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Factor market distortion correction, resource reallocation and potential productivity gains: An empirical study on China's heavy industry sector

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ABSTRACT

In this study, we develop a novel analysis framework for evaluating the effects of resource reallocation from the correction of factor market distortion (FMD) on total factor productivity (TFP) gains. We first measure FMD in China's heavy industry sector from 1995 to 2012, and then investigate the effects of resource reallocation from FMD correction by using the price elasticity of factor demands as a link, along with its potential TFP gains. The results indicate that: (1) Taking the price of capital as a reference, the prices of labour and energy in the study period were relatively higher to different extents. (2) If current FMD were fully corrected, the labour input in China's heavy industry sector would increase by 25.37%, whereas capital and energy inputs would decrease by 18.51% and 10.57%, respectively. (3) The resource reallocation effects resulting from current FMD correction will bring about significant TFP improvement (by 8.55%) in China's heavy industry sector, and there are evident industrial differences and stage characteristics for these promoting effects.

1. Introduction

Market-oriented reforms have played a key role in promoting China's economic growth ever since the late 1970s, when China adopted the reform and opening-up policies. To date, the Chinese government has made great progress in product market reforms (Zhang and Tan, 2007; Fan et al., 2011). Nevertheless, due to some institutional constraints, the pace of establishing integrated markets for essential productive factors (such as capital, labour, energy, and land) still lags behind, resulting in serious factor market distortion (FMD) among enterprises with different ownerships, within various sectors or regions, and between urban and rural areas (Brandt et al., 2013). Taking the capital market as one case, with a deducted rate for the preferential loan, the actual lending rate for China's state-owned enterprises (SOE) from 2001 to 2007 was only 1.6%, while the lending rate for private enterprises during the same period was up to 5.4% (Liu and Zhou, 2011). As stated by Wei et al. (2016), in regions with higher SOE shares, private firms encounter more difficulties in accessing financing and bear higher financial costs. Significant segmentations also occur in China's labour market (Cai et al., 2002; Knight and Li, 2005; Hertel and Zhai, 2006) and energy market (Ouyang and Sun, 2015; Shi and Sun, 2017; Ju et al., 2017).

FMD refers to the non-optimal allocation of productive factors in a national economy due to market imperfection, i.e., the actual prices of input factors deviate from the theoretical factor prices in a perfectly competitive market. During the past several decades, the relatively lower prices of essential productive factors has created significant cost advantages for investment-driven and export-oriented economic growth in China (Chen et al., 2015). However, this has inevitably resulted in substantial loss for industrial total factor productivity (TFP). On the one hand, lower factor prices would greatly reduce firms' willingness to enhance resource utilisation efficiency through technological innovation, resulting in the stagnation of resource-saving technical progress. On the other hand, the distorted price system fails to reflect the scarcity and opportunity costs of productive factors,

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which, in turn, hinders the function of factor markets in optimising resource allocation. Given that efficient allocation of resources is a key source of productivity growth (Kumbhakar et al., 2000; Zhang et al., 2009; Song et al., 2011), the misallocation of productive inputs will inevitably lead to the loss of TFP (Restuccia and Rogerson, 2008; Banerjee and Moll, 2010; Syverson, 2011; Bartelsman et al., 2013), thereby significantly hindering China's economic growth and the transformation of its development mode (Zhu, 2012).

During the last decade, numerous studies have focused on TFP losses resulting from resource misallocation caused by FMD. China, as a country undergoing the transition from a planned economy to a market economy, has naturally become the focus of scholars from home and abroad in recent years. Hsieh and Klenow (2009) examined the aggregate TFP loss from misallocation of inputs across firms in China from 1998 to 2005 and found that the manufacturing industry in this developing country can potentially improve its TFP by 30%–50% when capital and labour are hypothetically reallocated to equalise marginal products to the US level. Gong and Hu (2016) extended the above study by relaxing the assumption of constant returns to scale for differentiated products, and they insist that the extent of resource misallocation in China was overestimated by Hsieh and Klenow (2009). Brandt et al. (2013) examined TFP losses in China's non-agricultural economy associated with labour and capital misallocation across provinces and sectors from 1985 to 2007, and decomposed the overall TFP loss further into FMD within provinces (between state and non-state sectors) and distortions between provinces (within sectors). Du et al. (2014) found strong and consistent evidences of a systematic and worsening resource misallocation within the state sector and/or between the state sectors and private sectors over time. Adamopoulos et al. (2015) used a quantitative framework to measure the extent of resource misallocation in agriculture within villages, across villages, and over time in China and assessed the TFP gains from an efficient reallocation of resources. David et al. (2016) investigated the reduced aggregate productivity and output resulting from the misallocation of factors across heterogeneous firms due to informational frictions in China, India and the US. Focusing on the market distortions and aggregate productivity growth in China's energy sector, Dai and Cheng (2016) insisted that this sector has major potential for productivity gains from resource reallocation through the reduction of market distortions. Domestic studies have also demonstrated increasing interest in this field (Yuan and Xie, 2011; Nie and Jia, 2011; Wang and Wu, 2014; Gai et al., 2015).

Given the great progress in measuring TFP losses resulting from resource misallocation in the context of China's FMD, there are still some issues to be further discussed. On the one hand, most existing studies have focused only on the misallocation of capital and/or labour, while little attention has been paid to another important productive factor, i.e., energy. In the face of severe pressure from the perspectives of energy shortages and climate change in relation to China's current economic growth, incorporating energy market distortion, along with energy misallocation, into the analysis framework and evaluating its impact on China's TFP makes great sense. On the other hand, existing studies have placed their emphasis on the measurements of TFP losses resulting from FMD based on traditional analysis frameworks; however, little attention has been paid to not only the extents to which the productive factors have been misallocated but also how this kind of resource allocation has led to current TFP losses.

In this paper, we aim to investigate the potential TFP gains from the correction of FMD for China's heavy industry sector from 1995 to 2012. There are 18 two-digital industries in China's heavy industry sector including Mining and Washing of Coal (MWC), Extraction of Petroleum and Natural Gas (EPNG), Mining and Processing of Ferrous Metal Ores (MPFMO), Mining and Processing of Non-Ferrous Metal Ores (MPNFMO), Mining and Processing of Nonmetal Ores (MPNO), Processing of Petroleum, Coking and Processing of Nuclear Fuel (PPCPNF), Manufacture of Raw Chemical Materials and Chemical Products (MRCMCP), Manufacture of Non-metallic Mineral Products (MNMP), Smelting and Pressing of Ferrous Metals (SPFM), Smelting and Pressing of Non-ferrous Metals (SPNM), Manufacture of General Purpose Machinery (MGPM), Manufacture of Special Purpose Machinery (MSPM), Manufacture of Transport Equipment (MTE), Manufacture of Electrical Machinery and Apparatus (MEMA), Manufacture of Communication Equipment, Computers and Other Electronic Equipment (MCECOEE), Production and Supply of Electric Power and Heat Power (PSEPHP), Production and Supply of Gas (PSG), and Production and Supply of Water (PSW). As it is known, the heavy industry sector is currently the mainstay of China's economy, with the most serious misallocation of resources. For instance, with the primary target of sustaining rapid economic growth, China's energy sector (involving the four sub-sectors including MWC, EPNG, PPCPNF, and PSEPHP studied in this paper) is currently characterised by rigid governmental interventions and monopolistic SOEs. In this context, this sector is involved in several market distortions, such as monopolies, price regulations, subsidies, entry barriers, biased credit allocations, and the absence of a fully market-based wage determination system in SOEs (Dai and Cheng, 2016), which inevitably trigger resource misallocations and distort firms' entries and exits. Wei and Li (2017) also present quantitative evidence on resource misallocation in the Chinese manufacturing sector, especially the widespread underpaid for labour and the substantial over-use of energy in some energy-intensive sectors, such as Chemical, Non-metallic, Ferrous metals and Non-ferrous metal.

The marginal contributions of this paper lie in the following two aspects: (1) energy input is incorporated into the model when we study the resource misallocation and aggregated TFP losses of China's heavy industry resulting from FMD. (2) The effects of resource reallocation from the full correction of FMD are directly calculated using price elasticities of factor demands as a link, based on which, the potential TFP gains from the full correction of FMD are further evaluated. The remainder of the paper is structured as follows: Section 2 measures the degree of FMD for China's heavy industry sector from 1995 to 2012 and describes the dataset; Section 3 examines the effects of resource reallocation when fully correcting current FMD, using the price elasticities of factor demands as a link; Section 4 evaluates the potential TFP gains from resource reallocation led by FMD correction; and Section 5 concludes the paper and proposes some key issues that are worth studying in the future.

2. Measurement of FMD

2.1. Methodologies

Thus far, there are various conventional approaches for FMD measurement, such as production possibilities frontier technology, shadow price approach, and production function method. The production possibilities frontier technology, put forward by Skoorka (2000), has the main advantage of evaluating the degree of entire market distortions, including the product market and the factor market; but it fails to distinguish different types of distortions among input factors. In addition, relative price distortions cannot be studied by this method. The shadow price approach, developed by Atkinson and Halvorsen (1984), enables measurement of the absolute and relative price distortions of input factors. However, the estimation for the trans-log cost function usually requires quite a large study sample; otherwise the degree of distortion cannot be measured annually. In this paper, the production function method is employed to evaluate the FMD of China's heavy industry sector for two reasons. First, the definitions for absolute and relative distortions of input factors within this analysis are very clear and have very solid theoretical foundations. Second, the flexible function form allows us to measure the absolute price distortion for each factor, along with the relative price distortion between different factors over time.

According to the theory of neoclassical economics, the equilibrium condition for a firm to maximise its profit is to make the "marginal revenue" of each input factor equal to its "marginal cost" in a perfect competition market. Due to some restrictive factors such as government regulations and monopoly power, "marginal revenue" of productive factors usually deviates from their "marginal cost". Therefore, the degree of price distortion for a specific input factor can be evaluated by comparing its marginal revenue product (*MRP*) to the corresponding marginal cost, i.e., its actual market price.

Since the actual prices of input factors can be acquired directly from official statistics, the computation of the marginal revenue product for each factor becomes a crucial step in measuring FMD of China's heavy industry sector. First, we assume that all the sub-sectors operate their production in the form of a trans-log production function, written as,

$$LnY = \beta_0 + \sum_i \beta_i LnX_i + \frac{1}{2}\sum_i \sum_j \beta_{ij} LnX_i LnX_j + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + u + \varepsilon \quad (i, j = K, L, E) \tag{1}$$

where Y is actual industrial added value (*IAV*) and X_i is the ith factor input. Trend time t reflects technical change effects. The individual effect u captures the amount by which predictions of *IAV* in one unit must be adjusted either upward or downward, holding a given level of X. ε is the random noise.

Then, the annual marginal revenue product for each factor (K, L, E) can be evaluated by multiplying its output elasticity by the corresponding productivity, respectively represented as,

$$\begin{aligned} MRP_{K,t} &= (\beta_k + \beta_{kk} LnK_t + \beta_{kl} LnL_t + \beta_{ke} LnE_t) \cdot \frac{Y_t}{K_t} \\ MRP_{L,t} &= (\beta_l + \beta_{ll} LnL_t + \beta_{kl} LnK_t + \beta_{le} LnE_t) \cdot \frac{Y_t}{L_t} \\ MRP_{E,t} &= (\beta_e + \beta_{ee} LnE_t + \beta_{ke} LnK_t + \beta_{le} LnL_t) \cdot \frac{Y_t}{E_t} \end{aligned} \tag{2}$$

According to the theoretical analysis above, the absolute price distortion of the ith factor can be written as,

$$Dis_i = \frac{MRP_i}{P_i} \tag{3}$$

where MRP_i is the marginal revenue product of the ith factor and P_i represents its actual market price. Dis_i stands for the degree of absolute price distortion. If Dis_i equals to 1, there is no absolute price distortion; if it is >1, there is a negative distortion; if it is <1, there is a positive distortion.

Compared with the absolute prices of productive factors, managers of firms are more concerned with the relative prices of different factors. The relative price distortions between input factors can be further represented as:

$$Dis_{ij} = \frac{Dis_i}{Dis_j} = \frac{MRP_i}{MRP_j} \cdot \frac{P_j}{P_i} \tag{4}$$

Similarly, Dis_{ij} being equal to 1 implies that there is no relative price distortion between the two factors; Dis_{ij} being greater (less) than 1 indicates that the price of the ith factor is relatively lower (higher), compared with that of the jth factor.

2.2. Data descriptions

A total of 18 two-digit sub-sectors within China's heavy industry sector from 1995 to 2012 are investigated. It can be observed from Eqs. (3) and (4) that the variables involved include the amount of input and actual price of each factor (K, L, and E) in various sub-sectors over the years; in addition, the industrial added values are also required. Because of the differences in statistical standards[1] adopted by the National Bureau of Statistics (NBS) in different periods, the extrapolation method is adopted in this study to adjust the data from 1995 to 1997 to the statistical standard adopted since 1998. Additionally, to offset the impact of price changes on the results, all the statistics involving price information (such as industrial added value, and various factor prices) are deflated with corresponding price indices by using the year 1995 as the base period.

2.2.1. Capital input and capital price

Capital stock is one of the most popular indices for measuring capital input (K). Because capital stock data are not found in any Chinese official statistics, the perpetual inventory method is used to calculate the capital stock of each industry from 1995 to 2012. Unlike most previous studies, which have assumed a constant depreciation rate for all the studied sub-sectors, the rates of depreciation are estimated in this study by different sub-sectors, following Chen (2011), to distinguish the inherent differences in equipment service life. Related data are acquired from the annual *China Statistical Yearbook*.

Capital price, i.e., the user cost of capital, is the sum of the depreciation rate and the interest rate (Pindyck and Rubinfeld, 2013). The depreciation rates have been obtained, as above, and the bank lending rate is measured by a 1 to 3 year benchmark interest rate, as retrieved from the official website of the People's Bank of China. Given the frequent adjustments of the benchmark interest rate in some years, the annual average of the benchmark interest rate is calculated as the weighted average based on the number of days on which various interest rates have been maintained.

2.2.2. Labour input and labour price

Labour input is represented by the annual average number of employees, and the data are obtained from annual *China Statistical Yearbooks* and annual *China Industrial Economic Statistical Yearbooks*. Labour price is measured by the average real wages of staff and workers, deflated on the nominal wage of workers with CPI. There are two data sources of workers' nominal wages in different sub-sectors: the data for 1995–2002 are from annual *China Labour Statistical Yearbooks* and the data for 2003–2012 are from annual *China Statistical Yearbooks*.

2.2.3. Energy input and energy price

Energy inputs are represented by total energy consumption, as acquired from annual *China Energy Statistical Yearbooks*. The sub-sector energy price over the years is obtained in three steps, including (1) total cost of energy use in 1995, (2) energy prices in 1995, and (3) energy prices from 1995 to 2012. First, the total cost of energy usage of various industries in 1995 are computed as follows,

$$EC_i = \sum_j E_j^i \cdot P_j (i = 1, 2 \ldots 18;\ \ j = 1, 2 \ldots 13) \tag{5}$$

where EC_i means the total cost of energy use for the ith industry in 1995, E_j^i represents the total consumption of the jth fuel input in the ith industry in the same year, and P_j is the price of the jth fuel in 1995. A total amount of 13 types of fuels (such as raw coal, washed fine coal, other washed coal, coke, coke oven gas, other gas, crude oil, gasoline, kerosene, diesel oil, fuel oil, natural gas, electric power) are included in this study, and the individual prices of fuels in the base year are acquired from *Data Collection on Industrial Census of the People's Republic of China in 1995*.

Secondly, energy price in every industry (with the unit "Yuan/tce") in 1995 is calculated by dividing the total energy use cost in that year

[1] The statistical standard after 1998 was "all SOEs (state-owned enterprises) and non-SOE enterprises with annual revenue of 20 million RMB Yuan or above," while that before 1998 was "state-owned industrial enterprises with independent accounting." Data under these two standards have significant disparity for part of the studied industries.

Table 1
Descriptive statistics of the dataset.

Variables	Units	Mean	Std.D.	Min	Max	Obs.
IAV	Billion Yuan	267.31	390.83	1.27	2686.36	324
K	Billion Yuan	457.99	686.88	3.78	5205.28	324
L	Thousand person	3430.04	2911.19	160	13,854.17	324
E	Million tce	71.22	104.05	2.68	596.68	324
P_k	Yuan	0.12	0.02	0.10	0.16	324
P_l	Yuan/person	15,810.18	9123.91	4443.21	46,591.59	324
P_e	Yuan/tce	640.89	232.45	204.81	1395.71	324

by the corresponding energy consumption. Finally, by using the purchasing price index for fuel and power over the years, the energy prices of each industry from 1996 to 2012 are further estimated.

2.2.4. Actual industrial added value

The nominal industrial added value in 1995–2007 and the annual producer price indices (PPI) for industrial products are obtained from the *China Statistical Yearbook*. The actual industrial added value is calculated by deflating the nominal industrial added value with corresponding PPI. In addition, given that the statistical authority has not released figures for sub-sector industrial added value since 2008, the actual added value data from 2008 to 2012 are estimated based on the growth rate of the industrial added value of various industries.

The descriptive statistics of the dataset are summarized in Table 1.

2.3. Econometric analysis

To avoid spurious regression and ensure the efficiency for the estimate results of coefficients, panel unit root tests are first carried out to check the stationary properties of the variables. In this paper, we conduct two different tests, including the common unit root process—Levin-Lin-Chu (LLC) test and the individual unit root process—Fisher-ADF test. The results, which are presented in Table 2, confirm that all the seven variables in natural logarithms are stationary at the 1% significance level.

Selecting an appropriate panel regression specification is an important procedure in obtaining convincing results. In general, there are three widely-used specifications: the pooled model, the fixed-effect (FE) model and the random-effect (RE) model. The Fischer test (F test) is first conducted to decide whether the pooled model should be used. The statistic of the F test (the null hypothesis is that all the individual effect $u_i = 0$) is 57.78, showing the inappropriateness of using the pooled model in the present paper. The Hausman test is usually executed to decide between the FE and the RE models. However, a recent study by Clark and Linzer (2015) points out that the Hausman test statistic has insufficient power to select between FE and RE when the within variation of regressors is very low. Following Papyrakis et al. (2016), Filippini and Heimsch (2016), and Wang et al. (2017), a random effects estimation technique is employed in this study; this technique has the merit of being much more efficient for variables with little variation over time (which is the case for the explanatory variables in the current study). The estimation results of parameters are reported in Table 3. It is noted that half of the parameter estimates are statistically significant at the 1% level, implying the appropriate specification of translog function form.

Table 2
Tests for panel unit roots.

Variables	LLC test	Fisher-ADF test
Output and inputs		
IAV	-1.8245^{**}	6.5205^{***}
K	-4.0803^{***}	6.3973^{***}
L	-5.3365^{***}	5.3400^{***}
E	-8.2655^{***}	7.9464^{***}
Factor prices		
P_k	-10.9956^{***}	24.6808^{***}
P_l	-4.3417^{***}	4.3398^{***}
P_e	-4.7137^{***}	14.9287^{***}

Note: (1) All the variables are in natural logarithms.
(2) **, *** indicate statistical significance at 5%, 1% level, respectively.

Table 3
Estimation results for the parameters of translog production function.

Variables	Parameters	Std. Err.	Variables	Parameters	Std. Err.
β_k	1.3803^{***}	0.2314	β_{kl}	0.2121^{***}	0.0399
β_l	-1.3925^{***}	0.3828	β_{ke}	-0.0217	0.0704
β_e	-0.4585	0.3775	β_{el}	-0.0674	0.0704
β_{kk}	-0.2377^{***}	0.0615	β_t	0.0768^{***}	0.0162
β_{ll}	0.0882	0.0821	β_{tt}	-0.00015	0.0007
β_{ee}	0.1542	0.1065	β_0	2.9438^{**}	1.4685
σ_u	0.4158				
σ_ε	0.2298		$\rho = \sigma_u^2/(\sigma_u^2 + \sigma_\varepsilon^2)$	0.7659	

Note: **, *** indicate statistical significance at 5%, 1% level, respectively.

2.4. Degree of FMD

Based on Eqs. (3) and (4), the degree of FMD for China's heavy industry sector from 1995 to 2012 can be evaluated. Because the managers of firms pay more attention to the relative prices of factors than to their absolute prices, this study focuses on the results of relative price distortions between labour and capital (Dis_{LK}) and between energy and capital (Dis_{EK}) in various industries over the whole study period. The results are reported in Table 4.

Table 4 shows that the annual mean of relative price distortions between labour and capital (Dis_{LK}) is 0.41, which indicates that labour price should be decreased by 59% relative to capital price -to eliminate completely the relative price distortion between the two factors in China's heavy industry sector. The underlying reasons for the relatively lower price of capital (or the relatively higher price of labour) are twofold. On the one hand, the Chinese financial system possesses all the typical features of financial repression, which usually leads to lowering of the interest rates by a certain extent (Huang and Wang, 2010). As it is known, heavy industries such as metallurgy, thermal power, and petrochemical are typically capital-intensive industries. To implement the strategy of heavy industry priority development, the central government implemented strict interest rate control policies, with the main purpose of providing abundant low-cost capital to the producers and investors. It is reckoned that the one-year actual lending rate was, on average, 3.56% during 2000–2012, far below the theoretical level of the lending rate (roughly 7%) in this period. Worse still, the actual lending rates became negative in 2008 and 2011 (Chen et al., 2014). On the other hand, China's heavy industry sectors are usually characterised by a significant ownership monopoly for a long period of time in the past. Excess profits can be acquired by some of the monopoly industries through occupying unique resources and/or using some administrative privileges (Zhang and Chen, 2008), resulting in very high wages for the employees. For instance, the average wages of employed persons in urban units for some heavy industry sub-sectors with obvious features of ownership monopoly, such as EPNG and PSEPHP, were >80,000 Yuan in 2015, nearly twice of that of the average for the whole manufacturing industry (NBSC, 2017).

In contrast, the annual mean of relative price distortions between energy and capital (Dis_{EK}) is 0.88, indicating that the energy price needs to be reduced by 12% relative to capital price to eliminate the relative distortions between energy and capital in China's heavy industry sector. In general, the heavy industry sector possesses dual characteristics of being both capital-intensive and energy-intensive. As a result, maintaining the energy price at a relatively low level also helps reduce the cost of using energy resources, although it inevitably stimulates the overuse of energy in high energy-consuming sectors, resource-intensive enterprises, and low-value-added industrial products (Ju et al., 2017). Thus, it is no wonder that there is no

Table 4
Relative price distortions of input factors over the years.

	Dis_{LK}					Dis_{EK}				
	1995	2000	2005	2010	Mean Value	1995	2000	2005	2010	Mean Value
MWC	0.153	0.200	0.133	0.135	0.167	0.450	0.770	0.638	0.765	0.727
EPNG	0.733	1.164	0.697	0.513	0.765	0.653	0.718	0.963	1.234	0.980
MPFMO	0.055	0.115	0.095	0.123	0.109	0.159	0.265	0.217	0.429	0.284
MPNFMO	0.160	0.192	0.155	0.223	0.193	0.276	0.506	0.294	0.473	0.413
MPNO	0.086	0.123	0.091	0.114	0.111	0.426	0.534	0.238	0.363	0.400
PPCPNF	0.861	0.766	0.558	0.592	0.722	0.753	0.708	0.484	0.559	0.649
MRCMCP	0.388	0.403	0.341	0.312	0.374	0.261	0.399	0.286	0.375	0.343
MNMP	0.148	0.174	0.189	0.202	0.188	0.269	0.402	0.266	0.301	0.329
SPFM	0.367	0.464	0.397	0.557	0.490	0.144	0.206	0.133	0.142	0.165
SPNM	0.276	0.342	0.352	0.377	0.374	0.254	0.266	0.205	0.227	0.243
MGPM	0.140	0.148	0.102	0.106	0.128	0.554	1.011	0.736	0.940	0.835
MSPM	0.132	0.168	0.133	0.123	0.149	0.622	1.130	0.909	1.177	**1.084**
MTE	0.236	0.240	0.194	0.171	0.223	1.251	1.702	1.541	1.416	**1.548**
MEMA	0.194	0.183	0.115	0.105	0.156	1.527	2.239	1.406	1.517	**1.753**
MCECOEE	0.279	0.208	0.162	0.118	0.194	2.827	2.318	2.022	2.004	**2.261**
PSEPHP	1.561	1.316	1.239	3.012	**1.499**	1.285	1.374	1.349	1.423	**1.414**
PSG	0.523	0.508	0.645	0.684	0.664	1.267	0.941	1.131	1.719	**1.377**
PSW	1.175	0.670	0.663	0.651	0.785	1.081	1.004	1.111	1.018	**1.115**
Annual mean of all the industries	0.41					0.88				

Note: the columns named "Mean Value" represent the average relative price distortions of an individual industry over the whole studied period.

significant relative price distortion between energy and capital in China's heavy industry sector.

Lastly, significant industrial differences, in terms of relative price distortions among input factors, are observed. For example, regarding labour-capital relative price distortions (Dis_{LK}), the annual mean is merely 0.109 for the industry of Mining and Processing of Ferrous Metal Ores, due to its very low MRP_L and relatively higher MRP_K. In contrast, the annual mean of Dis_{LK} is 1.499 for the industry of Production and Supply of Electricity Power and Heat Power; this can mainly be attributed to its relatively higher MRP_L and very low MRP_K. Similar situations are also observed in respect of energy-capital relative price distortions (Dis_{EK}). The annual mean of Dis_{EK} is 0.165 for the industry of SPFM, while it is up to 2.261 for the industry of MCECOEE.

3. Effects of resource reallocation from FMD correction

3.1. Theoretical framework and models

Using elasticity of factor substitution as a link, this study builds a bridge between FMD correction and resource reallocation. On the basis of an estimation of sub-sector elasticities of factor substitution, we first examine the reallocation of input factors in the scenario that the FMD of China's heavy industry sector is completely corrected. Then, by comparing the allocation status of input factors in the two scenarios (before and after FMD correction), the effects of resource reallocation from FMD correction can be studied.

3.1.1. Method on substitution elasticity estimation

In this study, a translog cost function is used to estimate the elasticity of factor substitution. The function form is as follows:

$$\begin{aligned}\ln C = \alpha_0 + \sum_i \alpha_i \ \ln P_i + \frac{1}{2}\sum_i \sum_j \alpha_{ij} \ \ln P_i \ \ln P_j + \sum_i \alpha_{iY} \ \ln P_i \ \ln Y \\ + \sum_i \alpha_{iT} \ \ln P_i \cdot T \\ i, j = K, L, E,\end{aligned} \tag{6}$$

where C stands for total production cost; P_K, P_L, and P_E represent the prices of capital, labour, and energy, respectively; Y stands for total output; T is the time trend term used to account for technical progress.

According to the Shephard's lemma implying that $\partial C/\partial P_i = X_i$ (Shephard, 1953), the cost share of the ith input factor (S_i) in a specific industry can be derived as follows (Yang et al., 2014),

$$S_i = \frac{X_i \cdot P_i}{C} = \frac{\partial C}{\partial P_i} \cdot \frac{P_i}{C} = \frac{\partial C}{C} \cdot \frac{P_i}{\partial P_i} = \frac{\partial C/C}{\partial P_i/P_i} = \frac{\partial \ \ln C}{\partial \ \ln P_i} \tag{7}$$

Combining Eqs. (6) and (7), the cost share of the ith input factor (S_i) can further be expressed as:

$$S_i = \frac{\partial \ \ln C}{\partial \ \ln P_i} = \alpha_i + \sum_j \alpha_{ij} \ \ln P_j + \alpha_{iY} \ \ln Y + \alpha_{iT} T, (i, j = K, L, E) \tag{8}$$

According to the linear homogeneity of the cost function with respect to the price of each input factor, and in conjunction with the adding-up criterion of system Eq. (8), some constraint conditions should also be satisfied as follows (Cho et al., 2004; Thompson, 2006),

$$\sum_i \alpha_i = 1, \ \ \sum \alpha_{ij} = \sum \alpha_{ji} = \sum \alpha_{iY} = \sum \alpha_{iT} = 0, \ \ \alpha_{ij} = \alpha_{ji} \tag{9}$$

By estimating the parameters in Eq. (8) with the restrictive conditions in Eq. (9), the own-price elasticity (η_{ii}) of each productive factor as well as the cross-price elasticity (η_{ij}) between factors can be calculated in turn,

$$\begin{aligned}\eta_{ii} &= \frac{\alpha_{ii} + S_i(S_i - 1)}{S_i} \\ \eta_{ij} &= \frac{\alpha_{ij} + S_i S_j}{S_i} (i \neq j)\end{aligned} \tag{10}$$

3.1.2. Effects of resource reallocation evaluation

The effects of resource reallocation resulting from FMD correction can be investigated by the following three steps. First, according to the results of the relative price distortions among input factors ($Dis_{LK} = 0.41$, $Dis_{EK} = 0.88$) reported in Table 4, it can be inferred that the prices of labour and energy should be reduced by 59% and 12%, respectively, relative to capital price[2] to fully correct the relative FMD in China's

[2] Since it is relative price distortion, there are several plans that can be implemented to fully correct current FMD; for example, through raising the prices of capital and energy by different extents (taking the price of labour as a reference); or by raising the price of capital and reducing the price of labour simultaneously (taking energy price as a reference). To maintain the stability of financial markets, the prices of labour and energy are assumed to be reduced by 59% and 12%, respectively (capital price is kept constant), in this study.

heavy industry sectors. Second, according to the results of own-price elasticity of each factor, as well as the cross-price elasticities between factors, the changing rate of demand for each input factor in the production process can be reckoned when the price of a certain factor changes by 1%. Finally, the combined effects of price adjustments for labour and energy on the inputs for various productive factors (ΔX_i), i.e., the effects of FMD correction on resource reallocation, can be expressed as follows:

$$\Delta X_i = \Delta X_i^L + \Delta X_i^E = X_i * (1 - Dis_{LK}) * \eta_{iL} * 100 + X_i * (1 - Dis_{EK}) * \eta_{iE} * 100 \ (i = K, L, E) \quad (11)$$

where ΔX_i^L and ΔX_i^E stand for the changes in input for the ith factor caused by the price adjustments of labour and energy, respectively.

3.2. Empirical results

3.2.1. Results of elasticity of factor substitution

The seemingly unrelated regressions (SUR) method is employed to estimate the simultaneous Eq. (8) with constraint conditions (9); the regression results are reported in Appendix A. It can be observed that two-thirds of the estimation results of the parameters shown in Eq. (10) are statistically significant at a 1% critical level. Subsequently, the elasticities of factor substitution in each industry can further be computed with Eq. (10); the results are shown in Table 5:

Table 5 shows that: (1) for all the sub-sectors, the own-price elasticity of each input factor is negative, that is, as factor prices increase, the demands for them decline by different extents. In terms of the value of own-price elasticities, they are all <1 (capital −0.566, labour −0.540, energy −0.749), indicating that all the factor demands are price inelastic. (2) The cross-price elasticities between any two factors are positive, indicating that mutual substitution relationships exist between each factor. Similarly, all the values of cross-price elasticities are <1 (even <0.5), showing weak impacts of a price change of one factor on the demands for other factors. (3) Significant differences in terms of elasticity of factor substitution can be observed among different sub-sectors.

3.2.2. Results of resource reallocation

According to Eq. (11), the effects of FMD correction on resource reallocation in China's heavy industry sector can be evaluated; the results are shown in Table 6:

Table 6 shows that considerable effects of resource reallocation from FMD correction can be observed. Specifically, when the distorted factor markets in China's heavy industry sector are fully corrected, the inputs for capital and energy will be decreased by 18.51% and 10.57%, respectively, during 1995–2012; on the contrary, the labour input will be increased by 25.37% over the same period.

The reasons leading to these resource reallocations are as follows: (1) Increase in labour input: as the price elasticity of labour demand is negative (−0.54), it is obvious that a large decrease in labour price will lead to the rise of labour input. (2) Decrease in energy input: it seems paradoxical that energy input will decline in the context of decreasing energy price. In fact, this result consists of two components. On the one hand, energy input will indeed increase by a certain extent (7.27%) in the face of a fall in energy price. On the other hand, due to the stable substitution between labour and energy, the fall in labour price will, in turn, lead to a great decrease in energy input (by 17.84%). Taking the two aspects together, energy input declines from the full correction of current FMD. (3) Decrease in capital input: given that both labour and energy are substitutes for capital, decrease in the prices of labour and energy will result in reduction in capital input of 15.55% and 2.96%, respectively.

4. Potential TFP gains from resource reallocation

By conducting a comparison of the TFP of China's heavy industry sector between the two scenarios, i.e., before and after the correction of current FMD, this study investigates the potential TFP gains from resource reallocation.

4.1. Measurement of TFP

In this paper, a Malmquist productivity index is constructed as the proxy of TFP measurement; this index can be calculated using the data envelopment analysis (DEA) technique. To this end, we first define an input-oriented technical efficiency (TE) measure based on the directional distance function ($\overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t)$), as follow:

$$TE^t = 1 - \overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t) \quad (12)$$

where $\overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t) = \sup\{\beta : (\boldsymbol{x}^t - \beta \cdot \boldsymbol{x}^t, \boldsymbol{y}^t) \in T\}$ is defined on the production possibility set $T = \{(\boldsymbol{x}^t, \boldsymbol{y}^t)$: $\boldsymbol{x}^t$ can produce $\boldsymbol{y}^t\}$, and $\boldsymbol{x}^t$ and $\boldsymbol{y}^t$ are the vectors of input and output, respectively.

Table 5
Elasticities of factor substitution in each industry during 1995–2012.

	Own-price elasticity			Cross-price elasticity					
	η_{kk}	η_{ll}	η_{ee}	η_{kl}	η_{lk}	η_{ke}	η_{ek}	η_{le}	η_{el}
MWC	−0.625	−0.418	−0.826	0.472	0.233	0.153	0.239	0.185	0.587
EPNG	−0.435	−0.693	−0.746	0.192	0.412	0.243	0.486	0.281	0.260
MPFMO	−0.662	−0.433	−0.712	0.408	0.133	0.254	0.154	0.299	0.558
MPNFMO	−0.633	−0.514	−0.709	0.364	0.210	0.268	0.239	0.304	0.471
MPNO	−0.662	−0.390	−0.775	0.467	0.154	0.195	0.165	0.236	0.609
PPCPNF	−0.482	−0.709	−0.673	0.167	0.354	0.315	0.439	0.355	0.234
MRCMCP	−0.601	−0.662	−0.589	0.209	0.229	0.393	0.294	0.433	0.294
MNMP	−0.645	−0.535	−0.667	0.335	0.188	0.309	0.221	0.347	0.445
SPFM	−0.651	−0.738	−0.381	0.058	0.080	0.593	0.215	0.658	0.166
SPNM	−0.630	−0.693	−0.504	0.156	0.173	0.474	0.253	0.521	0.251
MGPM	−0.644	−0.342	−0.869	0.537	0.202	0.106	0.191	0.141	0.679
MSPM	−0.627	−0.360	−0.884	0.532	0.234	0.095	0.218	0.126	0.666
MTE	−0.567	−0.429	−0.896	0.479	0.314	0.088	0.298	0.115	0.598
MEMA	−0.613	−0.335	−0.927	0.560	0.252	0.053	0.207	0.083	0.720
MCECOEE	−0.581	−0.369	−0.935	0.534	0.294	0.047	0.241	0.075	0.695
PSEPHP	−0.314	−0.739	−0.793	0.116	0.491	0.198	0.615	0.248	0.178
PSG	−0.409	−0.665	−0.816	0.236	0.459	0.174	0.506	0.206	0.309
PSW	−0.408	−0.692	−0.780	0.198	0.447	0.210	0.514	0.246	0.266
Annual means of all the industries	**−0.566**	**−0.540**	**−0.749**	**0.334**	**0.270**	**0.232**	**0.305**	**0.270**	**0.444**

Note: the results of elasticities of factor substitution are the mean values over the whole studied period.

Table 6
The effects of resource reallocation from FMD correction.

	Effects of labour price correction (%)			Effects of energy price correction (%)			Total effects of FMD correction (%)		
	ΔK	ΔL	ΔE	ΔK	ΔL	ΔE	ΔK	ΔL	ΔE
MWC	−29.11	24.63	−35.40	−1.63	−2.23	9.99	−30.74	22.40	−25.42
EPNG	−12.92	40.34	−15.37	−2.49	−3.19	8.97	−15.41	37.15	−6.40
MPFMO	−26.34	24.77	−33.84	−2.58	−3.34	8.81	−28.92	21.43	−25.03
MPNFMO	−21.38	30.38	−27.49	−3.19	−3.65	8.47	−24.56	26.73	−19.02
MPNO	−26.92	22.35	−35.34	−2.46	−2.69	9.18	−29.38	19.66	−26.15
PPCPNF	−10.32	41.74	−14.17	−3.86	−4.27	7.96	−14.18	37.47	−6.21
MRCMCP	−13.31	38.92	−17.82	−4.54	−5.18	7.10	−17.84	33.75	−10.72
MNMP	−19.05	31.50	−25.57	−3.84	−4.16	7.87	−22.89	27.34	−17.70
SPFM	−2.34	43.53	−9.06	−7.37	−7.90	4.34	−9.71	35.63	−4.72
SPNM	−8.77	40.96	−14.50	−5.82	−6.29	5.92	−14.59	34.67	−8.58
MGPM	−33.18	19.69	−41.10	−1.08	−1.65	10.50	−34.27	18.04	−30.60
MSPM	−32.67	21.02	−40.12	−0.95	−1.49	10.67	−33.63	19.53	−29.46
MTE	−29.26	25.08	−36.06	−0.98	−1.37	10.79	−30.24	23.71	−25.27
MEMA	−34.78	18.45	−44.45	−0.54	−0.96	11.16	−35.31	17.49	−33.29
MCECOEE	−34.21	18.87	−44.24	−0.46	−0.84	11.27	−34.68	18.03	−32.97
PSEPHP	−6.91	43.56	−10.58	−2.30	−2.95	9.56	−9.21	40.61	−1.02
PSG	−13.76	39.09	−18.25	−1.89	−2.48	9.80	−15.65	36.61	−8.45
PSW	−12.28	40.72	−15.96	−2.50	−2.94	9.35	−14.78	37.79	−6.61
Combined effects of all the sub-sectors	−15.55	28.30	−17.84	−2.96	−2.93	7.27	**−18.51**	**25.37**	**−10.57**

Notes: (1) In order to conduct a comparison of the effects from FMD correction on the inputs of different factors in various sub-sectors, the resource reallocation effects are shown in proportion.
(2) All the results of resource reallocation effects in Table 4 are accumulated over 1995–2012.

$\overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t)$ determines the benchmark of input conservations by which producers use a minimum of inputs $\boldsymbol{x}^t - \beta \cdot \boldsymbol{x}^t$ to yield a given level of output $\boldsymbol{y}^t$. *TE* measures the technical efficiency scores, and takes the value greater than zero and less than or equal to 1. $TE = 1$ for one producer implies that the producer has been operating on the production frontier, so that no superfluous input factors can be saved. $TE < 1$ means it is possible for a producer to further reduce its inputs by making full use of current frontier technology without adjusting the economic output.

To conduct the TFP measurement, the intertemporal change of *TE* is employed to construct the Malmquist productivity index (*MPI*), as follows:

$$MPI^{t,t+1} = \left(\frac{1 - \overrightarrow{D}_I^t(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1})}{1 - \overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t)} \cdot \frac{1 - \overrightarrow{D}_I^{t+1}(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1})}{1 - \overrightarrow{D}_I^{t+1}(\boldsymbol{x}^t, \boldsymbol{y}^t)} \right)^{1/2} \tag{13}$$

where $\overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t)$ and $\overrightarrow{D}_I^{t+1}(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1})$ are the maximum feasible contraction proportions of inputs capturing the distances of the observed data from current technical frontiers. Similarly, $\overrightarrow{D}_I^t(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1})$ and $\overrightarrow{D}_I^{t+1}(\boldsymbol{x}^t, \boldsymbol{y}^t)$ compare the observed data of one producer at period $t + 1$ (or t) to the frontier at period t (or $t + 1$). $MPI^{t,\,t+1}$ measures the intertemporal changes of TE scores. $MPI^{t,\,t+1} > 1$ (<1) indicates productivity improvement (retrogress) for one producer in period $t + 1$ compared to period t.

To evaluate $MPI^{t,\,t+1}$, four distance functions, including two contemporaneous and two mixed-period distance functions, need to be computed. In this study, a sequential DEA technique is employed in our calculations; the main merit of this technique is eliminating the possibility of registering any technical regress by the definition (Shestalova, 2003). Then, the benchmark at time period t is $\overline{T}^t = T^1 \cup T^2 \cup \ldots \cup T^t$ (Yang and Yang, 2015), where T^t derived from the observed data of a set of N entities at time t can be written as:

$$\begin{aligned} T^t(\boldsymbol{x}^t, \boldsymbol{y}^t) &= \{(\boldsymbol{x}^t, \boldsymbol{y}^t) : \boldsymbol{x}^t \text{ can produce } \boldsymbol{y}^t\} \\ &= \left\{ (\boldsymbol{x}^t, \boldsymbol{y}^t) : \sum_{k=1}^{N} \lambda_k^t x_{ik}^t \le x_{ik}^t, \sum_{k=1}^{N} \lambda_k^t y_k^t \ge y_k^t, \lambda_k^t \ge 0, k = 1, \ldots\ldots, N; i = L, K, E \right\} \end{aligned}$$

λ_k^t is the weight assigned to the corresponding observation. The inequality constraints on factor inputs and economic output reflect the strong disposability. Then, the contemporaneous distance function for the kth producer at time period t can be calculated by solving the following linear programming,

$$\begin{aligned} &\overrightarrow{D}_I^t(\boldsymbol{x}^t, \boldsymbol{y}^t) = \min \quad -\beta_k^{t,t} \\ &\text{s.t.} \quad \beta_k^{t,t} \cdot x_{ik}^t + \sum_{s=1}^{t} \sum_{k=1}^{N} \lambda_k^s x_{ik}^s \le x_{ik}^t, i = L, K, E \\ &\qquad \sum_{s=1}^{t} \sum_{k=1}^{N} \lambda_k^s y_k^s \ge y_k^t, \\ &\qquad \lambda_k^s \ge 0, \beta_k^{t,t} \ge 0, \text{for all } k; \;\; k = 1, \ldots, N \end{aligned} \tag{14}$$

The mixed-period distance function $\overrightarrow{D}_I^t(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1})$ for the kth entity can be computed by solving the following linear programming,

$$\begin{aligned} &\overrightarrow{D}_I^t(\boldsymbol{x}^{t+1}, \boldsymbol{y}^{t+1}) = \min -\beta_k^{t,t+1} \\ &\text{s.t.} \quad \beta_k^{t,t+1} \cdot x_{ik}^{t+1} + \sum_{s=1}^{t} \sum_{k=1}^{N} \lambda_k^s x_{ik}^s \le x_{ik}^{t+1}, i = L, K, E \\ &\qquad \sum_{s=1}^{t} \sum_{k=1}^{N} \lambda_k^s y_k^s \ge y_k^{t+1}, \\ &\lambda_k^s \ge 0, \beta_k^{t,t+1} \ge 0, \;\; \text{for all } k; \;\; k = 1, \ldots, N \end{aligned} \tag{15}$$

Likewise, $\overrightarrow{D}_I^{t+1}(\boldsymbol{x}^t, \boldsymbol{y}^t)$ can also be calculated by solving a similar linear programming.

4.2. Potential TFP improvement

According to Eqs. (14) and (15), the average TFP of China's 18 heavy industries before and after the correction of FMD during 1995–2012 are evaluated; the results are presented in Fig. 1.

Fig. 1 shows that, for all the 18 studied sub-sectors in China's heavy industry, the correction of current FMD will increase their TFP by different extents. Overall, the multi-year average of TFP for the whole heavy industry sector was 8.54% before FMD correction; after the distorted factor markets are corrected, the multi-year average of TFP for all sub-sectors reaches up to 9.27%, improving by 8.55%. Therefore,

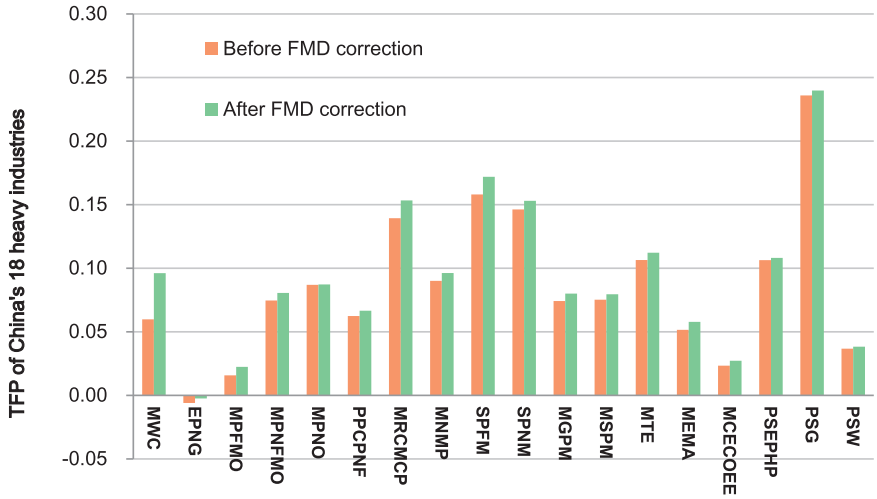

Fig. 1. Potential TFP improvement from FMD correction by sub-sector. Note: The results are the mean values of TFP of various sub-sectors during 1995–2012.

promoting the market-oriented reform in China's factor markets and fully correcting current FMD are very important measures for enhancing resource allocation efficiency and, in turn, improving the TFP. With regard to specific sub-sectors, MWC sees the greatest TFP improvement, with its average TFP level increasing from 5.98% before FMD correction to 9.61% after FMD correction. In addition, the impacts for MRCMCP and SPFM are also quite considerable. Conversely, the effects of TFP improvement from FMD correction in MCECOEE, PSEPHP, and PSW are minor.

To examine the stage characteristics of the effects of FMD correction on potential TFP improvement, this study further conducts a comparative analysis of intertemporal TFP changes of China's heavy industry sector over the years in the two scenarios; the results are shown in Fig. 2.

Fig. 2 shows that the effects of FMD correction in China's heavy industry sector on aggregated TFP improvement have obvious stage characteristics over the whole study period. According to the intertemporal changing trend of the TFP gap between the two scenarios, the promoting effects can roughly be divided into three phases. (1) From 1996 to 2000 (i.e., the Ninth Five-year Plan period), the resource reallocation effects arising from FMD correction have had significantly positive impacts on TFP improvement in China's heavy industry sector; the effect was most evident in 1998 and 1999. (2) From 2001 to 2007, the potential effects of FMD correction on the TFP have become greatly weakened, with the annual mean changing rate being merely 2.77% and even turning negative in 2003 and 2004. (3) From 2008 to 2012, the effects experienced drastic fluctuations. For instance, there were obvious TFP improvements, as in 2011, while there were serious constraints, as in 2012.

5. Conclusions and outlooks

Promoting market-oriented reforms for various productive factors and gradually establishing a rational pricing system for them is of great importance for enhancing the efficiency of resources allocation, which would, in turn, both improve China's industrial TFP and boost the economic growth significantly. In this study, we develop a novel analysis framework to evaluate the effects of resource reallocation, in addition to potential TFP gains from the correction of factor market distortion (FMD) in China's heavy industry sector. To this end, the degree of relative price distortions of China's heavy industry sector during 1995–2012 is first evaluated, and the effects of resource reallocation from FMD correction, along with its potential TFP gains, are then investigated by using the price elasticity of factor demands as a link.

Three distinct conclusions can be drawn: (1) there is persistent FMD in China's heavy industry sector. Taking capital price as a

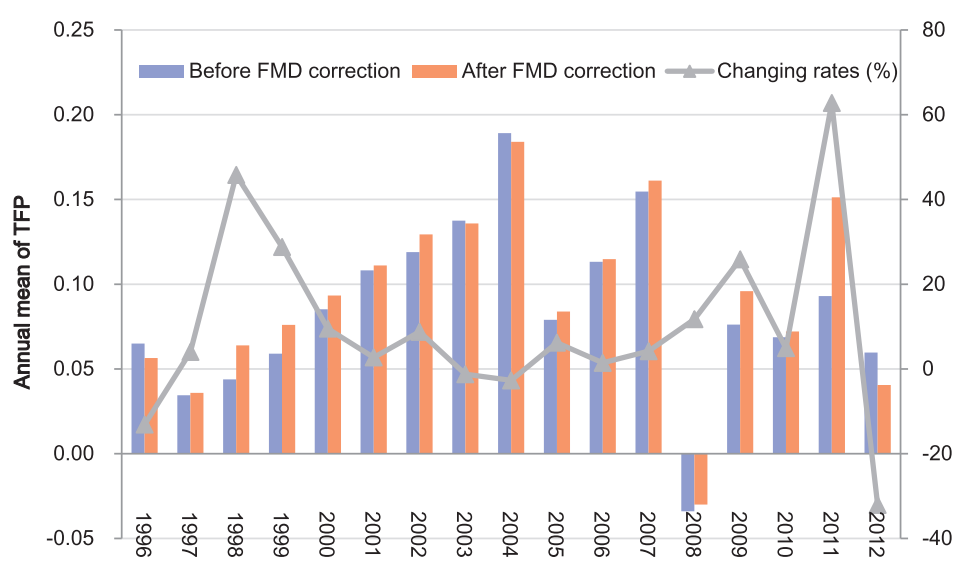

Fig. 2. Intertemporal TFP changes of China's heavy industry in the two scenarios. Note: The results are the mean values of the whole heavy industry sector in China in each year.

reference, the prices for labour and energy are both relatively higher over the whole study period. (2) A full correction of current FMD will lead to 25.37% increase in labour input, while the demands for capital and energy will decline by 18.51% and 10.57%, respectively. (3) The resource reallocation effects resulting from current FMD correction will result in evident TFP improvement in China's heavy industry sector, which increases from 8.54% before FMD correction to 9.27% after it, increasing by 8.55%. In addition, there are significant industrial differences and stage characteristics for this promoting effect. Therefore, promoting market-oriented reform for various productive factors will undoubtedly provide considerable impetus to China's economic growth and the transformation of current development mode.

Given the research works presented above, there are still some follow-on works that are worthwhile extending in the future. First, this paper measures the degree of relative price distortions between factors in China's heavy industry sector and then examines the potential TFP gain from a full correction of current FMD. However, the market-oriented reform of various factors is a gradual process that cannot be achieved overnight. Therefore, it is very necessary to conduct the analysis while considering different scenarios of FMD correction. Secondly, since there are significant differences in the degree of FMD across sub-sectors, a uniform plan of FMD correction will impact the TFP of various sub-sectors by different extents. Part of the sub-sectors may even suffer from TFP losses due to over-correction of their factor prices. Therefore, determining an optimal factor price system, with the aim of maximising the aggregated TFP of China's heavy industry sector, is also a very key theoretical issue. Last but not least, although a nearly 10% industrial TFP improvement is of great significance to China's economic growth, the precondition of achieving it, i.e., a full correction of current FMD, would involve many arduous tasks. For example, due to strong wage rigidity, decreasing the labour price by 59% relative to capital price to eliminate their relative price distortion is extremely difficult, let alone the fact that it will greatly change the capital–labour ratio in China's heavy industry sector. As a result, the complexities and uncertainties of using the conclusion in current study as prescriptions of policy should be deeply studied in future works.

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Appendix A

Table A1
Parameter estimates of the factor cost-share equations.

Parameters	Estimated values	Standard errors	Parameters	Estimated values	Standard errors
α_K	0.0040	0.0203	α_{LE}	−0.0189***	0.0064
α_{KK}	0.0226***	0.0059	α_{LY}	0.0020	0.0016
α_{KL}	−0.0012	0.0057	$\alpha_{L\tau}$	0.0003	0.0008
α_{KE}	−0.0214***	0.0064	α_E	0.3678***	0.0280
α_{KY}	−0.0026	0.0020	α_{EE}	0.0403***	0.0107
$\alpha_{K\tau}$	−0.0001	0.0008	α_{EY}	0.0007	0.0029
α_L	−0.0522***	0.0155	$\alpha_{E\tau}$	−0.0002	0.0010
α_{LL}	0.0201	0.0072			

*** Denotes that the estimated values are statistically significant at 1% critical level.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2017.11.021.

References

Adamopoulos, T., Brandt, L., Leight, J., Restuccia, D., 2015. Misallocation, selection and productivity: a quantitative analysis with panel data from China. Available at:. http://economics.cornell.edu/sites/default/files/files/events/ABLR_China_paper.pdf.
Atkinson, S.E., Halvorsen, R., 1984. Parametric efficiency tests, economies of scale, and input demand in U.S. electric power generation. Int. Econ. Rev. 25 (3), 647–662.
Banerjee, A., Moll, B., 2010. Why does misallocation persist? Am. Econ. J. Macroecon. 2 (1), 189–206.
Bartelsman, E., Haltiwanger, J., Scarpetta, S., 2013. Cross-country differences in productivity: the role of allocation and selection. Am. Econ. Rev. 103 (1), 305–334.
Brandt, L., Tombe, T., Zhu, X., 2013. Factor market distortions across time, space and sectors in China. Rev. Econ. Dyn. 16, 39–58.
Cai, F., Wang, D., Du, Y., 2002. Regional disparity and economic growth in China: the impact of labor market distortions. China Econ. Rev. 13, 197–212.
Chen, S., 2011. Reconstruction of sub-industrial statistical data in China (1980–2008). China Econ. Q. 10 (3), 735–776 (In Chinese).
Chen, Y., Chen, X., Chen, W., 2014. Interest rate control and the imbalance of aggregated demand structure. Econ. Res. J. (2), 18–31 (In Chinese).
Chen, Y., Ma, Xiao, Liu, Xi, 2015. Factors price distortions, enterprise investment and output level. J. World Econ. (9), 29–55 (In Chinese).
Cho, W.G., Nam, K., Pagan, J.A., 2004. Economic growth and interfactor/interfuel substitution in Korea. Energy Econ. 26, 31–50.
Clark, T.S., Linzer, D.A., 2015. Should I use fixed or random effects? Polit. Sci. Res. Methods 3 (2), 399–408.
Dai, X., Cheng, L., 2016. Market distortions and aggregate productivity: evidence from Chinese energy enterprises. Energ Policy 95, 304–313.
David, J.M., Hopenhayn, H.A., Venkateswaran, V., 2016. Information, misallocation, and aggregated productivity. Q. J. Econ. 131 (2), 943–1005.
Du, J., Liu, X., Zhou, Y., 2014. State advances and private retreats? –evidence of aggregate productivity decomposition in China. China Econ. Rev. 31, 459–474.
Fan, G., Wang, X., Ma, G., 2011. Contribution of marketization to China's economic growth. Econ. Res. J. (9), 4–16 (In Chinese).
Filippini, M., Heimsch, F., 2016. The regional impact of a CO_2 tax on gasoline demand: a spatial econometric approach. Resour. Energy Econ. 46, 85–100.
Gai, Q., Zhu, X., Cheng, M., Shi, Q., 2015. Factor market's distortion, markup and TFP. Econ. Res. J. (5), 61–75 (In Chinese).
Gong, G., Hu, G., 2016. The role of returns to scale in measuring frictions in resource allocation: revisiting misallocation and manufacturing TFP in China. Econ. Lett. 138, 26–29.
Hertel, T., Zhai, T., 2006. Labor market distortions, rural–urban inequality and the opening of China's economy. Econ. Model. 23, 76–109.
Hsieh, C.T., Klenow, P.J., 2009. Misallocation and manufacturing TFP in China and India. Q. J. Econ. 124 (4), 1403–1448.
Huang, Y., Wang, B., 2010. Cost distortions and structural imbalances in China. Chin. World. Econ. 18 (4), 1–17.
Ju, K., Su, B., Zhou, D., Wu, J., 2017. Does energy-price regulation benefit China's economy and environment? Evidence from energy-price distortions. Energ Policy 105 (6), 108–119.
Knight, J., Li, S., 2005. Wages, firm profitability and labor market segmentation in urban China. China Econ. Rev. 16 (3), 205–228.
Kumbhakar, S.C., Denny, M., Fuss, M., 2000. Estimation and decomposition of productivity change when production is not efficient: a panel data approach. Econ. Rev. 19 (4), 425–460.
Liu, X., Zhou, X., 2011. Testing on the allocation relationship between financial resources and entity economy. J. Financ. Res. (2), 57–70 (In Chinese).
National Bureau of Statistics of China (NBSC), 2017. China Labour Statistical Yearbook 2016. China Statistical Press, Beijing (In Chinese).
Nie, H., Jia, R., 2011. Firm-level productivity and resource misallocations of China's manufacturing industry. J. World Econ. (7), 27–42 (In Chinese).
Ouyang, X., Sun, C., 2015. Energy savings potential in China's industrial sector: from the perspectives of factor price distortion and allocative inefficiency. Energy Econ. 48, 117–126.
Papyrakis, E., Rieger, M., Gilberthorpe, E., 2016. Corruption and the extractive industries transparency initiative. J. Dev. Stud. 4, 295–309.
Pindyck, R.S., Rubinfeld, D.L., 2013. Microeconomics. Eighth edition. Pearson education, New Jersey.
Restuccia, D., Rogerson, R., 2008. Policy distortions and aggregate productivity with heterogeneous plants. Rev. Econ. Dyn. (11), 707–720.
Shephard, R., 1953. Cost and Production Functions. Princeton, Princeton University Press.
Shestalova, V., 2003. Sequential Malmquist indices of productivity growth: an application to OECD industrial activities. J. Prod. Anal. 19 (2), 211–226.
Shi, X., Sun, S., 2017. Energy price, regulatory price distortion and economic growth: a case study of China. Energy Econ. 63, 261–271.
Skoorka, B.M., 2000. Measuring market distortion: international comparisons, policy and competitiveness. Appl. Econ. 32, 253–264.
Song, Z., Storesletten, K., Zilibotti, F., 2011. Growing like China. Am. Econ. Rev. 101 (1), 196–233.
Syverson, C., 2011. What determines productivity. J. Econ. Lit. 49 (2), 326–365.
Thompson, H., 2006. The applied theory of energy substitution in production. Energy Econ. 28 (4), 410–425.

Wang, P., Wu, Y., 2014. The market distortions and total factor productivity of Chinese energy industry. Econ. Res. J. (6), 142–155 (In Chinese).
Wang, H., Smyth, R., Cheng, Z., 2017. The economic returns to proficiency in English in China. China Econ. Rev. 43, 91–104.
Wei, C., Li, C.Z., 2017. Resource misallocation in Chinese manufacturing enterprises: evidence from firm-level data. J. Clean. Prod. 142, 837–845.
Wei, X., Chen, Y., Zhou, M., Zhou, Y., 2016. SOE preference and credit misallocation: a model and some evidence from China. Econ. Lett. 138, 38–41.
Yang, F., Yang, M., 2015. Analysis on China's eco-innovations: regulation context, intertemporal change and regional differences. Eur. J. Oper. Res. 247 (3), 1003–1012.
Yang, M., Fan, Y., Yang, F., Hu, H., 2014. Regional disparities in carbon dioxide reduction from China's uniform carbon tax: a perspective on interfactor/interfuel substitution. Energy 74 (9), 131–139.
Yuan, Z., Xie, D., 2011. The effect of labor misallocation on TFP: China's evidence 1978–2007. Econ. Res. J. (7), 4–17 (In Chinese).
Zhang, Y., Chen, J., 2008. Human capital or industry characteristics? Cause analysis on the differences of cross-section salary reward in China. J. World Econ. (5), 68–80 (In Chinese).
Zhang, X., Tan, K.Y., 2007. Incremental reform and distortions in China's product and factor markets. World Bank Econ. Rev. 21 (2), 279–299.
Zhang, J., Chen, S., Jefferson, G.H., 2009. Structural reform and industrial growth in China. Econ. Res. J. (7), 4–20 (In Chinese).
Zhu, X., 2012. Understanding China's growth: past, present, and future. J. Econ. Perspect. 26 (4), 103–124.