results of each regression model considering the selection effect

Industry Code	S (1)	R^2 (2)	S (3)	A (4)	R^2 (5)	S (6)	A (7)	D (8)	R^2 (9)
47	0.1584	0.7358	0.0892	0.0882	0.9050	-0.0627	0.1841	0.5963	0.9781
	(0.05)**		(0.07)**	(0.01)**		(0.28)	(0.04)**	(0.27)*	
48	0.0951	0.6576	0.0469	0.1067	0.9371	-0.0028	0.1453	0.7333	0.9607
	(0.05)**		(0.21)	(0.03)**		(0.23)	(0.03)***	(0.29)*	
49	0.4424	0.4608	-0.0083	0.1969	0.8887	-0.1989	0.2674	0.5521	0.9573
	(0.04)		(0.14)	(0.03)***		(0.47)	(0.03)***	(0.11)***	
50	0.2213	0.9106	0.0431	0.1413	0.9654	0.0268	0.1724	0.7528	0.9844
	(0.04)*		(0.04)**	(0.02)***		(0.14)	(0.07)*	(0.25)*	
Overall	0.3295	0.5549	0.0429	0.1001	0.7842	-0.2063	0.1783	0.4670	0.9853
	(0.05)**		(0.30)	(0.03)		(0.21)	(0.04)**	(0.25)**	

Table 3. Correlation results of each model without considering the selection effect

Industry Code	A (1)	R^2 (2)	A (3)	D (4)	R^2 (5)
47	0.1485 (0.01)***	0.7969	0.1473 (0.01)***	0.7825 (0.08)***	0.9446
48	0.1450 (0.02)***	0.7766	0.1433 (0.01)***	0.7465 (0.21)**	0.9590
49	0.1867 (0.02)***	0.8696	0.1865 (0.02)***	0.9644 (0.12)***	0.8718
50	0.2267 (0.05)***	0.3396	0.2168 (0.04)***	0.4482 (0.08)***	0.8997
All	0.1192 (0.01)***	0.7757	0.1188 (0.01)***	0.8939 (0.10)**	0.7999

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Figure 1. Nuclear density distribution map of various industries in China's construction industry