CO_2 emissions reduction of Chinese light manufacturing industries: A novel RAM-based global Malmquist–Luenberger productivity index

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Abstract

Climate change has become one of the most challenging issues facing the world. Chinese government has realized the importance of energy conservation and prevention of the climate changes for sustainable development of China's economy and set targets for CO_2 emissions reduction in China. In China industry contributes 84.2% of the total CO_2 emissions, especially manufacturing industries. Data envelopment analysis (DEA) and Malmquist productivity (MP) index are the widely used mathematical techniques to address the relative efficiency and productivity of a group of homogenous decision making units, *e.g.* industries or countries. However, in many real applications, especially those related to energy efficiency, there are often undesirable outputs, *e.g.* the pollutions, waste and CO_2 emissions, which are produced inevitably with desirable outputs in the production. This paper introduces a novel Malmquist–Luenberger productivity (MLP) index based on directional distance function (DDF) to address the issue of productivity evolution of DMUs in the presence of undesirable outputs. The new RAM (Range-adjusted measure)-based

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global MLP index has been applied to evaluate CO_2 emissions reduction in Chinese light manufacturing industries. Recommendations for policy makers have been discussed.

Keywords. Data envelopment analysis (DEA), range-adjusted measure (RAM), directional distance function (DDF), energy efficiency

1. Introduction

Since the implementation of reform and open policy in 1978 in China, significant progress has been achieved in terms of economic and social developments. The statistical data from China Statistical Yearbook 2010 illustrates that China's nominal industrial gross domestic product (GDP) increased by 66.02 times between 1981 and 2009 (204.84 vs. 13523.99 billion RMB Yuan). However, the rapid economic growth of industries in China has also resulted in high energy consumption and serious environmental problems, *e.g.* huge amount of CO_2 emissions and industrial solid waste, which hindering the sustainability of China's economic growth. BP (2011) argued that China's total energy consumption was only half of the United States' about ten years ago but overtook the United States to become the world's largest energy user in 2010.The amount of industrial solid waste produced in 2009 (2.04 billion tons) was 5.42 times that of 1981 (Bian *et al.* 2015).China Statistics show that the annual average growth rate of GDP in China was 10.2%, while the industry expanded by 11.9% on annual average in the period of 1981–2011, and the share of industrial added value exceeded 40% of GDP in the past three decades, and the industry contributes 84.2% of the total CO_2 emissions in China (Chen 2011). Wang *et al.* (2013b) also noted that China has already surpassed the USA and become the world's largest energy consumer and contributor of CO_2 emissions since 2007.

Think tanks such as the World Pensions Council (WPC) have argued that the keys to success lie in convincing U.S. and Chinese policy makers: "*as long as policy makers in Washington and Beijing didn't put all their political capital behind the adoption of ambitious carbon-emission capping targets, the laudable efforts of other G20 governments often remained in the realm of pious wishes.*"(Nicolas and Firzli 2015). Chinese government has also realized the importance of energy conservation and prevention of the climate changes for sustainable development of China's economy. To tackle the global climate change actively, Chinese central government announces 12th five-year plan intended to establish a "green, low-carbon development concept", which states that in 2015 China will increase the proportion of non-fossil fuels in energy generation to 11.4%, reduce energy consumption per unit of GDP by 16%, as well as reduce CO_2 emissions per unit of GDP by 17% from the levels in 2010, especially in Chinese manufacturing industries, as the industrial sector contributes most of carbon emissions in China. Furthermore, Chinese State Council released officially the "National Climate Change Plan (2014-2020)" in the September 2014and announced China's CO_2 emissions to gross domestic product in 2020 would be reduced by 40% to 45% on the basis of 2005.

There has been a lot of literatures on this issue, *e.g.* Chinese provinces' environmental productivity (Nakano and Managi 2008), total-factor carbon emission performance of the Chinese transportation industry (Zhang *et al.* 2015), regional environmental efficiencies (Yang *et al.* 2015), industrial total factor CO_2 emission performance (Fan *et al.* 2015). See literature review in the next Section 2. This paper aims to address the CO_2 emission reduction issue in Chinese manufacturing industries. Different from other existing literatures on this topic, this paper proposes a new RAM (Range adjusted model)-based Malmquist–Luenberger productivity (MLP) index and extends it to global one to avoid the infeasibility problem which may occurs when DMUs located beyond the efficiency frontier due to the mixed period models in the process of calculating MLP index. Moreover in the meantime the global MLP index based on RAM model can avoid the slacks problem and inconsistency problem.

The rest of the paper is organized as follows: Section 2 reviewed the related literatures. Section 3 describes the existing RAM model and extends it to incorporate undesirable factors. Section 4 focuses on the RAM-based global MLP index. Section 5 provides an empirical study on the productivity evolution of Chinese light manufacturing industries. Section 6 concludes this paper.

2 Literature review

Climate change has become one of the most challenging issues facing the world. Zhang *et al.* (2015) estimated the total-factor carbon emission performance of the Chinese transportation industry. Watanabe and Tanaka (2007) conducted the efficiency analysis of Chinese industry based on a directional distance function approach. Yang *et al.* (2015) investigated the regional environmental efficiencies in

China. Wang *et al.* (2015) studied environmental protection mechanisms and economic development of 211 cities in China. Fan *et al.* (2015) estimated the industrial total factor CO_2 emission performance of industrial sub-sectors of Shanghai city in China. Nakano and Managi (2008) investigated the environmental productivity of Chinese provinces. Bian *et al.* (2015) measured Chinese regional industrial systems efficiency using two-stage DEA model. An *et al.* (2015) conducted the environmental efficiency evaluation of thermal power enterprises. Zhou *et al.* (2014) investigated the energy efficiency performance of China's transport sector. Bi *et al.* (2014a) studied how the environmental regulations affect energy efficiency in China's thermal power generation. Besides China, more and more countries are concerned with reducing energy consumption and CO_2 emissions while increasing the efficiency and productivity of the industrial sectors. Molinos-Senante *et al.* (2014) integrated environmental impacts in the assessment of the efficiency of estimating pure and mixed environmental performance indices on 60 Spanish wastewater treatment plants. Sueyoshi and Goto (2014a) compared Photovoltaic power stations between Germany and the United States to examine which country provides renewable energy in their usages more efficiently. Sueyoshi and Goto (2014b) discussed how to measure operational and environmental efficiency by considering energy utilization and environmental protection. Vlontzos *et al.* (2014) evaluated the energy and environmental efficiency of the primary sectors of the EU member state countries. Khodakarami *et al.* (2014) proposed a gradual efficiency improvement model to measure sustainability of the community of manufacturing and service businesses.

Arabi *et al.* (2015) investigated the productivity evolution of 18 steam power plants in Iran using a new slacks-based MLP (S-MLP) index.

Most of the above literatures used data envelopment analysis (DEA) as the quantitative tool to measure the performance or efficiencies of decision-making units (DMUs). DEA is one of the widely used mathematical techniques to measure the relative efficiencies of a group of homogenous DMUs (Cook and Seiford 2009). Among DEA related studies, the Malmquist productivity (MP) index is an important concept which was first introduced by Malmquist (1953) and has further been studied and developed in the non-parametric framework by several authors (*e.g.* Caves *et al.* 1982, Färe and Grosskopf 1992, Thrall 2000). Lall *et al.* (2002) pointed out productivity has been widely recognized as an indirect measure of economic prosperity, standard of living and the competitiveness of an economy. It is an index which represents Total Factor Productivity (TFP) growth of a DMU, in that it reflects (a) progress or regress in efficiency along with (b) progress or regress of the frontier technology between two periods of time under the multiple inputs and multiple outputs framework (Cooper *et al.* 2007).

In real practices there are often undesirable outputs, e.g., the pollutions, waste and CO_2 emissions, which are produced inevitably with desirable outputs in the production. In order to recognize the undesirable outputs the MLP index based on directional distance function (DDF) was originally developed by Chambers *et al.* (1996) and applied by Chung *et al.* (1997) in environmental studies, which has been widely used to measure the productivity of DMUs with undesirable outputs, *e.g.*

manufacturing industries (Färe *et al.* 2001), power plants (Arabi *et al.* 2014), Iron and steel enterprises (He *et al.* 2013), the public sector (Yu *et al.* 2008) and countries (Yörük and Zaim 2005, Kumar 2006).

In this period, the DDF formulations has been extended from radial measure to non-radial measure, *e.g.* the weighted non-radial DDF (Zhou *et al.* 2012), slacks-based measure (Arabi *et al.* 2014, 2015), the enhanced Russell measure (An *et al.* 2015). Subsequently the MLP index has also been extended much from its original form. Arabi *et al.* (2015) proposed a S-MLP index and they pointed out that S-MLP index may encounter infeasibility problem in the presence of undesirable outputs and when DDF is employed to measure MLP index and proposed a possible approach to avoid this problem. Following the weighted non-radial directional distance function proposed in Zhou *et al.* (2012), Zhang *et al.* (2015) proposed a non-radial Malmquist CO_2 emission performance index for measuring dynamic changes in total-factor CO_2 emission performance over time. Ramli and Munisamy (2015) employed the RAM model incorporating undesirable output to measure the efficiency of Malaysian manufacturing industry with CO_2 emissions.

The above works enable the consideration of non-radial slacks. However Tone (2001) argued that four properties should be considered as important when designing measures, including Unit invariance, Monotone, Translation invariance and Reference-set dependent. Cooper *et al.* (1999) also proposed four mathematical properties to satisfy when they designed their inefficiency measure. Based on these properties, we think that for the S-MLP index in Arabi *et al.* (2015): (1) it neglects the input slacks, (2) the objective function of their DDF is not the traditional sense of relative distance and its range may be beyond the [0,1], (3) the target(s) on the frontier of evaluated DMU may not be the closest one(s). Zhang *et al.* (2015)'s index selects weights of slacks arbitrarily and the range of the objective function may be beyond the [0,1]. Furthermore their index may also encounter infeasibility problem. Furthermore Aparicio *et al.* (2013) found inconsistency problem in MPL index besides the commonly known infeasibility problem and slacks problem.

Chung *et al.* (1997) introduced the MLP index as a measure of productivity change in the context of a production technology incorporating undesirable outputs production based on the DDF proposed by Chambers *et al.* (1996). Subsequently MLP index has been widely applied in previous researches. For example, Färe *et al.* (2001) employed MLP index to account for both marketed output and the output of pollution abatement activities of U.S. state manufacturing sectors for 1974–1986. Kumar (2006) examined conventional and environmentally sensitive TFP in 41 developed and developing countries over the period of 1971 to 1992. Zhang *et al.* (2011) evaluated China's growth in total factor productivity with undesirable outputs during the period from 1989 to 2008. He *et al.* (2013) measured the energy efficiency and productivity change of China's iron and steel industry over the period 2001–2008. Arabi *et al.* (2014) used S-MLP index to measure the efficiency, eco-efficiency, and technological changes of the power plants over the 8-year period in Iran. However several weakness of MLP index in its original form has also been found in the application process. Aparicio *et al.* (2013) summarized these main weaknesses, including (1) infeasibility problem may occur when the estimation of the shift in technology between two periods of time is based on the distance from the period t observation to the period s technology, (2) slacks may be neglected when using DEA model based on DDF, and (3) inconsistency is implied in the set of postulates traditionally assumed in the joint production of desirable and undesirable outputs. Subsequently they proposed a redefinition of the assumption set to solve the inconsistency problem.

(1) Infeasibility problem. Pastor and Lovell (2005) introduced the concept of a global MPI index, which uses a base period technology to estimate and decompose productivity change. Following this line of research, Oh (2010) adapted the same idea to the MLP index, incorporating the negative effect of environmentally harmful by-products. Arabi *et al.* (2015) showed the shortcoming of the approach proposed by Aparicio *et al.* (2013) to tackle the infeasible problem based on a new direction function using slacks-based measurement.

(2) Slacks problem. Grifell-Tatje *et al.* (1998) proposed a new non-radial efficiency measure which incorporates all slacks on the selected side and a quasi-MP index. Chen (2003) extended the MPI into a non-radial index where the decision maker's preference over performance improvement can be incorporated. It should be noted that their approaches is also applicable in MLP index. Arabi *et al.* (2015) proposed a slack based MLP index which used the sum of slacks of desirable and undesirable outputs as the objective function of their models. Zhang *et al.* (2015) proposed a non-radial Malmquist CO_2 emission performance index on the weighted non-radial DDF, which selects weights of slacks arbitrarily and the range of the objective function may be beyond the [0,1]. Dharmapala (2010) demonstrated with an application to banking that MPI loses its meaning whenever slacks are present and proposed intrinsic assurance regions to be appended to the DEA models to neutralise the effect of slacks.

(3) Inconsistency problem. Aparicio *et al.* (2013) argued that while the MLP index may signal a decline in the environmental productivity, the opposite may actually be occurring. This erroneous result represents a serious drawback and casts important doubts on the correctness and robustness of the results obtained by MLP index. Therefore they proposed a solution to the inconsistency issue based on assuming a new postulate for the technology when good and bad outputs are produced that avoids the problems with the interpretability of the MLP index.

The above three main problems encountered in MLP index reduce the use of this index as an empirical tool for productivity measurement in presence of undesirable outputs.

3. RAM model

In this section we first restate the RAM model and then we incorporate undesirable factors into this model. Let us consider $X = (x_1, x_2, \dots, x_m) \in \mathbb{R}^{+}_{m\times n}$ and $Y = (y_1, y_2, \dots, y_s) \in \mathbb{R}^{+}_{\mathrm{s}\times\mathrm{n}}$ be input and output vectors of m and s dimension respectively. Assume that there are n DMUs $(\mathrm{j} = 1, \dots, \mathrm{n}$ DMUj) over T time periods $(\mathrm{t} = 1, \dots, \mathrm{T})$, then the Production Possibility Set (PPS) in period is defined by

$$PPS^t = \{(X^t, Y^t) | X^t \; can \; produce \; Y^t\}, \; t = 1, \dots, T. \tag{1}$$

3.1 RAM model proposed by Cooper *et al.* (1999)

In order to avoid the shortcomings in measures, such as commonly used radial measures, which fail to reflect inefficiencies (such as non-zero slacks), Cooper *et al.* (1999) proposed the RAM model (BCC-type) in period t as follows:

$$min\,\theta = 1 - (R_X^{tT} d_X^t + R_Y^{tT} d_Y^t)$$

$$s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j X_j^t + d_X^t = X_0^t \\ \sum_{j=1}^{n} \lambda_j Y_j^t - d_Y^t = Y_0^t \\ \sum_{j=1}^{n} \lambda_j = 1\,, d_X^t, d_Y^t, \lambda_j \geq 0 \end{cases} \tag{2}$$

where $R_X^{tT} = (R_X^{1t}, R_X^{2t}, \dots, R_X^{mt})^T$ and $R_Y^{tT} = (R_Y^{1t}, R_Y^{2t}, \dots, R_Y^{st})^T$ and

$$R_X^{it} = (m+s)^{-1}\left(max\{x_{ij}^t | j = 1, \dots, n\} - min\{x_{ij}^t | j = 1, \dots, n\}\right)^{-1}, i = 1,2, \dots m \tag{3}$$

$$R_Y^{rt} = (m+s)^{-1}\left(max\{y_{rj}^t | j = 1, \dots, n\} - min\{y_{rj}^t | j = 1, \dots, n\}\right)^{-1}, r = 1,2, \dots, s \tag{4}$$

Cooper *et al.* (1999) showed that RAM measure θ satisfied the following mathematical properties:

(P1) $0 \leq \theta \leq 1$

(P2) $\theta = \begin{cases} 1 \Leftrightarrow DMU_0 \; is \; fully \; efficient \\ 0 \Leftrightarrow DMU_0 \; is \; fully \; inefficient \end{cases}$

(P3) θ is invariant to

$$\begin{cases} alternative \; optima \\ alternative \; units \; in \; which \; inputs \; or \; outputs \; might \; be \; measured \end{cases}$$

(P4) θ is strongly monotonic.

3.2 RAM model with undesirable outputs

Sueyoshi *et al.* (2010) extended the basic RAM model with the incorporation of undesirable outputs. This model measures the efficiency by maximizing the distance from the efficient frontier whereby outputs are maximized and inputs are minimized simultaneously. Tsang *et al.* (2014) proposed a RAM-based MP index to estimate dynamic productivity in the presence of negative data and undesirable outputs. In this subsection we restate the RAM model (BCC-type) incorporating undesirable factors. We further assume a vector of undesirable outputs denoted by the vector $B = (b_1, b_2, \dots, b_k) \in \mathbb{R}^{+}_{k\times n}$. There are also n DMUs ($j = 1, \dots, n$ DMUj) over T time periods ($t = 1, \dots, T$). Thus we need to expand the definition on PPS in formula (1) as follows:

$$PPS_D^t = \{(X^t, Y^t, B^t) | X^t \; can \; produce \; (Y^t, B^t)\}. \tag{5}$$

This technology gives a description of all technologically feasible relationships between inputs and outputs. Färe *et al.* (2007) pointed out that there are six axioms are required to model the production technology: (a) Finite amounts of inputs can only produce finite amounts of outputs; (b) Inactivity is always possible; (c) The strong disposability of inputs is assumed; (d) Any proportional contraction of desirable and undesirable outputs together is feasible if the original combination of them is in the PPS; (e) The strong disposability of desirable outputs is assumed, and (f) Null-jointness condition is assumed.

Based on the above technology, we can have the following RAM model (BCC-type) with undesirable outputs:

$$min \, \theta = 1 - (R_X^{tT} d_X^t + R_Y^{tT} d_Y^t + R_B^{tT} d_B^t)$$

$$
s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j X_j^t + d_X^t = X_0^t \\ \sum_{j=1}^{n} \lambda_j Y_j^t - d_Y^t = Y_0^t \\ \sum_{j=1}^{n} \lambda_j B_j^t + d_B^t = B_0^t \\ \sum_{j=1}^{n} \lambda_j = 1, d_X^t, d_Y^t, d_B^t, \lambda_j \geq 0 \end{cases} \tag{6}
$$

where d_X^t, d_Y^t, d_B^t are slack vectors of inputs, desirable outputs, and undesirable outputs, respectively. Symbols $R_X^{tT} = (R_X^{1t}, R_X^{2t}, \dots, R_X^{mt})^T$, $R_Y^{tT} = (R_Y^{1t}, R_Y^{2t}, \dots, R_Y^{st})^T$ and $R_B^{tT} = \left(R_B^{1t}, R_B^{2t}, \dots, R_B^{kt}\right)^T$ are standardization factors, and

$$
R_X^{it} = (m+s+k)^{-1}\left(max\{x_{ij}^t | j = 1, \dots, n\} - min\{x_{ij}^t | j = 1, \dots, n\}\right)^{-1}, i = 1,2, \dots m, \tag{7}
$$

$$
R_Y^{rt} = (m+s+k)^{-1}\left(max\{y_{rj}^t | j = 1, \dots, n\} - min\{y_{rj}^t | j = 1, \dots, n\}\right)^{-1}, r = 1,2, \dots, s, \tag{8}
$$

$$
R_B^{qt} = (m+s+k)^{-1}\left(max\{b_{qj}^t | j = 1, \dots, n\} - min\{b_{qj}^t | j = 1, \dots, n\}\right)^{-1}, q = 1,2, \dots, k. \tag{9}
$$

In model (5) we can see that there are an extra constraint $\sum_{j=1}^{n} \lambda_j B_j^t + d_B^t = B_0^t$ to address the undesirable outputs. Furthermore the objective function of model (6) is the sum of range adjusted slacks for inputs, desirable outputs and undesirable outputs. We can also easily verify that RAM measure with undesirable factors satisfy the mathematical properties (P1)-(P4).

Based on model (6) we can easily have CCR-type RAM model with undesirable outputs as follows:

$$
\begin{gathered} min\, \theta = 1 - (R_X^{tT} d_X^t + R_Y^{tT} d_Y^t + R_B^{tT} d_B^t) \\ s.t.\begin{cases} \sum_{j=1}^{n} \lambda_j X_j^t + d_X^t = X_0^t \\ \sum_{j=1}^{n} \lambda_j Y_j^t - d_Y^t = Y_0^t \\ \sum_{j=1}^{n} \lambda_j B_j^t + d_B^t = B_0^t \\ d_X^t, d_Y^t, d_B^t, \lambda_j \geq 0 \end{cases} \end{gathered} \tag{10}
$$

4. A RAM-based global MLP index

4.1 MLP index and global MLP index

MP index was first introduced by Malmquist (1953) and has further been studied and developed in the non-parametric framework by several authors (*e.g.* Färe and Grosskopf 1992, Thrall 2000). Lall *et al.* (2002) argued that productivity has been widely recognized as an indirect measure of economic prosperity, standard of living and the competitiveness of an economy. Cooper *et al.* (2007) pointed out that MPI is an index which represents Total Factor Productivity (TFP) growth of a DMU, in that it reflects (a) progress or regress in efficiency along with (b) progress or regress of the frontier technology between two periods of time under the multiple inputs and multiple outputs framework. The productivity index is based on the benchmark technology.

As international concerns increase about the sustainable growth, there are more and more attempts to develop measures of productivity growth incorporating the undesirable or harmful by-products in the process of producing desirable products. Chung *et al.* (1997) modified the MP index and integrated the concepts of the MP index and DDF to measure environmentally sensitive productivity growth which was named the MLP index. Subsequently MLP index was used widely to measure the performance of a wide range of DMUs, *e.g.* Iran power industries (Arabi *et al.* 2015), Environmental productivity of Chinese provinces (Nakano and Managi 2008), Productivity growth in OECD countries (Yörük and Zaim 2005). However conventional MLP index may encounter the infeasibility problem in measuring cross-period DDFs and is not circular in its geometric mean form. In order to resolve these problems, Oh (2010) proposed the global MLP index which is circular and free of infeasibility problem by employing concepts of the global MP index of Pastor and

Lovell (2005). This suggested index is employed in analyzing 26 OECD countries for the period 1990-2003. Tohidi *et al.* (2012) proposed is a global cost MP index based on the cost MP index defined by Maniadakis and Thanassoulis (2004). This global cost index is circular and free of infeasibility when the production technology exhibit variable returns to scale (VRS).

First we define global PPS as $PPS_D^G = conv\{PPS_D^1, PPS_D^2, \dots, PPS_D^T\}$, where $conv\{*\}$ denotes the convex hull. Thus a global MLP index (output-oriented) is defined on PPS_D^G as

$$MLP^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1}) = \frac{1+\vec{D}_{DDF}^G(X^t, Y^t, B^t, g_Y, g_B)}{1+\vec{D}_{DDF}^G(X^{t+1}, Y^{t+1}, B^{t+1}, g_Y, g_B)} \tag{11}$$

where $\vec{D}_{DDF}^G(X^p, Y^p, B^p, g_Y, g_B) = max\{\beta: (X^p, Y^p + \beta g_Y, B^p - \beta g_B) \in PPS_D^G\}, p = t, t+1$. If we further assume the direction vector $(g_Y, g_B) = (Y^p, B^p)$ and constant returns to scale (CRS) on the technology PPS_D^G, thus we have

$$\vec{D}_{DDF,c}^G(X^p, Y^p, B^p, g_Y, g_B) = max\,\beta$$
$$s.t.\begin{cases} \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} X_j^t \le X^p \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} Y_j^t \ge (1+\beta) Y^p \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} B_j^t = (1-\beta) B^p \\ \lambda_{jt} \ge 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{12}$$

and under VRS technology:

$$\vec{D}_{DDF,v}^G(X^p, Y^p, B^p, g_Y, g_B) = max\,\beta$$
$$s.t.\begin{cases} \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} X_j^t \le X^p \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} Y_j^t \ge (1+\beta) Y^p \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} B_j^t = (1-\beta) B^p \\ \sum_{t=1}^T \sum_{j=1}^n \lambda_{jt} = 1 \\ \lambda_{jt} \ge 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{13}$$

4.2 A RAM-based global MLP index

In model (12) or model (13) we can see that there may be some missing slacks in the inequalities $\sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t \leq X^p$ and $\sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t \geq (1+\beta)Y^p$. Therefore in this paper we attempt to formulate a RAM-based global MLP index using RAM measure to reflect DDFs of DMUs. We define the global RAM-based MLP index (non-oriented) on PPS_D^G as

$$MLP^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1}) = \frac{\vec{D}_{DDF}^G(X^{t+1}, Y^{t+1}, B^{t+1})}{\vec{D}_{DDF}^G(X^t, Y^t, B^t)} \tag{14}$$

where $\vec{D}_{DDF}^G(X^p, Y^p, B^p) = min\{\theta = 1 - \left(R_X^{pT} d_X^p + R_Y^{pT} d_Y^p + R_B^{pT} d_B^p\right): \left(X^p - d_X^p, Y^p + d_Y^p, B^p - d_B^p\right) \in PPS_D^G\}, p = t, t+1.$

If we further assume CRS on the technology PPS_D^G, thus we have

$$\vec{D}_{DDF,c}^G(X^p, Y^p, B^p) = min\,\theta = 1 - \left(R_X^{pT} d_X^p + R_Y^{pT} d_Y^p + R_B^{pT} d_B^p\right)$$
$$s.t. \begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t + d_X^p = X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t - d_Y^p = Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t + d_B^p = B^p \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{15}$$

where $R_X^{pT} = \left(R_{X1}^p, R_{X2}^p, \dots, R_{Xm}^p\right)^T$, $R_Y^{pT} = \left(R_{Y1}^p, R_{Y2}^p, \dots, R_{Ys}^p\right)^T$ and $R_B^{pT} = \left(R_{B1}^p, R_{B2}^p, \dots, R_{Bk}^p\right)^T$, and

$R_X^{pT} = (m+s+k)^{-1}\left(max\left\{x_{ij}^p | j = 1, \dots, n\right\} - min\left\{x_{ij}^p | j = 1, \dots, n\right\}\right)^{-1}, i = 1,2, \dots m,$ (16)
$R_Y^{pT} = (m+s+k)^{-1}\left(max\left\{y_{rj}^p | j = 1, \dots, n\right\} - min\left\{y_{rj}^p | j = 1, \dots, n\right\}\right)^{-1}, r = 1,2, \dots, s,$
(17) $R_B^{pT} = (m+s+k)^{-1}\left(max\left\{b_{qj}^p | j = 1, \dots, n\right\} - min\left\{b_{qj}^p | j = 1, \dots, n\right\}\right)^{-1}, q = 1,2, \dots, k,$(18)

$p = t, t+1,$ and under VRS technology:

$$\vec{D}_{DDF,v}^{G}(X^p,Y^p,B^p)=min\,\theta=1-\left(R_X^{pT}d_X^p+R_Y^{pT}d_Y^p+R_B^{pT}d_B^p\right)$$
$$s.t.\begin{cases}\sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t+d_X^p=X^p\\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t-d_Y^p=Y^p\\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t+d_B^p=B^p\\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}=1\\ \lambda_{jt}\geq 0, j=1,\dots,n; t=1,\dots,T\end{cases}\tag{19}$$

The global RAM-based MLP index can be decomposed into components of productivity growth under CRS and VRS assumptions, respectively, as follows:

Under CRS assumption:

$$MLP_c^G(X^t,Y^t,B^t,X^{t+1},Y^{t+1},B^{t+1})=\frac{\vec{D}_{DDF,c}^{G}(X^{t+1},Y^{t+1},B^{t+1})}{\vec{D}_{DDF,c}^{G}(X^t,Y^t,B^t)}=\frac{\vec{D}_{DDF,c}^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{\vec{D}_{DDF,c}^{t}(X^t,Y^t,B^t)}\times \left[\frac{\vec{D}_{DDF,c}^{G}(X^{t+1},Y^{t+1},B^{t+1})/\vec{D}_{DDF,c}^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{\vec{D}_{DDF,c}^{G}(X^t,Y^t,B^t)/\vec{D}_{DDF,c}^{t}(X^t,Y^t,B^t)}\right]=\frac{TE^{t+1}}{TE^t}\times\left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}\right]=EC^{t,t+1}\times BPC^{t,t+1}$$

(20)

where TE^t and $EC^{t,t+1}$ denote the technical efficiency (TE) in period t and the efficiency change (EC) in period t to $t+1$. Variable $BPG_t^{t,t+1}$ denotes the best practice gap between traditional technology frontier and global technology frontier. Thus $BPC^{t,t+1}$ denotes the best practice gap change, which measures technical change between two time period t and $t+1$.

Under VRS assumption:

$$MLP_v^G(X^t,Y^t,B^t,X^{t+1},Y^{t+1},B^{t+1})=\frac{\vec{D}_{DDF,v}^{G}(X^{t+1},Y^{t+1},B^{t+1})}{\vec{D}_{DDF,v}^{G}(X^t,Y^t,B^t)}\times\left(\frac{SE^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{SE^t(X^t,Y^t,B^t)}\right)= \frac{\vec{D}_{DDF,v}^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{\vec{D}_{DDF,v}^{t}(X^t,Y^t,B^t)}\times\left[\frac{\vec{D}_{DDF,v}^{G}(X^{t+1},Y^{t+1},B^{t+1})/\vec{D}_{DDF,v}^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{\vec{D}_{DDF,v}^{G}(X^t,Y^t,B^t)/\vec{D}_{DDF,v}^{t}(X^t,Y^t,B^t)}\right]\times \left(\frac{SE^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{SE^t(X^t,Y^t,B^t)}\right)=\frac{PTE^{t+1}}{PTE^t}\times\left[\frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}}\right]\times\left(\frac{SE^{t+1}(X^{t+1},Y^{t+1},B^{t+1})}{SE^t(X^t,Y^t,B^t)}\right)=PEC^{t,t+1}\times BPC^{t,t+1}\times SCH^{t,t+1}\tag{21}$$

where PTE^t and $PEC^{t,t+1}$ denote the pure technical efficiency (PTE) in period t

and the pure efficiency change (PEC) in period t to $t+1$. Variable $BPG_t^{t,t+1}$ denotes the best practice gap between traditional technology frontier and global technology frontier. Thus variable $BPC^{t,t+1}$ denotes the best practice gap change, which measures technical change between two time period t and $t+1$. Variable SE^t means the scale efficiency on global benchmark in period t and

$$SE^t(X^t, Y^t) = \vec{D}_{DDF,c}^G(X^t, Y^t, B^t) / \vec{D}_{DDF,v}^G(X^t, Y^t, B^t) \tag{22}$$

Variable $SCH^{t,t+1}$ is the ratios of scale efficiencies of the two bundles from the two periods as the global benchmarks under the VRS assumption.

It is easy to verify that the $MLP_c^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1})$ or $MLP_v^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1})$ is circular. We take $MLP_c^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1})$ as an example. $MLP_c^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1}) \times MLP_c^G(X^{t+1}, Y^{t+1}, B^{t+1}, X^{t+2}, Y^{t+2}, B^{t+2}) = \frac{\vec{D}_{DDF,c}^G(X^{t+1}, Y^{t+1}, B^{t+1})}{\vec{D}_{DDF,c}^G(X^t, Y^t, B^t)} \times \frac{\vec{D}_{DDF,c}^G(X^{t+2}, Y^{t+2}, B^{t+2})}{\vec{D}_{DDF,c}^G(X^{t+1}, Y^{t+1}, B^{t+1})} = \frac{\vec{D}_{DDF,c}^G(X^{t+2}, Y^{t+2}, B^{t+2})}{\vec{D}_{DDF,c}^G(X^t, Y^t, B^t)} = MLP_c^G(X^t, Y^t, B^t, X^{t+2}, Y^{t+2}, B^{t+2})$.

Similarly we can verify its components in formula (20) are also circular. We can further verify $MLP_v^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1})$ and its decomposed components in formula (21) are also circular.

The global RAM-based MLP index can be roughly illustrated through the following Figure 1[1]. In Figure 1 PPS_D^t and PPS_D^{t+1} denote the traditional PPS of period t and $t+1$.

[Figure 1 about here]

[1]We only illustrate the desirable and undesirable outputs in this figure.

We can see that the $MLP^G(X^t, Y^t, B^t, X^{t+1}, Y^{t+1}, B^{t+1})$ for DMU A_1 could be represented as $\frac{A_2D_2}{A_1D_1} = \frac{A_2B_2}{A_1B_1} \times \frac{A_2D_2/A_2B_2}{A_1D_1/A_1B_1}$. It should be noted that we assume the CRS technology in this Figure. If we assume VRS technology, there should be a factor $SCH^{t,t+1}$ which reflects the changes of scale efficiencies in different periods, which cannot be illustrated in this figure directly.

The RAM-based global MLP index can be easily extended to conduct variable specific analysis. See Appendix A for the extensions of this index.

5. CO_2 emissions in Chinese light manufacturing industries

5.1. Dataset and indicators

In this study we selected the two-digit light manufacturing industries in China as the DMUs[2]. Light industry refers to the section of an economy's industry characterized by less capital-intensive and more labor-intensive operations. Products made by an economy's light industry tend to be targeted toward end consumers rather than other businesses. In this study we use the data of Chinese manufacturing industries from 2004 to 2012, which is derived from China Statistical Year Book 2005-2013, China Industry Statistical Year Book 2013, and China Energy Statistical Year Book 2005-2013. In the period of 2004-2012, there are some changes on the statistical coverage of industries in China. Before 2007, the industry statistics cover all state owned and non-stated owned above designated size (which is 5 million Yuan of annual revenue from primary business). From 2007 to 2010, the industry statistics

[2]Note: The classification of light and heavy industries in Chinese manufacturing industries is based on the information from National Bureau of Statistics of P.R.China (http://www.sc.stats.gov.cn/tjzs/cswd/201504/t20150401_181042.html).

cover all industries above designated size (5 million Yuan). From 2011 on, the standard starting point of industrial enterprises above designated size was adjusted to 20 million Yuan of annual revenue from primary business.

From 2012, National Bureau of Statistics of China (NBS) enforces new standard on Industrial Classification for National Economic Activities (GB/T4754-2011). The number of two-digit light manufacturing industries changed from 18 to 17. The Manufacture of Rubber and the Manufacture of Plastics merged into Manufacture of Rubber and Plastics Products. Thus we merged the data of those two manufacturing industries at 2011 and before as one DMU and use 17 two-digit light manufacturing industries in China as the DMUs in this study. See Table B-1 for details in the Appendix B.

The following Table 1 shows the summary of input and output indicators used in previous studies on Chinese environmental efficiency in recent three years. From this table we can see that labour, capital and energy consumption are the most frequently used input indicators and Gross Domestic Products (GDP) and CO_2 emission are the most frequently used desirable and undesirable outputs respectively. In this paper we use the Gross Industrial Output Value (GIOV) instead of GDP because this paper aims to investigate the productivity evolution of 17 two-digit light Chinese manufacturing industries.

[Table 1 about here]

We select three input variables including Labour, Asset and Energy and two output variables, including GIOV as a desirable output and CO_2 emissions as an undesirable output.

(1) Labour: Labour input refers to the amount of Labour in Chinese manufacturing industries. Because of the mobility of Labour, the amount of Labour input is different at different time in one year, so the number of annual average employed persons is taken as the indicator. This indicator is from China Statistical Year Books 2005-2012directly. In China Statistical Year Book 2013 the data of Labour indicator is not reported, which is the latest Statistical Year Book published at the time we writing this paper. Therefore we use the average ratio of GIOV to Labour of all the provinces in China to estimate this indicator for the last year in this study by sub-level manufacturing industries respectively under the assumption that the technology level of the whole country is the average of all provinces.

(2) Asset: Asset refers to the amount of total assets in Chinese manufacturing industries. Total Assets input is from China Statistical Year Books and refers to all resources that are owned or controlled by enterprises through previous trades or transactions with expectation of making economic profits. Classified by the degree of liquidity, total assets include current assets, and non-current assets. Current assets can be classified into monetary assets, trading financial assets, notes receivable, accounts receivable, advanced payments, other prepaid money and inventories. Non-current assets can be divided into long-term equity investment, fixed assets, intangible assets and other non-current assets. Data on this indicator are obtained by the year-end figures of total assets in the Assets and Liability Table of accounting records of enterprises. In order to ensure the comparability, we transformed the value of this indicator to constant price in 2010 using the Consumer Price Index (CPI) of China, as shown in the following Table 2. The CPI data is derived from OECD (2010).

[Table 2 about here]

(3) Energy: We use Total Energy Consumption from China Statistical Year Book 2005-2012 as the indicator for Energy in our study. Total Energy Consumption refers to the total consumption of energy of various kinds by the production sectors in the country in a given period of time. It is a comprehensive indicator to show the scale, composition and pace of increase of energy consumption. Total energy consumption includes that of coal, crude oil and their products, natural gas and electricity. However, it does not include the consumption of fuel of low calorific value, bio-energy and solar energy. According to China Energy Statistical Yearbook 2013, the coefficients of transforming different types of transforming different types of energy into SCE are shown in the following Table 3.

[Table 3 about here]

(4) GIOV: The GIOV is used in our study as a desirable output and can be obtained from China Statistical Year Books 2005-2012. Note that this indicator is not reported in China Statistical Year Book 2013. However we can find the indicator Sales Ratio of Products (SRP) from China Statistical Year Book 2013 and use the indicator Industrial Sales Output Value (ISOV) from China Industry Statistical Year Book 2013 to calculate GIOV for each sub-level manufacturing industry using the formula $\mathrm{GIOV} = \mathrm{ISOV/SRP}$ for the year 2013. In order to ensure the comparability, we also transform the value of this indicator to constant price in 2010 using the CPI of China, as shown in Table 2.

(5) CO_2 emissions. CO_2 is the main by-product of industrial activities as the combustion of fossil fuels in the manufacturing process produces CO_2 (Oggioni *et al.* 2011, Benhelal *et al.* 2013). Thus the CO_2 emission is the undesirable output in our study. The data for this indicator is not provided directly in China Statistical Year Books or China Industry Statistical Year Books. Hence we estimated it based on the consumption of different types of energy. The main source of (net) global CO_2 emissions to the atmosphere is the use of fossil fuels (see, Green 2000). Thus the most widely used method for the estimation of CO_2 emissions is based on the consumption of fossil fuels including coal, crude Oil and natural gas. These three types of fossil fuels count for more than 85% CO_2 emission in China (Chen 2009). In our study, we also use the CO_2 emission from coal, crude oil and natural gas as the total CO_2 emissions of sub-level Chinese manufacturing industries.

Intergovernmental Panel on Climate Change (IPCC 2006) published IPCC Guidelines for National Greenhouse Gas Inventories, in which the equation for calculating CO_2 emissions from fossil fuels is provided as follows:

$$CO_2 = \sum_{i=1}^{3} CO_{2,i} = \sum_{i=1}^{3} E_i \times NCV_i \times CEF_i \times COF_i \times (44/12) \tag{23}$$

where $CO_{2,i} (i = 1,2,3)$ denote the CO_2 emissions of coal, crude oil and natural gas, respectively. Variables E_i, NCV_i, CEF_i, and COF_i denote the total consumption (E), net calorific value (NCV), Carbon Emission Factors (CEF), and carbon oxidation factor (COF) of these three types of energy. Constant values of 44 and 12 are the molecular weights of CO_2 and carbon respectively. Furthermore we need to transform different types of energy into SCE, whose coefficients are provided by China Energy Statistical Yearbook 2005-2013. According to the above formula and Chen (2009)'s research, we list the coefficients for CO_2 emissions estimation of Chinese manufacturing industries as follows:

[Table 4 about here]

5.2 Descriptive statistics

Table5 shows the means of five indicators in the period 2004-2012 of Chinese light manufacturing industries. We can see that all inputs and outputs except Labour increased significantly. From 2004 to 2012, the GIOV grew from 5352.3770 to 17361.0300 in the unit of 100 million RMB (Yuan). In the meantime the CO_2 emissions grew from 2815.0114 to 4563.7849 in the unit of 10 000 tons.

[Table 5 about here]

5.3 Results

In this paper we employ global MLP index based on RAM model under VRS assumption (model 21) to conduct analysis on 17 Chinese light manufacturing industries. As discussed in subsection 5.1, we separate our study periods into three clusters/stages: (1) 2004-2006, (2) 2007-2010, and (3) 2011-2012. We have the averages of global MLP index and its components of all Chinese manufacturing industries as shown in Table 6. We can also see the changes of averages of global MLP index and its components from Figure 2.

[Table 6 about here]

In the first stage (2004-2006), the global MLP index declined slightly from 1.0236 to 1.0043, which reflected the productivity of Chinese light manufacturing industries increased in this stage but the speed declined. The pure technical efficiency (PTE) change (PEC) declined from 1.0039 to 1.0014, which indicated the PTE of Chinese light manufacturing industries decreased slightly in this period. However the BPC increased significantly from BPC=1.0280 to 1.0363, which indicated the contemporaneous frontier shifted slightly towards the global technology frontier in the direction of more desirable outputs and less undesirable outputs. Also the scale efficiency change factor (SCH) decreased from SCH=0.9934 to SCH=0.9726 which indicated the scale economies of Chinese light manufacturing industries dropped slightly in the first period. From 2003, the Chinese economy has entered the expansion cycle and the investments on manufacturing industry increased year by year. However manufacturing industry encountered severe overcapacity issue due to the lack of consumption in term of the total retail sales of consumer goods. Thus the drop of scale economies of Chinese light manufacturing industries is natural.

In the second stage (2007-2010), the global MLP index increased slightly from 0.9948 to 1.0084. The PEC increased from 0.9831 to 1.0006, which indicated the PTE of Chinese light manufacturing industries increased slightly in this period. Also the

BPC increased slightly from BPC=1.0132 to BPC=1.0358, which indicated the contemporaneous frontier shifted slightly towards the global technology frontier in the direction of more desirable outputs and less undesirable outputs. Also the scale efficiency change factor (SCH) decreased from SCH=1.0016 to SCH=0.9819 which indicated the scale economies of Chinese light manufacturing industries dropped slightly in the second period. In 2008 Chinese government invested 4,000 billion RMB on the construction of basic infrastructure. However it exacerbated the industrial overcapacity issue in China. Therefore the scale economies of Chinese light manufacturing industries decreased continuously.

In the third stage (2011-2012), the global MLP index is 0.9931, which shows that the productivity of Chinese manufacturing industries went down in this period. The PTE change (PEC=0.9967) illustrated that the average technical efficiency also dropped. However the BPC is 1.0046 which means the contemporaneous frontier still shifted towards the global technology frontier in the direction of more desirable outputs and less undesirable outputs. Furthermore we can see SCH=0.9921 which indicated the scale economies of Chinese light manufacturing industries dropped slightly in the third period. See Figure 2 for details.

[Figure 2 about here]

In the end, we can see that contemporaneous frontier shifted continually towards the global technology frontier in the direction of more desirable outputs and less undesirable outputs in the period of 2004-2012, which indicates that Chinese light manufacturing industries paid much attention on the CO_2emissions reduction in the process of increasing GIOV. However the scale efficiency of Chinese light manufacturing industries dropped gradually, which means Chinese light manufacturing industries went away farther and farther from their optimal operation scale. Among these light manufacturing industries, the SCH of some industries, *e.g.* Manufacturing of Textile, Wearing Apparel and Accessories and Manufacturing of Raw Chemical Materials and Chemical Products, are the lowest relatively.

If we use traditional global MLP index based on model (13) which is associated with radial measure, we have the values of this traditional index and its components of Chinese 17 light manufacturing industries under VRS technology as follows:

[Table 7 about here]

It should be noted that there are some differences between Table 6 and Table 7 especially on the SCH factor. We can see that SCHs in three stages in Table 6 are all smaller than 1. On the contrary in Table 7 they are all larger than 1. According to the common sense in China, most people think that light manufacturing industries declined in this period. That means our RAM-based MLP index is more accurate than traditional radial-based MLP index so that we can have more accurate MLP index and its components to support the decision-making.

We also listed the global MLP index and its decompositions of each light manufacturing industry. Please see Table B-2 in the Appendix B. From this table, we can see that the detailed changes of global MLP indexes of those 17 Chinese light manufacturing industries. It is worth noting that, among these light manufacturing industries, the SCH of some industries, *e.g.* Manufacturing of Textile, Wearing Apparel and Accessories and Manufacturing of Raw Chemical Materials and Chemical Products, are the lowest relatively.

6 Conclusions and policy implications

This paper proposes a new RAM-based global MLP index which considers the slacks of inputs, desirable outputs and undesirable outputs all together. This new MLP index overcomes with three main weakness of the standard MLP including (1) infeasibility problem, (2) slacks neglect, and (3) inconsistency problem. We further analyzed the possibility of CO_2emissions reduction in Chinese light manufacturing industries. It is evident that the CO_2 emissions grew by about 60% during the analysis period (2004- 2012). In the three stages of the analysis we concluded that: during (2004-2006), the global MLP index declined slightly from 1.0236 to 1.0043, while in the second stage (2007-2010), the global MLP index increased slightly from 0.9948 to 1.0084. In the third stage (2011-2012), the global MLP index is 0.9931, which shows that the productivity of Chinese manufacturing industries went down in this period. Interestingly in all stages the contemporaneous frontier shifted towards the global technology frontier in the direction of more desirable outputs and less undesirable outputs, which indicates that Chinese light manufacturing industries paid much attention to the CO_2emissions reduction in the process of increasing GIOV. Those facts mean that Chinese government has made great efforts on improving the GIOV using limited resources and in the meantime reducing the CO_2 emissions in the process of production. Researchers interested can apply this new index to other manufacturing in China or elsewhere.

For policy makers it is important to note that the scale efficiency of Chinese light manufacturing industries dropped gradually during 2004-2012, which means Chinese light manufacturing industries went away farther and farther from their optimal operation scale, i.e. Chinese manufacturing industry currently encountered severe overcapacity issue due to the lack of consumption in term of the total retail sales of consumer goods, as well as too much CO2 emissions. Thus we suggest that (1) Chinese government could encourage domestic manufacturers to input more resources into the research and development (R&D) on advanced manufacturing technology to improve their R&D abilities to upgrade their products and increase their value-added to produce more GIOV and less CO2 emissions using the limited resources. (2) Chinese government could encourage domestic manufacturers to learn and introduce advanced experiences and equipment from industrialised countries in the world to help improve their own production technology and management. (3) Chinese government could provide incentives for CO2 emissions reduction for domestic manufacturers. For example, Chinese government could provide specific fund for manufacturers with relatively low energy consumption and CO2 emissions to support them improve their competitiveness in the market and to promote the economic growth mode shift from conventional high energy consumption and CO2 emissions to clean production with low energy consumption and CO2 emissions.

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Appendix A. Some extensions of global MLP index

The RAM-based global MLP index can be easily extended to conduct variable specific analysis as follows:

(1) For input slacks, we can define the distance function DDF as follows:

If we assume CRS on the technology PPS_D^G, thus we have

$$\vec{D}_{DDF,c}^{G}(X^p, Y^p, B^p) = min\, \theta = 1 - R_X'^{pT} d_X^p$$
$$s.t. \begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t + d_X^p = X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t \geq Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t \leq B^p \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{A-1}$$

where $R_X'^{pT} = \left(R_{X1}'^{p}, R_{X2}'^{p}, \dots, R_{Xm}'^{p}\right)^T$ and

$$R_X'^{pT} = (m)^{-1}\left(max\left\{x_{ij}^p | j = 1, \dots, n\right\} - min\left\{x_{ij}^p | j = 1, \dots, n\right\}\right)^{-1}, i = 1,2, \dots m, \tag{A-2}$$

$p = t, t + 1$, and under VRS technology:

$$\vec{D}_{DDF,v}^{G}(X^p, Y^p, B^p) = min\, \theta = 1 - R_X'^{pT} d_X^p$$
$$s.t. \begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t + d_X^p = X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t \geq Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t \leq B^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt} = 1 \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{A-3}$$

(2) For slacks of desirable outputs, we can define the distance function DDF as follows:

If we assume CRS on the technology PPS_D^G, thus we have

$$\vec{D}_{DDF,c}^{G}(X^p, Y^p, B^p) = min\,\theta = 1 - R_Y^{\prime pT} d_Y^p$$
$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t \leq X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t - d_Y^p = Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t \leq B^p \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{A-4}$$

where $R_Y^{\prime pT} = \left(R_{Y1}^{\prime p}, R_{Y2}^{\prime p}, \dots, R_{Ys}^{\prime p}\right)^T$ and

$$R_Y^{\prime pT} = (s)^{-1}\left(max\left\{y_{rj}^p | j = 1, \dots, n\right\} - min\left\{y_{rj}^p | j = 1, \dots, n\right\}\right)^{-1}, r = 1,2, \dots s, \tag{A-5}$$

$p = t, t+1$, and under VRS technology:

$$\vec{D}_{DDF,v}^{G}(X^p, Y^p, B^p) = min\,\theta = 1 - R_Y^{\prime pT} d_Y^p$$
$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t \leq X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t - d_Y^p = Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t \leq B^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt} = 1 \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{A-6}$$

(3) For slacks of undesirable outputs, we can define the distance function DDF as follows: If we assume CRS on the technology PPS_D^G, thus we have

$$\vec{D}_{DDF,c}^{G}(X^p, Y^p, B^p) = min\,\theta = 1 - R_B^{\prime pT} d_B^p$$
$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t \leq X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t \geq Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t + d_B^p = B^p \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{A-7}$$

where $R_B^{\prime pT} = \left(R_{B1}^{\prime p}, R_{B2}^{\prime p}, \dots, R_{Bk}^{\prime p}\right)^T$ and

$$R_B^{\prime pT} = (k)^{-1}\left(max\left\{b_{qj}^p | j = 1, \dots, n\right\} - min\left\{b_{qj}^p | j = 1, \dots, n\right\}\right)^{-1}, q = 1,2, \dots k, \tag{A-8}$$

$p = t, t+1$, and under VRS technology:

$$\vec{D}^{G}_{DDF,v}(X^p, Y^p, B^p) = min\,\theta = 1 - R'^{pT}_{B} d^p_B$$
$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}X_j^t \leq X^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}Y_j^t \geq Y^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt}B_j^t + d_B^p = B^p \\ \sum_{t=1}^{T}\sum_{j=1}^{n}\lambda_{jt} = 1 \\ \lambda_{jt} \geq 0, j = 1, \dots, n; t = 1, \dots, T \end{cases} \tag{A-9}$$

Similar to formulae (20) and (21), we can easily to build global MLP index to conduct variable specific analysis (Inputs, desirable outputs and undesirable outputs respectively) based on the distance function DDFs of (A-1) to (A-9).

Table 1. The inputs and outputs variables used in literatures on Chinese environmental efficiency.

Authors	Year	Input and output variables
Zhang et al.	2015	**Inputs:** (1) Employees, (2)Total fixed assets, (3) Energy consumption **Outputs:** (1) Gross product, (2) CO_2 emissions
Yang et al.[3]	2015	**Inputs:** (1) Capital, (2) Labour input, (3) Energy consumption, (4) CO_2 emission, (5) SO_2 emission **Outputs:** (1) GDP
Wang et al.	2015	**Inputs:** (1) Labour, (2) Capital, (3) Energy **Outputs:** (1) GDP, (2) SO_2 emission
Fan et al.	2015	**Inputs:** (1) Capital stock, (2) Labour force, (3) Energy consumption **Outputs:** (1) Gross industrial output; (2) CO_2 emissions
Bian et al.	2015	Inputs: (1) Fixed assets, (2) Labour, (3) Energy consumption, (4) Industrial pollution abatement investment Outputs: (1) GDP, (2) COD (chemical oxygen demand); (3) SO_2 ; (4) Ammonia nitrogen (NH4eN); (5) Output value of products made from comprehensive utilization of industrial waste (OPUW)
An et al.	2015	**Inputs:** (1) Production time, (2) Coal consumption

[3]In this research the authors used undesirable outputs as inputs.

		Outputs: (1) Total industrial output value, (2) Electric energy production, (3) Solid waste
Zhu et al.	2014	**Inputs:** (1) Environmental impact quotient (EIQ), (2) Chemical oxygen demand (COD), (3) ammonia nitrogen (AN), (4) hazardous solid waste (HSW) **Outputs:** (1) The average market price, (2) The area treated
Zhou et al.	2014	**Inputs:** (1) Labour, (2) Capital stock, (3) Transport fuel **Outputs:** (1) Transport services, (2) CO_2 emissions
Zhang et al.	2014	**Inputs:** (1) Labour,(2) Capital, (3) Energy **Outputs:** (1) GDP, (2) SO_2 emissions, (3) COD, (4) CO_2 emissions
Yin et al.	2014	**Inputs:** (1) Total water consumption, (2) Comprehensive energy consumption, (3) Construction land area, (4) Total investment in fixed assets, (5) Numbers of employed person **Outputs:** (1) Waste water emission, (2) COD emission, (3) CO_2 emission, (4) SO_2 emission, (5) Soot emission ,(6) Industrial dust emission, (7) Solid waste emission, (8) Gross domestic production
Wu et al.	2014	**Inputs:** (1) Total investment in fixed assets of industry, (2) Electricity consumption by industry **Outputs:** (1) Gross regional product of industry, (2) Total volume of nitrogen dioxide pollutant emissions
Wang et al.	2014	**Inputs:** (1) Capital Stock, (2) Labour, (3) Energy consumption **Outputs:** (1) GDP
Wang and Wei	2014	**Inputs:** (1) Net value of fixed assets of industrial enterprises, (2) Number of employed person of industrial enterprises, (3) Total energy consumption of industrial enterprises **Outputs:** (1) Value-added of industrial enterprises, (2) Total volume of industrial SO_2 emissions, (3) Total volume of industrial carbon dioxide emissions
Li et al.	2014	**Inputs:** (1) Network length above 35 kV, (2) Transformers capacity

		above 35 kV, (3) Number of employees, (4) Cost of the main business **Outputs:** (1) Electric power supply amount, (2) Power supply reliability, (3) The quality of the voltage, (4) Line loss
Huang et al.	2014	**Inputs:** (1) Capital, (2) Labour input, (3) Land input, (4) Energy **Outputs:** (1) GDP, (2) Environmental pollutants
Hou et al.	2014	**Inputs:** (1) Cost except Labour, (2) Labour **Outputs:** (1) Revenue, (2) Soil loss, (3) Nitrogen loss
Du et al.	2014	**Inputs:** (1) Labour, (2) Capital stock, (3) Energy consumption **Outputs:** (1) Gross regional product, (2) Carbon dioxide emissions
Bi et al.	2014a	**Inputs:** (1) Installed capacity, (2) Labour, (3) Coal total, (4) Gas total **Outputs:** (1) Annual net electricity generated, (2) Sulfur dioxide emission, (3) NOx, (4) Soot
Bi et al.	2014b	**Inputs:** (1) Labour, (2) Capital, (3) Energy **Outputs:** (1) Value-added, (2) CO_2 emissions
Long et al.	2013	**Inputs:** (1) Capital stock, (2) Human resources stock, (3) Employment, (4) Coal consumption **Outputs:** (1) Gross Regional Product (GRP), (2) SO_2 emissions
Wang et al.	2013a	**Inputs:** (1) Capital Stock, (2) Labour, (3) Energy **Outputs:** (1) GDP, (2) CO_2 emissions
He et al.	2013	**Inputs:** (1) Net fixed assets, (2) Employees, (3) Energy **Outputs:** (1) Value added, (2) Waste gas, (3) Waste water, (4) Solid Waste
Yang and Wang	2013	**Inputs:** (1) Capital investment, (2) Labour, (3) Energy **Outputs:** (1) GDP, (2) CO_2 emissions
Yuan et al.	2013	**Inputs:** (1) Employees, (2) Fixed assets, (3) Current assets **Outputs:** (1) Gross output value, (2) Wastewater, (3) SO2, (4) Soot
Wang et al.	2013b	**Inputs:** (1) Energy consumption, (2) Labour, (3) Capital stock **Outputs:** (1) GDP, (2) CO_2 emissions

Zhang and Choi	2013a	**Inputs:** (1) Capital, (2) Labour, (3) Energy **Outputs:** (1) Regional GDP, (2) CO_2 emissions
Zhang and Choi	2013b	**Inputs:** (1) Capital, (2) Fossil fuel, (3) Labour **Outputs:** (1) The electricity output, (2) CO_2 emissions
Zhang and Choi	2013c	**Inputs:** (1) Labour, (2) Capital, (3) Energy consumption **Outputs:** (1) GDP, (2) Industrial value added, (3) The employment rate, (4) SO_2 emissions, (5) COD, (6) CO_2 emissions

Table 2. The CPI of China.

Date	Value
2003	81.8313
2004	85.0227
2005	86.5673
2006	87.8369
2007	92.0238
2008	97.4532
2009	96.7834
2010	100.0000
2011	105.4706
2012	108.2221
2013	111.0703

Note: According to OECD statistics, we set Index 2010=100.

Table 3. Coefficients of transforming different types of energy into SCE.

Energy types	Coefficients of transforming	Units
Coal	0.7143	kg SCE/kg
Coke	0.9714	kg SCE/kg
Crude Oil	1.4286	kg SCE/kg
Gasoline	1.4714	kg SCE/kg
Kerosene	1.4714	kg SCE/kg
Diesel Oil	1.4571	kg SCE/kg
Fuel Oil	1.4286	kg SCE/kg
Natural Gas	1.3300	kg SCE/cm
Electricity	0.1229	kg SCE/kh

Note: This data is derived from China Energy Statistical Yearbook 2013.

Table 4. The coefficients for CO_2 emissions estimation.

Energy types	The coefficients of transforming different types of energy into SCE		Estimated CO_2 emission factors	
	Value	Units	Value	Units
Coal	0.7143	kg SCE/kg	2.763	kg/kg SCE
Crude oil	1.4286	kg SCE/kg	2.145	kg/kg SCE
Natural gas	1.3300	kg SCE/cm	1.642	kg/kg SCE

Table 5. The average of the means of five indicators in different years.

Year	Assets (100 million Yuan)	Labour (10 000 persons)	Energy (10 000 tons of SCE)	GIOV (100 million yuan)	CO_2 emissions (10 000 tons)
2004	5190.9667	235.0992	2257.5403	5352.3770	2815.0114
2005	4953.7836	172.7765	2494.0765	5778.5302	3190.7223
2006	5694.7751	183.7624	2735.1631	7002.5491	3286.4728
2007	6451.2878	195.6365	2947.3121	8538.2248	3474.7669
2008	7239.5170	216.6782	3185.6595	9954.5629	4055.6167
2009	8177.7884	215.4412	3194.5659	11151.0962	4028.6364
2010	9441.7888	229.0665	3242.8776	13514.3629	4117.4074
2011	10158.8990	214.1376	3563.1452	15513.7319	4454.6316
2012	11598.7355	238.1396	3755.3489	17361.0300	4563.7849

Table 6. The global MLP index and its components of Chinese light manufacturing industries under VRS technology.

Years	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012
Global MLP	1.0236	1.0043	N/A	0.9948	1.0037	1.0084	N/A	0.9931
PEC	1.0039	1.0014	N/A	0.9831	0.9998	1.0006	N/A	0.9967
BPC	1.0280	1.0363	N/A	1.0132	1.0159	1.0358	N/A	1.0046
SCH	0.9934	0.9726	N/A	1.0016	0.9899	0.9819	N/A	0.9921

Note: N/A denotes "not available".

Table 7. The traditional global MLP index and its components of Chinese light manufacturing industries under VRS technology.

Years	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012
Global MLP	1.1178	1.0659	N/A	1.0167	1.0243	1.0606	N/A	0.9830
PEC	1.0259	1.0134	N/A	0.9869	0.9994	1.0094	N/A	0.9875
BPC	1.0615	1.0272	N/A	1.0010	1.0217	1.0035	N/A	0.9970
SCH	1.0322	1.0267	N/A	1.0253	1.0039	1.0184	N/A	1.0006

Note: N/A denotes "not available".

Appendix B.

Table B-1. The comparison of two-digit light manufacturing industries in 2011 (and before) and2012[4].

2011 and before		**2012**	
No.	Two-digit manufacturing	No.	Two-digit manufacturing
1	Processing of Food from Agricultural Products	1	Processing of Food from Agricultural Products
2	Manufacture of Foods	2	Manufacture of Foods
3	Manufacture of Beverages*	3	Manufacture of Liquor, Beverages and Refined Tea*
4	Manufacture of Tobacco	4	Manufacture of Tobacco
5	Manufacture of Textile	5	Manufacture of Textile
6	Manufacture of Textile Wearing Apparel, Footware and Caps*	6	Manufacture of Textile, Wearing Apparel and Accessories*
7	Manufacture of Leather, Fur, Feather and Related Products*	7	Manufacture of Leather, Fur, Feather and Related Products and Footwear*
8	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	8	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products
9	Manufacture of Furniture	9	Manufacture of Furniture
10	Manufacture of Paper and Paper Products	10	Manufacture of Paper and Paper Products
11	Printing, Reproduction of Recording Media	11	Printing and Reproduction of Recording Media
12	Manufacture of Articles For Culture, Education and Sport Activities*	12	Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities*
13	Manufacture of Raw Chemical Materials and Chemical Products	13	Manufacture of Raw Chemical Materials and Chemical Products
14	Manufacture of Medicines	14	Manufacture of Medicines
15	Manufacture of Chemical Fibres	15	Manufacture of Chemical Fibres
16	Manufacture of Rubber	16	Manufacture of Rubber and Plastics Products
17	Manufacture of Plastics		
18	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work*	17	Manufacture of Measuring Instruments and Machinery*

Note: * means that there are minor changes of industries' name at the beginning of 2012

[4]For details, please refer the following link: http://www.stats.gov.cn/tjsj/tjbz/hyflbz.

Table B-2. Productivity growth, efficiency and technical changes of Chinese light manufacturing industries (VRS technology).

DMUs	2004-2005				2005-2006			
	Global MLP	PEC	BPC	SCH	Global MLP	PEC	BPC	SCH
Processing of Food from Agricultural Products	1.0376	1.0000	1.0382	0.9994	1.0119	1.0000	1.0094	1.0024
Manufacture of Foods	1.0181	1.0115	1.0075	0.9990	1.0048	1.0035	1.0004	1.0008
Manufacture of Liquor, Beverages and Refined Tea	1.0176	1.0146	1.0020	1.0010	1.0033	1.0027	0.9999	1.0006
Manufacture of Tobacco	1.0014	1.0000	1.0000	1.0014	1.0032	1.0000	1.0000	1.0032
Manufacture of Textile	1.0770	1.0000	1.0764	1.0006	1.0042	1.0000	1.2071	0.8319
Manufacture of Textile, Wearing Apparel and Accessories	1.0559	1.0000	1.0500	1.0056	1.0067	1.0000	1.0517	0.9572
Manufacture of Leather, Fur, Feather and Related Products and Footwear	1.0303	1.0000	1.0299	1.0004	1.0118	1.0000	1.0093	1.0024
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	1.0216	1.0103	1.0123	0.9989	1.0019	1.0035	0.9978	1.0006
Manufacture of Furniture	1.0114	1.0000	1.0000	1.0114	1.0033	1.0000	1.0000	1.0033
Manufacture of Paper and Paper Products	1.0217	1.0165	1.0049	1.0002	0.9977	1.0003	0.9969	1.0005
Printing and Reproduction of Recording Media	1.0170	1.0088	1.0101	0.9981	1.0014	1.0108	0.9891	1.0016
Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities	1.0166	1.0000	1.0000	1.0166	1.0149	1.0000	1.0000	1.0149
Manufacture of Raw Chemical Materials and Chemical Products	0.9986	1.0000	1.1826	0.8444	0.9866	1.0000	1.2710	0.7762
Manufacture of Medicines	1.0113	1.0045	1.0062	1.0005	1.0013	1.0031	0.9978	1.0004
Manufacture of Chemical Fibres	1.0070	1.0000	1.0091	0.9980	1.0052	1.0000	1.0116	0.9937
Manufacture of Rubber and Plastics Products	1.0454	1.0000	1.0463	0.9991	1.0111	1.0000	1.0754	0.9402
Manufacture of Measuring Instruments and Machinery	1.0133	1.0000	1.0000	1.0133	1.0044	1.0000	1.0000	1.0044

Table B-2 (cont'd). Productivity growth, efficiency and technical changes of Chinese light manufacturing industries (VRS technology).

DMUs	2007-2008				2008-2009			
	Global MLP	PEC	BPC	SCH	Global MLP	PEC	BPC	SCH
Processing of Food from Agricultural Products	1.0333	1.0000	1.0244	1.0086	0.9860	1.0000	0.9904	0.9956
Manufacture of Foods	0.9962	0.9971	0.9985	1.0006	1.0033	1.0005	0.9994	1.0033
Manufacture of Liquor, Beverages and Refined Tea	0.9950	0.9961	0.9985	1.0004	1.0034	1.0028	1.0008	0.9998
Manufacture of Tobacco	1.0005	1.0000	0.9996	1.0010	1.0001	1.0000	0.9992	1.0009

Manufacture of Textile	0.9947	0.8032	1.2386	0.9998	1.0239	1.0124	1.0117	0.9997
Manufacture of Textile, Wearing Apparel and Accessories	0.9965	1.0000	1.0014	0.9951	1.0231	1.0000	1.0462	0.9779
Manufacture of Leather, Fur, Feather and Related Products and Footwear	0.9997	1.0000	0.9774	1.0229	1.0136	1.0000	1.0098	1.0038
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	0.9945	0.9895	1.0019	1.0031	1.0057	1.0106	0.9974	0.9978
Manufacture of Furniture	1.0009	1.0000	0.9989	1.0020	1.0067	1.0000	1.0011	1.0056
Manufacture of Paper and Paper Products	0.9883	0.9953	0.9935	0.9995	0.9966	0.9944	1.0024	0.9998
Printing and Reproduction of Recording Media	0.9983	1.0000	0.9924	1.0060	1.0010	1.0000	1.0000	1.0010
Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities	0.9988	1.0000	0.9957	1.0030	1.0066	1.0000	1.0040	1.0026
Manufacture of Raw Chemical Materials and Chemical Products	0.9321	1.0000	0.9346	0.9973	0.9910	1.0000	1.1851	0.8362
Manufacture of Medicines	0.9978	1.0007	0.9975	0.9996	0.9997	0.9995	1.0009	0.9994
Manufacture of Chemical Fibres	1.0004	1.0000	1.0122	0.9884	1.0003	1.0000	0.9936	1.0068
Manufacture of Rubber and Plastics Products	0.9893	0.9310	1.0629	0.9997	1.0052	0.9766	1.0295	0.9998
Manufacture of Measuring Instruments and Machinery	0.9957	1.0000	0.9958	0.9999	0.9971	1.0000	0.9984	0.9987

Table B-2 (cont'd). Productivity growth, efficiency and technical changes of Chinese light manufacturing industries (VRS technology).

DMUs	2009-2010				2011-2012			
	Global MLP	PEC	BPC	SCH	Global MLP	PEC	BPC	SCH
Processing of Food from Agricultural Products	1.0142	1.0000	1.0097	1.0044	1.0084	1.0000	1.0052	1.0032
Manufacture of Foods	1.0026	0.9990	1.0028	1.0008	0.9913	0.9838	1.0037	1.0039
Manufacture of Liquor, Beverages and Refined Tea	1.0012	0.9988	1.0027	0.9997	0.9966	0.9934	1.0039	0.9993
Manufacture of Tobacco	1.0027	1.0000	1.0012	1.0015	1.0013	1.0000	1.0000	1.0013
Manufacture of Textile	1.0145	1.0112	1.0033	1.0000	1.0100	0.9971	1.0132	0.9997
Manufacture of Textile, Wearing Apparel and Accessories	1.0147	1.0000	1.0472	0.9690	0.9898	1.0000	1.0701	0.9250
Manufacture of Leather, Fur, Feather and Related Products and Footwear	1.0172	1.0000	1.0132	1.0039	0.9810	1.0000	1.0000	0.9810
Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products	1.0042	1.0000	1.0061	0.9981	1.0000	1.0000	1.0000	1.0000
Manufacture of Furniture	1.0050	1.0000	1.0000	1.0050	0.9951	1.0000	1.0000	0.9951

Manufacture of Paper and Paper Products	1.0025	1.0023	1.0009	0.9994	0.9937	0.9922	1.0017	0.9998
Printing and Reproduction of Recording Media	1.0019	1.0000	0.9977	1.0042	0.9956	1.0000	0.9930	1.0026
Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities	1.0161	1.0000	1.0003	1.0157	1.0180	1.0000	1.0000	1.0180
Manufacture of Raw Chemical Materials and Chemical Products	1.0323	1.0000	1.5182	0.6800	0.9303	1.0000	1.0000	0.9303
Manufacture of Medicines	1.0005	0.9996	1.0016	0.9993	0.9882	0.9852	1.0040	0.9990
Manufacture of Chemical Fibres	1.0037	1.0000	0.9934	1.0104	0.9959	1.0000	0.9836	1.0125
Manufacture of Rubber and Plastics Products	1.0028	0.9987	1.0044	0.9997	1.0002	0.9927	1.0081	0.9994
Manufacture of Measuring Instruments and Machinery	1.0072	1.0000	1.0058	1.0014	0.9872	1.0000	0.9924	0.9948