# Productivity gap and Factor misallocation in Chinese manufacturing sector – micro perspective

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# Productivity gap and Factor misallocation in Chinese manufacturing sector – micro perspective

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## Abstract

This paper explores the heterogeneity of resource efficiency and investigate the associations of productivity and efficiency in relationship to ownership, region and access to capital within the Chinese manufacturing sector. We use the Hicks- Moorsteen Index to decompose within a firm efficiency conditional on ownership, sectors, and provinces for the period from 1998 until 2007. The results show a high heterogeneity of labor and capital resource efficiency among the firms. The pace of economic growth required capital investment in the sector. The consolidated results show higher misallocation of capital for State Owned Enterprises (SOEs) compared to private firms. The factor accumulation within SOEs contributed to a higher deterioration of resources. Our findings indicate necessity for growth in efficiency and support policy development for improved resource reallocation.

JEL classification: D24, L53, O12, O53

Key words: Total Factor Productivity (TFP), China's new development stage, Industrial Upgrading in China, Output and TFP Growth Potential

# 1 Introduction

“Improvements in productivity are fundamental precondition for sustainable improvements in standards of living" (O’Donnel, 2010). Improving Total Factor Productivity (TFP) in China is a very urgent task for policy makers. As China is catching up and integrating into the world economy, sustainability of rapid economic growth imposes structural changes and more efficient use of the resources. This pace of growth has created uneven development path among the regions and industry sectors. Chinese companies are facing huge differences in technologies used, productivity and production efficiency. For moving towards the strategies that emphasize green growth and efficient use of resources, improvements in productivity and efficiency are urgent. This paper studies the firm level heterogeneity among the Chinese firms within the manufacturing sector and investigate the association of TFP and firm’s efficiency on ownership structure and different access to financial capital between the firms.

We use Hicks- Moorsteen Index to decompose the firm efficiency. Our main reference is paper from O'Donnell and Laurenceson (2011). We estimate the efficiency conditional on ownership, different sectors and provinces within the period from 1998 until 2007. This period is characterized by the structural and institutional changes in China, a period of privatization and trade liberalization. Chinese economy was booming; companies grew fast, productivity was steadily improving and growing, the labor force was expanding, domestic investment in industrial capacity and infrastructure outpaced the demand, and the government policies supported low input prices. We find that these economic settings triggered a high variation of TFP among the Chinese firms, caused by the differences in labor and capital resource efficiency among the different ownership structures and provinces of studied industrial sectors. The economic reforms were huge and economic growth followed the same direction. The growth model encouraged a high rate of investment and export. Such pace of economic growth relied on capital factor accumulation within SOEs what contributed to a certain deterioration in the resources and environmental misusage. This paper contributes the empirical analysis on firm level resource allocation in China and supports the policy improvements.

Throughout the analyzed period, manufacturing was leading export sector and in average contributed to 40 percent of GDP share. We focus our study on the manufacturing sector and use the firm level data from the Annual survey conducted by the National Bureau of Statistics (NBS). The NBS survey data is a useful source for studying performance of manufacturing sector. Still, for the data analysis and interpretation we firstly need to solve for the measurement issues. There is possible sample selection issue for non-SOEs, as only firms with sales exceeding 5 million RMB were included in the industrial survey. Further to this, firms with high revenue but with lower number of employees might be included in the survey, indicating sample selection is biased towards highly productive small firms. The second sample selection issue is due to the possible enter and exit issue. The sales threshold rule for non-SOEs having sales below 5 million RMB tends not to hold strictly in the panel years. Some firms that were reported in the sample year but whose sales dropped below the threshold in the subsequent year tend to continue reporting voluntarily. We observe that this threshold rule is not strictly enforced. Enter exit issue might be enforced due to the restructure or legal changes like merge, ownership change within the firms.

Construction of the panel is done over the unique panel ID. In case of firms's ID change, firms were identified over additional variables or matching information such as firms' name, address or similar. We improve firms' matching for around 12% of firms that changed NBS ID throughout the years due to the legal changes. This panel is consistent to the panel created for the same data source in the other studies, like for example Brandt et al. (2012).

The focus of our study, the differences in TFP and efficiencies of labor and capital, is measured over the restricted and unrestricted production frontier. We control for the heterogeneity of firms operating within the different industries, regions and operating under different ownership structures. The estimated technology frontiers represent cluster of the firms with similar technology (sub-sector cluster), similar structure (province) and size and legal structure (ownership). Technology, respectively production frontier is estimated for each peer group cluster. We use the Hicks-Moorsteen TFP Index (HM Index) to decompose within a firm inefficiency estimated over the production possibilities frontier. The HM Index possesses an important property that allows decomposition into technical, scale and mix efficiency. This allows us to find the extent at which inputs can be mobilized for allocation into other sectors and firms. Aggregated input and output production technologies are estimated over the distance function. We estimate a production function for each industry sector, province and ownership and summarize the results as weighted mean of different components of TFP levels and TFP growths among the firms for each cluster. These important characteristics enables us to identify major sources of inefficiency, as different policies can be applied. For example, findings on technical inefficiencies can be improved over company's management, as these findings are related to the production input mix allocation towards the efficiency. This can be utilized throughout the various mean of production improvements like firms' core process optimization or technology changes over investment in R&D or human capital.

Similar like Brandt et al. (2012) we measure industry level average TFP growth of 12 percent annually. This high growth rate indicates a huge "catch up" effect within the firm level growth. Still, when we decompose TFP growth on productivity, efficiency, scale and scope measure and compare each firm based on the sample reference production frontier, we observe a huge gap between the firm's efficiency. On the national level, we calculate cumulative misallocation effect of 34 percent for labor and 40 percent for capital distortion while keeping the production level on aggregated sector output demand. Further, we find that there is a high variance in efficiency of using labor and capital employed within the Chinese firms. These differences are correlated with the ownership structure and access to the financial capital, indicating significant differences in rental ratio and capital share in value added among the firms. Our analysis shows significant structural difference among the firms in terms of firm's size, profitability and usage of resources, associated with a different ownership structure. Despite the dynamic firms' entry and exit, we observe continuous increase in firm's formation over the years, driven by the non-SOEs firms that grew for more than ten times over the period of ten years. But in terms of the size, SOE firms have in average twice higher output (value added) than non-SOEs, more than two and a half times higher capital and around three times bigger human capital base (see Table 1). The size of the capital is correlated with the ownership structure as SOEs have more favorable access to financing then non-SOEs. In average, we observe higher capital distortion of SOEs and at the same time lower rental ratio due to lower cost of capital.

Analyzing the micro level, we were challenged with the issue on how to measure TFP for the multi-input multi-output production technologies within the heterogeneous firm's environment. We follow O'Donnell (2008) and use the distance functions and the associated indexes of total factor productivity (TFP) change. This multiplicatively complete indexes combined with the production frontier are used to measure technical change and various measures of efficiency without making any assumptions on the competition or company behavior. In order words, technical efficiency change measures movements towards or away from the frontier, and scale and mix efficiency change measures productivity gains associated with the economies of scale and scope (O'Donnell 2008).

To calculate Hick-Moorsteen index of TFP (HM Index), some authors use data envelope analysis (DEA). Alternative approach to estimate technical change and technical efficiency is to apply stochastic frontier analysis (SFA) (Wu, 2009). Due to the important characteristic of DEA estimator being more robust and perform better than parametric estimators when technology is heterogeneous and return to scale are not constant, we use DEA to estimate the production frontier and measure components of HM Index for industry sector cluster. Technical and mix inefficiency indexes are used to estimate aggregated resource allocation effects while keeping output demand unchanged. To our knowledge this is unique paper that provides comprehensive analysis for the firm-level TFP estimates of factor utilization misallocation for the Chinese companies. Our results are absent or distinct from the previous studies on firm level productivity and efficiency decomposition in China.

The remaining parts of the paper are organized as follows. We continue with an analysis on the related study of productivity in China. In section 3 we introduce the model that uses aggregate quantity framework to compute and decompose HM-Index. In section 4, we describe the data set. Section 5 present the results and explores the aggregate effects on input factor allocation. Section 6 concludes.

# 2 Related literature on productivity in China

There has been significant literature contribution for the sources of growth related to the TFP in China. What has been less discussed in the literature is firm level empirical analysis on Chinese companies. Brandt et al., (2012) use an index number method to calculate Solow residual over firm's specific and industry average input difference and output difference and argue that the trade liberalization increases productivity throughout attracting the mostly productive entrance and private firms. Other valuable reference study on firm's dynamic in China is related to the horizontal and vertical spillovers associated with FDI (Jeon, et al., 2013).

The misallocation and utilization of production factors when focusing on the Chinese manufacturing sector is important. This sector contributes up to 90 percent of the total exports. The huge regional disparities and structural differences of provinces represents the challenge facing the Chinese fast-growing economy. There is evident gap between the well managed and poorly managed companies in Chinese manufacturing sector. Improvements in management and governance at the firm level is important component for Chinese sustainable growth. Basu, Fernald and Kimball (2006) provide very good literature reference for accounting for factor utilization. Still, according to our knowledge, there is less reference available on micro level. Significant contribution is given by Brandt, Biesebroeck and Zhang (2009), though the authors use residual or the growth accounting method. Later Brandt, Biesebroeck, Wang and Zhang (2012) expand the analysis and provide very comprehensive micro-level research on firm level productivity growth and conduct analysis on factor comparison relative to factor contribution. The authors indicate that the growth is positively correlated to firm dynamic over entry and exit and resource allocation from less to more productive firms. They apply Olley and Pakes (1996) SFA[1] and found that the value-added production function productivity growth was 7.7 percent in average for the period from 1998 until 2007.

[1] Stochastic frontier model

Consistent to these results, we calculate average TFP growth over HM TFP Index for the same period at 8.6 percent per annum. Song et al. (2011) use Solow residual for one sector aggregate production function and similarly found that more than two third of TFP growth comes from reallocation of input factors to more productive firms. Chen et.al. (2011) concludes that out of 6.7 percent TFP growth in the period from 1980 until 2008, almost 40 percent can be accounted to more productive sector. The study uses stochastic frontier analysis (SFA) to conduct the analysis over the two-digit manufacturing sector.

We follow O'Donnell (2008) and use distance function and an associated index of total factor productivity (TFP) change. To calculate the Hick-Moorsteen index of TFP we use DEA to estimate production frontier and measure components of HM Index for two-digit industry sector. Technical and mix inefficiency indexes are then used to estimate aggregated resource allocation effects while keeping the output demand unchanged. To our knowledge this is an unique paper that provides comprehensive analysis for the firm-level TFP estimates for factor utilization misallocation in China. Like Hsieh and Klenow (2009), we argue that factor market restrictions can influence factor allocation and high productivity distortion. According to Hsieh and Klenow (2009), there is a large portion of poorly managed companies in China and reallocation of capital and labor to equalize the US efficiency would result in 30 up to 50 percent of TFP increase, or double effect on the aggregated output. To quantify for the potential extent of misallocation in China, Hsieh and Klenow (2009) measures sizable gaps in the marginal products of labor and capital across the plants and within the narrowly defined industries in China. The paper is seen as an important reference on research study for the micro-level productivity in China. Still different to Hsieh and Klenow (2009) that use USA environment for benchmark reference, we use within sector, province and ownership cluster to compare TFP Index levels and measure distance from unrestricted production frontier for firm and period.

# 3 Methodology for measure of Hicks-Moorsteen (HM) TFP Index and DEA estimation

The productivity of a firm is defined as a ratio of a firm's outputs to its inputs, and firm can be compared being "efficient" or more or less "productive" across the time or within the firms. It is measured as a "residual" following the Solow (1957). The conversion of row data where the producer uses multiple inputs to produce mixed outputs over aggregated input output function into input output indexes is a complex undertaking. The methodology used in this paper is mathematical approach over the aggregator function as described by O'Donnell (2008).

The differences in production technology, scale of operation, in operating efficiencies and scope the firm operates can be properly attributed over representing TFP indexes. TFP indexes have an important property that satisfy multiplicatively- completeness requirement. TFP Indexes as ratio of output quantity over input quantity can be decomposed into the measure of technical, efficiency and scale mix efficiency level and change. We use binary Hicks-Moorsteen (HM) TFP Index, proposed firstly by Bjurek (1996). HM TFP Index is used to compare single binary comparison (two firms in time t or between two time periods). HM TFP Index can be computed without price data and this is the property we use in our paper.

HM TFP components presented in Figure 1 are detailed explained in O'Donnell (2012).

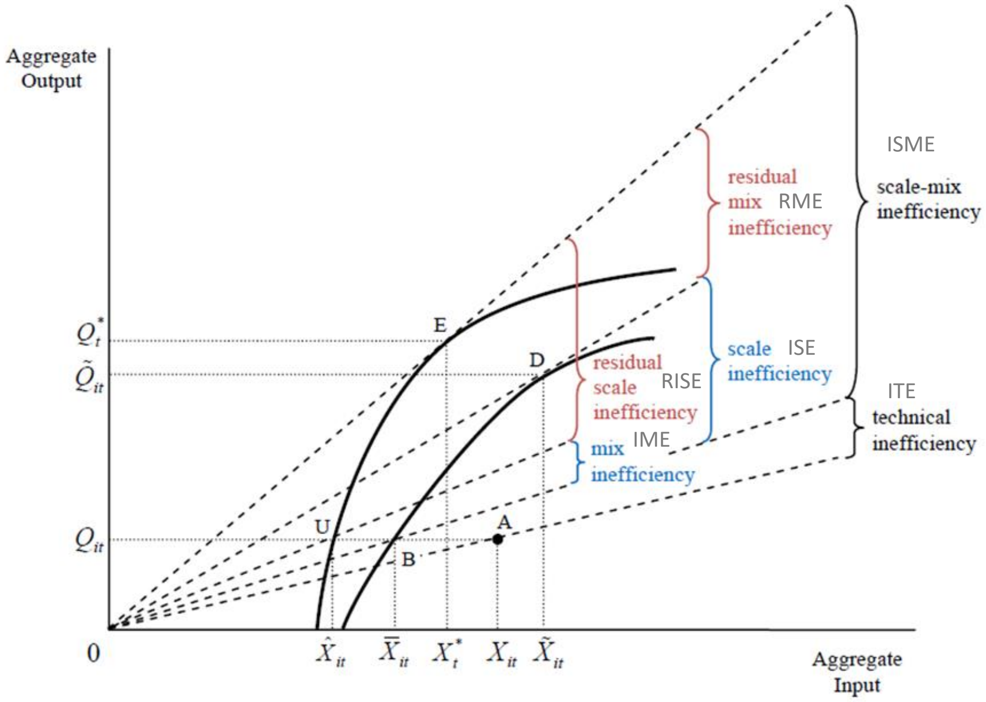


Figure 1. Input oriented efficiency indexes in aggregate input-output space[2]

Multiplicatively- complete TFP Index, Hick- Moorsteen TFP Index changes represents a natural measure of technical change. The economy or industry experiences technical progress or regress as the term is greater than or less than 1. The other ratios on the right-hand side are measures of technical efficiency change, scale efficiency change, and residual mix efficiency change.

$$(1)\ TFP_{0t} = \frac{\mathrm{TFP_t}}{\mathrm{TFP_0}} = \left(\frac{\mathrm{TFP_t^*}}{\mathrm{TFP_0^*}}\right) \times \left(\frac{\mathrm{ITE_t}}{\mathrm{ITE_0}} \times \frac{\mathrm{ISE_t}}{\mathrm{ISE_0}} \times \frac{\mathrm{RME_t}}{\mathrm{RME_0}}\right)$$

In the literature, the class of multiplicatively-complete indexes includes Laspeyres, Paasche, Tornquist, Fischer and Löwe. Hicks-Moorsteen TFP Indexes represent geometric average of the popular Malmquist TFP Index (Caves et.al.,1982) and satisfy all economically relevant

[2] O`Donnell (2012)

axioms and test from index number theory. We use binary Hicks-Moorsteen (HM) TFP Index firstly proposed by Bjurek (1996) that can be used to compare single binary comparison (two firms in time t or between two time periods). HM TFP Index can be computed without price data. The following section summarizes the model used and explains all notations needed to appropriate analyze data of N firms over T time periods.

The characteristic of multiplicatively- complete TFP indexes to be decomposed as the function ratio of tangent angels in aggregate quantity space has been conceptualized by O`Donnell (2008). Decomposing TFP over the Hick-Moorsteen index after estimating the production frontier allows estimation of different components of efficiency: technical, scale- mix and residual efficiency.

The idea is to map technically feasible input-output combinations into aggregate quantity space.

TFP efficiency is defined as the ratio of TFP of firm A and TFP* as maximal TFP possible on unrestricted production frontier, using the technology available in period t.

Let $x_{it} = (x_{1it}, \ldots., x_{Kit})'$ and $q_{it} = (q_{1it}, \ldots, q_{Jit})'$ represent vectors of K inputs and J output quantities for firm i in period t. Then TFP of the firm i in time t can be presented over aggregator function for input $X_{it} \equiv X(x_{it})$ and output $Q_{it} \equiv Q(q_{it})$ . Aggregator function is non-negative, non-decreasing and linearly-homogenous. If $TFP_t^*$represents the maximum TFP possible with available technology in time t then TFP efficiency is denoted as

(2) $TFPE_{it} = \mathrm{TFP_{it}}/\mathrm{TFP}_t^* \leq 1$

Input-oriented Technical Efficiency (ITE) measures the difference between observed TFP and the maximum TFP possible when holding the input mix, output mix and output level fixed. Input-oriented Scale Efficiency (ISE) measures the difference between TFP at a technically-efficient point and the maximum TFP that is possible while holding the input and output mixes fixed (but allowing the levels of output and input to vary). Residual Mix Efficiency (RME) indicates the difference between TFP at a point on a mix-restricted frontier and the maximum

TFP possible when input and output mixes (and levels) can vary. Input-oriented Mix Efficiency (IME) represents the difference between TFP at a technically-efficient point on the mix-restricted frontier and the maximum TFP possible when holding the output level fixed. Residual Input-oriented Scale Efficiency (RISE) indicates the difference between TFP at a technically- and mix-efficient point and TFP at the point of maximum productivity. Any movement around an unrestricted production frontier is a movement from one mix-efficient point to another, and any improvement in TFP is essentially a scale effect. TFP Efficiency (TFPE) measures the difference between observed TFP and the maximum TFP possible using the available technology. The summary of the model used is further explained in Appendix 1.

# 4 Data and methodology

We use annual firm level data for the period between 1998 and 2007. The data are conducted from the Annual survey conducted by the National Bureau of Statistics (NBS). The data includes all state-owned and all above the threshold with sales exceeding 5 million RMB non-state-owned industrial enterprises in all Chinese provinces. Dominant industry sector is manufacturing. Some of the companies are coded as services within the other defined industry sectors that include mining; food and beverages; textile, furniture and housing; chemical and pharmaceutical; metal processing; equipment manufacturing; transportation equipment manufacturing; electrical equipment manufacturing; other manufacturing, resources supply within 31 Chinese provinces.

Construction of unbalanced panel data is created with unique panel code. The yearly data surveys are merged over unique firms' code. Due to the changes of firm code throughout the period, firms were merged over additional information such as firm's name or address. As indicated in Table 1., despite the dynamic of firm's entry and exit, there is increasing size of total number of firms from 134,656 in 1999 to 373,048 in 2007. The growth in size of the firms is mainly coming from the non-SOEs. In year 1998 there were twice number of the non-SOEs firms than SOEs and 10 times more after 10 years. Still in terms of size, SOE firms have in average double output (value added) then non-SOEs, more than twice higher capital and three times bigger human capital base. The size of the capital is correlated with the more favorable access to financing for SOE firms, we observe up to 60 percent lower rental ratio than for non-SOEs firms.

Table 1. Summary statistic per Ownership weighted mean for Firm Panel Data

| Year | No. of Firms observed | | No. of Employees Ø | | Value added Ø in ¥ 10.000 | | Capital Ø in ¥ 10.000 | | Rental ratio in % | |
|---|---|---|---|---|---|---|---|---|---|---|
| | SOE | non SOE | SOE | non SOE | SOE | non SOE | SOE | non SOE | SOE | non SOE |
| 1998 | 42.953 | 91.703 | 15.522 | 12.559 | 1.237.968 | 1.194.821 | 6.361.923 | 3.678.551 | 3.3 | 4.7 |
| 1999 | 44.141 | 103.021 | 18.310 | 4.749 | 2.026.337 | 594.260 | 7.512.223 | 2.592.277 | 2.9 | 4.2 |
| 2000 | 36.575 | 105.341 | 17.043 | 4.822 | 3.782.784 | 793.352 | 7.426.923 | 3.373.541 | 2.3 | 3.5 |
| 2001 | 33.189 | 118.668 | 16.526 | 3.957 | 3.819.308 | 675.525 | 8.293.267 | 2.661.181 | 2.1 | 3.3 |
| 2002 | 31.198 | 134.197 | 14.983 | 5.564 | 2.620.359 | 2.172.926 | 7.502.070 | 4.145.625 | 2.3 | 3.1 |
| 2003 | 29.030 | 160.071 | 14.357 | 5.008 | 3.013.989 | 2.348.155 | 10.779.167 | 4.123.194 | 2.1 | 3.0 |
| 2004 | 28.235 | 230.812 | 15.693 | 5.091 | 4.699.461 | 2.566.390 | 11.119.196 | 5.254.546 | 1.9 | 2.7 |
| 2005 | 25.499 | 237.392 | 15.661 | 5.838 | 5.940.496 | 3.861.198 | 14.125.179 | 6.676.919 | 1.7 | 2.4 |
| 2006 | 27.804 | 277.870 | 16.969 | 6.940 | 6.974.893 | 4.892.921 | 16.241.407 | 7.607.449 | 1.7 | 2.6 |
| 2007 | 30.967 | 342.081 | 20.704 | 6.583 | 8.035.897 | 4.863.885 | 19.474.776 | 8.493.743 | 1.7 | 2.8 |

## 4.1 Data construction

The measurement and decomposition of TFP over HM Index we conduct over the following variables; Value added, Employees and Total employee compensation, Capital stock and Investment. Estimation for the production frontier within the peer group is done by using Data envelope analysis- DEA (Farrell, 1975) linear programming.

Each firm is coded under the industry, ownership and province code. In order to improve the data consistency and to reduce the reporting errors on a survey reported data, we conduct plausibility check and use bottom up calculation and reconcile it with top down reported variables. We run plausibility checks and simulations on accuracy and deviation analysis.

Value added

We use value added variable as output variable for measuring TFP Indexes. Compared to output, the property of value added variable is that inter-sector and inter-industry effects are netted out. Value added is reported in the survey data, but there are missing data for the years in 2001 and 2004. Value added is calculated as gross output net of material inputs and netted for income from affiliated companies. For data consistency and due to the missing values, we calculate gross output using bottom up method starting from the variable operating profit inclusive tax. Material input is reported variable, but we again recalculate it over cost of goods sold reduced by the depreciation cost of capital; and wages inclusive total welfare benefits payed to the employees. In the case of missing input data, we calculate value added using aggregated data on output incl. value added tax less input. We use output deflator constructed in Brandt, Biesebroeck and Zhang (2009). Output deflator is calculated as ratio of nominal to real output as index to base year, averaged on sectoral and provincial level.

Industry classification

The firm level data is classified over 4-digit sector code using the Chinese Industry Classification (CIC) system. In 2003 classification has been redefined to expand granularity of some sectors whereas some sectors have been merged. This requires reclassification and matching the sector codes for sector reporting. We harmonize codes by clustering data based on 2 digits sector code, based on NBS industry classification.

Capital stock

Each firm report their capital stock at book value calculated at purchase price less accumulated depreciation, which represents a sum of accumulated nominal values increases over the years. Reported nominal book value of capital stock cannot be used in analysis as it is not comparable over the years and firms, and as such would lead to biases in the results. We calculated capital stock by converting reporting values into the real values. We firstly estimate the real value of capital stock at the base year which is either first year firm operate in our data or firms birth year. We start by calculating nominal value of the capital stock for birth year[3]. We use a nominal capital growth rate for province-sector level data and report a nominal capital value at

[3] Some companies report different birth year, in this case we take min year reported by the firm.

the firm's first reporting year. Estimating a real capital stock in the first year in which the firm appears in data set is done over capital deflator. We use capital deflator constructed by Wu (2009). We make several plausibility checks for the reported nominal values of the capital due to the errors in data format, like for example, for reporting the capital at negative values. We also conduct interpolation of data for missing year entries for capital variable, in case of reporting error.

We calculate the real capital growth rate CAGR for the period from 1993 until 1998 and report the real capital at panel starting year 1998. For calculating the real capital stock for the following year in the panel starting from 1998 until 2007 we use the perpetual inventory model. We use reported nominal value from the firm's depreciation and in case of missing inputs we apply depreciation rate per sector and province constructed according to Wu (2009). Nominal net add after depreciation is used for calculation of nominal value for investment.

Employees and Wages

Number of employees variable and wages including social benefits are reported in the data. We use different deflator for input variables. The input deflator is calculated as an adjusted output deflator with the data from the National Input-Output table[4]. We use separate deflator for input since input prices increased at doubled rate than output prices for the reported period. Wages are not used for calculation of TFP HM Index. Nevertheless, we use wages for summary statistics.

[4] National Input-Output tables from 2002

## 4.2 Creation of panel data

Calculation of HM Index and DEA linear programming requires that the data used are balanced panel data. We conduct data interpolation for missing observations variables due to reporting errors. We use the firm real growth rate or the industry province weighted mean real growth rate for labor, capital and value added. We argue that the possible biasness for constructing of missing reported data does not influence data quality since the TFP indexes have been calculated on weighted mean sectoral and provincial level. Interpolation due to the missing values is adding less than 1 percent of total observations, whereas missing data created over average peer growth rate for single variable is done for less than 5 percent of observations. We follow the argumentation against potential bias given by Brandt et. al (2012). The authors argue that the full census of the firms would contribute for around 9.9 percent of output in 2004. This supports an assumption on the representative sample and weaken indication on selection biasness.

# 5 Results

## 5.1 Resource allocation

A period after the China's attrition to the World Trade Organization (WTO) counts for the high economic growth. A high rate of investment accumulated over the high rate of savings[5] enabled this momentum (Chamon, Liu, Prasad et al. 2010). Manufacturing sector benefited substantially from the resource allocation and sector shifts with rural workers migrating from the agriculture sector. Still, this development did not come for free. The pace of high economic growth contributed to the environment deterioration and exceeded resource distortion. Further

[5] In the recent years it is evident that the demographic changes in China are influencing saving rate starting to decline from 51.9 (2009) to 48.7 (2014)

to this, recent trends of slowing down the world economy, input price increase and liberalization of the market calls for efficiency and resource reallocation.

To measure the firm level resource efficiency, we need to decompose productivity from the efficiency. The first measures contribution from innovation (or technical shift on the production frontier) and the second diffusion and learning (or catching up and resource optimization). The focus of this research is mainly on the technical and efficiency levels and indexes on firm's level data while making no assumption on the quantity demand. We calculate decomposed HM Indexes for industry sector mean among provinces and ownership for a period from 1998 until 2007. We present our results aggregated for industry and provinces grouped by the firm's ownership. Ownership structure is in our analysis an important variable. To analyze the resource distortion followed by the assumption that two firms with the same technology but different access to capital financing will have different marginal product of capital. In that sense, an aggregated output could be higher if the capital was reallocated to the firm with a higher marginal product. The intuition behind is that the SOEs have significantly higher capital (compared to the value added) and up to 60 percent lower rental costs than for non-SOEs.

Looking into the index growth, the results of per province mean of TFP Index growth from the period between 1998 to 2007, decomposed as TFP change, technical change, efficiency change and mix change are represented in Figures 2. and 3. The highest TFP growth comes from the provinces on the developed east coast. The region has favorable access to the global market supply chain, stronger domestic policy liberalization as well as technology transfer and spillover effect through the Special Economic Zones located in the coastal area. We observe higher heterogeneity in the firm level productivity across the provinces then across the industries. The analysis requires further interpretation on index change. TFP change (growth) represents change in the aggregated output over change in the aggregated input, relative to the previous period. Similarly, technical change measures shift in maximum possible TFP due to change in technology (i.e. $TFP_t^* \quad TFP_{t-1}^*$), or shift of the frontier of technology. Change in efficiency refers to change in TFP efficiency (i.e. the ratio of TFP change over technical change)[6]. Compared to the national firm average TFP growth for 8 percent, an average firm TFP growth, clustered per province, equals 15 percent. Similar to Brandt, Biesebroeck, Wang and Zhang (2012) we measure industry level average TFP growth of 12 percent.

The difference comes from the estimation of different frontier of technology for each cluster due to the structural differences across the Chinese provinces. We measure technology frontier for each peer group of observation as the production function is estimated based on the mean of firms within the province and ownership. Analog approach is taken when we compare the productivity levels and indexes among the industry sub-sector and ownership, or on national level. This allows us to estimate technology frontiers at the given time and technology growth for the next period based on the peer group as the reference in estimation, based on the weighted mean of the firm level TFP growth and other efficiency growth components. For example if we analyze growth for Beijing, average non-SOE firm increased in TFP for observed period around 11 percent (compared to 21 percent TFP growth for the SOE company). Reported technical change (or shift in the frontier technology) grew for around 29 percent for non-SOEs and 18 percent for SOEs, and measured TFPE change (i.e. efficiency change) declined for 5 percent for non-SOEs and increased for 9 percent in efficiency compared to the maximum productivity possible with available technology for SOEs.

As presented in Table 2, the average TFP growth per industry sector accounted for 12 percent increase within a period from 1998 until 2007. Technical change grew for only 4 percent and efficiency change for 9 percent. It is evident that TFP and technology growth index for SOE firms are lower (11 percent and 2 percent respectively) than for the non-SOEs (19 percent and 6 percent). That can be interpreted over a catch-up for the non-SOEs to compete with the SOEs and pressure due to a higher cost of financing or less favorable operating environment. The same is evident for the efficiency change and technology efficiency change. The highest TFP change (growth) for SOEs is evident for Chemical and Pharmaceutical sub-sector (33% in average p.a. growth) and Resource supply sector for non-SOEs (28%).

[6] Similar interpretation is done for the other index changes (ITE, ISME, etc.).

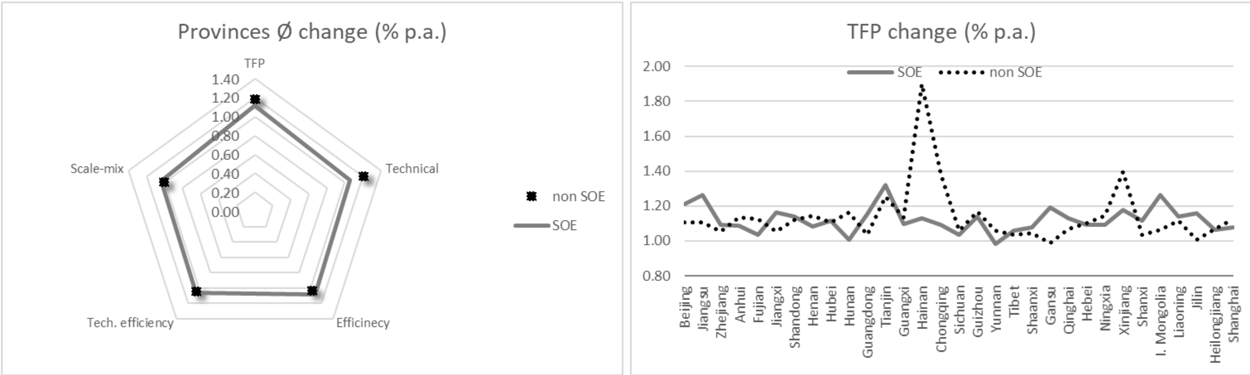


Figure 2. TFP HM Index average change between 1998 to 2007 and TFP change % p.a. province view

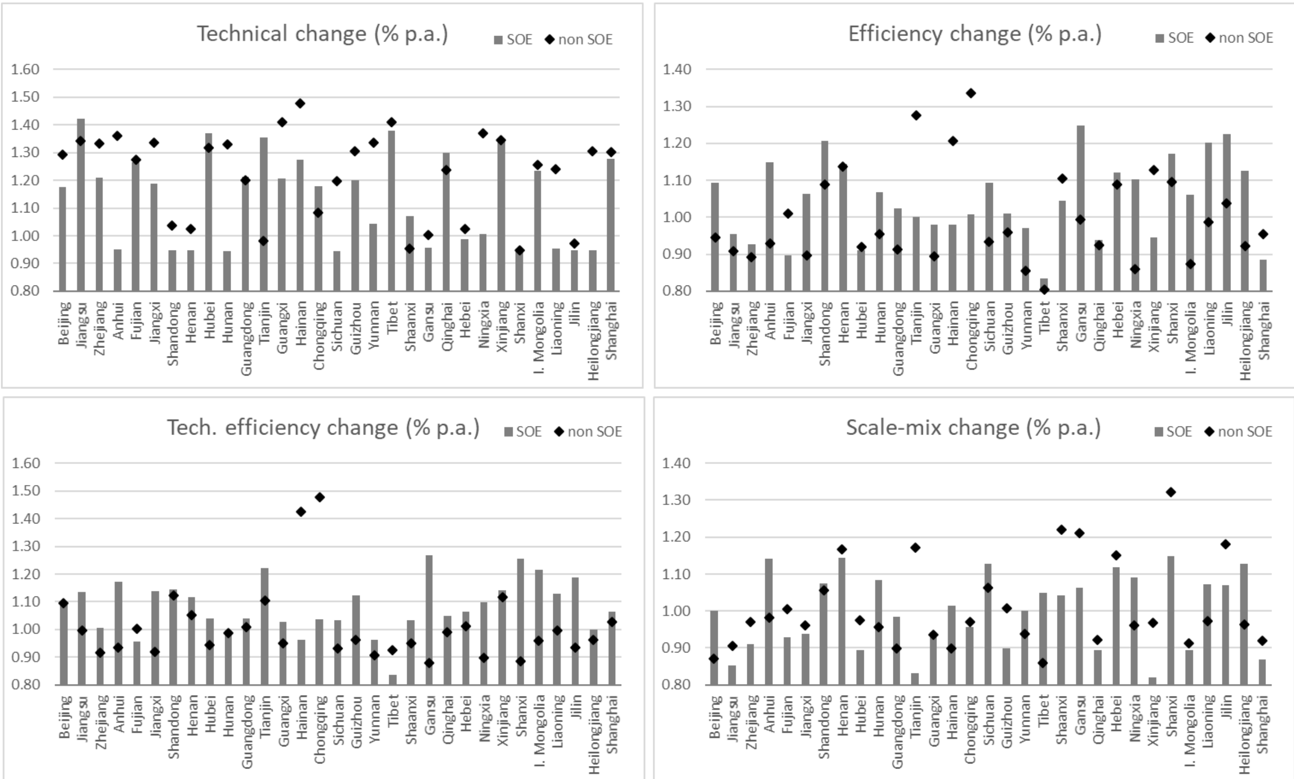


Figure 3. TFP HM Index average change between 1998 to 2007- province view

Table 2. TFP HM Index average change between 1998 to 2007- industry sector view

| Industry | TFP change (% p.a.) | | Technical change (% p.a.) | | Efficinecy change (% p.a.) | | Tech. efficiency change (% p.a.) | | Scale-mix change (% p.a.) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | non SOE | SOE | non SOE | SOE | non SOE | SOE | non SOE | SOE | non SOE | SOE |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Mining | 1.07 | 1.06 | 1.09 | 1.02 | 0.99 | 1.06 | 1.05 | 1.00 | 0.94 | 1.06 |
| Food and Beverages | 1.01 | 1.03 | 1.04 | 0.99 | 0.98 | 1.07 | 1.01 | 1.00 | 0.97 | 1.07 |
| Textile. furniture and housing | 1.16 | 1.14 | 1.07 | 0.97 | 1.10 | 1.21 | 0.97 | 1.11 | 1.13 | 1.08 |
| Chemical and Pharmaceutical | 1.17 | 1.33 | 1.06 | 1.07 | 1.10 | 1.25 | 1.03 | 1.18 | 1.07 | 1.04 |
| Metal processing | 1.14 | 1.17 | 1.06 | 1.02 | 1.08 | 1.18 | 0.97 | 1.20 | 1.11 | 1.01 |
| Equipment manufacturing | 1.05 | 1.11 | 1.06 | 1.04 | 1.00 | 1.07 | 1.00 | 1.08 | 1.00 | 0.99 |
| Transportation equipment | 1.16 | 1.12 | 1.05 | 0.97 | 1.11 | 1.18 | 1.06 | 1.09 | 1.02 | 1.07 |
| Electrical equipment | 1.11 | 1.23 | 1.03 | 1.02 | 1.07 | 1.22 | 1.07 | 1.18 | 1.00 | 1.03 |
| Other Manufacturing | 1.03 | 1.10 | 1.02 | 1.09 | 1.01 | 1.01 | 1.00 | 1.04 | 1.01 | 0.98 |
| Resources supply | 1.28 | 1.27 | 1.07 | 1.12 | 1.23 | 1.13 | 1.27 | 1.33 | 0.95 | 0.94 |
| Industry Ø | 1.19 | 1.11 | 1.06 | 1.02 | 1.14 | 1.11 | 1.14 | 1.07 | 0.99 | 1.05 |
| | 1.12 | | 1.04 | | 1.09 | | 1.07 | | 1.02 | |

The differences of index change volatility between the provinces and sectors show higher mobility of resource allocation within the industry sectors compared to mobility among the regions, respectively within the provinces. Still both cluster groups represent high growth in economic terms.

## 5.2 Heterogeneity of TFP and efficiency

Tables 3 and 4 show the average index levels and index growth for different measures of technical, scale and mix efficiency[7]. Comparing a product of technical, scale and mixed inefficiency (mean over 10-years period) we observe a gradual heterogeneity among the different industry sectors and different province levels. For the SOEs, TFP efficiency level as

[7] All Index levels represent firm level mean averaged over panel period at cluster mean for either industry sector or province. Variables q and x represent aggregate level of output and input, tfp is total factor productivity for respective cluster mean, tfp* is maximal tfp on unrestricted production frontier, tfpe stands for TFP efficiency as ration of tfp over tfp*. Variable ote is output oriented technical efficiency, osma is output oriented scale-mix efficiency. Similarly, ite is input oriented scale-mix efficiency and isme is input oriented scale-mix inefficiency.

presented in Table 3, indicates that there is in average uplift for 60 percent of efficiency (averaged on the industry mean) and in average up to 85 percent productivity was not utilized compared to the maximum productivity possible using the technology available in this period based on the provincial mean. Compared to non-SOEs, TFP Efficiency level for industry mean indicates around 50 percent possible productivity increase for available technology frontier or 75 percent increase averaged on provinces. This provides evidence for source of resource savings or better utility within the Chinese firms.

Table 3. Decomposition of resource allocation – mean over industry sector and province

| Period 1998-2007 | q | x | tfp | tfp* | tfpe | ote | osme | ite | isme |
|---|---|---|---|---|---|---|---|---|---|
| Industry Ø non SOE | 0.67 | 1.85 | 0.51 | 1.05 | 0.48 | 0.70 | 0.68 | 0.71 | 0.68 |
| Industry Ø SOE | 0.80 | 1.84 | 0.73 | 2.06 | 0.37 | 0.81 | 0.48 | 0.78 | 0.53 |
| Provinces Ø non SOE | 0.45 | 3.27 | 0.25 | 1.87 | 0.23 | 0.46 | 0.50 | 0.44 | 0.54 |
| Provinces Ø SOE | 0.70 | 2.30 | 0.60 | 10.95 | 0.15 | 0.71 | 0.24 | 0.68 | 0.27 |

Table 4. Growth of resources and TFP indexes – national mean

| Average 1998-2007 | TFP change (% p.a.) | Technical change (% p.a.) | Efficinecy change (% p.a.) | Tech. efficiency change (% p.a.) | Scale-mix change (% p.a.) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Industry Ø non SOE | 1.19 | 1.06 | 1.14 | 1.14 | 0.99 |
| Industry Ø SOE | 1.11 | 1.02 | 1.11 | 1.07 | 1.05 |
| Industry Ø | 1.12 | 1.04 | 1.09 | 1.07 | 1.02 |
| Provinces Ø non SOE | 1.19 | 1.21 | 1.03 | 1.05 | 1.00 |
| Provinces Ø SOE | 1.11 | 1.06 | 1.08 | 1.06 | 1.04 |
| Provinces Ø | 1.15 | 1.20 | 1.01 | 1.02 | 0.99 |
| Ø non SOE | 1.09 | 1.10 | 0.99 | 1.00 | 0.99 |
| Ø SOE | 1.07 | 1.10 | 0.97 | 1.00 | 0.97 |
| Ø National | 1.08 | 1.10 | 0.98 | 1.00 | 0.98 |

Table 4. represents national mean for TFP index change. In terms of growth, TFP Efficiency grew in average for 10 percent. But in terms of TFP growth, average TFP growth was 8 percent, which is consistent with the other research done on the same panel data for the same period in China. For example, Ding, Guariglia, and Harris (2015) found 9.6 percent TFP growth for the same panel data using GMM estimation. Again, we observe consistent lower growth of TFP

for SOEs (for industry cluster 11%, provinces 11% or national mean 7%) than for non-SOEs (industry 19%, provinces 19%, national 9%). We argue that the private firms counted for higher productivity and efficiency growth compared to state- owned enterprises.

## 5.3 Aggregate effects for potential reallocation gains

We calculate an input factor misallocation effect for capital and labor while keeping the firm's level demand unchanged. For this we use the sector technical efficiency on restricted (ITE) and unrestricted (*ITE x IME*)[8] production level. The effects are visually illustrated within Figure 1. This represents the input efficiency decomposition where a firm level TFP can be optimized by moving towards restricted production frontier (ITE) and unrestricted production frontier (IME) while keeping the quantity level unchanged. We use those two indexes for calculating the aggregated effects of possible resource misallocation while keeping the existing output demand. In other words, we calculate possible resource savings based on the constant output demand. We calculate the effects for capital and labor separately, by starting from the firm level data and aggregating it up to the national level.

Firm level TFP for the respective panel year is determined as aggregated input over aggregated output. The ratio is defined in (1) $TFP_{it} = \frac{Q_{it}}{X_{it}}$. Single factor productivity is defined as the ratio of output over single input: factor productivity for labor $= \frac{Q_{it}}{L_{it}}$ and for capital $= \frac{Q_{it}}{K_{it}}$. Similar, single input allocation of labor and capital are defined over labor to value added and capital to value added ratio. We calculate an aggregated demand for capital and labor for industry sector or province by aggregating the firm level demand for each input factor, if each firm would produce on the optimal level, which represents production on the unrestricted production frontier.

For comparison we use province and industry index level on restricted production frontier (ITE) and unrestricted production frontier (IME), calculated over the weighted mean firm level

[8] ITE- Technical inefficiency, IME- mix inefficiency.

data per sector and province level. For example, the $IMEITELVA_{it}$ variable represents labor per value added changed for the reduced labor input over the saving effects when the firm A produces the same output on restricted (ITE) und unrestricted (IME) production frontier available in time t based on the available technology. $IMEITEKVA_{it}$ represents savings on firm's capital inputs based on the "industry sector" ratio of possible savings.

(3) $IMEITELVA_{it} = L_{it}/VAit * (ITE_{st} * IME_{st})$

(4) $IMEITEKVA_{it} = K_{it}/VAit * (ITE_{st} * IME_{st})$

(5) $IMEITEL_{st} = \sum_{i=1}^{Ms} IMEITEL_{it} = \sum_{i=1}^{Ms}\{L_{it} * (ITE_{st} * IME_{st})\}$

(6) $IMEITEK_{st} = \sum_{i=1}^{Ms} IMEITEK_{it} = \sum_{i=1}^{Ms}\{K_{it} * (ITE_{st} * IME_{st})\}$

(7) $L_{st} = \sum_{i=1}^{Ms} L_{it}$ and $K_{st} = \sum_{i=1}^{Ms} K_{it}$

Calculated difference (Table 5) represents potential savings for each input factor. On a national level we calculate the cumulative misallocation effect for these selected industry sectors and for the observed firms. In total we calculate 34 percent for labor and 40 percent for capital savings that might be (either) reallocated into the other sectors or saved while keeping a production level on the aggregated sector output demand. The calculated misallocation effect of capital for SOEs is almost as twice higher than for non-SOEs. In terms of employees (labor resources) savings for non-SOEs sector is up to 28 percent or 12 million employees, and for SOEs savings potential is up to 49 percent or 9 million employees. In terms of capital non-SOEs saving potential is 30 percent versus saving potential for SOEs up to 52 percent. In total we measure possible resource reallocation for 21 million workers and 3.5 billion RMB capital.

Table 5. Aggregated effect for reallocation of input factors

| | | | | | Saving potential over industry | | Saving potential over provinces | |
|---|---|---|---|---|---|---|---|---|
| | Ownership | Nr of Firms observed | Labour in Million | Capital in Billion ¥ | Labor % | Capital % | Labor % | Capital % |
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 1998 | non SOE | 91,703 | 24.7 | 2.2 | -36% | -43% | -70% | -71% |
| | SOE | 42,953 | 28.3 | 3.2 | -58% | -67% | -71% | -72% |
| 1999 | non SOE | 103,021 | 27.9 | 2.5 | -35% | -41% | -65% | -65% |
| | SOE | 44,141 | 27.6 | 3.7 | -54% | -58% | -67% | -66% |
| 2000 | non SOE | 105,341 | 28.5 | 2.8 | -31% | -38% | -62% | -62% |
| | SOE | 36,575 | 22.3 | 3.2 | -53% | -58% | -62% | -61% |
| 2001 | non SOE | 118,668 | 32.3 | 3.2 | -32% | -38% | -63% | -62% |
| | SOE | 33,189 | 19.7 | 3.5 | -52% | -57% | -62% | -60% |
| 2002 | non SOE | 134,197 | 35.5 | 3.8 | -33% | -40% | -63% | -62% |
| | SOE | 31,198 | 17.5 | 3.4 | -51% | -57% | -62% | -59% |
| 2003 | non SOE | 160,071 | 40.6 | 4.4 | -26% | -33% | -61% | -59% |
| | SOE | 29,030 | 15.0 | 3.5 | -48% | -54% | -61% | -57% |
| 2004 | non SOE | 230,812 | 51.0 | 5.8 | -25% | -33% | -75% | -74% |
| | SOE | 28,235 | 13.5 | 3.4 | -39% | -46% | -67% | -66% |
| 2005 | non SOE | 237,392 | 56.0 | 7.0 | -24% | -23% | -73% | -74% |
| | SOE | 25,499 | 12.0 | 3.5 | -37% | -43% | -62% | -61% |
| 2006 | non SOE | 277,870 | 60.8 | 8.3 | -23% | -22% | -71% | -71% |
| | SOE | 27,804 | 11.1 | 3.8 | -36% | -45% | -66% | -65% |
| 2007 | non SOE | 342,081 | 66.4 | 9.8 | -26% | -24% | -75% | -75% |
| | SOE | 30,967 | 10.6 | 3.9 | -33% | -43% | -58% | -61% |
| Mean | non SOE | | 42.4 | 5.0 | -28% | -30% | -69% | -69% |
| | SOE | | 17.8 | 3.5 | -49% | -52% | -65% | -63% |
| | National | | 60.2 | 8.5 | -34% | -39% | -68% | -67% |

We find that there is a high dispersion in efficiency of using labor and capital employed within the Chinese firms. There is significant structural difference among the firms in terms of financing, size of the firms, profitability or usage of resources within a different ownership structure.

The *t*-test for the rental ratio with current capital level and with capital level if producing the same value added on the available technology frontier shows six percent higher effect for SOEs. This indicates higher capital distortion enabled over the lower rental rate or lower financing cost of capital. The second t-test we run is on capital per value added ratio. We observe huge disparity between ownership, 15 times higher effect for SOE firms if producing on the optimal level.

Table 6. t-test for SOEs and non-SOEs differences in Rental ratio / Capital in Value added after Capital adjustment for IMEITE

| Paired t test | Nr of observation | | Mean (SD) | | Pr(\|T\| > \|t\|) | |
|---|---|---|---|---|---|---|
| | SOE | non SOE | SOE | non SOE | SOE | non SOE |
| Capital in Valu added | 1,802,687 | 292,347 | 14.51 (1059.46) | 1.80 (52.71) | | |
| Capital in Valu added after treatement | 1,802,687 | 292,347 | 6.47 (367.79) | 1,30 (38.76) | | |
| Difference | | | 8.05 (706.31) | 0.50 (16.58) | 0.000 | 0.000 |
| | | | | | | |
| Rental Ratio | 1,802,687 | 292,347 | 0.08 (44.20) | 0.21 (135.20) | | |
| Rental Ratio after treatement | 1,802,687 | 292,347 | 0.27 (101.41) | 0.33 (217.80) | | |
| Difference | | | *-0.18 (57.63) | *-0.12 (82.88) | 0.0825 | 0.0477 |

# 6 Conclusion

Development trends like rising labor costs at higher rate than productivity, declining global demand, slowing down of government subventions on energy resources and pressure from the financial markets is calling for the policies stimulating sustainable growth, technology improvements and scale and scope optimization. Resource optimization is becoming important component for a sustainable growth in China.

In this paper, we examine the effects of variation in TFP and firm's efficiency of labor and capital used between the Chinese firms, conditional on ownership structure. Based on our findings, we calculate the aggregated quantitative effect for potential reallocation of labor and capital.

We use the HM Index that allows decomposition into technical, scale and mix efficiency. This allows us to calculate the potential input savings or reallocation into the other sectors or firms. Our results could serve for policy recommendations to promote reallocation of labor and capital towards more productive sectors. Recommendations on efficiency improvements include optimization on production input mix, firm's core process optimization and technology changes over investment in R&D or know-how. On the contrary, scale-mix efficiencies require production output optimization influenced over the changes on demand function. For example, policy adjustments on monetary and fiscal changes that reflects relative prices and market demand changes. Information on heterogeneity in efficiency for majority of manufacturing sector is valuable contribution to the existing literature. Still, the limitation of our interpretation is possible selection bias due to sample selection issues for non-SOEs threshold selection within the reporting years, as well as due to the firm's dynamics on entry or exit. Our results are absent or distinct from previous studies on the firm level productivity and efficiency decomposition in China.

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# Appendix 1

In our study we calculate all mixed efficiency indexes as illustrated.

(1) $ITE_{it}$ =$(Q_{it}/X_{it})/(Q_{it}/\bar{X}_{it})$= $\bar{X}_{it}/X_{it} \leq 1$: technical efficiency, defined as minimum aggregate input possible to produce quantity $Q_{it}$ on the restricted production frontier illustrated in Figure 1, $ITE_{it} = \|B\|/\|A\|$

(2) $ISE_{it}$= $(Q_{it}/X_{it})/(\widetilde{Q_{it}}\ /\widetilde{X_{it}}) \leq 1$: pure scale efficiency

(3) $IME_{it}$= $(Q_{it}/X_{it})/(Q_{it}/\overline{X_{it}}) = (\hat{X}_{it}/\overline{X_{it}}) \leq 1$: pure mix efficiency, defined as minimum aggregate input possible to produce quantity $Q_{it}$ on unrestricted production frontier illustrated in Figure 1, and

(4) $ISME_{it}$= $(Q_{it}/\overline{X_{it}})/\ TFP_t^* \leq 1$: scale-mix efficiency

Similarly, output oriented TFP indexes can be decomposed into following measures: OTE (output- oriented technical efficiency), OSE (output-oriented scale efficiency), OME (output-oriented mix efficiency), ROSE (residual –output oriented scale efficiency), RME (residual mix efficiency) and OSME (output- oriented scale-mix efficiency).

$\overline{Q_{it}} \equiv Q_{it}D_O(x_{it}, q_{it}, t)^{-1}$ represents the maximum aggregate output possible when using $x_{it}$ to produce a scalar multiple of $q_{it}$, whereas $\overline{X_{it}} \equiv X_{it}D_I(x_{it}, q_{it}, t)^{-1}$ is the minimum aggregate input possible over scalar multiple of $x_{it}$ to produce $q_{it}$. $\widehat{Q_{it}}(\ \widehat{X_{it}})$ is the maximum aggregated output (minimum aggregated input) possible to produce any output (input) vector. $\widetilde{Q_{it}}\ and\ \widetilde{X_{it}}$ are obtained when TFP is maximized subject to the constraint that the output and input vectors are scalar multiples of $q_{it}$ and $x_{it}$.

The estimation of total factor productivity requires the estimation of production technology and assumptions on the aggregator function. We estimate production technology using DEA linear programming. For that, the DPIN computer program developed by O'Donnell (2008) to compute and decompose productivity index numbers is used. Compared to other parametric and non-parametric estimators, Data Envelope Analysis (DEA) is the best estimator when technology is heterogeneous and return to scale are not constant, which impose no assumption on production function and allows straight forward computation. Nevertheless, DEA is sensitive to outliners, and each firm with highest ratio for input –output combination is 100 percent efficient. We avoid those while checking for outliner observations and scaling all inputs and outputs variables to have unit means. We calculate the total factor productivity (TFP) as the ratio of aggregated output over aggregated inputs, whereas we observe value added as aggregated output over aggregated input of labor and capital factors. We use HM TFP Index as its computation does not require any price data.

Aggregated resource misallocation of capital and labor calculated from the firm level demand for two factor inputs if each firm would produce on optimal level on unrestricted production frontier sector value added we calculate while keeping output demand unchanged. In index terms we calculate aggregate effects of technical inefficiency (ITE) and mixed inefficiency (IME).

Applying DEA methodology assumes that production frontier takes the form:

(1) Q($q_{it}$)$\leq f(x_{it}, t)$ ($f \geq 0$ , non-decreasing and concave in inputs)
(2) DEA applies that $f(x_{it}, t)$ is locally linear (in order to estimate efficiency using linear programing)
(3) $Q_{it} = A(t)X(x_{it})$, where A is TFP change. This form of production frontier requires following assumptions: there is no technical inefficiency (Q($q_{it}$)= $f(x_{it}, t)$), technology is homothetic[9] and technical change is Hicks-neutral
(4) Marginal revenue products equal factor prices (i.e. perfect competition) and input aggregator function $X_{it} = X(x_{it})$ has a Cobb-Douglas functional form.

Again, input $x_{it} = (x_{1it}, \dots, x_{kit})'$ and output $q_{it} = (q_{1it}, \dots, q_{kit})'$ quantity vectors of firm i in period t are aggregated over aggregator function $X_{it} = X(x_{it})$ and $Q_{it} = Q(q_{it})$ which is non-decreasing, non- negative and linearly homogenous. Input aggregator function is derived over Shephard (1953) input- output distance function technology feasible in time t. The HM Index needs to be multiplicatively complete for decomposition and comparison. For this, aggregator function for input

[9] Homothetic assumption requires linear function homogenous of degree1, CRS (constant return to scale)

$X(x) = [D_I(x, q_{hs}, s)D_I(x, q_{it}, t)]^{\frac{1}{2}}$ and output $Q(q) = [D_O(x_{hs}, q, s)D_O(x_{it}, q, t)]^{\frac{1}{2}}$ is used to estimate TFP Hicks-Moorsteen index

(5) $TFPhs, it = [\ D_O(x_{hs}, q_{it}, s)D_I(x_{hs}, q_{hs}, s)D_O(x_{it}, q_{it}, t)D_I(x_{hs}, q_{it}, t)/$

$D_O(x_{hs}, q_{hs}, s)D_I(x_{it}, q_{hs}, s)D_O(x_{it}, q_{hs}, t)D_I(x_{it}, q_{it}, t)]^{\frac{1}{2}}$ [10]

In our estimation we have only two input factors, labor and capital, and one output factor. This simplifies input aggregator function $(x) = [D_I(x, q_s)D_I(x, q_t)]^{\frac{1}{2}}$ .

The estimation of production function is done over DEA linear programming. DEA is based on assumption that input and output distance functions representing the technology available in period t have following form:

*(6)* $D_O\ (x_{it}, q_{it}, t) = (q_{it}'\alpha)/(\gamma + x_{it}'\beta)$
*(7)* $D_I\ (x_{it}, q_{it}, t) = (x_{it}'\eta)/(q_{it}'\phi - \delta)$

The solution is in selecting parameters α,β,δ,φ,η, in order to minimize

min $OTE_{it}^{-1} = D_O\ (x_{it}, q_{it}, t)^{-1}$ and maximize max $ITE_{it}\ = D_I\ (x_{it}, q_{it}, t)^{-1}$.

The output distance function measures the inverse of the largest radial expansion of the output vector that is possible while holding the input vector fixed and input distance function measures the largest radial contraction of the input vector technically feasible while holding the output vector fixed.

$$\text{LP: min } OTE_{it}^{-1} = D_O\ (x_{it}, q_{it}, t)^{-1}$$
$$= \min_{\alpha,\gamma,\beta}\{\gamma + x_{it}'\beta: \gamma I + X'\beta \geq Q'\alpha; q_{it}'\alpha = 1; \alpha \geq 0; \beta \geq 0\}$$

[10] The Hicks-Moorsteen index is detailed in Diewert (1992) and Bjurek (1996)

$$(8)\ LP\text{:}\max ITE_{it} = D_I\,(x_{it}, q_{it}, t)^{-1} = \max_{\phi,\delta,\eta}\{q'_{it}\phi - \delta : Q'\phi \le \delta I + X'\beta; x'_{it}\eta = 1; \phi \ge 0; \eta \ge 0\}$$

This assume variable return of scale for production function (VRS); or by imposing δ=$\gamma$=0, CRS (constant return to scale) constraint can be included. Further, $q'_{it}\alpha = 1$ and $x'_{it}\eta = 1$ are constraints for assuring single solution (O'Donnell, 2011). Output matrix Q (JxM) and input matrix X (KxM) and unit vector l ($M_t$) are used for estimation of production frontier for time t over unit of measurements – in our case firms level data averaged for estimation purposes based on weighted mean per sectors and provinces and ownership. Once the production function has been estimated Hicks-Moorsteen estimates are obtained by taking the geometric average of the Malmquist-hs and Malmquist-it estimates.