Impact of Structural Distortions on Resource Allocation in China:

Evidence from An Innovative Empirical Model

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This paper examines the impact of structural distortions on resource allocation among industries, regions (provinces), and ownerships in China, using data from 2003 to 2019. This paper innovatively develops an empirical model to measure multi-dimensional structural distortions and assesses the resource misallocation degrees regarding industries, regions, and ownerships. The results indicate that China's most serious resource misallocation is related to industries, followed by regions and ownerships, and the most severe capital misallocation is associated with ownership, and labor misallocation exists in industries. The present study contributes to the literature by creating an innovative two-layer empirical model to address the limitations of Hsieh and Klenow's model (Hsieh & Klenow, 2009). The findings have identified which group (industry, region, and ownership) is excessive or insufficient in resource usage, and the results have profound policy and practical implications.

Keywords: structural distortion, resource misallocation; total factor productivity, China

JEL classification: O11, 047, O53

INTRODUCTION

China has recently entered a so-called "*new normal*" development era featuring low-speed economic growth. This move signals the end of the "demographic dividend" and the decline of investment efficiency – both are fundamental driving forces for China's rapid growth in the last four decades (Yao, 2010). In other words, China's growth in the past mainly depended on the accelerated expansion of production factors and consumption of resources driven by the government's strategies and policies rather than a robust productivity improvement. It is, therefore, imminent to improve productivity by optimizing the efficiency of resource allocation.

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As such, more scholars have paid attention to the research on improving Total Factor Productivity (TFP), optimizing resource allocation, and reforming structural distortion to find the alternative driving forces for sustaining Chinese economic growth (Li, 2009).

The Theory of Economic Growth, proposed by Solow (1956), suggests that the driving force of economic growth comes not only from the increase of production inputs but also from the improvement of TFP – the latter even plays a more critical role than the former (Hall and Jones, 1999). TFP is a measure of productivity that interprets economic growth via technological innovation, labor skills, and capital efficiency. Logically, for China to sustain its economic growth in the future, focusing on improving TFP should be the Chinese government's vital strategy (Cai, 2013).

There are two ways to improve TFP: one is making technological progress in firms (companies, enterprises), and the other is to optimize resource allocation via transferring production factors from firms with lower production efficiency to those having higher production efficiency, i.e., correcting resource misallocation. The latter approach can increase aggregate products in a country under non-increased total production factors (Restuccia & Rogerson, 2013; Hopenhayn, 2014).

Resource misallocation and structural distortion, in the forms of imbalanced industrial structure, ownership discrimination, and market segmentation, have attracted increasing attention from scholars in recent years (see, Midrigan & Xu, 2014; Yao, 2015; Caggese et al., 2017; Fajgelbaum et al., 2018; David & Venkateswaran, 2019; Hsieh & Moretti, 2019 Wen, 2019; Monge-Naranjo et al., 2019; Anagnostou et al., 2021). In China, for example, Brandt et al. (2012) and Yang (2015) examines the extent of technological progress and resource allocation to aggregate productivity using different decomposition methods. Their conclusions indicate that the contribution of optimizing resource allocation to productivity growth is relatively low.

To understand the effect of optimizing resource allocation on China's productivity growth, it is necessary to comprehensively assess the extent of losses that result from resource allocation inefficiencies caused by structural distortions (i.e., distortions in industries, regions, and ownerships). For instance, using the HK model, Han and Zheng (2014) find that the misallocation of production factors in the sub-industries of manufacturing is a 4.72% loss of

TFP. Brandt et al. (2013) suggest that the misallocation among provinces is 8% loss of TFP. Zhang and Zhang (2016) indicate that the misallocation among ownerships is 7.4% loss of TFP. However, these studies each only focus on one type of structural distortion. We need more studies that can investigate different structural distortions in a single study to provide more dynamic pictures and evaluate which type of structural distortion is more serious than the others. The answers to this question would have meaningful policy and practical implications for China's structural reform and resource management.

In the literature, the HK model (Hsieh & Klenow, 2009) and Aoki model (Aoki, 2012) are the most cited models to measure resource misallocation degree, but the HK model was designed to detect resource misallocations for firms in the same industry, and therefore the model assumes no resource misallocation exists between industries. Nevertheless, resource misallocations among industries are highly possible. Previous studies have modified the HK model to determine the degrees of different structural distortions. For example, Jin et al. (2018) and Wang and Niu (2019) constructed a unified model to assess the resource misallocation degree at both firm and industry levels. Similar to the HK model, their model refers to the three-layer structure of the HK model, which includes the firm, the group (e.g., province/region, industry/sector, ownership), and the state (country) level. Nonetheless, these models still require firm data. In China, high-quality company data can only be obtained from China Industrial Enterprise Database, which was only available until 2007. Using outdated or unreliable firm data could make our research findings irrelevant and misleading.

As such, to evaluate the resource misallocation degree in China, this paper first develops an empirical model that can measure multi-dimensional structural distortions. More importantly, this unified model does not require firm data. Second, using our model, we are able to assess the resource misallocation degrees regarding industries, regions, and ownerships for a sample from 2003 to 2019 collected from China's Industrial Statistics Yearbook. Following rigorous analysis, we have identified which group (industry, region, and ownership) is excessive or insufficient in resource usage and their severities in structural distortion. In other words, this paper innovatively creates a two-layer model that can directly assess group productivity. The accurate group data are easily obtained from China's Industrial Statistics Yearbook. In this regard, the model used in this paper is more applicable, and the findings are more objective.

The rest of the paper is organized as follows. Section 2 explains the new empirical model and data used. Sections 3 and 4 present the analytical results regarding resource misallocation degree and production input intensity, respectively, with an in-depth discussion to help understand the findings. Section 5 accommodates the conclusion, contributions and implications, limitations, and future research direction.

EMPIRICAL MODEL AND DATA

The innovative empirical model

In the literature, the HK model is used to assess the resource misallocation degree; however, the model requires using firm data as one of the three layers - the whole economy (state), the industries and the firms (enterprises), where $Y = \prod_{i=1}^{N} Y_i^{\theta_i}$ and $Y_i = (\sum_{j=1}^{M_i} Y_{ij}^{\phi})^{\frac{1}{\phi}}$ with Y is the output of the entire economy, Y_i is the output of industry i, and Y_{ij} is the output of enterprise j in the industry i. The model also supposes $Y_i = AK_i^{\alpha} L_i^{1-\alpha}$ and $Y_{ij} = A_{ij} K_{ij}^{\alpha} L_{ij}^{1-\alpha}$, where K represents capital and L denotes labor. By dividing the status into two subsections - effective status and distorted status, the resource misallocation degree is $\frac{A}{A^*} = \frac{Y}{Y^*} = \prod_{i=1}^{N} (\frac{Y_i}{Y_i^*})^{\theta_i} = \prod_{i=1}^{N} (\frac{A_i K_i^{\alpha} L_i^{1-\alpha}}{A_i^* K_i^{*\alpha} L_i^{*1-\alpha}})^{\theta_i}$ where A denotes the productivity under the distorted shape. In contrast, A^* denotes productivity under the effective form. The model finally expresses as $\frac{A}{A^*} = \prod_{i=1}^{N} (\frac{A_i}{A_i^*})^{\theta_i}$ that means the resource misallocation is only among enterprises in the industry i with the assumption of no distortion among sectors.

However, this paper aims to assess resource misallocation degrees in industries (also in regions and ownerships); therefore, the HK model is not applicable. Jin et al. (2019) attempt to construct a model that can assess resource misallocation in enterprises and groups, including industries. They suppose that the output of the whole economy Y is a CES (Constant elasticity of substitution) aggregate of group's output Y_i, $Y = (\sum_{i=1}^{N} w_i Y_i^{\varphi})^{\frac{1}{\varphi}}$, and they also set the outputs Y, Y_i and Y_{ij} are the CD function of their inputs K and L, K_i and L_i, K_{ij} and L_{ij}, $Y = AK^{\alpha} L^{1-\alpha}$,

$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}$, $Y_{ij} = A_{ij} K_{ij}^{\alpha} L_{ij}^{1-\alpha}$, and then they can get the productivity A of the whole economy and the productivity A_i of the group i, $A = [\sum_{i=1}^{N} w_i (A_i k_i^{\alpha} l_i^{1-\alpha})^{\varphi}]^{\frac{1}{\varphi}}$ and $A_i = [\sum_{j=1}^{M_i} (A_{ij} k_{ij}^{\alpha} l_{ij}^{1-\alpha})^{\phi}]^{\frac{1}{\phi}}$, where A_{ij} denotes the productivity of firm j in group i, and $k_i=K_i/K$, $l_i=L_i/L$, $k_{ij}=K_{ij}/K_i$, $l_{ij}=L_{ij}/L_i$, which denote the shares of factors and can be calculated in two statuses - effective status and distorted status.

Assessing the productivity of group i is vital to obtaining the resource misallocation degree in groups. However, suppose we use this model to evaluate the resource misallocation degree in different groups. In that case, we also must use firms' productivities to fit the respective group's productivity, but this process may lead to the group's productivity deviation. For example, they should use the equation $A_i = [\sum_{j=1}^{M_i} (A_{ij} \tau_{ij}^{K-\alpha} \tau_{ij}^{L-\alpha})^{\frac{\phi}{1-\phi}}]^{\frac{1-\phi}{\phi}} \tau_i^{K\alpha} \tau_i^{L1-\alpha}$, where the parameters $\tau_i^K, \tau_i^L, \tau_{ij}^K, \tau_{ij}^L$ represent the distortion index of capital or labor in group i or firm j, then the productivity of group i under the effective state is, $A_i^* = [\sum_{j=1}^{M_i} A_{ij}^{\frac{\phi}{1-\phi}}]^{\frac{1-\phi}{\phi}}$. We also find that the value of the group's productivity is affected by the number of firms M_i. Suppose that ϕ is equal to 2/3, and there are two groups, where there are two firms in group A, and each firm's productivity is 0.5, there are three firms in group B, and each firm's productivity also is 0.5. According to this assumption, except for the number of firms, the firms' productivities in groups A and B are the same, suggesting the productivities of groups A and B are the same. However, according to the equation of the group's productivity under the effective state, we can find that the productivity of group A is $\sqrt{2}/2$, and the productivity of group B is $\sqrt{3}/2$. The productivity of group B is higher than that of group A, just because the number of firms in group B is higher than that in group A. The more firms there are in the group, the higher productivity of the group will be. Therefore, this will also affect the measurement results of resource misallocation[2]. Moreover, such a model structure requires comprehensive firm data, which is difficult to obtain in China.

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[2] Wang and Niu (2019) develop one similar model to assess the resource misallocation in enterprises and groups. The functions of the state's output Y and the group i's output Y_i is the same as HK model, $Y = \prod_{i=1}^{N} Y_i^{\theta_i}$, $Y_i = (\sum_{j=1}^{M_i} Y_{ij}^{\frac{\eta-1}{\eta}})^{\frac{\eta}{\eta-1}}$ and $Y_{ij} = A_{ij} K_{ij}^{\alpha_i} L_{ij}^{1-\alpha_i}$. Within this model, Wang and Niu (2019) suggest that the productivity A_i*

If following the HK model or Jin et al. (2019), it is impossible to assess the resource misallocation degree in groups in the absence of enterprise data, or unable to correctly estimate the group's productivity, suggesting the models in the literature are not applicable. Thus, one possible approach is to change the model into one that does not require enterprise data but instead it requires group data. Brandt et al. (2013) provided an idea for this feasible method. That is, the state's output Y is also a CES function of the group's output $Y_i, Y=(\sum_{i=1}^{N} Y_i^{\sigma})^{\frac{1}{\sigma}}$, the group is only a representative enterprise, and it is no longer assumed that the group is composed of heterogeneous enterprises. With such a two-layer model, the TFP of the whole economy can be: $A=(\sum_{i=1}^{N} Y_i^{\sigma})^{\frac{1}{\sigma}} / K^{\alpha} L^{1-\alpha}=[\sum_{i=1}^{N}(A_i k_i^{\alpha} l_i^{1-\alpha})^{\sigma}]^{\frac{1}{\sigma}}$

However, both Hsieh and Klenow (2009) and Brandt et al. (2013) set the CD function of output on production factors to a constant return to scale: $Y=AK^{\alpha}L^{1-\alpha}$. But other studies (Chen & Chen, 2017; Lian & Lu, 2012) show that the assumption of constant return to scale cannot be satisfied, which means that these models are still not applicable. Therefore, this assumption needs to be relaxed. Similar to Brandt et al. (2013), we also set $Y=(\sum_{i=1}^{N} Y_i^{\sigma})^{\frac{1}{\sigma}}$, but the CD production function of the state's output Y and group's output Y_i are both not constant return to scale, and now are as: $Y=AK^{\alpha}L^{\beta}$ and $Y_i=AK_i^{\alpha}L_i^{\beta}$. The TFP of the whole economy is $A=(\sum_{i=1}^{N} Y_i^{\sigma})^{\frac{1}{\sigma}} / K^{\alpha} L^{\beta}=[\sum_{i=1}^{N}(A_i k_i^{\alpha} l_i^{\beta})^{\sigma}]^{\frac{1}{\sigma}}$, where k_i and l_i are still the shares of capital and labor in group i, $k_i=\frac{K_i}{K}$, $l_i=\frac{L_i}{L}$. If the shares of factors l_i, k_i under distorted state, and l_i^*, k_i^* under effective state can be obtained, the total factor productivity A and A^* under these two states will be obtained. Then, the loss degree of TFP caused by misallocation among groups is $d=A^*/A-1$.[3]

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of group i under the effective status is $A_i^*=[\sum_{j=1}^{M_i} A_{ij}^{\eta-1}]^{\frac{1}{\eta-1}}$. We can find that the productivity A_i* will be affected by the number of firms M_i in group i.

[3] Chen and Hu (2011) refer to Aoki model and put forward a method to calculate the loss degree of TFP and output caused by the misallocation in industries. Their evaluation formula is

The possible policy implications from applying the new model

Based on Hsieh and Klenow (2009) and Brandt et al. (2013), the distorted status has been reached by setting the distorted price of capital $\tau_i^k r$ and distorted price of labor $\tau_i^l w$, respectively, where the τ_i^k and τ_i^l are the coefficients of distorted factors' price. Correspondingly, the effective status reaches if the coefficients of distorted factors' price τ_i^k and τ_i^l to be 1. To get the shares of capital and labor k_i, l_i under the distorted form, we can solve the problem of profits maximization of state and group to get the first-order conditions, where the problems of profits maximization are $\max_{Y_i}\left\{PY-\sum_{i=1}^{N}(P_iY_i)\right\}$ and $\max_{K_i,L_i}\left\{P_iA_iK_i^{\alpha}L_i^{\beta}-\tau_i^k rK_i-\tau_i^L wL_i\right\}$

So, the shares of capital and labor under distorted status and effective status are respectively:

$$k_i=\frac{\left[A_i\tau_i^{k-\alpha}\tau_i^{l-\beta}\right]^{\frac{\sigma}{1-(\alpha+\beta)\sigma}}\tau_i^{k-1}}{\sum_{i=1}^{N}\left[A_i\tau_i^{k-\alpha}\tau_i^{l-\beta}\right]^{\frac{\sigma}{1-(\alpha+\beta)\sigma}}\tau_i^{k-1}},\ l_i=\frac{\left[A_i\tau_i^{k-\alpha}\tau_i^{l-\beta}\right]^{\frac{\sigma}{1-(\alpha+\beta)\sigma}}\tau_i^{l-1}}{\sum_{i=1}^{N}\left[A_i\tau_i^{k-\alpha}\tau_i^{l-\beta}\right]^{\frac{\sigma}{1-(\alpha+\beta)\sigma}}\tau_i^{l-1}};l_i^*=k_i^*=\frac{A_i^{\frac{\sigma}{1-(\alpha+\beta)\sigma}}}{\sum_{i=1}^{N}A_i^{\frac{\sigma}{1-(\alpha+\beta)\sigma}}}$$

In addition, we can find that if the return to scale remains unchanged, $\alpha+\beta=1$, then the shares of capital and labor under two status respectively are:

$$k_i=\frac{\left[A_i\tau_i^{k-\alpha}\tau_i^{l1-\alpha}\right]^{\frac{\sigma}{1-\sigma}}\tau_i^{k-1}}{\sum_{i=1}^{N}\left[A_i\tau_i^{k-\alpha}\tau_i^{l1-\alpha}\right]^{\frac{\sigma}{1-\sigma}}\tau_i^{k-1}},\ l_i=\frac{\left[A_i\tau_i^{k-\alpha}\tau_i^{l1-\alpha}\right]^{\frac{\sigma}{1-\sigma}}\tau_i^{l-1}}{\sum_{i=1}^{N}\left[A_i\tau_i^{k-\alpha}\tau_i^{l1-\alpha}\right]^{\frac{\sigma}{1-\sigma}}\tau_i^{l-1}};l_i^*=k_i^*=\frac{A_i^{\frac{\sigma}{1-\sigma}}}{\sum_{i=1}^{N}A_i^{\frac{\sigma}{1-\sigma}}}$$

$(Y/Y_{efficient})=\prod_{i=1}\left(\frac{(\frac{s_{it}\beta_{Ki}}{\beta_K}\gamma_{Kit}K_t)^{\beta_{Ki}}(\frac{s_{it}\beta_{Li}}{\beta_L}\gamma_{Lit}L_t)^{\beta_{Li}}(\frac{s_{it}\beta_{Mi}}{\beta_M}\gamma_{Mit}M_t)^{\beta_{Mi}}}{(\frac{s_{it}^*\beta_{Ki}}{\beta_K}K_t)^{\beta_{Ki}}(\frac{s_{it}^*\beta_{Li}}{\beta_L}L_t)^{\beta_{Li}}(\frac{s_{it}^*\beta_{Mi}}{\beta_M}M_t)^{\beta_{Mi}}}\right)^{s_{it}}=\prod_{i=1}((\gamma_{Kit})^{\beta_{Ki}}(\gamma_{Lit})^{\beta_{Li}}(\gamma_{Mit})^{\beta_{Mi}})^{s_{it}}$, where the parameter s_i and M represent the shares of industry i, and the intermediate input. The parameter γ represents the distortion index of factors, and their evaluation formulae are $\gamma_{Ki}=(\frac{K_i}{K})/(\frac{s_i\beta_{Ki}}{\beta_L})$, $\gamma_{Li}=(\frac{L_i}{L})/(\frac{s_i\beta_{Li}}{\beta_L})$, $\gamma_{Mi}=(\frac{M_i}{M})/(\frac{s_i\beta_{Mi}}{\beta_M})$. However, their model shows that the output share s_i of industry i in the first step of their evaluation formula is obtained under the distorted state, while the s_i^* in the denominator is the share under the effective status. The meaning and value of the two parameters are not the same, so it is impossible to get the expression of the second step by mutual reduction. Moreover, the share s_i^* under effective status cannot be calculated by the model consistently.

These are the same as those in the model of Brandt et al. (2013). This proves our proposed model is a reliable and more applicable model.

We can also use the first-order conditions of profits maximization to get the coefficients of distorted factors' price $\tau_i^l = \frac{Y_i^{nor}}{L_i}$, where Y_i^{nor} represents the nominal output of group *i*. , and the TFP of group *i* is $A_i(t) = \frac{Y_i(t)}{K_i^{\alpha} L_i^{\beta}}$. Then referring to Brandt et al. (2013), we set the value of σ to be 1/3, and we will use the econometric methods to get the values of *α* and *β*.

We further measure the misallocation degree of different production factors. Taking the misallocation degree of capital as an example, assuming that there is no misallocation of labor which means τ_i^l =1, the difference between the productivity A_k under the status that only the capital allocation is distorted and the productivity A^* under the effective status which means the allocation of labor and capital are both effective, is the misallocation degree of capital, $d_k = \frac{A^*}{A_k} - 1$. Similarly, the formula for calculating the misallocation degree of labor is $d_l = \frac{A^*}{A_l} - 1$, where A_l represents the productivity with only the labor allocation distorted. So we can call the misallocation of capital and labor a total factor misallocation.

In the previous studies, their similar models were used that could use a formula to assess the degree of productivity caused by misallocation of production factors (Hsieh & Klenow 2009). However, these formulas can only indicate the misallocation degree, but they do tell which group has excessive characteristics and which group is insufficient. Notably, the answers to these questions will guide the optimization direction of factors allocation in the future, resulting in more critical policy implications. This distinguishes an important contribution of this paper. We construct the indicators of excessive or insufficient input of production factors, $p_i^k = \frac{k_i}{k_i^*}$ which can also be called the index of input intensity. If p_i^k is greater than 1, it indicates that the capital input of group *i* is excessive. If p_i^k is less than 1, it suggests that the capital input of group *i* is insufficient. Also, if p_i^l is greater than 1, the labor input of group *i* is excessive, and if p_i^l is less than 1, the labor input of department *i* is insufficient.

Data

Three structural distortions relating to industry, region and ownership are calculated. The industrial structure is focused on a sub-industry – manufacturing because it is China's major productivity force. Regional and ownership structure calculations are also limited to the manufacturing industry (Dai & Cheng, 2019). The structural distortion in regions refers to the resource misallocation in different provinces. The ownership's structural distortion is the resource misallocation of the state-owned (the state-owned and the state-controlled enterprises) and non-state-owned sectors.

The data are collected from China's Industrial Statistics Yearbook, covering 2003 to 2019. It is worth noting that the model developed in the last section indicates that the output should be measured by industrial-added value. However, the database only discloses the industrial added value for 2003, 2005, 2006, and 2007, while the industrial gross output value in the database is complete. Thus, the industrial gross output value is used to replace industrial added value. The net value of fixed assets measures capital stocks in various industries and ownership sectors. Still, the yearbook does not include all provinces' net fixed asset value; we then use the total fixed assets to measure capital stocks. Regarding the number of employees, the 2012 figure was missing. We thus use the average year before and after (i.e., 2011 and 2013).

This paper uses the factory price index of industrial products to adjust the industrial gross output value and the fixed asset investment price index to adjust fixed assets. The factory price index of industrial products in the sub-industry is included in the database, but the sub-industry's fixed-asset investment price index is not available. We thus adopt the price index at the national level for data consistency. Another challenge is China's Industry Classification Standard was changed in 2012. Specifically, from 2008 to 2011, it was based on the industrial classification for national economic activities of 2002 (GB-T4754-2002); from 2012 onward, it adopted the industrial type of 2011 (GB-T4754-2011). In addition, the tobacco and recycling industries were eliminated in 2012. We rectify the industrial classification for data consistency and accurate comparison.[4]

THE RESULTS – RESOURCE MISALLOCATION DEGREE

Estimation of the production function

To assess the resource misallocation, we estimate the output elasticity coefficients of capital and labor (α and β). On the one hand, we adopt the fixed-effects model (FE) and random-effects model (RE) to estimate the Cobb-Douglas production function. The estimation model is $\ln Y_{it} = c + \alpha \ln K_{it} + \beta \ln L_{it} + u_i + \lambda_t + \varepsilon_{it}$, u_i is an individual dummy variable, λ_t is a time dummy variable, and ε_{it} is the random error. In addition, to alleviate the endogenous bias, we use the two-stage least-squares (2SLS) estimator with the lagged capital and labor as instruments for current capital and labor, and when using the fixed-effects model denoted as FMM, and the random-effects model denoted as RMM. On the other hand, we use the random frontier model to estimate the production function, $\ln Y_{it} = c + \alpha \ln K_{it} + \beta \ln L_{it} + \lambda_t + \varepsilon_{it} - \xi_i$, where ξ is the output-oriented (technical) inefficiency, and it can be divided into the model with time-invariant technical efficiency (denoted as SFA1) and the model with time-varying technical efficiency (denoted as SFA2). The estimation results are shown in Table 1. As the Hausman test indicates, to adopt the RE model and control the endogenous bias, we choose the RMM model. Moreover, column (6) shows η is not significantly zero, indicating that the SFA2 model is more suitable than SFA1. Therefore, we take the average of the estimated values of the RMM model and SFA2 model as the final estimated values, where α is 0.385 and β is 0.852.

TABLE 1

Estimation of Production Functions

	FE	RE	FMM	RMM	SFA1	SFA2
	(1)	(2)	(3)	(4)	(5)	(6)
lnk	0.364***	0.361***	0.363***	0.362***	0.361***	0.407***
	(0.030)	(0.030)	(0.036)	(0.036)	(0.029)	(0.031)
lnl	0.864***	0.846***	0.859***	0.840***	0.845***	0.864***
	(0.037)	(0.032)	(0.044)	(0.038)	(0.032)	(0.038)
Constant	-2.002***	-1.909***	-1.818***	-1.723***	-0.914***	-1.191***
	(0.151)	(0.137)	(0.172)	(0.148)	(0.182)	(0.212)
Hausman test	1.40					

[4] The detailed rectification is available from the authors upon request.

ξ					0.990^{***}	1.353^{***}
					(0.197)	(0.307)
η						-0.023^{***}
						(0.003)
N	527	527	496	496	527	527

Notes: Standard error in parentheses.* denotes $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

China's manufacturing productivity under different types of groups

Productivity A and the growth rate of China's manufacturing industry (based on our model) are shown in Table 2. The productivity A, taking industry as the group layer, is represented by the symbol A_{ind}, province as the group layer is represented by the symbol Apro, and ownership sector as group layer is represented by the symbol A_{own}. Moreover, the growth rates of productivity A under the three types of groups are represented by the symbols g_{ind}、 g_{pro} and g_{own}, respectively.

TABLE 2

China's TFP of Manufacturing Industry under Three Types of Group

	(1)	(2)	(3)	(4)	(5)	(6)
Year	A_{ind}	A_{pro}	A_{own}	g_{ind}	g_{pro}	g_{own}
2003	1.0000	1.0000	1.0000			
2004	1.0448	1.1849	1.1556	0.0438	0.1697	0.1446
2005	1.1413	1.3096	1.2815	0.0884	0.1000	0.1034
2006	1.2534	1.4600	1.4004	0.0936	0.1088	0.0887
2007	1.4162	1.6784	1.5793	0.1222	0.1394	0.1202
2008	1.4210	1.7296	1.6154	0.0034	0.0300	0.0226
2009	1.5987	1.8267	1.6933	0.1178	0.0546	0.0471
2010	1.7117	2.0055	1.8856	0.0683	0.0934	0.1076
2011	2.0219	2.3818	2.1963	0.1665	0.1719	0.1525
2012	2.1222	2.4787	2.2703	0.0485	0.0399	0.0331
2013	2.2999	2.6235	2.3824	0.0804	0.0568	0.0482
2014	2.4107	2.6888	2.4247	0.0470	0.0246	0.0176
2015	2.5901	2.7561	2.4678	0.0718	0.0247	0.0176
2016	2.7809	2.9483	2.5968	0.0711	0.0674	0.0509
2017	2.8286	2.9947	2.7840	0.0170	0.0156	0.0696
2018	2.6822	3.2248	2.9458	-0.0532	0.0740	0.0565
2019	2.8875	3.4275	3.0736	0.0738	0.0610	0.0425

Notes: The symbols A_{ind}, A_{pro}, A_{own} represent TFP which uses industry, province, and ownership as the group, respectively. Meanwhile, the symbols g_{ind}、 g_{pro}, g_{own} represent the growth rate of TFP accordingly.

Table 2 shows that all the values of TFP getting from this model have increasing trends. However, due to different structural arrangements, the fitted values of TFP differ. According to the indexes of the productivity growth rate in Table 2, Columns (4) to (6), the TFP of China's manufacturing industry grew rapidly before 2007; the growth rate was even more than 10% per year. This result is consistent with that of Brandt et al. (2012). However, after the financial crisis in 2008, the growth rate of TFP declined rapidly. Besides the rebound in 2010 and 2011, the relatively lower productivity growth rate remained until 2019. This proves the financial crisis has a long-term and noticeable impact on China's productivity growth. It also can be seen that the results obtained based on our model align with the facts about China's economic development, which also proves that our model in this paper is valid.

Regarding the deterioration of the international economic environment caused by the financial crisis, China's exports and foreign direct investment have been reduced compared with those before the financial crisis. This process will inevitably reduce China's "learning effect" from foreign countries (Greenaway & Kneller, 2007), which is an essential source of China's technological progress. Therefore, the rapid growth of China's TFP in future must inevitably depend more on independent innovation and internal resource allocation optimization through economic structural reform.

The resource misallocation degree caused by the distorted industrial structure

The resource misallocation degrees of different production factors caused by distorted industrial structures are shown in Figure 1. It shows that the total factors of misallocation in industries caused an average annual loss of 17.32% from 2003 to 2019, while structural misallocation was loss of 18.19% in 2019. Considering Table 1, China's TFP only increased by about 7% in 2019, but the resource misallocation degree in industries here is a loss of 18.19%. This comparison suggests that if the optimal allocation of production factors in industries can be achieved, it would have a massive increase in China's TFP growth. Further calculation shows that labor misallocation among industries led to a TFP loss of 17.42% in 2019. In comparison, a loss of 1.59% was for capital misallocation in the same year. The results indicated the misallocation among industries is mainly caused by the misallocation of labor.

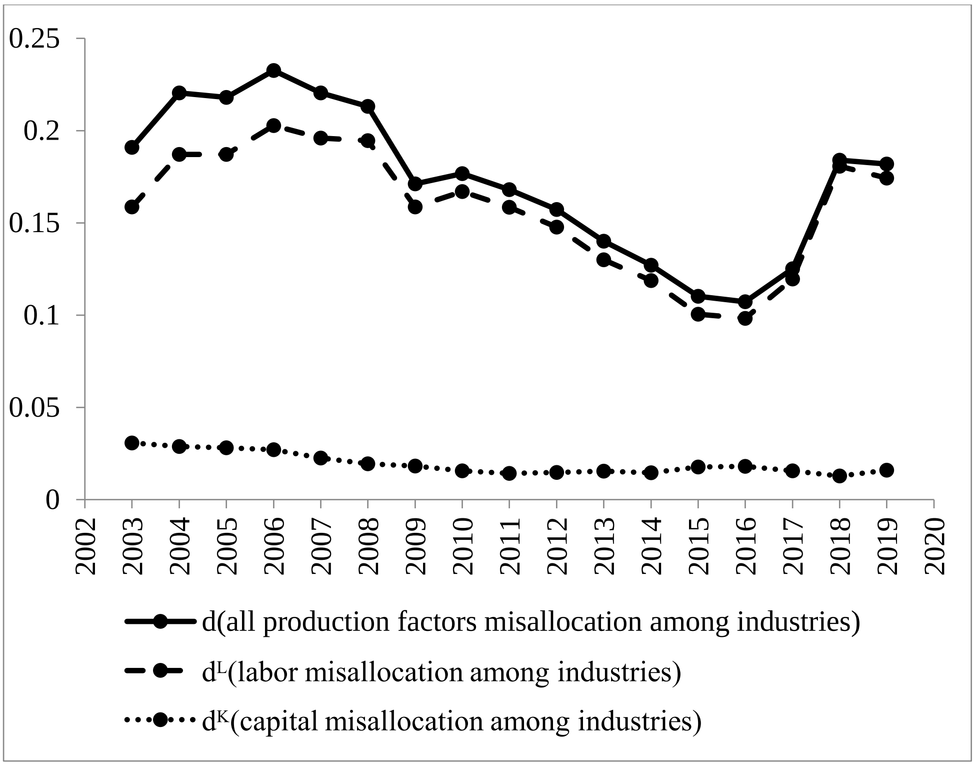


FIGURE 1. Misallocation Degree of Different Factors among Industries

The trend suggests that the misallocation degree among industries fluctuated before 2009 but it has been relatively stable since 2009, attributed mainly to the labor misallocation. In contrast, the mitigation trend of capital misallocation is slight. It might be due to the improvement of labor knowledge level and learning ability and the cross-industries mobility of labor. The clear mitigation trend of the labor misallocation among industries in China could last if there are no other unexpected events.

From 2016 onwards, the misallocation degree presents an apparent rebound trend. This is because the Chinese government seriously started tackling environmental issues through the deliberation and approval of a series of regulations, e.g., the Environmental Protection Supervision Scheme (for Trial Implementation), in July 2015. Since then, environmental protection has become one of the essential assessment criteria for governments' performance at different levels. Meanwhile, China launched the supply-side structural reform at the end of 2015. These policies and measurements have accelerated the adjustment of industrial structures. The strengthening of environmental regulations often promotes capital flow from low-tech industries with high pollution to advanced industries with low pollution, which can improve the efficiency of capital allocation.

Nevertheless, in terms of labor, because most of the labor force in low-tech industries is characterized by low skills, advanced industries cannot accommodate these low-skill workers in the short term. Thus, they most likely flow to labor-intensified low-skill sectors. This situation would further worsen the excessive labor investment in such industries and aggravate the overall labor misallocation. In addition, Sino-US trade frictions have gradually intensified since 2017. The full outbreak of the Sino-US trade war in 2018 changed the original resource allocation pattern guided by China's tariff structure. This continuous event significantly affects the optimization effect of relevant policies on resource allocation in sectors, resulting in the distortion of resource allocation.

The misallocation degree caused by the distorted regional structure

The factor misallocation caused by the distorted regional structure is calculated at the provincial level due to data availability, and the results are shown in Figure 2. The total factor misallocation under the regional structural distortion from 2003 to 2019 resulted in an average annual loss of 8.99% and 9.04% in 2019. This indicates that if the production allocation of all production factors is optimized, China's TFP would increase by 9.04%. Compared to the 6% increase of China's TFP in recent years, the allocation optimization among regions would have a considerable potential. Furthermore, Figure 2 shows that capital misallocation is more severe than labor misallocation. For example, in 2019, capital misallocation caused a loss of TFP at 5.67%, while labor misallocation only caused a loss of TFP at 3.56%.

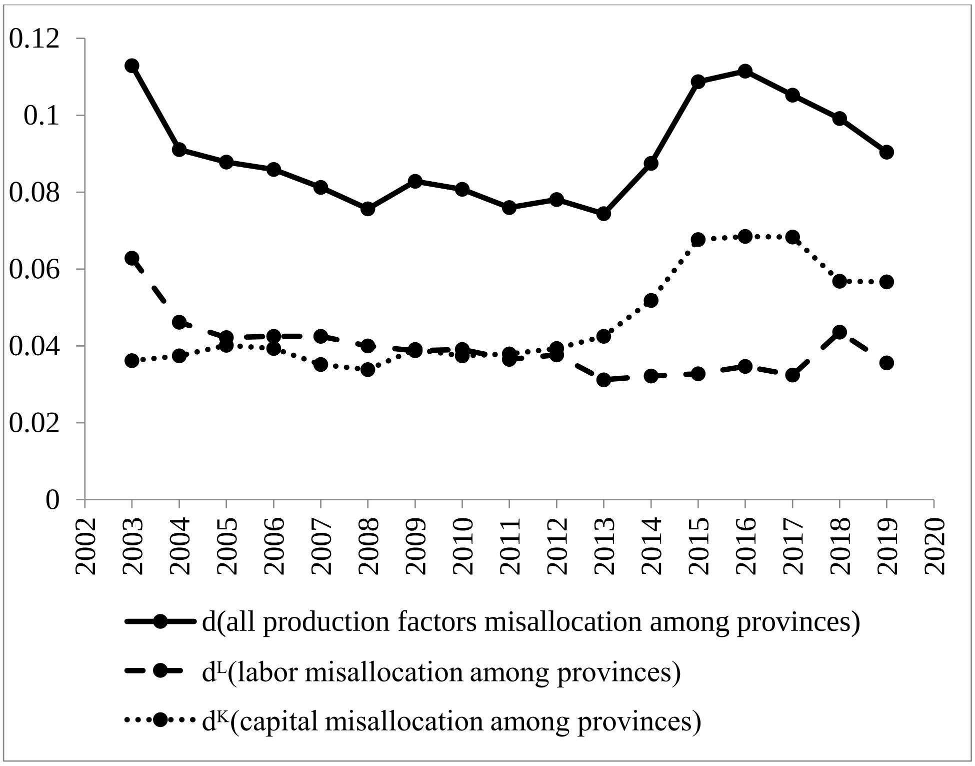


FIGURE 2. Misallocation Degree of Different Factors among Provinces

The evolutionary trend of structural misallocation among regions is different from that applied to industries (see Figure 2). Before 2008, the total factor misallocation among regions showed a mitigation trend, significantly by labor misallocation. However, between 2008 and 2013, the inter-regional allocation efficiency of capital gradually deteriorated, resulting in the postponement of the mitigation trend. From 2014 to 2016, the total factor misallocation suggested a rapid deterioration trend. In 2016, the degree of inter-regional misallocation reached a peak stage - even close to the severity of the initial sample. Subsequently, the inter-regional misallocation has shown a mitigation trend since 2017. Figure 2 indicates that inter-regional misallocation in recent years is primarily caused by capital misallocation.

There is an insight behind the inter-regional misallocation problem. In China, to increase short-term GDP for booming political performance, local government officials favor taking local investment as the priority in their administrations by sacrificing optimizing capital allocation at the national level, leading to severe regional market segmentation. Although the 18th National Congress emphasized that the performance evaluation for local government officials should not be purely based on GDP, GDP is still the core assessment index. Along with the promulgation of the Environmental Protection Supervision Scheme (for Trial

Implementation) and the supply-side structural reform announced in 2015, local governments' effective resource allocation and inefficient investment have been monitored with relevant legislation. The progress has received a positive reflection in the improvement of capital allocation efficiency at the regional structure level. As to labor misallocation, despite the continuous development of transportation infrastructure, there has not been a relatively rapid mitigation momentum in the past ten years, apart from the relatively fast mitigation trend before 2005. Another important reason for labor misallocation is that China has the world's most restricted household registration system, which severely hinders labor flow across regions.

The misallocation degree caused by the distorted ownership structure

The factor misallocation caused by the distorted ownership structure is calculated as shown in Figure 3. The existence of a large-scale and robust state-owned sector is a profound political feature in China (Guo, 1999; Zhu et al., 2019). By calculating the factor misallocation between state-owned and non-state-owned sectors, we can see that the average annual loss of TFP was about 6.57% from 2003 to 2019, and the loss was 8.20% in 2019. The calculation shows that capital misallocation is more severe than labor misallocation, with a loss of TFP at 6.63% for the former and a loss of TFP at 3.57% for the latter.

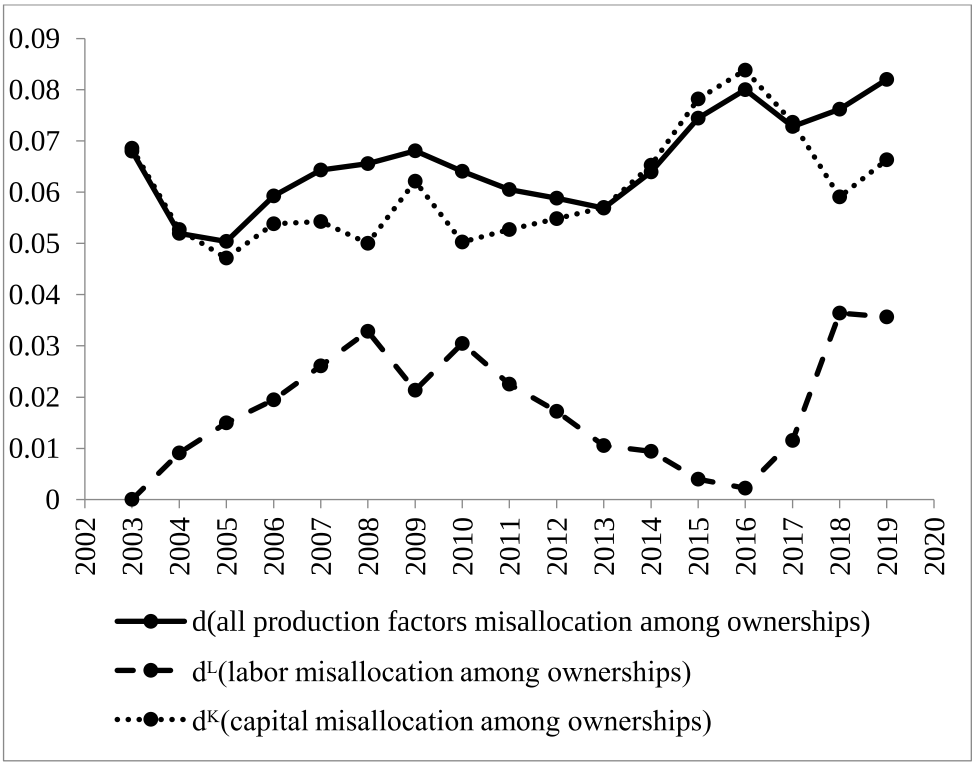


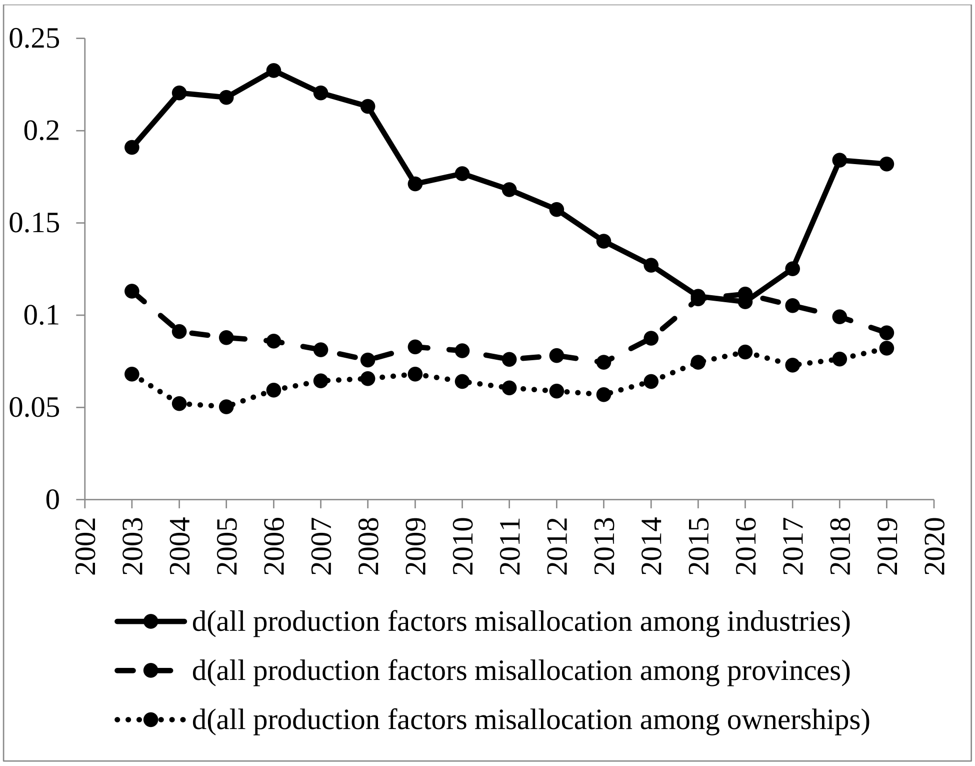
FIGURE 3. Misallocation Degree of Different Factors among Ownerships

The total factor misallocation under the distorted ownership structure has fluctuated since 2003. The factor component analysis suggests the rising and falling of labor misallocation, while capital misallocation is the opposite. The total factor misallocation eventually contributes the counterbalance of the two opposite trends. After 2008, the trend of misallocation between the two factors is entirely different. The cause of the capital factor trend might be caused by the fact that the Chinese government increased investment in the manufacturing industry in response to the impact of the global financial crisis. Due to the ownership of the government, most of these investments are invested in the state-owned sector. However, most of these policies are designed to focus on achieving economic growth at the expense of efficiency, proving by the evidence that the resource mismatch between ownership sectors had significantly increased after the financial crisis until 2016. In September 2015, the State Council published the Opinions on the Development of Mixed Ownership Economy to “encourage state-owned capital to participate in non-state-owned enterprises in various ways”. To a certain extent, the heterogeneous shareholders in state-owned enterprises might alleviate the capital misallocation.

Contrary to the capital factor, labor in the state-owned sector is underinvested compared with the non-state-owned industry (see Table 5 in 4.3). The reason perhaps is that the government’s policy goal of employment stability undertaken by state-owned enterprises had played a positive role in offsetting the financial crisis’s impact on employment. However, the process of correcting the distorted allocation of labor was temporary. With the gradual fading of the effects of the financial crisis, the distortion of labor in the ownership sector would reemerge. Figure 3 shows that since 2016, labor misallocation has gradually intensified and even exceeded the previous highs.

Comparison and discussion on different factors misallocations under various structural distortions

The misallocation degree under different structural distortions is investigated, as shown in Figure 4. The comparison of the total factor misallocation is shown in Figure 4a, followed by each factor in Figure 4b and Figure 4c.


0.25
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d(all production factors misallocation among industries)
d(all production factors misallocation among provinces)
d(all production factors misallocation among ownerships)

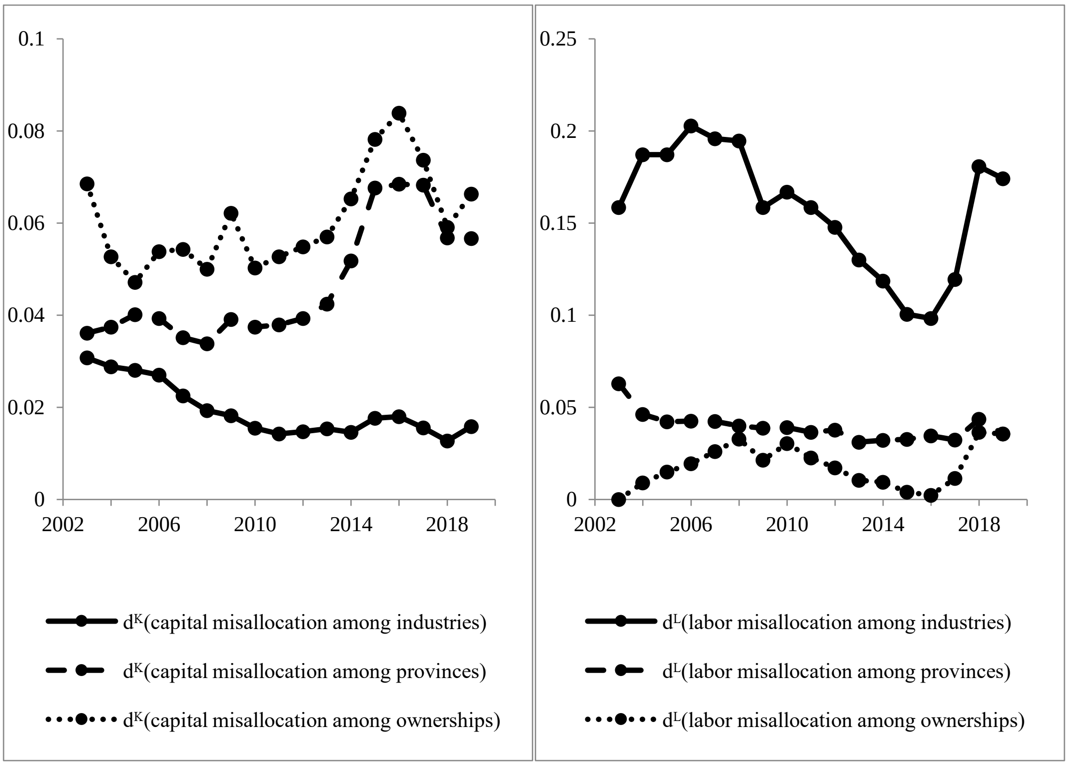
0.1
0.08
0.06
0.04
0.02
0
2002
2006
2010
2014
2018
d^K(capital misallocation among industries)
d^K(capital misallocation among provinces)
d^K(capital misallocation among ownerships)
0.25
0.2
0.15
0.1
0.05
0
2002
2006
2010
2014
2018
d^L(labor misallocation among industries)
d^L(labor misallocation among provinces)
d^L(labor misallocation among ownerships)

FIGURE 4. Comparison of different production factors misallocation caused by various structural distortions. (**a**) Comparison of total resource misallocations caused by different structural distortions. (**b**) Comparison of capital misallocations caused by other structural distortions. (**c**) Comparison of labor misallocations caused by various structural distortions.

Figure 4a shows that taking the mean value from 2003 to 2019 as the criterion, the misallocation among industries is the most serious, followed by regions and ownership sectors; the results are consistent even to the nearest 2019. Since 2006, the misallocation among sectors has tended to ease first and then worsen. By contrast, after the 2008 financial crisis, the misallocation among provinces tended to worsen first and then ease, while the misallocation among ownership sectors remained stable until 2013 but deteriorated from 2014.

From Figures 4b and 4c, we can find that the capital misallocation among ownership departments is the most serious, while that among industries is the least. Contrary to capital, the labor misallocation among sectors is the most serious, followed by provinces and ownerships.

THE RESULTS – PRODUCTION INPUT INTENSITY

The results reported in Section 3 can inform specific loss degrees of TFP caused by misallocation in China, but it is still impossible to determine the optimization direction of factors allocation. To be precise, further information is required to suggest what production factors (capital or labor) should flow from which group (industry, region/province, ownership) to which group (industry, region/province, ownership) in the future. These findings will be constructive and meaningful in providing specific policy recommendations. Therefore, we used the capital and labor input intensity index p_i^l constructed by our model to answer this question. If either p_i^k or p_i^l is greater than 1, it means that the corresponding input is excessive. If less than 1, it indicates that the corresponding input is insufficient.

Inputs Intensity in various industries

Only the latest inputs in 2019 are listed in Table 3 for discussion. About the labor input, the p_i^l values exceeding 1.5 (meaning that the labor input in these industries is over 50% of the effective allocation) are found in industries including the manufacture of wide-ranging textiles, manufacture of furniture, printing and recorded media, manufacture of articles for culture, education, art, sports, entertainment, and manufacture of rubber and plastics. The result suggests that these industries have excessive labor. Conversely, the p_i^l value of about 0.6 or even lower is found in the industries such as the processing of food from agricultural products, processing of petroleum, coking, processing of nuclear fuel, manufacture of chemical raw materials and chemical products, manufacture of chemical fibres, smelting and processing of metals, and smelting and processing of non-ferrous metals. The finding indicates a 40% or higher gap to reach the effective allocation in these industries.

TABLE 3

Input Intensity in Various Industries in 2019

Industry code	Industry	p_i^l	p_i^k
13	Processing of food from agric. Products	0.5644	0.5585
14	Manufacture of foods relabeled	1.1562	1.1608
15	Manufacture of alcohol, beverages, and refined tea	0.8925	1.1726
17	Manufacture of wide-ranging textiles (including textiles, clothing, apparel industry, leather, fur, feather and related products, footwear)	2.7644	1.1860
20	Processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products	1.2297	0.6584
21	Manufacture of furniture	2.3543	1.0705
22	Manufacture of paper and paper prod	1.1474	1.8561
23	Printing and recorded media	1.8184	1.3796
24	Manufacture of articles for culture, education, art, sports, entertainment, and other manufacturing industry	2.0115	0.8413
25	Processing of petroleum, coking, nuclear fuel	0.0857	0.4253
26	Manufacture of chemical raw materials and chemical products	0.5800	1.5960
27	Manufacture of medicines	1.0450	1.3430
28	Manufacture of chemical fibers	0.4296	0.9662
29	Manufacture of rubber and plastics	1.6089	1.2830
30	Manufacture of non-metallic mineral products	0.9870	1.3304
31	Smelting and processing of ferrous metals	0.2639	0.9825
32	Smelting and processing of non-ferrous metals	0.2672	0.7751
33	Manufacture of metal products	1.2089	0.8814
34	Manufacture of general-purpose machinery, measuring instruments and machinery for cultural activity and office work	1.3507	1.0127
35	Manufacture of special-purpose machinery	1.3282	1.0604
37	Manufacture of transport equipment	0.6522	0.8842
38	Manufacture of electrical machinery and equipment	0.9462	0.7247
39	Manufacture of communication equipment, computers and other electronic equipment	0.8942	0.7706

Notes: The industry classification standard changed in 2012, where the industry classification standard issued in 2002 (GB-T4754-2002) was adopted from 2008 to 2011, and the industry classification standard issued in 2011 (GB-T4754-2011) was adopted from 2012. So, we revised the industry classification for consistency.

As to capital input, their p_i^k values exceeded 1.3 are found in the industries, i.e., manufacture of paper and paper prod industry, printing and recorded media, manufacture of chemical raw materials and chemical products, manufacture of medicines, and manufacture of non-metallic mineral products, indicating that the capital investment in these industries is seriously excessive with more than 30% redundancy. In contrast, the p_i^k values lower than 0.8 are found in the sectors such as the processing of food from agricultural products, processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products, processing of petroleum, coking, nuclear fuel, smelting and processing of non-ferrous metals, manufacture of electrical machinery and equipment and manufacture of communication equipment, computers and other electronic equipment, meaning that there is at least 20% capital gap in these industries.

Inputs Intensity in various provinces

Table 4 shows a high association between the labor input intensity and capital input intensity in every province, i.e., the provinces with higher labor input intensity also have higher capital input intensity.

TABLE 4
Input Intensity in Various Provinces in 2019

Province code	Province	Area	p_i^l	p_i^k	Province code	Province	Area	p_i^l	p_i^k
11	Beijing	Bohai Rim	0.4544	0.6658	41	Henan	Central section	1.7184	0.8375
12	Tianjin	Bohai Rim	0.6407	0.6819	42	Hubei	Central section	0.9869	0.4788
13	Hebei	Bohai Rim	1.0078	0.8193	43	Hunan	Central section	1.1408	0.4516
14	Shanxi	Northwest	2.0958	2.1009	44	Guangdong	Southeast	1.4008	0.4251
15	Inner Mongolia	Northwest	0.8271	1.7731	45	Guangxi	Southwest	0.9873	0.7197
21	Liaoning	Northeast	0.9202	0.8922	46	Hainan	Southwest	0.4900	0.7941
22	Jilin	Northeast	0.8931	0.7990	50	Chongqing	Southwest	1.0406	0.6795
23	Heilongjiang	Northeast	1.6433	1.7083	51	Sichuan	Southwest	0.9657	0.7489
31	Shanghai	Southeast	0.6120	0.4214	52	Guizhou	Southwest	1.4260	1.4307
32	Jiangsu	Southeast	1.0007	0.5283	53	Yunnan	Southwest	0.8967	1.4819
33	Zhejiang	Southeast	1.3670	0.6015	61	Shaanxi	Northwest	0.9324	0.9678

34	Anhui	Central section	1.0241	0.6050	62	Gansu	Northwest	1.5221	2.4195
35	Fujian	Southeast	1.0004	0.3944	63	Qinghai	Northwest	1.0026	2.5273
36	Jiangxi	Central section	1.0087	0.4815	64	Ningxia	Northwest	0.9220	2.0432
37	Shandong	Bohai Rim	0.9502	0.6331	65	Xinjiang	Northwest	1.1482	2.6616

Notes: Data for Tibet, Hong Kong, Macao, and Taiwan are unavailable. According to the economic development level, China is divided into six economic regions: Northeast, Bohai Rim, Southeast, Central, Southwest and Northwest. The current division method has more economic implications than the previous one, which only divides China into East, Central and West.

The inputs are relatively insufficient in the areas of Bohai Rim, Southeast, Central, and the provinces of Guangxi, Hainan and Sichuan from the Southwest. Conversely, the inputs are seriously excessive in the provinces of Guizhou, Yunnan, Heilongjiang and the whole area of Northwest China. However, labor input in the provinces of Zhejiang and Guangdong is relatively excessive, which may be due to the data being from the manufacturing industry; the industrial structure of Zhejiang and Guangdong has been shifted from manufacturing to service industries, a large number of migrant workers who were gathered and majorly engaged in the manufacturing industry in the past has been relatively excessive nowadays.

This finding has an important policy implication as it highlights a deficit in China’s regional development strategy. In the past, the Chinese government heavily invested in the West, Northeast and Southwest areas, where economies are less developed, to make a regional development balance. However, the figures in Table 4 provide strong evidence that this kind of capital investment is inefficient and misallocated while other infrastructures are not developed synchronously. As such, the government should switch the investment by focusing to the provinces in the southeastern coastal and Bohai Rim regions, where capital investments are needed and productivity is efficient. Meanwhile, reforming the household registration system is of great importance to accelerate the labor flow from the less developed provinces to regions with highly developed economies, e.g., Bohai Rim and the Central regions, to alleviate labor misallocation.

Inputs Intensity in ownerships

Table 5 shows that the capital in the state-owned sector is excessive, while that in the non-state-owned sector is insufficient. The reason is obvious that state-owned banks dominate China’s financial market (Walter & Howie, 2012), the congenital intimacy between state-owned enterprises and state-owned banks makes it easier for state-owned enterprises to obtain more bank credit and enjoy lower interest rates (Dollar & Wei, 2007), while the non-state-owned enterprises always face serious financing discrimination (Claessens & Tzioumis, 2006). According to the analysis report of Unirule Institute of Economics (2011), the average interest rate for state-owned and state-controlled industrial enterprises is about 2.25%, while the average interest rate for private enterprises is 9.13%, meaning the financing cost of the non-state-owned sector is four times higher than their state-owned counterpart. As Lu and Yao (2004) pointed out, although the non-state-owned sector contributes more than 70% of China's GDP, only less than 20% of the traditional bank loans are granted to them, and while the remaining 80% or more of bank credits are issued to the state-owned sector. The low cost and large scale of financing obtained by the state-owned enterprises encourage them to over-invest in scale, leading to capital excessive seriously. Contrarily, the corresponding capital in the non-state-owned sector is seriously inadequate.

TABLE 5

Input Intensity in Ownerships from 2003 to 2019

	Non-state-owned Sector		State-owned Sector	
Year	p_i^l	p_i^k	p_i^l	p_i^k
2003	0.8905	0.4395	1.1288	1.6589
2004	1.0728	0.5143	0.9264	1.4914
2005	1.1305	0.5439	0.8742	1.4395
2006	1.1563	0.5169	0.8520	1.4574
2007	1.2000	0.5186	0.8168	1.4409
2008	1.2460	0.5410	0.7830	1.4048
2009	1.1614	0.4804	0.8500	1.4827
2010	1.2329	0.5359	0.7951	1.4084
2011	1.1807	0.5182	0.8364	1.4362
2012	1.1408	0.5031	0.8703	1.4578
2013	1.0823	0.4855	0.9222	1.4862
2014	1.0630	0.4525	0.9397	1.5241
2015	0.9880	0.4031	1.0120	1.5987
2016	0.9549	0.3836	1.0461	1.6301
2017	1.0751	0.4270	0.9279	1.5499
2018	1.2553	0.5017	0.7762	1.4367
2019	1.2429	0.4729	0.7846	1.4674

Paradoxically, the labor input in the state-owned sector is relatively insufficient and excessive in the non-state-owned sector. This is caused by the fact that the privilege inherited awards the state-owned enterprises with high administrative monopoly power (Jin et al., 2015) and high monopoly profits. The monopoly profits, which should be owned by the state and shared stakeholders, make a higher margin in wages and social welfare of the state-owned sector compared to that in the non-state-owned sector. The high labor cost and low capital cost motivate state-owned enterprises to reduce labor input and increase capital input. As a result, in the state-owned sector, the labor allocation is distorted, and the labor input is insufficient, while the situation in the non-state-owned sector is on the opposite side.

CONCLUSION

Based on our innovative empirical model, we assess the resource misallocation degrees among China's industries, regions and ownerships. The results suggest that if we use the annual average as the criterion, the misallocation for industries is most serious, followed by provinces and ownerships. Specifically, resource misallocation among industries has eased first and then worsened since 2009; among provinces, it has worsened first and then eased after the financial crisis in 2008; and among ownerships, it remained small fluctuations until 2013, but has deteriorated since 2014. Regarding production factors, the capital misallocation among ownerships is the most serious, followed by regions (i.e., provinces) and industries. By contrast, labor misallocation among industries is the most serious.

Meanwhile, there are relatively minor labor misallocations found in provinces and ownerships. In the last section, we have provided in-depth discussions of the reasons behind the findings. The findings have important implications for policymakers as they highlight the focus of structural reform in the future. Besides, this paper constructs the factor's input intensity index to indicate which group (i.e., industry, region, ownership) has been over-(or under-)invested. Therefore, the findings should have meaningful implications as they can point out the direction toward optimizing factors allocation. The results have provided detailed suggestions about what factors (capital, labor) should increase or decrease in each group (industry, region/province, ownership). To sum up, this paper sheds light on China's complicated resource misallocation and structural distortion through rigorous analysis and provides insightful discussions in the research context with meaningful policy implications.

This paper’s contribution to the literature is threefold: First, avoiding using firm data is incredibly beneficial because company (enterprise) data is generally difficult to obtain in any country. Our proposed model only requires collecting sector/industry, province, and ownership data without compromising the results. In China, these data have more extended time series and are easier to manage. In the models used in Hsieh and Klenow (2009), Jin et al. (2018), and Wang and Niu (2019), the group (e.g., industry) productivities are calculated by the weighted average productivities of firms which inevitably leads to the deviation of the group productivities. Avoiding firm data would be more accurate for groups’ productivity (e.g., input and output). Second, the method used in both Hsieh and Klenow (2009) and Brandt et al. (2013) have an assumption that the CD (Cobb–Douglas) function of output on production factors is a constant return to scale, though Brandt et al. (2013) suggest a feasible method. However, this assumption is not applicable in the Chinese context. Gong and Hu (2013) point out that the output elasticity of China’s capital and labor does not meet the constant return to scale assumption. Therefore, we could argue that the model used in this paper is scientifically robust because it drops the firm layer and relaxes the assumption of constant return to scale, presuming the results would be more objective. Lastly, while investigating the resource misallocation degree of structural distortions, it is also necessary to consider the direction of structural reform in the future. The answer can be obtained by assessing which group(s) are over-invested and relatively insufficient. We can further construct an index to serve this purpose.

Our findings lead to several profound policy implications for policymakers. First, the resource misallocation of the industry is the most severe structural distortion compared to the other two (regions and ownerships). This finding highlights a colossal challenge facing China's economy and the focus policy of the Chinese government in the industry structure’s transformation and upgrading. In particular, the resources invested in low-technology industries such as textile, furniture, rubber, and plastic products have not received adequate returns due to excessive labor input and low productivity. The government should have good policies to guide the capital flow to the high technology and efficient industries to dissolve the labor mismatch and achieve the potential total factor productivity.

Second, it is urgent to alleviate regional resource misallocation by improving the efficiency of capital allocation because it persists. In the future, the government should compensate for insufficient capital investment in high-productivity regions such as Southeast and Central regions while alleviating the excessive capital investment in some Western and Northeastern regions. Moreover, regional segmentation is a crucial obstacle to the free flow of resources among regions. Thus, the future policies of the Chinese government should look at how to break the market segmentation and smooth the capital flow to promote competition in regions to achieve high productivity and the efficiency of resource allocation.

Third, although the structure misallocation with the ownership is the smallest in scale, it shows a rising trend and should not be ignored. Policymakers should address the issues that resource allocation is always inclined to the state-owned sector, which consistently receives excessive capital and recessive financial guarantee. On the one hand, this causes discrimination against the non-state-owned sector. On the other hand, it also leads state-owned organizations to prefer low-cost capital to labor, resulting in further resource misallocation.

The limitation of this paper is that the study mainly utilizes the HK model's definition of the degree of factor allocation distortion, which is the loss of aggregate national output and TFP due to the inequality of marginal factor output among incumbent firms as a result of the distortion. However, this is only an intensive distortion, as Banerjee and Moll (2010) pointed; a more comprehensive distortion also includes distortions in firms' entry and exit behavior, i.e., extensive distortion. As such, future research direction could introduce the entry-exit process of firms into the model to analyze the relative severity of the three structural distortions more comprehensively.

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