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Re-estimation of firms' total factor productivity in China's iron and steel industry☆

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ABSTRACT

Using the firm-level census data, this paper re-estimated the total factor productivity (TFP) of firms in China's iron and steel industry and examined its potential determinants over the period 1998–2007. To deal with the "endogenous input" problem, we used the semi-parametric regression techniques for estimating the firm-level TFP. The results suggest that firms' TFP in China's iron and steel industry has been steadily increasing over time with the key drivers of productivity improvement differing substantially between firms with different characteristics including their size, ownership type and geographical location. Notably, the productivity of small firms is positively related to market share and negatively related to R&D. Large state-owned enterprises' productivity is relatively insensitive to changes in market share and R&D, while the non-state owned enterprises are more likely to obtain their productivity gains through export. Increasing firm size is generally positively correlated to firms' performance in TFP, and it is more so in the less developed Western than the Eastern and Central regions. The findings suggest that different policy instruments targeting firms with different characteristics in the process of restructuring the industry may be desirable.

1. Introduction

The rapid expansion of China's iron and steel industry (hereafter "the industry") since the early 21st century has been remarkable in terms of both the speed and scale of its development. Yet there is an issue regarding the "quality" of the industry's expansion as to whether the rapid growth was driven primarily by increases in inputs or gains in productivity. There is no consensus as to which factors have been more important for driving the ongoing wave of the industrial expansion which underscores the current resource boom. However, a more sustainable and healthy development of the industry should be based on continuing firm-level productivity growth — a representation of both the technological progress and efficiency improvement. Examining the change of firm-level productivity and its determinants over the past decade therefore becomes an important empirical question.

There have been many attempts made to quantify productivity of China's iron and steel firms and its determinants by using micro-economic (or firm-level) data. Jefferson (1990) was the first to estimate firms' total factor productivity (TFP) for the industry by using a log-linear production function with the cross-sectional data from 120 large- and medium-sized enterprises (hereafter LMEs) in 1986. Kalirajan and Cao (1993) and Wu (1996) adopted the stochastic frontier analysis to distinguish between firms' technical efficiency and their technological progress using the cross-sectional and panel data of LMEs covering the periods up to the 1990s respectively. Zhang and Zhang (2001) examined the technical efficiency of China's iron and steel firms in

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the 1990s using the data envelop analysis and Ma, Evans, Fuller, and Stewart (2002) and Movshuk (2002) focused on the ownership reform undertaken in the late 1990s and its consequent impact on firms' TFP in the industry.

These studies provided important insights in looking at the changes in firms' productivity in the industry and its determinants in the 1990s. However, these studies provided quite different results with respect to whether the industry's productivity and/or efficiency had increased or not over the periods under study. For example, Zhang and Zhang (2001) found that the average technical efficiency of China's iron and steel firms has been increasing in the 1990s while Ma et al. (2002) and Movshuk (2002) found the contrary results.

There are three possible explanations relating to both the methodological and data issues for this inconsistency. The first is that studies estimating productivity via the stochastic frontier method (or the data envelope analysis method) identify technological efficiency by assuming that best performed firms are at the production frontier. This assumption is likely to generate the results that are sensitive to sample choices. The second is that LMEs (usually state-owned) were dominant across all samples used by previous studies (due to data availability). This means that some important information on the prolific small and private enterprise (hereafter SE) sector is excluded from these studies. The third is that by utilizing data covering the period from the late 1980s to the late 1990s, when many reforms such as corporate restructuring and ownership reform in the industry had not been fully implemented, or were yet to bear fruit, thus these studies might not fully capture the fundamental changes resulting from economic reforms which underscore the micro-foundation for the improved firms' performance. Due to these factors, it may not be surprising that the earlier studies generated ambiguous results with respect to the impact of reform on industry productivity.

This paper applies the newly developed econometric techniques to re-estimate Chinese iron and steel firms' TFP by using an updated firm census data over the period 1998–2007. The approach adopted here includes the two-step method applied by Olley and Pakes (1996) and Levinsohn and Petrin (2003) and the GMM method proposed by Ackerberg, Caves, and Frazer (2006) and Wooldridge (2009) for estimating the industry's production function with the gross output assumption. These methods overcome the "simultaneity bias" between capital usage and unobserved productivity changes caused by the assumption of exogenous inputs (i.e. capital) that plagues traditional analysis (Olley & Pakes, 1996). As to the data, we believe that the census data for Chinese manufacturing industry is the most recent vintage ever incorporated into a study of this type.

Three questions are to be addressed. First, how has firm-level productivity in the industry changed over time? Second, what are the major driving forces behind firm-level productivity growth in the industry over the past decade? Third, are there any significant differences in productivity growth between firms with different characteristics such as firm size, ownership type and geographical location? Answers to these questions may show that productivities of firms of different types in the Chinese iron and steel industry are not only different over the period under the study, but also responsive to different reform measures undertaken in the industry. If that is the case, the findings may imply that further improvement in productivity and quality of the Chinese iron and steel industry may be enhanced by different policy instruments targeting firms with different characteristics in the process of restructuring the industry.

The remainder of the paper is arranged as follows. Section 2 briefly describes the development of China's iron and steel industry over the reform period. Some key factors associated with changes in firms' productivity in the industry, such as marketization reform, government sponsored investment and intensified competition, have been addressed. Section 3 presents the model specifications and the two-step approach for estimating firms' TFP, followed by a proposed regression for identifying its determinants. The semi-parametric TFP estimation techniques and the related literature are highlighted for their role in dealing with the problem of "endogeneous input choice". Section 4 discusses the estimation results and Section 5 concludes.

2. China's iron and steel industry and its microeconomic performance

While China' iron and steel industry grew along with the rest of the economy in the first decade of the reform era beginning in the late 1970s, it was not until the early 1990s that the sector began to expand at a remarkable rate in responding to the rapidly growing demand for steel products. During the period 1990–2007, China's production of iron ores, pig irons and crude steels have increased from 179 million tonnes (mt), 62 mt and 66 mt to 582 mt, 404 mt and 422 mt, representing average annual growth of 7.6%, 12.4% and 12.3% a year respectively. China's output of iron ores and crude steels rose to above one third of the global total, while its pig iron output rose closer to one half of world production over the same period. The rapid expansion of output in the industry has been accompanied by a significant industrial structural adjustment, characterized by a substantial increase in the number of enterprises and an enlargement of scale at individual firm level. The total number of firms in the industry increased from 1589 in 1990 to 11,596 in 2007 while the average real output value per firm (at 1990 constant price) increased from US$17.2 million in 1990 to US$32.5 million in 2008.[1] As a consequence, competition among firms in the industry has been intensified and firms' productivity has also increased rapidly over time. Fig. 1 shows the positive relationship between the real output value of China's iron and steel industry (at 1990 constant prices) and its average labor productivity between 1985 and 2007.

There are three factors that seem most relevant for assessing the rapid increase of firms' productivity. First, marketization reforms rendered more autonomy to enterprises (especially to SOEs) thereby helping to increase their production efficiency. Second, the rapid increase in fixed investment and the associated boost to average production capacity have helped to foster

[1] Ma et al., (2002) outline the increasing trend in the enlargement of existing firms' scale.

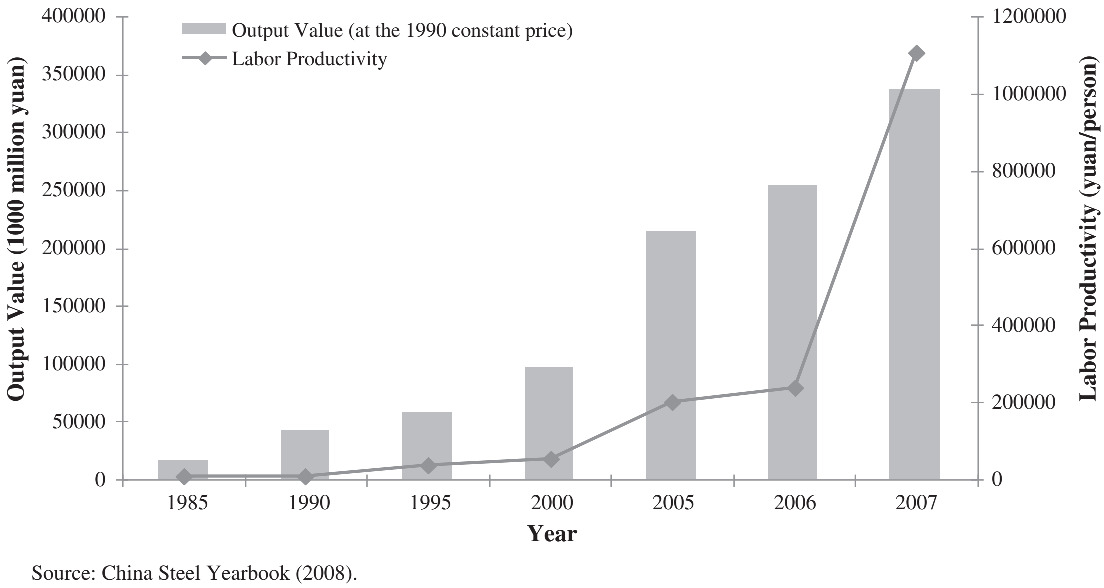


Fig. 1. Output value and labor productivity in China's iron and steel industry: 1985–2007 (1000 million yuan, yuan/per worker). Source: China Steel Yearbook (2008).

firm-level technological progress. Third, free entry of SEs (driven by profit motivations) that have reduced LMEs' market power and intensified competition in the industry. We consider each of these factors in turn.

First, the iron and steel industry in China has historically been dominated by the large integrated state owned enterprises (hereafter SOEs). By integrated enterprises, we mean for those ferrous metals firms, which produce all items across the spectrum from iron ore to finished steel, rather than those which specialize in producing a single product. In 1990, there were a total of 1589 iron and steel enterprises in China, among which 163 were state-owned or state controlled enterprises. In terms of output value, the SOEs accounted for more than 80 cent of the industry total. Given that the SOE structure imposed a heavy burden on these firms in the form of non-productive spending such as housing, pensions and other welfare expenses which provided scant executive incentives to pursue productivity gains. This is the chief reason as to why the management efficiency of those enterprises was weak. Since the early 1990s, a series of microeconomic reform policies aiming to promote the marketization of SOEs have been implemented. These include the reform of the profit distribution system; the provision of incentives for increasing productivity; reform of the management system; market based reform especially with respect to pricing; introducing foreign direct investment; and a free entry policy. The most recent reform is what has been termed the 'modern enterprises system' and 'shareholding structure reform', which began in the early 2000 and is still underway for a few very large enterprises. These reforms have made the SOEs more independent from the government with respect to both financial arrangement and managerial appointment. In 2007, the share of output volume accounted for by SOEs had fallen to 43.1% while the number of SOEs had decline to 67 (accounting for only 5.2% of the total number of firms). As a consequence of these changes, the productivity and management efficiency at the firm level have been improved.

Second, the rapid increase of investment in new plants and equipments and the accompanied technological changes has assisted productivity gains at the firm level. The industry has historically been characterized as a mix of old and advanced production technologies, with the average level of technology lagging far behind the conditions in the industrialized countries. In 1990, the continuous casting ratio in China's iron and steel industry was only 22%, which is far less than the ratio of above 95% in the other main steel-making countries. Around 15% of crude steel was still being produced in open-hearth furnaces (OHF) in China, which have effectively been scrapped in most steel-producing countries. To catch up with the world leaders in technology, a very large amount of capital has been invested in new equipments during the past two decades. These investments have been jointly funded by the central and provincial governments and considerable amount of capital investment have been coming from SOEs themselves and private sources. Between 1990 and 2005, the average annual fixed assets investment in China's iron and steel industry has increased from US$2.7 billion to US$ 31.5 billion yuan (the exchange rate used for deflating the series comes from China Statistical Yearbook, 2009). This massive increase in investment has substantially improved the industry's production technology. In 2005, the continuous casting ratio of the industry had increased to 94% and crude steels produced from basic oxygen furnaces (BOF) and electric arc furnaces (EAF) accounted for 88.1% and 11.7% of the total respectively. Such rapid improvements in production technology argue for significant gains in firm and industry level of productivity.

Third, the intensified competition due to free entry of SEs and its associated re-allocation of market share and resources has favored those with advanced production technology, promoting productivity growth in the quest for profits. The industry is believed to be one of the few sectors that can realistically expect increasing return to scale to occur given the large amount of sunk costs embedded in most steel enterprises. Thus, firms aiming to obtain higher productivity through increasing returns to scale must seek to achieve both gains of market share and the expansion of productive capacity, as well as securing additional access to intermediate inputs including finance. With the increased number of firms in the industry, the share of national crude steel production accounted for by the top 8 firms between 1998 and 2007 has declined from 33.0% to 17.9%; the Herfindahl index of industrial concentration at the 3-digit level (defined as the squared share of top 8 firms' market sales revenue in the total revenue of the industry, see Brown, & Warren-Boulton, 1988) has accordingly decreased from 0.11 in 1998 to 0.05 in 2007.

The discussions provide some background information on the role of investment and economic reforms and the potential impact on firms' productivity in the industry. The next step is to detect the trend of the firm-level productivity and to identify the main factors which determine the trend. In the following section, we start with estimating firms' TFP by using the newly developed endogeneous capital usage method.

3. Model specifications: the endogenous input usage and firms' productivity

Estimating productivity as a residual after accounting for measureable inputs and then decomposing the TFP into its proximate determinants is a long standing preoccupation of empirical economists, going back to the seminal paper by Solow (1957). While the Solow "growth accounting" framework has been widely applied for economy wide analysis, the technique can be easily adapted to microeconomic analysis. The standard approach is to assume a Cobb-Douglas, quadratic or trans-log production function with an additive, time-consistent firm effect and to solve the unobserved endogeneity problem by using fixed-effect general least square (GLS) estimation method. However, the fixed-effect estimator still assumes strict exogeneity of the inputs (i.e. labor, capital and various intermediate inputs) which is conditional on firms' heterogeneity in productivity (Wooldridge, 2002). This assumption requires that inputs must not be chosen in response to productivity shocks — a severe and unrealistic restriction on analyzing firm behavior.

To deal with this problem, econometricians have resorted to using the instrumental variable method (say, using lagged inputs as instruments for inputs) to relax the strict exogeneity assumption for inputs. For example, Arellano and Bover (1995) and Blundell and Bond (1998) use this approach to correct the estimation of their production functions. Although this method works well in some cases, it is open to two criticisms. The first is that introducing lags into the regression (or differencing) removes much of the variation in the explanatory variables and can exacerbate measurement error of the inputs. The other is that the instruments available after differencing are often weakly correlated with the differenced explanatory variables.

Olley and Pakes (1996, hereafter OP) arrived at an alternative way to deal with the endogeneous input problem. Rather than allowing for time-constant firm heterogeneity, OP show that, under certain assumptions, investment can be used as a proxy variable for unobserved, time-varying productivity. In other words, productivity can be expressed as an unknown function of capital and investment (when investment is strictly positive and monotonically increasing with firms' productivity). This, for the first time, took the simultaneity problem explicitly into account when estimating a production function by introducing an estimation algorithm. Following this innovation, Levinsohn and Petrin (2003, hereafter LP) later proposed a modification of OP's method to address the problem of lumpy investment. They suggested the use of intermediate inputs as a proxy for unobserved productivity, a method that generated a better result than the use of an investment variable. Generally, both the OP and LP methods suggest a two-step process to consistently estimate the coefficients on variables inputs. In the first stage, semi-parametric methods are used to estimate the coefficients on the variable inputs along with the nonparametric function linking productivity to capital and investment (or intermediate inputs). In a second step, the parameters on capital inputs can be identified under the assumptions on the dynamics of the productivity process, usually one degree auto-regression process (i.e. AR(1)). Both the OP and LP methodologies have been widely used in the recent literature on firm-level TFP measures, though the LP method is more preferred to the OP method in practice since it can save more observations when firms may not carry out long-term investment on an annual base.

More recently, Ackerberg, Lanier Benkard, Berry, and Pakes (2007) (hereafter, ACF) argued that, while there are some solid and intuitive identification ideas in the paper by Olley and Pakes (1996) and Levinsohn and Petrin (2003), their two-step semi-parametric techniques may suffer from a potential problem with identification of parameter in the first stage estimation. Namely, if all inputs (including labor usage) are determined by a productivity shock (and thus optimally chosen by the firm), they all enter the deterministic function of unobserved productivity and stated variables. As a consequence, the coefficient on the variable input is non-parametrically unidentified. ACF showed that specifying popular functional forms for the production process does not help with solving this problem. In the Cobb-Douglas case (and some others), labor could disappear after substituting unobserved productivity as a function of inputs (Wooldridge, 2009). This problem is more serious for the LP estimation since the potential collinearity between labor and intermediate inputs is usually stronger in practice. To deal with this problem, ACF proposed a hybrid of the OP and LP approaches, along with the assumptions on the timing of decisions concerning firms' input choice. Specifically, ACF resolved the potential lack of identification by still using a two-step estimation method but does not attempt to identify any production parameters in the first stage. Instead, identification is made in the second stage through a non-linear estimation procedure solving zero moment condition on the lagged terms. Later, Wooldridge (2009) further extended the estimation method by using a unified GMM estimation, which allows for the possibility that the first stage of OP or LP actually contains identifying information for parameters on the variable inputs, such as labor. Since the Woodridge method is one-step GMM procedure, it can use the cross-equation correlation to enhance efficiency and the optimal weighting matrix efficiently and accounts for serial correlation and heteroskedasticity. Thus, the Woodridge GMM method for production function estimation is the most preferred regarding its consistency and effectiveness in estimation.

In this paper, we use the one-step Woodridge GMM method to estimate firms' TFP, while checking the robustness of our results by using the OP, LP and ACF methods as well as some other traditional measures including the first differencing method and within effects method. Specifically, we assume that the production function of China's iron and steel firms takes Cobb–Douglas form with endogenous capital and labor usage.[2]

$$Y_{it} \;=\; A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} M_{it}^{\beta_m} \tag{1}$$

where Y_{it} represents physical output of firm i in period t; L_{it}, K_{it} and M_{it} are inputs of labor, capital and intermediate inputs respectively and A_{it} is the Hicks neutral efficiency level of firm i in period t. Taking natural logs and differentiating the equation yields a linear production function as follows:

$$y_{it} \;=\; lnA_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} \tag{2}$$

where lower-case letters refer to natural logarithms and $lnA_{it} = \beta_0 + \omega_{it}$, and ω_{it} measure unobserved firm-level TFP over time.

Based on Eq. (2), the unobservable firms' productivity $\omega_{it} = g(k_{it}, m_{it})$ is assumed to be a three-degree polynomial of capital (k_{it}) and intermediate inputs (m_{it}), where the intermediate inputs are used as proxy (as in LP). Under the assumption of $E(y_{it}|l_{it}, k_{it}, m_{it}) = 0$ (where $t = 1, 2, \ldots T$), we thus have the following regression function:

$$E(y_{it}|l_{it}, k_{it}, m_{it}) \;=\; \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + g(k_{it}, m_{it}) \;=\; \beta_l l_{it} + h(k_{it}, m_{it}) \tag{3}$$

where $h(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + g(k_{it}, m_{it})$

Following Wooldridge (2009), two simultaneous equations can be constructed for estimating β_l, β_k and β_m from Eq. (3)

$$y_{it} \;=\; \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + g(k_{it}, m_{it}) + \varepsilon_{it} \qquad V \;\; t = 1, \ldots, T \tag{3.1}$$

and

$$y_{it} \;=\; \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + f[g(kit{-}1, mit{-}1)] + v_{it} \qquad V \;\; t = 1, \ldots, T \tag{3.2}$$

where $f(v)$ is approximated by a three-degree polynomial in v. With the assumption that productivity follows a random walk, identification is made with just current values and one lag in the conditioning set.

To identify Eqs. (3.1) and (3.2) in the GMM estimation, two groups of instruments are used which include (lnk_{it}, the polynomials of lnk_{it} and lnm_{it} and its one-period lag) for the first equation and (lagged lnl_{it}, lagged lnk_{it} and the lagged polynomials of lnk_{it} and lnm_{it}) for the second equation. The potential assumptions are (1) the firm-level productivity follows a random walk, so current values and one lag are independent in generating productivity shocks; (2) there is no contemporaneous value of lnl_{it} and lnm_{it} being used and only one-period lag of the polynomial of lnk_{it} and lnm_{it} has been used.

Finally, Ackerberg et al. (2006) did not employ cross-equation correlation information as Wooldridge (2009), but it allows for the identification of more complicated $g(k_{it}, m_{it})$ and $f(v)$ in most cases. Therefore, we have also adopted the ACF two-step procedure to estimate the production function as a robustness check.

With the estimation of coefficients for labor, capital and intermediate inputs, the firm-level TFP can be estimated as:

$$tfp_{it} \;=\; y_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} \tag{4}$$

where β_l, β_k and β_m are estimated by using the Woodridge GMM method as well as other methods including the OP, LP and ACF regressions. With these estimation results, the relationship between firms' productivity and its determinants, including marketization reform, changes in market share, export and so on, can be examined on the basis of

$$tfp_{it} \;=\; \gamma_0 + \sum_l \gamma_l X_{lit} + u_i + v_{it} \tag{5}$$

where X_{lit} is a vector containing the determinants of firms' TFP and u_i is the firm-specific unobserved effects and v_{it} is the residual. To specify the causal relationship between firm-level TFP and its determinants, the system GMM regression technique can be applied to Eq. (5) to deal with the potential endogeneity problem and two periods of lagged X_{ijt} are used as the instrumental variables to identify the regressions.

4. Data and summary statistics

The data used in this study are taken from the firm census carried out by the National Bureau of Statistics (hereafter NBS) annually during the period 1998–2007. The census covers all state owned enterprises and private enterprises above a designated size (with annual sales reaching at least RMB 5 million). Iron and steel firms are defined as the firms registered with the sector of

[2] The estimation method can also be used for adopting other types of production functions, provided that some basic requirements are met (Ackerberg et al., 2006).

"smelting and pressing of ferrous metals" (namely, the 32nd category according to the 2-digit Chinese Industrial Classification Code, CICC).

To get more reliable and consistent estimates of TFP, we used a three step procedure for matching the firms to minimize the mismatch or inconsistency resulting from possible changes in firms' ID and names over the period under study. We first used the registered firms' ID and firms' name as the first criterion. We then used the information including firms' location code, zip code, telephone number and legal person status, major products to identify whether the firm has changed its registration ID and name over the period under study. Finally, we manually checked those unmatched firms by examining their key characteristics and the consistencies in those characteristics so as to reduce the mismatch in those firms. The three-step procedure adopted should enable us to significantly reduce the mismatch of iron and steel firms included in the sample.

After tracing firms over time by using firms' identification code, name, regional code, telephone, legal person status and so on which is similar to the approach adopted by Brandt, Van Biesebroeck, and Zhang (2012) and discarding firms with incomplete data left 33,778 observations, ranging from 1654 firms in 1998 to 4929 firms in 2007. These firms have accounted for more than 70% of the total number of enterprises in the industry and their combined output and asset shares are around 90% of the total. Table 1 shows a statistical summary of these firms. Compared with those data used in previous studies, our sample is more representative in that it covers not only the state owned LMEs, but also a large number of SEs and private firms reaching the production level required to be included in the census. This helps reduce the selection bias significantly.

The output of iron and steel firms is defined as the total output value discounted by using the producer price index at the firm level. Our reasoning for this choice of deflator is that the industry is composed of multiple types of enterprise with different output structures. The vertically integrated enterprises produce all of the products in the product chain, including iron ore, metallurgical coke, pig iron, ferroalloys, refractories and finished steel products. Others may produce only one or two items in the chain of iron and steel production. From this perspective, output values are much better than physical output as means of comparison. All the output values are benchmarked to the 1990 price level.

Capital usage is defined as the value of net fixed assets equaling to total fixed assets less the accumulated depreciation, which is deflated using the fixed asset investment price index for the industry. Although it is argued that net fixed assets is a problematic measure of the total capital of China's iron and steel enterprises (Jefferson, 1990), there is little we can do to adjust them due to the data limitations at the firm level.[3] Labor usage is defined as the number of employees working in the industry at the end of each calendar year rather than the total of all labor employed during the course of the year. In this study, we did not make distinctions between skilled and unskilled workers due to lack of consistent data on workers' education level over time.

Intermediate inputs are defined as the total output value (current price) minus value-added plus the value-added tax, which is consistent with the approach of the NBS. To eliminate the impact of inflation, a "single deflation" approach, which assumes identical deflators for all intermediate materials and valued added, is used to adjust the impact of price changes on the estimation of intermediate input quantity. In other words, a firm-level ratio of real to nominal gross industrial output is calculated and used to deflate the intermediate input values.

Finally, we also define a series of variables that may reasonably be expected to have impacted on firms' productivity. They include: (1) the Herfindahl index — defined as the squared share of the top 8 firms' sale revenue in the industry total at 3-digit level CICC sectors; (2) an index for marketization, which is defined as the share of non-state-ownership in firms' real capital; (3) a R&D proxy index, which is defined as the share of revenue from selling new products; (4) the scale indexes, which are defined as dummies distinguishing between small, medium and large firms; and (5) firms' export ratio, which is defined as the share of revenue from firms' export. The summary statistics on these variables including the mean, standard deviation, minimum and maximum values are shown in Table 2.

5. Firm-level TFP estimation and its determinants

Table 3 reports the estimated input elasticities in production function for China's iron and steel enterprises obtained using different methodologies. All reported estimates are obtained for applying the unbalanced panel data during the period 1998–2007. Each column reports a set of estimators obtained by using a specific method. The focus is principally on the column headed GMM_W with other columns (in particular the OP, LP and ACF estimations) for comparison.

The comparison between the estimated results obtained from using the non-parametric methods (including OP, LP, ACF and GMM_W) with those from the pooled OLS, first-differencing and within effects methods shows that coefficients in the former are lower in magnitude for both labor and intermediate inputs but higher for capital. In particular, the marginal contribution of capital is estimated to be significantly larger than that of labor in the Wooldridge GMM estimation (0.145 as compared with 0.014 from the pooled OLS estimation). This implies that capital usage plays a more important role than labor in the production of China's iron and steel firms. This finding is consistent with the capital-intensive characteristic of this industry. This finding also suggests that the problem of "endogenous input usage" applied in the previous studies surveyed is likely to have caused an underestimation of capital's contribution and a corresponding over-estimation of intermediate inputs' contribution to output

[3] Brandt et al. (2012) used the industry-level investment information (combined with firm-level investment information) to estimate firms' capital stock for the whole manufacturing industry in China. The method has certain advantages, but it is not quite suitable for estimating firms' capital stock in the iron and steel industry. The reason is that a significant proportion of capital stock in iron and steel enterprises was formed before 1998 (the starting year of our sample), as the industry is capital intensive sector. Thus, using the same industry-level investment information will significantly reduce cross-firm variation in capital stock for the sample period so as to bias the estimation of production function.

Table 1
Descriptive statistics of iron and steel enterprises in the sample: 1998–2007.

Year	Number of firms (unit)	Total output value (current price, billion yuan)	Total number of employees (million person)	Total fixed capital assets net value (billion yuan)	Total sales revenue from export (current price, billion yuan)	Total value-added (current price, billion yuan)
1998	1654	281.4	20.2	351.3	17.5	71.4
1999	1859	318.4	21.0	373.3	17.2	84.3
2000	2025	400.4	22.0	373.3	27.1	110.3
2001	2297	496.9	21.3	441.6	20.5	110.3
2002	2481	583.1	21.0	474.4	22.8	163.3
2003	2769	861.0	21.5	543.7	30.0	248.6
2004	4898	1338.6	21.9	606.2	63.4	316.7
2005	4952	1757.7	22.9	631.8	96.9	476.1
2006	5158	2097.5	23.6	890.5	150.3	562.0
2007	4929	2784.1	24.7	1055.4	216.8	739.9

Source: Authors' own calculations based on the data taken from the firm census data by NBS.

Table 2
Descriptive statistics on selected variables in Chinese iron and steel industry: 1998–2007.

	Number of observation	Mean	Std.	Minimum	Maximum
log(Capital/Labor)	33,022	−0.925	1.343	−13.347	5.350
R&D Index (New Product Share in Total Revenue %)	33,022	0.016	0.092	0.000	1.000
Market Share in the Industry	33,022	0.015	0.043	0.001	0.499
Herfindahl index	33,022	0.111	0.010	0.032	0.383
Dummy_for_Firm_Scale	33,022	0.043	0.203	0.000	1.000
Marketization Index (share of non-state owned capital in total equity)	33,022	0.771	0.040	0.000	1.000
Export Share in Total Revenue (%)	33,022	0.036	0.153	0.000	1.000

Source: Authors' own calculations based on the data taken from the firm census data by NBS.

(noting that the coefficient assigned to labor input is not changed significantly in GMM_W vis-a-via OLS or the within effects estimation). Thus, the application of the GMM_W estimation method is appropriate in this context.

In all the regressions, the estimated elasticity of intermediate inputs ranges from 0.68 to 0.94 and is statistically significant at the one percent level. On average they account for around 80% of contributions to total output. This finding shows that intermediate input usage plays an important role in the production of China's iron and steel enterprises. A possible explanation is that China's iron and steel production is mainly focusing on producing low value-added products such as sections and wires, where output growth have been mainly driven by increasing material inputs such as iron ore. As an example, long products accounted for 51.9% of China's steel product output in 2005 (China Steel Yearbook, 2006). This figure, though declining over time, is still far greater than the corresponding ones in Germany (23.8%), the United States (28.7%), Japan (37.8%) and South Korea (43.3%) more than a decade ago (Labson, Manson, & Gooday, 1995). These countries are all important producers of flat

Table 3
Estimates of the Cobb–Douglas production function of iron and steel firms with total output: 1998–2007.

	Pooled OLS	Within Est.	First Diff.	OP	LP	ACF	GMM_W
Dependent variable: lnREV							
log(Labor)	0.042***	0.056***	0.081***	0.037***	0.038***	0.066***	0.042***
	(0.002)	(0.006)	(0.007)	(0.002)	(0.002)	(0.024)	(0.011)
log(Capital)	0.014***	0.025***	0.011***	0.031***	0.058***	0.179***	0.145***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)	(0.015)	(0.012)
log(Intermediate)	0.942***	0.928***	0.860***	0.926***	0.887***	0.675***	0.890***
	(0.002)	(0.006)	(0.008)	(0.003)	(0.009)	(0.179)	(0.010)
Intercept	−0.324***	−0.360***	–	–	–	–	−0.550***
	(0.008)	(0.027)	–	–	–	–	(0.042)
R-squared	0.975	0.975	0.082	–	–	–	–
Chi-squared Test	–	–	–	–	2.60E+05	–	–
Arellano–Bond Test AR(1)	–	–	–	–	–	−16.89	–
Underidentification Test	–	–	–	–	–	776.35	23.90
Weak identification Test	–	–	–	–	–	–	15.95
Number of observations	33,022	33,022	22,646	6173	33,022	33,022	33,022

Source: Authors' own estimations. Note: a. "***", "**" and "*" represent the results which are statistically significant at 1%, 5% and 10% level respectively. The numbers in the parentheses are standard errors.

products, where value added in production is much higher. China's relatively weak penetration in flat products reflects that the fact that its industry is more highly input-intensive relative to its relevant peers especially in those industrialized countries.

Although the gross output (GO) function form based estimate (discussed above) provides some useful information, there are still some concerns as to whether the Wooldridge GMM method is more suitable for the gross value added function form (GVA) based estimate due to the potential identification issues (Wooldridge, 2009). To justify our estimation of production function with the semi-parametric approach, we further use the same methodology for the GVA function form based estimate as a robustness check.[4] Consistent with the GO function form based estimate, the GVA function form based estimate (with the OP, LP, ACF and GMM regression techniques) also shows that the contribution of capital has been significantly underestimated. In addition, a simple correlation tests show that the correlation coefficient between the GO function form based TFP estimates and the GVA function form based TFP estimates are more than 0.8, suggesting that the GO function form based estimates are both stable and robust.

Based on the preceding analysis of the estimates under the GMM method, we can use Eq. (4) to estimate firm-level TFP and examine its determinants with using Eq. (5).

Fig. 2 shows the trend of average and best performer's productivity in China's iron and steel industry over time. Between 1998 and 2007, there is a steady increase in average productivity at the firm level, with an annual growth rate of 2.1% a year. This, compared with the annual growth rate of firms' average output of 7.8% a year, suggests that firm-level productivity growth has on average accounted for 27% of output growth during the past decade. A further analysis on the relationship between the estimated TFP and some approximate determinants, such as marketization reform, firms' R&D investment, market structure and firms' export behavior, shows that these factors play different roles in affecting the productivity of China's iron and steel enterprises, depending upon, among others, different characteristics of the firms including firm size, R&D investment, ownership and exporting behavior (Tables 4 and 5).

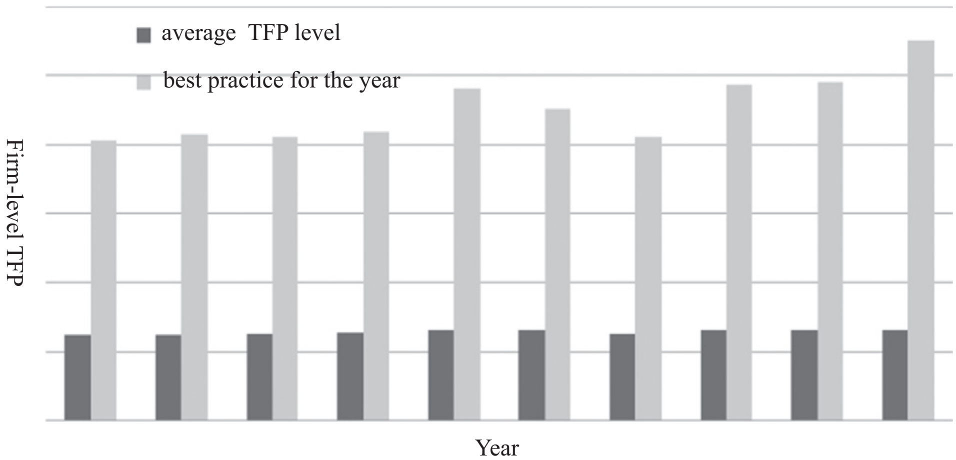
With the entire sample, our estimation from the system GMM regression shows that firms' TFP is generally positively related to R&D investment, firm size, market share and marketization reform while negatively related to market monopoly power (measured by the Herfindahl index for the top 8 firms), and firms' capital/labor ratio. As it is shown in Column 3 of Table 4, the estimated elasticities for firms' market share, the scale dummy and the marketization index are all positive and statistically significant at the 1% level while the estimated elasticity of firm's capital/labor ratio and market monopoly level is negative and also significant at the 1% level (in both the random and fixed effects frameworks). The results are robust to TFP estimations with the ACF method and the GVA based function form. These results imply that the operation of China's iron and steel firms has been on average rather labor-intensive. This, together with firm size, high proportion of private ownership and strong market share positions contributed positively to the improved level of productivity. However, exporting firms are less likely to have relatively high productivity vis-a-vis non-exporting ones. Also, to our surprise, the impact of R&D (the new products share index) on average is not quite significant (only at 10% level) though it is still positive. This may be consistent with the fact that a large number of iron and steel firms especially those non-state SEs are still using rather old and out of date technologies in their production and these firms have had less spending on R&D.

When the whole sample is split into two categories characterized by firm size: LMEs and SEs (Table 5), we find that the drivers for improving productivity differ substantially with firm size. For the LMEs, different degrees of privatization generally have no significant impact on their productivity performance (as it is shown in the system GMM model) though new products do contribute to the improvement in productivity. This result implies that the large state owned steel enterprises have already been competitive as compared with large private enterprises resulting from the reform measures implemented in the state sector (Ma et al., 2002). However, for the SEs, those with high levels of privatization have significant higher TFP than other types of SEs (in both the random and fixed effect model), implying that the marketization reform is still important for the large number of SEs in the industry. An alternative interpretation of the finding is that these private firms enjoyed some ownership advantages such as more efficient management, which help these firms to enhance their productivity. This is a significant finding as it supports the policy of deepening the ownership reform in the industry in order to further improve the industry's efficiency and productivity.

In terms of the relationship between firm ownership and productivity, our estimation results show that SOEs are more likely to obtain productivity improvement through increasing R&D innovation and enlarged scale of production resulting from large amount capital investment; while the non-SOE LMEs are more likely to obtain their productivity gains through exports. As it is shown in Table 6, the estimated coefficient of exports for the non-SOEs is positive and statistically significant at 5% level while that for the SOEs is statistically insignificant. For both SOEs and non-SOEs, increasing the production scale contributes significantly to the improvement of the TFP.

The next factor to be considered is the industrial location. Iron and steel firms have been physically distributed rather unevenly across different regions in China due to both the historical and policy reasons. To examine different drivers of firms' productivity related to different locations, we have split the sample into three sub-groups: the Eastern, Central and Western regions and the estimation results are reported in Table 7. The key findings are as follows. Although the general impact of firms' capital/labor ratio and scale on their TFP is similar, the impact of market share on productivity is much stronger in the Eastern region while the impact of marketization and market power is most evident in the Western region. This finding is consistent with the fact that market-oriented reforms have been more thoroughly undertaken in the Eastern than both the Central and Western

[4] Although the GVA based estimates have some advantages in identification, it is commonly agreed in literature that the GVA based estimate would be more likely to be biased comparing to the GO based estimate (Basu & Fernald, 1997). In this paper, we stick to the GO based estimates with the GVP based estimates as a robustness check. For simplicity, the GVP based estimate is not reported in this paper but they are available from authors upon request.



Source: Authors' own calculation.

Fig. 2. Changes in TFP level of China's iron and steel firms: 1998–2007. Source: Authors' own calculation.

regions as measured by the relatively low share of SOEs in total industry in the Eastern region. The increased competition makes the changes in market share an important factor in influencing firms' productivity in the Eastern region.

For the same reason, further reform in deepening the process of marketization plays a more important role in those Central and Western regions which have a less competitive environment due to the relatively slow progress in reform. Finally, although increasing firm size is positively correlated to firms' performance in TFP for all the three regions, it generates a much larger impact (as measured by the magnitude of the coefficient estimates) in the Western region than elsewhere.

Table 4
Determination of TFP in China's iron and steel firms (all firms): 1998–2007.

	GMM TFP estimate			ACF TFP estimate		
	Panel(FE)	First fDiff.	SYS GMM	Panel(FE)	First Diff	SYS GMM
log(Capital/Labor)	−0.105***	−0.032***	−0.559***	−0.031***	−0.033***	−0.018***
	(0.003)	(0.003)	(0.013)	(0.004)	(0.004)	(0.001)
R&D Index (New Product Share in Total Revenue %)	0.000**	0.054**	0.091*	0.020	0.047	0.098*
	(0.000)	(0.032)	(0.052)	(0.036)	(0.040)	(0.106)
Market Share in the Industry	0.066***	0.491***	0.068***	0.196**	0.582***	−0.019
	(0.015)	(0.091)	(0.016)	(0.090)	(0.106)	(0.026)
Herfindahl Index	−0.240***	−0.020	−0.300***	−0.059	−0.029	−0.286**
	(0.030)	(0.046)	(0.109)	(0.049)	(0.049)	(0.121)
Dummy_for_Firm_Scale	0.060***	0.083***	0.549***	0.218***	0.100***	0.494***
	(0.011)	(0.017)	(0.031)	(0.033)	(0.019)	(0.038)
Marketization Index (share of non–state owned capital in total equity)	0.000***	−0.000*	0.001***	0.000	−0.000	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Export Share in Total Revenue (%)	−0.010	−0.040	0.084	−0.015	−0.039	0.127
	(0.023)	(0.030)	(0.083)	(0.023)	(0.029)	(0.093)
Intercept	−0.580***	0.021***	−0.352***	0.057***	0.030***	−0.291**
	(0.012)	(0.007)	(0.111)	(0.026)	(0.008)	(0.124)
Number of Observations	26,215	17,935	26,215	26,215	17,935	26,215
R-squared	0.103	0.044		0.159	0.040	
Wald Chi2(15)			3025.63			577.66
Arellano–Bond test for AR(1) in first difference			−9.32			−2.73
			(0.000)			(0.006)
Sargan test of overid. restriction			674.92			487.58
			(0.000)			(0.000)
Hansen test of overid. restrictions			410.0			411.1
			(0.000)			(1.000)

Note: a. "***", "**" and "*" represent the results which are statistically significant at 1%, 5% and 10% level respectively. The numbers in the parentheses are standard errors.
b. lnTFP is defined as lnY-beta_l*lnL-beta_k*lnK-beta_m*lnM.
Source: Authors' own estimation.

Table 5
Determination of TFP in China's iron and steel firms by firm size: 1998–2007.

	SEs		LMEs	
	GMM TFP	ACF TFP	GMM TFP	ACF TFP
log(Capital/Labor)	−0.047***	−0.054***	−0.091***	−0.042***
	(0.013)	(0.015)	(0.011)	(0.015)
R&D Index (New Product Share in Total Revenue %)	0.038	0.031	0.033***	0.064***
	(0.099)	(0.118)	(0.008)	(0.010)
Market Share of Product	3.396***	3.325***	0.111***	0.048***
	(0.533)	(0.677)	(0.014)	(0.012)
Herfindahl Index	−0.367***	−0.419***	−0.109	−0.276*
	(0.115)	(0.134)	(0.118)	(0.152)
Marketization Index (by ownership)	0.002***	0.003***	−0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Export Share in Total Revenue (%)	0.010	0.010	−0.266*	−0.143
	(0.081)	(0.094)	(0.135)	(0.172)
Intercept	−0.496***	−0.488***	1.336***	0.999***
	(0.103)	(0.116)	(0.342)	(0.356)
Number of Observations	25,022	25,022	1,323	1,323
Wald Chi2(15)	1,240.80	993.990	694.430	511.700
Arellano–Bond test for AR(1) in first difference	−9.00	−10.43	−3.82	−4.51
	(0.000)	(0.000)	(0.000)	(0.000)
Sargan test of overid. Restriction	959.2	1334.12	335.72	424.71
	(0.000)	(0.000)	(0.000)	(0.000)
Hansen test of overid. Restrictions	401.45	392.79	247.34	233.25
	(0.000)	(0.000)	(0.000)	(0.000)

Note: a. "***", "**" and "*" represent the estimation results which are statistically significant at 1%, 5% and 10% level respectively. The numbers in the parentheses are standard errors.
b. lnTFP is defined as lnY-beta_l*lnL-beta_k*lnK-beta_m*lnM.
Source: Authors' own estimation.

6. Conclusions

This paper aimed to provide some updated estimations on firms' total factor productivity in China's iron and steel industry and to examine its potential determinants over the period 1998–2007. The paper adopted the semi-parametric regression techniques

Table 6
Determination of TFP in China's iron and steel firms by ownership: 1998–2007.

	SOEs		Non-SOEs	
	GMM TFP	ACF TFP	GMM TFP	ACF TFP
log(Capital/Labor)	−0.037***	−0.006	0.109***	0.059*
R&D Index (New Product Share in Total Revenue %)	(0.013)	(0.015)	(0.033)	(0.035)
	0.032***	0.062***	−0.089	−0.098
	(0.008)	(0.009)	(0.261)	(0.264)
Market Share of Product	0.344*	0.296***	0.063***	−0.001
	(0.180)	(0.225)	(0.024)	(0.030)
Herfindahl Index	0.478***	0.376***	−0.084	0.061
	(0.142)	(0.157)	(0.205)	(0.228)
Dummy_for_Firm_Scale	0.516***	0.479***	0.540***	0.432***
	(0.038)	(0.044)	(0.084)	(0.087)
Export Share in Total Revenue (%)	−0.001	0.012	0.314*	0.310**
	(0.078)	(0.084)	(0.192)	(0.101)
Intercept	−0.650***	−0.062***	0.299**	0.097
	(0.253)	(0.281)	(0.142)	(0.152)
Number of observations	21,772	21,772	6906	6906
Wald Chi2(15)	2156.7	1296.86	2120.18	556.82
Arellano–Bond test for AR(1) in first difference	−7.92	−8.77	−4.12	−4.55
	(0.000)	(0.000)	(0.000)	(0.000)
Sargan test of overid. restriction	479.34	718.17	705.94	776.47
	(0.000)	(0.000)	(0.000)	(0.000)
Hansen test of overid. restrictions	339.71	320.05	268.17	281.72
	(0.000)	(0.000)	(0.169)	(0.064)

Note: a. "***", "**" and "*" represent the estimation results which are statistically significant at 1%, 5% and 10% level respectively. The numbers in the parentheses are standard errors.
b. lnTFP is defined as lnY-beta_l*lnL-beta_k*lnK-beta_m*lnM.
Source: Authors' own estimation.

Table 7
Determination of TFP in China's iron and steel firms by region: 1998–2007.

	Eastern Region		Central Region		Western Region	
	GMM TFP	ACF TFP	GMM TFP	ACF TFP	GMM TFP	ACF TFP
log(Capital/Labor)	−0.055***	−0.003	0.063***	−0.007	−0.036***	−0.030**
	(0.014)	(0.016)	(0.026)	(0.030)	(0.015)	(0.016)
R&D Index (New Product Share in Total Revenue %)	0.025	−0.018	−0.112	−0.129	0.113	0.153
	(0.092)	(0.101)	(0.129)	(0.165)	(0.181)	(0.197)
Market Share of Product	0.065***	−0.005	0.140***	0.075***	0.237**	0.138*
	(0.015)	(0.021)	(0.023)	(0.031)	(0.110)	(0.081)
Herfindahl Index	−0.024***	0.170***	0.220***	0.257***	0.719***	0.734***
	(0.001)	(0.056)	(0.074)	(0.092)	(0.251)	(0.270)
Dummy_for_Firm_Scale	0.562***	0.525***	0.450***	0.382***	0.487***	0.385***
	(0.034)	(0.039)	(0.054)	(0.063)	(0.083)	(0.088)
Marketization Index (by ownership)	0.000	0.001*	0.001***	0.002***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Export Share in Total Revenue (%)	0.085	0.022	0.021	−0.012	0.157	0.143
	(0.101)	(0.110)	(0.128)	(0.152)	(0.123)	(0.130)
Intercept	−0.302**	−0.311**	−0.317*	0.389***	−0.177	−0.195
	(0.144)	(0.157)	(0.167)	(0.185)	(0.249)	(0.275)
Number of observations	16,863	16,863	6967	6967	4289	4289
Wald Chi2(15)	2238.37	1128.62	1559.87	691.74	345.54	224.74
Arellano–Bond test for AR(1) in first difference	−6.34	−7.38	−4.83	−5.31	−5.02	−5.14
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sargan test of overid. restriction	516.18	591.14	409.23	549.48	434.05	489.88
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hansen test of overid. restrictions	388.33	387.57	288.84	297.72	246.27	258.13
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: a. "***", "**" and "*" represent the estimation results which are statistically significant at 1%, 5% and 10% level respectively. The numbers in the parentheses are standard errors.
b. lnTFP is defined as lnY-beta_l*lnL-beta_k*lnK-beta_m*lnM.
Source: Authors' own estimation.

to deal with the "endogenous input" problem. To check the robustness of the estimations, other estimation methods such as OP, LP and ACF and some traditional approaches such as the first differencing and within effects methods are also applied.

The estimation results suggest that firms' TFP in China's iron and steel industry has been steadily increasing over time and this increasing trend is generally consistent with the trend of all manufacturing industries over the sample period.[5] The firms' TFP is generally positively related to R&D investment, firm size, market share and marketization reform while negatively related to market monopoly power (measured by the Herfindahl index for the top 8 firms), and firms' capital/labor ratio.

The decomposition of derived TFP suggests that the key drivers of productivity improvement differ substantially with respect to different firm sizes, ownership types and geographical locations. Notably, the productivity of SEs is positively related to market share and negatively related to R&D. For SOEs, firm-level productivity is relatively insensitive to market share and R&D. The non-SOE firms are more likely to obtain their productivity gains through export. Finally increasing firm size is generally positively correlated to firms' performance in TFP, and it is more so in the less developed Western than the other two regions.

A policy implication from this study is that to further improve the productivity and quality of Chinese iron and steel enterprises, different policy instruments targeting firms with different characteristics in the process of restructuring the industry may be desirable. For example, policy measures aimed at market entry will work well for those relatively small firms; further progress on technological upgrading and marketization reform such as development of shareholding will be more conducive to those large SOEs; more opportunities for trade will help improve productivity for those non-state large firms; and an increase in firms' scale of production will be advantageous for those firms located in the Western region.

Finally, in relation to the previous studies surveyed, the empirical tests show that the problem of "endogenous input usage" applied in the previous studies is likely to underestimate capital's contribution and overestimate the contribution of intermediate inputs to output. However, we also acknowledge that some differences might occur from choosing different production function forms in model estimations or using different datasets with different time periods, and consider that the impact of choosing different production function forms on steel firms' productivity based on the same set of data could be examined in future research.

[5] The results show that the average trends of TFP are similar, although there are some differences between the iron and steel industry and other industries in terms of both the magnitudes and statistical significance of some of the estimates which could possibly be caused by industry-specific factors. The results are available upon request.

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