Malmquist Productivity Indices and Plant Capacity Utilisation: New Proposals and Empirical Application*

Kristiaan Kerstens[†], Jafar Sadeghi[‡], Ignace Van de Woestyne[§], Linjia Zhang[¶]

Initial submission: January 23, 2021
First revision: August 30, 2021
This version: April 20, 2022

Abstract

The purpose of this contribution is to compute the popular Malmquist productivity index while adding a component representing plant capacity utilisation. In particular, this is –to the best of our knowledge– the first empirical application estimating both input- and output-oriented Malmquist productivity indices in conjunction with the corresponding input- and output-oriented plant capacity utilisation measures. Our empirical application focuses on a provincial data set of tourism activities in China over the period 2008 to 2016. The results contain the output- and input oriented Malmquist productivity indices, some Spearman rank correlations between both, a t-test whether these indices differ from unity, and some bootstrapping analysis.

KEYWORDS: Data Envelopment Analysis; Free Disposal Hull; Malmquist Productivity Index; Decomposition; Plant Capacity.

---

*We acknowledge the most helpful comments of the constructive referees. The usual disclaimer applies.

†Corresponding author: Univ. Lille, CNRS, IESEG School of Management, UMR 9221 - LEM - Lille Économie Management, F-59000 Lille, France, Tel: +33 320545892 (switchboard), Fax: +33 320574855, k.kerstens@ieseg.fr

‡IESEG School of Management, 3 rue de la Digue, F-59000 Lille, France & Ivey Business School, Western University, London, Ontario, Canada j.sadeghi1987@gmail.com

§KU Leuven, Research Unit MEES, Brussels, Belgium, ignace.vandewoestyne@kuleuven.be

¶International Business School Suzhou, Xi'an Jiaotong-Liverpool University, 111 Ren'ai Rd., Suzhou Industrial Park, 215123, Suzhou, China, Linjia.Zhang@xjtlu.edu.cn

1 Introduction

Productivity is an important component of profitability. In fact, Total Factor Productivity (TFP) change, as the most encompassing measure of productivity change, is nothing but the "real" component of profitability change (see Balk (2003)). Productivity is therefore an important driver to changing standards of living. TFP growth is an index number aimed at capturing any output growth that is unexplained by input growth (e.g., Hulten (2001)). In the recent literature a lot of attention has been devoted to what has been aptly called theoretical productivity indices (see Russell (2018)). A theoretical productivity index is defined on the assumption that the technology is known and non-stochastic, but unspecified and thus most often approximated by a nonparametric multiple-input, multiple-output specification using some form of distance functions. The foundational concepts are on the one hand the Malmquist productivity index (initially developed by Caves, Christensen, and Diewert (1982)) and on the other hand the Hicks-Moorsteen productivity index (Bjurek (1996)). While the Malmquist productivity index is fundamentally a measure of the shift of the production frontier, the Hicks-Moorsteen productivity index is a ratio of an aggregate output index over an aggregate input index. Thus, the Malmquist productivity index measures local technical change (i.e., the local change of a production frontier) but in general not TFP change, while the Hicks-Moorsteen productivity index has a TFP interpretation.

In the last decades, awareness has developed that ignoring inefficiency may potentially bias productivity measures. Nishimizu and Page (1982) is probably the seminal article decomposing productivity into a technical change component and a technical efficiency change component. Caves, Christensen, and Diewert (1982) analyze the discrete time Malmquist productivity index using distance functions as general representations of technology. Caves, Christensen, and Diewert (1982) show that this Malmquist index happens to be related to the Törnqvist productivity index if a translog technology is assumed. However, the Törnqvist productivity index uses both price and quantity information, but it needs no knowledge on the technology. Färe, Grosskopf, Lindgren, and Roos (1995) are the first to propose a procedure to estimate the distance functions in the Malmquist productivity index by exploiting their relation with the radial efficiency measures computed relative to nonparametric technologies, and also integrate the two-part Nishimizu and Page (1982) decomposition. Bjurek (1996) offers an alternative Hicks-Moorsteen TFP index that can be defined as the ratio of an aggregate Malmquist output- over an aggregate Malmquist input-index.

From a theoretical point of view, these Malmquist and Hicks-Moorsteen productivity indexes are known to be identical only under two very stringent conditions: (i) inverse homotheticity of the technology; and (ii) constant returns to scale (see Färe, Grosskopf, and Roos (1996)). Therefore, from an empirical point of view both indices are in general expected to differ, since these two conditions that need to hold for their equality are unlikely to be met in practice. Kerstens and Van de Woestyne (2014) empirically show that the Malmquist productivity index offers a poor approximation to the Hicks-Moorsteen TFP index in terms of the resulting distributions, and that for individual observations one may well even encounter conflicting evidence regarding the basic direction of productivity growth or decline.

A substantial part of the subsequent literature extends these two theoretical productivity indices to incorporate on the one hand the possibility of technological inefficiency (i.e., operation below the production frontier), and on the other hand decompositions into a variety of components of productivity change (e.g., efficiency change, scale effects, input- and output-mix effects). It is fair to say that most focus has been on decomposing the Malmquist productivity index: this has led to various controversies that have been summarised in the now somewhat dated survey by Zofío (2007). The Hicks-Moorsteen TFP index has long been thought not to be amenable to decomposition, but a recent proposal for a decomposition is found in Diewert and Fox (2017).

In the literature, more general primal productivity indicators have meanwhile been proposed. Chambers, Färe, and Grosskopf (1996) introduce the Luenberger productivity indicator as a difference-based indicator of directional distance functions (Chambers (2002) provides the best background). These directional distance functions generalize traditional distance functions by allowing for simultaneous input reductions and output expansions and these are dual to the profit function. Briec and Kerstens (2004) define a Luenberger-Hicks-Moorsteen TFP indicator using these same directional distance functions. Though not as popular as the Malmquist productivity index, the Luenberger productivity indicator has been rather widely used. The Luenberger-Hicks-Moorsteen TFP indicator is relatively speaking less employed. Luenberger output (or input) oriented productivity indicators and Luenberger-Hicks-Moorsteen productivity indicators coincide under similar demanding properties spelled out in Briec and Kerstens (2004). Kerstens, Shen, and Van de Woestyne (2018) empirically document that the Luenberger productivity indicator provides a poor approximation to the Luenberger-Hicks-Moorsteen TFP indicator in terms of the resulting distributions, and that for individual observations one may obtain conflicting results with respect to the basic direction of productivity growth or decline.

In our contribution, we focus on one potentially neglected issue in the development of the Malmquist productivity index, namely that variations in capacity utilisation have so far largely been ignored. In traditional productivity decompositions -mainly based on parametric functional specifications- several proposals for incorporating measures of capacity utilisation have been available in the literature. Examples of such theoretical contributions include Hulten (1986), Morrison (1985) or Morrison Paul (1999) (see, e.g., Fousekis and Papakonstantinou (1997) for an empirical example). Since the basic Malmquist productivity index focuses on primal technologies, a seminal theoretical proposal to include an output-oriented plant capacity utilisation measure (proposed in Färe, Grosskopf, and Valdmanis (1989)) within an output-oriented Malmquist productivity index is found in De Borger and Kerstens (2000).[1]

For several decades the output-oriented plant capacity utilisation measure has been the only technical or engineering capacity notion available in the literature. However, recently two innovations have been proposed. First, Kerstens, Sadeghi, and Van de Woestyne (2019) criticize the traditional output-oriented plant capacity utilisation measure for not being attainable: it determines maximal outputs for potentially unlimited amounts of variable inputs, but it ignores the basic fact that the amounts of variable inputs needed to obtain these maximal outputs may well not be available at either the firm or the industry level. The same authors then go on to define an attainable output-oriented plant capacity utilisation measure: it modifies the basic output-oriented plant capacity utilisation measure by including an upper bound on the amount of available variable inputs. In empirical applications the problem is to determine a realistic upper bound on the amount of available variable inputs.

Second, an alternative input-oriented plant capacity utilisation measure has been introduced in Cesaroni, Kerstens, and Van de Woestyne (2017). It is based on a pair of input-oriented efficiency measures using a nonparametric frontier framework, very much in line with the output-oriented plant capacity utilisation measure that is based on a couple of output-oriented efficiency measures. In a recent study, Kerstens and Shen (2021) use these plant capacity concepts to measure hospital capacities in the Hubei province in China during the outbreak of the COVID-19 epidemic. Using the medical literature indicating that mortality rates increase with high capacity utilization rates leads to the preliminary conclusion that this relatively new input-oriented plant capacity concept correlates best with mortality.

Therefore, this contribution sets itself two main goals. First, it develops a proper decomposition of the input-oriented Malmquist productivity index that is compatible with the new input-oriented plant capacity notion. This decomposition is distinct from the existing decomposition of the output-oriented Malmquist productivity index developed in De Borger and Kerstens (2000). In addition, the existing decomposition of the output-oriented Malmquist

[1] An alternative proposal that does not yield an adequate decomposition is found in Sena (2001).

productivity index is extended by including the attainable output-oriented plant capacity utilisation measure.

Second, we are -to the best of our knowledge- the first empirical application of both these basic decompositions of the input-oriented and output-oriented Malmquist productivity indices using an empirical data set. In particular, we employ Chinese provincial data from tourism activities. For a lack of realistic upper bound on the amount of available variable inputs in our empirical application, we refrain from estimating the output-oriented Malmquist productivity index with the attainable output-oriented plant capacity utilisation measure.

Third, we are the first empirical application of both these basic decompositions of the Malmquist productivity index that test for the impact of the convexity assumption. While the impact of convexity is generally known to be considerable for technical efficiency measurement, its effect on the measurement of capacity utilisation and the computation of the Malmquist productivityindex remain under-explored. Cesaroni, Kerstens, and Van de Woestyne (2017) show that convex and nonconvex input- and output-oriented plant capacity concepts differ significantly. Kerstens and Van de Woestyne (2014) are the only ones known to us that empirically illustrate that convex and nonconvex Malmquist productivity index results differ. Therefore, it is useful to see the impact of convexity on the above mentioned decompositions of the Malmquist productivity index.

This contribution is structured as follows. The next Section 2 defines the basic technologies, the Malmquist productivity indices, the necessary plant capacity concepts, as well as integration of these plant capacity concepts in the corresponding Malmquist productivity indices. Section 3 provides a succinct literature review about efficiency and productivity measurement in the tourism industry. The next Section 4 discusses the specification and the data employed. Empirical results are listed and discussed in Section 5. The empirical results contain the output- and the input oriented Malmquist productivity indices and their components, some Spearman rank correlations between both indices and their components, a t-test whether these indices differ from unity, and some robustness check under the form of a bootstrapping analysis. Section 6 concludes.

2 Technology, Primal Productivity Indices, and Plant Capacity: Definitions

We first introduce the assumptions on technology and the definitions of the required efficiency measures. Then, we define the Malmquist productivity indices (MPI) as well as the necessary plant capacity utilisation notions. The latter elements are then finally integrated into the components of the Malmquist productivity indices.

2.1 Technology and Efficiency Measures

This subsection introduces basic notation and defines the production technology. Assume that for periods $t = 1, ..., T$, $N-$dimensional input vectors $x^t \in \mathbb{R}^N_+$ are employed to produce $M-$dimensional output vectors $y^t \in \mathbb{R}^M_+$. In each period t, the production possibility set or technology S is defined as follows: $S^t = \{(x^t, y^t)|x^t \text{ can produce at least } y^t\}$. A first alternative definition of technology S^t is the input set denoting all input vectors x^t capable of producing a given output vector y^t: $L^t(y^t) = \{x^t|(x^t, y^t) \in S^t\}$. A second alternative definition of technology S^t is the output set denoting all output vectors y^t that can be produced from a given input vector x^t: $P^t(x^t) = \{y^t|(x^t, y^t) \in S^t\}$.

The following standard assumptions are imposed on the technology S^t:

(T.1) Possibility of inaction and no free lunch, i.e., $(0, 0) \in S^t$ and if $(0, y^t) \in S^t$, then $y^t = 0$.

(T.2) S^t is a closed subset of $\mathbb{R}^N_+ \times \mathbb{R}^M_+$.

(T.3) Strong input and output disposal, i.e., if $(x^t, y^t) \in S^t$ and $(\bar{x}^t, \bar{y}^t) \in \mathbb{R}^N_+ \times \mathbb{R}^M_+$, then $(\bar{x}^t, -\bar{y}^t) \geq (x^t, -y^t) \Rightarrow (\bar{x}^t, \bar{y}^t) \in S^t$.

(T.4) S^t is convex.

These traditional axioms on technology can be succinctly commented upon as follows (see, e.g., Hackman (2008) for details). First, inaction is feasible, and there is no free lunch. Second, the technology is closed. Third, we impose free or strong disposal of both inputs and outputs in that inputs can be wasted and outputs can be discarded. Finally, technology is convex. In our empirical analysis later on these axioms are not always simultaneously maintained.[2] In particular, in the empirical analysis one key assumption distinguishing some

[2]For instance, note that the convex variable returns to scale technology does not satisfy inaction.

of the technologies is convexity versus nonconvexity.

Turning to the definition of the input-and output-oriented efficiency measures needed to define Malmquist productivity index as well as the plant capacity notions, we start with the radial input efficiency measure that can be defined as follows:

$$DF_i^t(x^t, y^t) = \min\{\lambda \mid \lambda \geq 0, \lambda x^t \in L^t(y^t)\}. \tag{1}$$

This radial input efficiency measure characterizes the input set $L^t(y^t)$ completely. Its main properties are that it is smaller or equal to unity ($DF_i^t(x^t, y^t) \leq 1$), with efficient production on the boundary (isoquant) of $L^t(y^t)$ represented by unity, and that it has a cost interpretation (see, e.g., Hackman (2008)).

The radial output efficiency measure can be defined as follows:

$$DF_o^t(x^t, y^t) = \max\{\theta \mid \theta \geq 0, \theta y^t \in P^t(x^t)\}. \tag{2}$$

This radial output efficiency measure offers a complete characterization of the output set $P^t(x^t)$. Its main properties are that it is larger than or equal to unity ($DF_o^t(x^t, y^t) \geq 1$), with efficient production on the boundary (isoquant) of the output set $P^t(x^t)$ represented by unity, and that this radial output efficiency measure has a revenue interpretation (e.g., Hackman (2008)).

In the short run, it is customary to distinguish between fixed and variable inputs. Thus, we can partition the input vector into a fixed and a variable part. In particular, we denote $x^t = (x_f^t, x_v^t)$ with $x_f^t \in \mathbb{R}_+^{N_f}$ and $x_v^t \in \mathbb{R}_+^{N_v}$ such that $N = N_f + N_v$. In an analogous way, a short-run technology $S_f^t = \{(x_f^t, y^t) \in \mathbb{R}_+^{N_f} \times \mathbb{R}_+^M \mid$ there exists some x_v^t such that (x_f^t, x_v^t) can produce at least $y^t\}$ and the corresponding short-run input set $L_f^t(y^t) = \{x_f^t \in \mathbb{R}_+^{N_f} \mid (x_f^t, y^t) \in S_f^t\}$ and short-run output set $P_f^t(x_f^t) = \{y^t \mid (x_f^t, y^t) \in S_f^t\}$ can be defined (see Cesaroni, Kerstens, and Van De Woestyne (2019) for more details).

Denoting the radial output efficiency measure of the short-run output set $P_f^t(x_f^t)$ by $DF_o^t(x_f^t, y^t)$, this short-run output-oriented efficiency measure can be defined as follows:

$$DF_o^t(x_f^t, y^t) = \max\{\theta \mid \theta \geq 0, \theta y^t \in P_f^t(x_f^t)\}. \tag{3}$$

The sub-vector input efficiency measure reducing only the variable inputs is defined:

$$DF_i^t(x_f^t, x_v^t, y^t) = \min\{\lambda \mid \lambda \geq 0, (x_f^t, \lambda x_v^t) \in L^t(y^t)\}. \tag{4}$$

Finally, we need the following particular definition of technology: $L^t(0) = \{x^t \mid (x^t, 0) \in S^t\}$ is the input set with a zero level of outputs. The sub-vector input efficiency measure reducing variable inputs evaluated relative to this input set with zero outputs level is:

$$DF_i^t(x_f^t, x_v^t, 0) = \min\{\lambda \mid \lambda \geq 0, (x_f^t, \lambda x_v^t) \in L^t(0)\}. \tag{5}$$

Given data on K observations ($k = 1, \cdots, K$) consisting of a vector of inputs and outputs $(x_k^t, y_k^t) \in \mathbb{R}_+^{N+M}$, a unified algebraic representation of convex and nonconvex nonparametric frontier technologies under the flexible or variable returns to scale assumption is possible as follows:

$$S^{t,\Gamma} = \left\{(x^t, y^t) \mid x^t \geq \sum_{k=1}^{K} z_k x_k^t, y^t \leq \sum_{k=1}^{K} z_k y_k^t, z = (z_1, \ldots, z_k) \in \Gamma, \right\}, \tag{6}$$

where

(i) $\Gamma \equiv \Gamma^{\mathrm{C}} = \left\{z \mid \sum_{k=1}^{K} z_k = 1 \text{ and } z_k \geq 0\right\}$;

(ii) $\Gamma \equiv \Gamma^{\mathrm{NC}} = \left\{z \mid \sum_{k=1}^{K} z_k = 1 \text{ and } z_k \in \{0, 1\}\right\}$.

The convexity axiom is represented by the activity vector z of real numbers summing to unity. This same sum constraint with each vector element being restricted to be a binary integer represents the nonconvexity axiom. The convex technology satisfies axioms (T.1) (except inaction) to (T.4), while the nonconvex technology complies with axioms (T.1) to (T.3). In the remainder, we condition the above notation of the efficiency measures relative to these nonparametric frontier technologies by distinguishing between convexity (convention C) and nonconvexity (convention NC).

Kerstens and Van de Woestyne (2014) empirically illustrate that to measure local technical change using a Malmquist productivity index one obtains the most precise results for variable returns to scale rather than for the often used constant returns to scale assumption. Furthermore, these authors show that convex and nonconvex Malmquist productivity results can differ substantially. Another pragmatic reason to opt for variable returns to scale is that some plant capacity notions may not be well defined under constant returns to scale.

2.2 Malmquist Productivity Indices: Definitions

Using the output-oriented radial efficiency measures one can define the output-oriented Malmquist productivity index in base period t as follows:

$$M_o^t(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{DF_o^t(x^t, y^t)}{DF_o^t(x^{t+1}, y^{t+1})}. \tag{7}$$

Values of this base period t output-oriented Malmquist productivity index above (below) unity reveal productivity growth (decline).

Similarly, a base period $t+1$ output-oriented Malmquist productivity index is defined:

$$M_o^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{DF_o^{t+1}(x^t, y^t)}{DF_o^{t+1}(x^{t+1}, y^{t+1})}. \tag{8}$$

Again, values of this base period $t+1$ output-oriented Malmquist productivity index above (below) unity reveal productivity growth (decline).

To avoid an arbitrary selection among base years and inspired by Caves, Christensen, and Diewert (1982), Färe, Grosskopf, Lindgren, and Roos (1995) define the output-oriented Malmquist productivity index as a geometric mean of a period t and a period $t+1$ productivity index:

$$\begin{aligned} M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) &= \sqrt{M_o^t(x^t, y^t, x^{t+1}, y^{t+1}) \cdot M_o^{t+1}(x^t, y^t, x^{t+1}, y^{t+1})} \\ &= \sqrt{\frac{DF_o^t(x^t,y^t)}{DF_o^t(x^{t+1},y^{t+1})} \cdot \frac{DF_o^{t+1}(x^t,y^t)}{DF_o^{t+1}(x^{t+1},y^{t+1})}}. \end{aligned} \tag{9}$$

The base period of this productivity index changes over time: it can be conceptualized as an index computed in a two year window sliding over the observations through time. Moreover, this geometric mean output-oriented Malmquist index (9) can be decomposed into two mutually exclusive components:

$$M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \underbrace{\frac{DF_o^t(x^t, y^t)}{DF_o^{t+1}(x^{t+1}, y^{t+1})}}_{(i)} \underbrace{\sqrt{\frac{DF_o^{t+1}(x^{t+1}, y^{t+1})}{DF_o^t(x^{t+1}, y^{t+1})} \cdot \frac{DF_o^{t+1}(x^t, y^t)}{DF_o^t(x^t, y^t)}}}_{(ii)}. \tag{10}$$

The first component (i) measures the change in technical efficiency over time, while the second component (ii) is related to the shift of the frontier of the production technology (i.e., it captures technical change).

By analogy, an input-oriented Malmquist productivity index with base period t is defined as the ratio of two input efficiency measures as follows:

$$M_i^t(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{DF_i^t(x^t, y^t)}{DF_i^t(x^{t+1}, y^{t+1})}. \tag{11}$$

Values of this base period t input-oriented Malmquist productivity index below (above) unity reveal productivity growth (decline).

Similarly, an input-oriented Malmquist productivity index with base period $t+1$ can similarly be defined as:

$$M_i^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{DF_i^{t+1}(x^t, y^t)}{DF_i^{t+1}(x^{t+1}, y^{t+1})}. \tag{12}$$

Again, values of this base period $t+1$ input-oriented Malmquist productivity index below (above) unity reveal productivity growth (decline). Note that since the $DF_i(x, y) \leq 1$ and $DF_o(x, y) \geq 1$, the interpretation of equations (11) and (12) are inverse of the interpretation of equations (7) and (8).

To avoid an arbitrary choice of base period, the input-oriented Malmquist productivity index is defined as a geometric mean of a period t and $t+1$ productivity index:

$$\begin{aligned} M_i^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) &= \sqrt{M_i^{t+1}(x^t, y^t, x^{t+1}, y^{t+1}) \cdot M_i^{t+1}(x^t, y^t, x^{t+1}, y^{t+1})} \\ &= \sqrt{\frac{DF_i^t(x^t, y^t)}{DF_i^t(x^{t+1}, y^{t+1})} \cdot \frac{DF_i^{t+1}(x^t, y^t)}{DF_i^{t+1}(x^{t+1}, y^{t+1})}}. \end{aligned} \tag{13}$$

Note that when the geometric mean input-oriented Malmquist productivity index is larger (smaller) than unity, it points to a productivity growth (decline). Moreover, the Malmquist index (13) can be decomposed into two mutually exclusive components:

$$M_i^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \underbrace{\frac{DF_i^t(x^t, y^t)}{DF_i^{t+1}(x^{t+1}, y^{t+1})}}_{(i)} \underbrace{\sqrt{\frac{DF_i^{t+1}(x^{t+1}, y^{t+1})}{DF_i^t(x^{t+1}, y^{t+1})} \cdot \frac{DF_i^{t+1}(x^t, y^t)}{DF_i^t(x^t, y^t)}}}_{(ii)}. \tag{14}$$

The first component (i) measures the change in technical efficiency over time, while the second component (ii) is related to the shift of the frontier of the production technology (i.e., it captures technical change). Note that when this input-oriented Malmquist productivity index (14) is smaller (larger) than unity, it points to a productivity growth (decline). A similar interpretation applies to the separate components.

Following Ouellette and Vierstraete (2004), the sub-vector input-oriented Malmquist productivity index can now be defined as follows:

$$M_i^{t,t+1}(x_f^t, x_v^t, y^t, x_f^{t+1}, x_v^{t+1}, y^{t+1}) = \frac{DF_i^t(x_f^t, x_v^t, y^t)}{DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, y^{t+1})} \sqrt{\frac{DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, y^{t+1})}{DF_i^t(x_f^{t+1}, x_v^{t+1}, y^{t+1})} \cdot \frac{DF_i^{t+1}(x_f^t, x_v^t, y^t)}{DF_i^t(x_f^t, x_v^t, y^t)}}. \tag{15}$$

The interpretation of this sub-vector input-oriented Malmquist productivity index as well as its decomposition is exactly similar to the previous index (14).

Note that since the $DF_i(x, y) \leq 1$ and $DF_o(x, y) \geq 1$, the interpretation of equations (11) and (12) are inverse of the interpretation of equations (7) and (8). Moreover, when the input-oriented Malmquist productivity index (15) is smaller (larger) than unity, it points to a productivity growth (decline) while the interpretation of the output-oriented Malmquist productivity index (10) is exactly the inverse.

2.3 Plant Capacity Utilisation: Definitions

The informal definition of output-oriented plant capacity by Johansen (1968, p. 362) has been made operational by Färe, Grosskopf, and Valdmanis (1989) using a pair of output-oriented efficiency measures. We now recall the definition of their output-oriented plant capacity utilization (PCU). The output-oriented plant capacity utilization (PCU_o) in each period t is defined as:

$$PCU_o^t(x^t, x_f^t, y^t) = \frac{DF_o^t(x^t, y^t)}{DF_o^t(x_f^t, y^t)}, \tag{16}$$

where $DF_o^t(x^t, y^t)$ and $DF_o^t(x_f^t, y^t)$ are output efficiency measures including respectively excluding the variable inputs as defined before in (2) and (3).

Since $1 \leq DF_o^t(x^t, y^t) \leq DF_o^t(x_f^t, y^t)$, notice that $0 < PCU_o^t(x^t, x_f^t, y^t) \leq 1$. Thus, output-oriented plant capacity utilization has an upper limit of unity. This output-oriented plant capacity utilisation compares the maximum amount of outputs with given inputs to the maximum amount of outputs in the sample with potentially unlimited amounts of variable inputs, whence it is smaller than unity. It answers the question how the current amount of efficient outputs relates to the maximal possible amounts of efficient outputs. Following the terminology introduced by Färe, Grosskopf, and Valdmanis (1989) and Färe, Grosskopf, and Lovell (1994) one can distinguish between a so-called biased plant capacity measure $DF_o^t(x_f^t, y^t)$ and an unbiased plant capacity measure $PCU_o^t(x^t, x_f^t, y^t)$. Taking the ratio of efficiency measures eliminates any existing inefficiency and yields an in this sense cleaned concept of output-oriented plant capacity. This leads to the following output-oriented decomposition:

$$DF_o^t(x^t, y^t) = DF_o^t(x_f^t, y^t) \cdot PCU_o^t(x^t, x_f^t, y^t). \tag{17}$$

Thus, the traditional output-oriented efficiency measure $DF_o^t(x^t, y^t)$ can be decomposed into a biased plant capacity measure $DF_o^t(x_f^t, y^t)$ and an unbiased plant capacity measure $PCU_o^t(x^t, x_f^t, y^t)$.

Recently, Kerstens, Sadeghi, and Van de Woestyne (2019) have argued and empirically illustrated that the output-oriented plant capacity utilization $PCU_o^t(x^t, x_f^t, y^t)$ may be unrealistic in that the amounts of variable inputs needed to reach the maximum capacity outputs may simply be unavailable at either the firm or the industry level. This is linked to what Johansen (1968) called the attainability issue. Hence, Kerstens, Sadeghi, and Van de Woestyne (2019) define a new attainable output-oriented plant capacity utilization at the firm level. We now recall the definition of their attainable output-oriented plant capacity utilization ($APCU$) at level $\bar{\lambda} \in \mathbb{R}_+$ in each period t as follows:

$$APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda}) = \frac{DF_o^t(x^t, y^t)}{ADF_o^t(x_f^t, y^t, \bar{\lambda})}, \tag{18}$$

where the attainable output-oriented efficiency measure ADF_o^f at a certain level $\bar{\lambda} \in \mathbb{R}_+$ is defined by

$$ADF_o^t(x_f^t, y^t, \bar{\lambda}) = \max\{\varphi \mid \varphi \geq 0, 0 \leq \lambda \leq \bar{\lambda}, \varphi y^t \in P^t(x_f^t, \lambda x_v^t)\} \tag{19}$$

Again, for $\bar{\lambda} \geq 1$, since $1 \leq DF_o^t(x^t, y^t) \leq ADF_o^t(x_f^t, y^t, \bar{\lambda})$, notice that $0 < APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda}) \leq 1$. Also, for $\bar{\lambda} < 1$, since $1 \leq ADF_o^t(x_f^t, y^t, \bar{\lambda}) \leq DF_o^t(x^t, y^t)$, notice that $1 \leq APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda})$.

One can again distinguish between a so-called biased attainable plant capacity measure $ADF_o^t(x_f^t, y^t, \bar{\lambda})$ and an unbiased attainable plant capacity measure $APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda})$, whereby the latter is cleaned from any eventual inefficiency. This leads to the following output-oriented decomposition:

$$DF_o^t(x^t, y^t) = ADF_o^t(x_f^t, y^t, \bar{\lambda}) \cdot APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda}). \tag{20}$$

Therefore, the traditional output-oriented efficiency measure $DF_o^t(x^t, y^t)$ can be decomposed into a biased attainable plant capacity measure $ADF_o^t(x_f^t, y^t, \bar{\lambda})$ and an unbiased attainable plant capacity measure $APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda})$. Furthermore, Kerstens, Sadeghi, and Van de Woestyne (2019) note that if expert opinion cannot determine a plausible value, then it may be better to opt for the next input-oriented plant capacity measure that does not suffer from the attainability issue.

Cesaroni, Kerstens, and Van de Woestyne (2017) define a new input-oriented plant capacity measure using a pair of input-oriented efficiency measures. The input-oriented plant capacity utilization (PCU_i) in each period t is defined as:

$$PCU_i^t(x^t, x_f^t, y^t) = \frac{DF_i^t(x_f^t, x_v^t, y^t)}{DF_i^t(x_f^t, x_v^t, 0)}, \tag{21}$$

where $DF_i^t(x_f^t, x_v^t, y^t)$ and $DF_i^t(x_f^t, x_v^t, 0)$ are both sub-vector input efficiency measures reducing only the variable inputs relative to the technology, whereby the latter efficiency measure is evaluated at a zero output level.

Since $0 < DF_i^t(x_f^t, x_v^t, 0) \leq DF_i^t(x_f^t, x_v^t, y^t)$, notice that $PCU_i^t(x^t, x_f^t, y^t) \geq 1$. Thus, input-oriented plant capacity utilization has a lower limit of unity. This input-oriented plant capacity utilisation compares the minimum amount of variable inputs for given amounts of outputs with the minimum amount of variable inputs with output levels where production is initiated, whence it is larger than unity. It answers the question how the amount of variable inputs compatible with the initialisation of production must be scaled up to produce the current amount of outputs. Similar to the previous case, one can distinguish between a so-called biased plant capacity measure $DF_i^t(x_f^t, x_v^t, 0)$ and an unbiased plant capacity measure $PCU_i^t(x^t, x_f^t, y^t)$, the latter being cleaned of any prevailing inefficiency. This leads to the following input-oriented decomposition:

$$DF_i^t(x_f^t, x_v^t, y^t) = DF_i^t(x_f^t, x_v^t, 0) \cdot PCU_i^t(x^t, x_f^t, y^t). \tag{22}$$

Thus, the traditional sub-vector input-oriented efficiency measure $DF_i^t(x_f^t, x_v^t, y^t)$ is decomposed into a biased plant capacity measure $DF_i^t(x_f^t, x_v^t, 0)$ and an unbiased plant capacity measure $PCU_i^t(x^t, x_f^t, y^t)$.

It is important to notice that output- and input-oriented plant capacity notions differ with respect to the concept of attainability. The more recent input-oriented plant capacity notion is always attainable in that one can always reduce the amount of variable inputs such that one reaches an input set with zero output level. Indeed, due to the axiom of inaction it is normally possible to reduce variable inputs to reach zero production levels. Inaction simply means that one can halt production. Producing a zero output need not imply that no inputs are used. An example of zero production with positive amounts of variable inputs are maintenance activities in large industrial plants that bring production to a halt.

2.4 Integration of Plant Capacity Utilisation and Malmquist Productivity Indices

Following De Borger and Kerstens (2000), starting from the basic decomposition of the output-oriented Malmquist productivity index (10) into technical efficiency change and technical change one can isolate changes in capacity utilisation from technical efficiency change in the first component. In particular, incorporating (10) and (17) we can straightforwardly decompose the technical efficiency change component of the Malmquist productivity index $M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$ to obtain:

$$\begin{aligned} &M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \\ &\underbrace{\frac{DF_o^t(x_f^t, y^t)}{DF_o^{t+1}(x_f^{t+1}, y^{t+1})}}_{(i)} \cdot \underbrace{\frac{PCU_o^t(x^t, x_f^t, y^t)}{PCU_o^{t+1}(x^{t+1}, x_f^{t+1}, y^{t+1})}}_{(ii)} \underbrace{\sqrt{\frac{DF_o^{t+1}(x^{t+1}, y^{t+1})}{DF_o^t(x^{t+1}, y^{t+1})} \cdot \frac{DF_o^{t+1}(x^t, y^t)}{DF_o^t(x^t, y^t)}}}_{(iii)} . \end{aligned} \tag{23}$$

This expression (23) shows that productivity changes are the combined results of three separate phenomena. The first component (i) measures the change in technical efficiency assuming a constant degree of capacity utilization. Specifically, it evaluates the change in technical efficiency relative to a full capacity output technology between periods t and $t+1$.

The second component (ii) captures the change in the degree of plant capacity utilisation between t and $t+1$ while holding the level of technical efficiency constant. The third component (iii) is the same as in (10) and reflects pure technical change. When any of the components is larger (smaller) than unity, this indicates an improvement (deterioration) in the corresponding component, except for the component indicating changes in plant capacity utilization. For the latter, a number smaller (larger) than unity indicates an improvement (deterioration). In other words, this decomposition of the Malmquist productivity index provides a straightforward procedure for relating productivity growth to the dynamics of capacity utilization.

Similarly, we can now present a new decomposition of the technical efficiency change component of the attainable output-oriented Malmquist productivity index $M_i^{t,t+1}(x_f^t, x_v^t, y^t, x_f^{t+1}, x_v^{t+1}, y^{t+1})$ at level $\bar{\lambda}$. By incorporating (10) and (20) as follows:

$$M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1}) = \underbrace{\frac{ADF_o^t(x_f^t, y^t, \bar{\lambda})}{ADF_o^{t+1}(x_f^{t+1}, y^{t+1}, \bar{\lambda})}}_{(i)} \cdot \underbrace{\frac{APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda})}{APCU_o^{t+1}(x^{t+1}, x_f^{t+1}, y^{t+1}, \bar{\lambda})}}_{(ii)} \underbrace{\sqrt{\frac{DF_o^{t+1}(x^{t+1}, y^{t+1})}{DF_o^t(x^{t+1}, y^{t+1})} \cdot \frac{DF_o^{t+1}(x^t, y^t)}{DF_o^t(x^t, y^t)}}}_{(iii)}. \tag{24}$$

This expression (24) shows that productivity changes are the combined results of three separate statements. The first part (i) measures the change in technical efficiency assuming a constant degree of attainable capacity utilization. Specifically, it evaluates the change in technical efficiency relative to a full attainable capacity output technology between periods t and $t+1$. The second component (ii) captures the change in the degree of attainable plant capacity utilisation between t and $t+1$ while holding the level of technical efficiency constant. The third component (iii) is the same as in (10) and (23), and reflects pure technical change. When any of these components is larger (smaller) than unity, this indicates an improvement (deterioration) in the corresponding component, except for the component indicating changes in plant capacity utilization. For the latter, a number smaller (larger) than unity indicates an improvement (deterioration). In other words, this decomposition of the Malmquist productivity index provides a straightforward procedure for relating productivity growth to the dynamics of capacity utilization.

By analogy, we can now present a new decomposition of the technical efficiency change component of the input-oriented Malmquist productivity index $M_i^{t,t+1}(x_f^t, x_v^t, y^t, x_f^{t+1}, x_v^{t+1}, y^{t+1})$.

By incorporating (15) and (22), one obtains:

$$M_i^{t,t+1}(x_f^t, x_v^t, y^t, x_f^{t+1}, x_v^{t+1}, y^{t+1}) =$$
$$\underbrace{\frac{DF_i^t(x_f^t, x_v^t, 0)}{DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, 0)}}_{(i)} \cdot \underbrace{\frac{PCU_i^t(x^t, x_f^t, y^t)}{PCU_i^{t+1}(x^{t+1}, x_f^{t+1}, y^{t+1})}}_{(ii)} \underbrace{\sqrt{\frac{DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, y^{t+1})}{DF_i^t(x_f^{t+1}, x_v^{t+1}, y^{t+1})} \cdot \frac{DF_i^{t+1}(x_f^t, x_v^t, y^t)}{DF_i^t(x_f^t, x_v^t, y^t)}}}_{(iii)}. \tag{25}$$

This expression (25) shows that productivity changes are the combined results of three separate phenomena. The first component (i) measures the change in technical efficiency assuming a constant degree of capacity utilization. Specifically, it evaluates the change in technical efficiency relative to a full capacity input technology between periods t and $t+1$. The second component (ii) captures the change in the degree of input-oriented plant capacity utilisation between t and $t+1$ while holding the level of technical efficiency constant. The third component (iii) is the same as in (15) and reflects pure technical change. When any of these components is smaller (larger) than unity, this indicates an improvement (deterioration) in the corresponding component, except for the component indicating changes in plant capacity utilization. For the latter, a number larger (smaller) than unity indicates an improvement (deterioration). In other words, this decomposition of the Malmquist productivity index provides a straightforward procedure for relating productivity growth to the dynamics of capacity utilization.

Note that for all these three Malmquist index decompositions (23), (24), and (25) are defined relative to variable returns to scale technologies, which limits the scope for further decompositions (see Zofío (2007)). Note furthermore that for these three Malmquist index decompositions (23), (24), and (25) there is always the possibility that the frontier change component is infeasible. The incidence of infeasibilities is determined by the empirical data configurations (see Kerstens and Van de Woestyne (2014) for more details). Finally, to save space details on the mathematical programming problems needed to compute all components of these Malmquist index decompositions (23), (24), and (25) are available in Appendix A.

3 Efficiency and Productivity in Tourism: A Succinct Review

Tourism has become a major part of some countries economic activities. The notion of productivity is complex and multi-faceted to apply in the tourism sector with its mixture of complementary private and public sector activities (see, e.g., Ritchie and Crouch (2003) for a review). There is a rather substantial literature using traditional average practice specifications of technology and limiting itself to partial productivity indicators (for example, McMahon (1994)). Furthermore, a wide range of methodologies has been used to gauge productivity changes. The work by Blake, Sinclair, and Soria (2006) is one example that uses computable general equilibrium models to evaluate productivity change.

A lot of recent studies have opted for studying the efficiency and productivity based on best practice frontier technology specifications. While it is fair to say that the deterministic, nonparametric frontier methods (often denoted as Data Envelopment Analysis models) seem to be most popular in the tourism field at large, also stochastic frontier analysis is being used on a regular basis (e.g., Anderson, Fish, Xia, and Michello (1999)), and even Bayesian approaches are occasionally employed (for instance, Assaf and Tsionas (2018)). Furthermore, for each of these basic frontier methods, a plethora of methodological refinements is available: for instance, the basic deterministic, nonparametric frontier methods have been extended into a metafrontier to envelop groups of frontiers in, e.g., Huang, Ting, Lin, and Lin (2013).

Most existing published efficiency studies in tourism have focused on privately owned facilities. Popular themes of study have been the efficiency of hotels (e.g., Barros, Peypoch, and Solonandrasana (2009)), restaurants (for instance, Banker and Morey (1986)), and travel agencies (e.g., Sellers-Rubio and Nicolau-Gonzálbez (2009)), among others. Alternatively, some efficiency studies have attempted to evaluate the performance of public sector tourism infrastructures like museums (e.g., Mairesse and Vanden Eeckaut (2002)), national parks (for instance, Bosetti and Locatelli (2006)), or theaters (e.g., Last and Wetzel (2010)).

There are also proposals to analyse the efficiency and productivity in the tourism sector at an aggregate level (e.g., Peypoch and Solonandrasana (2008)). Furthermore, one can mention some other isolated attempts to judge certain aspects of tourism policies at the macro level. For example, Botti, Goncalves, and Ratsimbanierana (2012) develop a mean-variance portfolio approach to help destination management organizations minimize variance and maximize return of inbound tourism. In a similar vein, Botti, Peypoch, Robinot, Solonadrasana, and Barros (2009) analyse the tourism destination competitiveness of French regions. For instance, Wober and Fesenmaier (2004) assess the efficiency of advertising budgets of state tourism offices in the United States. As a final example, Cracolici, Nijkamp, and Rietveld (2008) evaluate 103 Italian regions for the single year 2001: the single output bed-nights relative to population is related to proxies for cultural and historical capital, human capital, and labour inputs.

Focusing on the hotel industry, perhaps the seminal article is Morey and Dittman (1995) who evaluate the performance of 54 hotels of a national chain in the USA. Since this classic article a wide variety of efficiency assessments have been made for hotels and hotel chains in a number of countries. Examples of more recent applications at the national or regional level include: Huang, Mesak, Hsu, and Qu (2012) for China; Zhang, Botti, and Petit (2016) for France; Bosetti, Cassinelli, and Lanza (2007) for Italy; Barros (2005) for Portugal; Assaf and Cvelbar (2011) for Slovenia; Devesa and Peñalver (2013) for Spain; Hathroubi, Peypoch, and Robinot (2014) for Tunesia; Anderson, Fish, Xia, and Michello (1999) for the US; among others. To the best of our knowledge, Moriarty (2010) is the only article analysing output-oriented plant capacity, among others, for the New Zealand hotel sector at large.

Reviewing the literature, there are a rather limited number of studies focusing on a dynamic productivity analysis of hotels over a minimal time period. Since these studies are relevant for our own study, we succinctly summarise key research findings. Sun, Zhang, Zhang, Ma, and Zhang (2015) evaluate an output-oriented MPI to Chinese regions from 2001 to 2009 and find positive productivity change driven by technological change and some regional heterogeneity. Barros, Peypoch, and Solonandrasana (2009) apply a Luenberger productivity indicator to 15 Portugese hotels for the 1998-2004 period and find an positive average productivity change that is mainly due to technological change. obtain, among others, a weak positive productivity change which is mainly driven by positive technological change.

4 Data and Specification

Tourism industry has grown rapidly in recent years. It has even become one of the most crucial sectors in China. With the booming of tourism, a fierce competition has been imposed on the hospitality industry. Also, substantial investment have been made in the industry. For instance, total assets have increased from 653 billion RMB in 2008 to 1 215 billion RMB in 2016. However, the profit versus total asset rate has dropped from 20.75% to 17.35% between 2008 and 2016. Thus, operational efficiency seems to have become a major concern for the Chinese accommodation industry.

In the tourism literature, there is still some argument about whether star-rated hotels can be regarded as representative of the hospitality industry (see Núñez-Serrano, Turrión, and Velázquez (2014)). Hence, in this paper our models are applied to the Chinese accommodation industry above a minimal designed size, since this is the most comprehensive range of data available.[3] In the sequel, we first discuss the specification of inputs and outputs in the technology in more detail. Then, we present some descriptive statistics for the sample.

4.1 Specification: Choice of Inputs and Outputs

One characteristic of the accommodation industry is the multitude of activities. The majority of hotels provides not only accommodation, but also other supplementary services, such as catering and entertainment. In our study, we consider that hotels propose three main services: (i) accommodation activity (rooms), (ii) food and beverage services (meals), and (iii) other services such as entertainment. Then, following past studies the revenues generated from each of these three activities are used to reflect the hotels' profitability (e.g., Hu, Chiu, Shieh, and Huang (2010)). As for the inputs, in total three variable inputs and one fixed input are considered. The three variable inputs are: (i) number of employees represents the indispensable core asset that make the hotels capable to offer all three services; (ii) current assets represent the hotel's capacity to support its daily operation; and (iii) main business costs describe the hotel's main expenses on its business activities. In addition, we follow economic tradition by considering as a single fixed input: (iv) total fixed assets reflect the hotel's support to its development and future extension.

4.2 Descriptive Statistics

To ensure the homogeneity of the hotel technology in this study, we have selected a sample of 31 provinces in mainland China with a period spanning from 2008 to 2016. As such, this represents a unique opportunity to evaluate the whole Chinese accommodation industry over a rather long period of time. To obtain the data for our inputs and outputs, we make use of a commercial database: the Wind Database. We have four inputs: (i) number of employees (in 10 000 persons); (ii) current assets (in CNY 100 million); (iii) main business cost (in CNY 100 million); and (iv) fixed assets (in CNY 100 million). Obviously, the first tree assets are variable inputs, while the fourth input is fixed following economic tradition. Note that also Barros, Dieke, and Santos (2010) consider fixed assets as a quasi-fixed input. We also have three outputs: (v) revenues from meals (in CNY 100 million); (vi) revenues from rooms (in CNY 100 million); and (vii) other revenues (in CNY 100 million).

As an initial step, some descriptive statistics for inputs and outputs are presented in Table

[3]According to the National Bureau of Statistics of China, the scope of statistics is the star-rated hotels and the accommodation industry activity units with annual operating income above at least 2 million yuan.

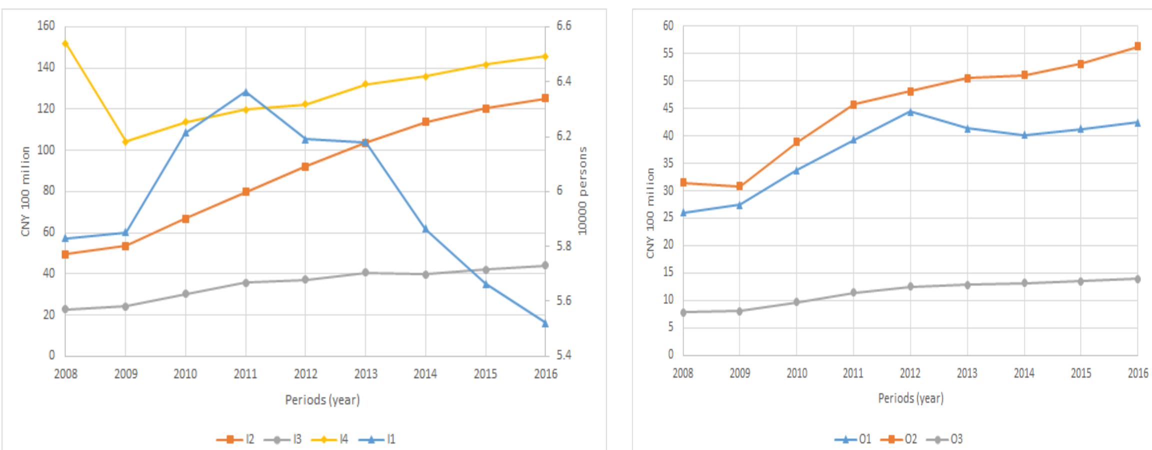
1 to contextualize our analysis: trimmed mean, standard deviation (St. Dev.), and minimum (Min.) and maximum (Max.). One observes a rather wide range of variation, which is not uncommon for this aggregate level of analysis.

Table 1: Descriptive statistics for Chinese hotels (2008-2016)

		Trimmed mean[a]	St. Dev.	Min.	Max.
I1: No. of Employees (10 000 persons)	variable input	5.879754	5.646	0.4202	30.6915
I2: Current Assets (CNY 100 million)	variable input	84.70244	110.639	2.2	667.0269
I3: Main Business Cost (CNY 100 million)	variable input	34.42739	35.447	1	202.1725
I4: Fixed Assets (CNY 100 million)	fixed input	124.8953	129.354	11.7	696.8
O1: Revenues from Meals (CNY 100 million)	output	36.32575	38.866	0.8	187.1
O2: Revenues from Rooms (CNY 100 million)	output	43.35068	49.699	1.3	271.9885
O3: Other Revenues (CNY 100 million)	output	10.54255	17.222	0.4	91.6624

Note: [a]10% trimming level.

To depict the evolution of the trimmed mean in Table 1 of all inputs and outputs over the different years, we use Figures 1a and 1b that trace the inputs and outputs , respectively. Note that since the first input, i.e., number of employees (No. of Employees), is reported in terms of 10000 persons, it is plotted against the secondary axis on the right-hand side in Figure 1a.



(a) Inputs

(b) Outputs

Figure 1: Inputs and outputs changes over different periods.

Figure 1a depicts the average evolution of the inputs. Clearly, two input variables have increased substantially and in a monotonous way: the number of current assets and main costs have increased by 152% and 92.92% respectively. However, for the number of employees we notice that after an initial increase there is a substantial 6.8% drop. While for the fixed-assets, there is a one year substantial drop and then a continuous increase that almost compensates this initial drop. This reduction in overall fixed assets is due to a shift in investments towards high-end hotels in major tourism provinces such as Beijing, Guangdong, Jiangsu, Shanghai, Shandong and Zhejiang.[4] Looking at the evolution of the inputs over time in Figure 1a, it is not straightforward to empirically determine the fixed nature of some of these inputs, partially because of the aggregate nature of the data.[5] All these numbers show that the Chinese accommodation industry has tried to rationalize its input usage, revealing that operational efficiency is clearly an objective for the policy makers involved.

Figure 1b shows the evolution of the three outputs over time. First, we observe that all three time series increase almost monotonously. Second, it is clearly visible that the shares of the room services and other services become relatively speaking more important. In fact, the revenue share of meals decreases slightly.

5 Empirical Results

5.1 Results for Output-Oriented Malmquist Productivity Index

Table 2 reports the basic descriptive statistics for the components of the output-oriented MPI (23) from 2008 to 2016. In this table, the first eight columns list the results under C, while the last eight columns report the results under NC. The rows of Table 2 include four parts. In each part, the first line lists the number of feasible observations for the components of the output-oriented Malmquist productivity index, while the next four lines list descriptive statistics: geometric mean, standard deviation, minimum and maximum. Note that the use of a geometric mean ensures that the multiplicative decomposition holds true exactly. Part (i) reports basic descriptive statistics for the first component of (23), i.e., the component $\frac{DF_o^t(x_f^t, y^t)}{DF_o^{t+1}(x_f^{t+1}, y^{t+1})}$ which shows the change in technical efficiency (or rather, the change in the degree of biased plant capacity utilisation) between periods t and $t+1$. To facilitate comparison between Part (ii) and other parts, we report the basic descriptive statistics for the

[4] According to the China National Bureau of Statistics, the fixed assets for star-rated hotels has increased 25.45% during the period 2008-2015.

[5] As a complementary empirical perspective on the eventual fixed nature of some of the inputs, we first have counted the number of changes among the provinces for each input over the years. We find that all of the inputs change for all 31 provinces over all years. Thus, this is not helpful. Furthermore, in Appendix B we report additional descriptive statistics on the change of all inputs measured in absolute percentage points over successive years. While all the inputs are somewhat volatile over the period, on average the first and fourth inputs are the least volatile. Thus, from an empirical point of view the number of employees (I1) is least volatile followed by the fixed input of fixed assets (I4). Hence, our choice of taking only fixed assets as a fixed input mainly relies on a priori economic arguments, and it could from an empirical point of view also be good to test the impact of adding the number of employees as another fixed input.

inverse of the second component of (23), i.e., $\frac{PCU_o^{t+1}(x^{t+1},x_f^{t+1},y^{t+1})}{PCU_o^t(x^t,x_f^t,y^t)}$ that shows the change in the degree of unbiased plant capacity utilisation between periods $t+1$ and t. Finally, part (iii) shows the third component of (23) that is related to the shift of the production frontier. Finally, the last part states the output-oriented MPI (23) as the product of its components. Thus, all components can be interpreted in the same way: a component larger than unity indicates growth, while a component smaller than unity indicates decline.

Table 2: Descriptive statistics for the output-oriented MPI and its components

	Convex								**Nonconvex**							
	2008	2009	2010	2011	2012	2013	2014	2015	2008	2009	2010	2011	2012	2013	2014	2015
	2009	2010	2011	2012	2013	2014	2015	2016	2009	2010	2011	2012	2013	2014	2015	2016
Part (i)																
Geometric mean	0.980	1.025	0.983	1.041	0.978	0.933	0.974	0.999	1.018	1.008	0.998	0.992	1.012	0.987	0.980	0.976
St. Dev.	0.169	0.086	0.090	0.128	0.116	0.128	0.111	0.131	0.119	0.046	0.050	0.078	0.076	0.072	0.074	0.118
Min	0.639	0.875	0.798	0.809	0.661	0.663	0.743	0.782	0.717	0.893	0.860	0.725	0.916	0.738	0.745	0.681
Max	1.566	1.253	1.237	1.353	1.175	1.426	1.248	1.385	1.440	1.201	1.167	1.212	1.294	1.191	1.232	1.291
Part (ii) (inverse)																
Geometric mean	0.982	1.032	0.981	1.041	0.992	0.927	0.970	1.000	1.018	1.008	0.998	0.992	1.012	0.987	0.980	0.976
St. Dev.	0.164	0.093	0.086	0.122	0.105	0.101	0.109	0.126	0.119	0.046	0.050	0.078	0.076	0.072	0.074	0.118
Min	0.655	0.880	0.813	0.809	0.681	0.663	0.728	0.782	0.717	0.893	0.860	0.725	0.916	0.738	0.745	0.681
Max	1.566	1.345	1.198	1.328	1.212	1.243	1.248	1.385	1.440	1.201	1.167	1.212	1.294	1.191	1.232	1.291
Part (iii)																
# Infeasible	3	2	2	2	2	2	2	3	3	2	2	3	3	2	2	3
Geometric mean	1.122	1.057	1.020	1.030	0.887	0.977	0.995	1.008	1.166	0.880	1.002	0.953	0.808	0.995	1.009	1.004
St. Dev.	0.077	0.077	0.060	0.113	0.071	0.043	0.045	0.039	0.151	0.165	0.158	0.245	0.152	0.239	0.219	0.144
Min	0.920	0.898	0.881	0.899	0.622	0.878	0.937	0.920	0.999	0.491	0.650	0.621	0.499	0.811	0.522	0.441
Max	1.325	1.243	1.113	1.525	0.997	1.053	1.155	1.094	1.558	1.170	1.226	1.749	1.026	2.163	1.964	1.303
MPI																
# Infeasible	3	2	2	2	2	2	2	3	3	2	2	3	3	2	2	3
Geometric mean	1.120	1.049	1.022	1.030	0.873	0.984	1.000	1.006	1.166	0.880	1.002	0.953	0.808	0.995	1.009	1.004
St. Dev.	0.079	0.082	0.066	0.124	0.092	0.068	0.051	0.054	0.151	0.165	0.158	0.245	0.152	0.239	0.219	0.144
Min	0.914	0.898	0.872	0.840	0.622	0.799	0.876	0.914	0.999	0.491	0.650	0.621	0.499	0.811	0.522	0.441
Max	1.325	1.243	1.113	1.525	1.057	1.186	1.155	1.154	1.558	1.170	1.226	1.749	1.026	2.163	1.964	1.303

Analysing the results in Table 2, we can infer the following conclusions. First, on average the change in the degree of biased plant capacity utilisation (part (i)) is rather close to the degree of unbiased plant capacity utilisation (part (ii)) for all periods under C. These two components turn out to be identical under NC. This is due to the fact that the numerator of plant capacity utilisation is always unity for all observations under NC: $DF_o^t(x^t, y^t) = 1$. Given that the biased plant capacity utilisation measures $DF_o^t(x_f^t, y^t) \leq 1$ are always smaller than unity, this leads to this particular result. Second, under C for the periods $2009-2010$ and $2011-2012$ the degree of biased and unbiased plant capacity utilisation improve. Under NC both the degree of biased and unbiased plant capacity utilisation improve in periods $2008-2009$, $2009-2010$ and $2012-2013$. Third, for the average of the frontier change (part (iii)), we obtain a minimum amount in period $2012-2013$ and a maximum amount in the period $2008-2009$ under both C and NC. Also, the average of part (iii) is larger than the averages of parts 1 and 2 for all periods, except for periods $2011-2012$ and $2012-2013$ under both C and NC and for period $2009-2010$ under NC only.

Note that there are a few computational infeasibilities for the frontier change component: this problem is identical for C and NC, except for the years $2011 - 2012$ and $2012 - 2013$ where there is one more infeasibility under NC.

Table 3 reports the Spearman rank correlation coefficients for components of the output-oriented MPI (23). This table is structured as follows. First, components on the diagonal (in bold) depict the rank correlation between the C and NC cases. Second, the components under the diagonal show the rank correlation between NC components, and the components above the diagonal show the rank correlation between the C components.

Table 3: Spearman rank correlations for the output-oriented MPI (23) and its components

		Part (i)	Part (ii)(inverse)	Part (iii)	MPI
Part (i)	Correlation Coefficient	**0.290****	0.950**	0.220**	0.294**
	N	**248**	248	230	230
Part (ii)(inverse)	Correlation Coefficient	*1.000***	**0.283****	0.201**	0.185**
	N	*248*	**248**	230	230
Part (iii)	Correlation Coefficient	*0.019*	*0.019*	**0.518****	0.906**
	N	*228*	*228*	**228**	230
MPI	Correlation Coefficient	*0.019*	*0.019*	*1.000***	**0.489****
	N	*228*	*228*	*228*	**228**

The following three conclusions emerge from studying Table 3. First, for the C results, one can observe that part (iii) and MPI have a very high rank correlation and part (i) and inverse of part (ii) have the highest rank correlation among all components of the output-oriented MPI. Second, for the NC results, part (iii) and MPI have a unity rank correlation while also part (i) and inverse of part (ii) have a unity rank correlation. Third, comparing C and NC results, the highest rank correlations are for MPI compared to part (iii), while parts 1 and 2 correlate weakly.

5.2 Results for Input-Oriented Malmquist Productivity Index

Table 4 is structured in a way similar to Table 2. This table reports the basic descriptive statistics for components of the input-oriented MPI (25) from 2008 to 2016. Analogously to subsection 5.1 , all components can now be interpreted in the same way: a component smaller than unity indicates growth, while a component larger than unity indicates decline.

Analysing the results in Table 4, one can draw the following conclusions. First, on average the change in the degree of biased plant capacity utilisation (part (i)) is almost close to the degree of unbiased plant capacity utilisation (part (ii)) for all periods under C while they are identical under NC. This is due to the fact that the numerator of input-oriented

Table 4: Descriptive statistics for the input-oriented MPI (25) and its components

	Convex								**Nonconvex**							
	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016
Part (i)																
Geometric mean	0.963	1.106	0.959	0.880	1.045	0.945	0.947	0.927	0.963	1.096	0.968	0.880	1.045	0.940	0.949	0.930
St. Dev.	0.123	0.101	0.116	0.147	0.366	0.045	0.069	0.072	0.123	0.123	0.140	0.147	0.366	0.061	0.066	0.072
Min	0.839	0.869	0.776	0.313	0.891	0.844	0.747	0.783	0.839	0.654	0.776	0.313	0.891	0.698	0.747	0.783
Max	1.528	1.300	1.309	1.239	3.028	1.044	1.048	1.221	1.528	1.300	1.416	1.239	3.028	1.044	1.048	1.221
Part (ii) (inverse)																
Geometric mean	0.955	1.102	0.960	0.874	1.034	0.953	0.954	0.923	0.963	1.096	0.968	0.880	1.045	0.940	0.949	0.930
St. Dev.	0.127	0.108	0.120	0.156	0.376	0.062	0.076	0.085	0.123	0.123	0.140	0.147	0.366	0.061	0.066	0.072
Min	0.709	0.879	0.766	0.313	0.779	0.817	0.733	0.743	0.839	0.654	0.776	0.313	0.891	0.698	0.747	0.783
Max	1.480	1.460	1.309	1.257	3.028	1.066	1.079	1.221	1.528	1.300	1.416	1.239	3.028	1.044	1.048	1.221
Part (iii)																
# Infeasible	26	12	11	13	13	10	7	7	30	29	29	29	28	29	28	25
Geometric mean	0.987	0.963	0.977	0.986	1.183	1.055	1.017	1.000	1.078	0.853	1.003	1.016	1.061	1.055	1.076	1.036
St. Dev.	0.070	0.082	0.057	0.118	0.148	0.095	0.082	0.081	0.000	0.268	0.066	0.110	0.047	0.090	0.110	0.056
Min	0.899	0.775	0.847	0.636	1.009	0.953	0.745	0.821	1.078	0.685	0.957	0.941	1.012	0.993	0.973	0.964
Max	1.086	1.103	1.120	1.199	1.702	1.392	1.180	1.237	1.078	1.064	1.051	1.097	1.106	1.120	1.193	1.115
MPI																
# Infeasible	26	12	11	13	13	10	7	7	30	29	29	29	28	29	28	25
Geometric mean	0.984	0.969	0.976	0.987	1.208	1.050	1.007	1.006	1.078	0.853	1.003	1.016	1.061	1.055	1.076	1.036
St. Dev.	0.069	0.092	0.067	0.134	0.177	0.111	0.091	0.090	0.000	0.268	0.066	0.110	0.047	0.090	0.110	0.056
Min	0.899	0.800	0.864	0.636	0.910	0.911	0.745	0.821	1.078	0.685	0.957	0.941	1.012	0.993	0.973	0.964
Max	1.092	1.106	1.136	1.208	1.702	1.392	1.181	1.237	1.078	1.064	1.051	1.097	1.106	1.120	1.193	1.115

plant capacity utilisation is always unity for all observations under NC: $DF_i^t(x_f^t, x_v^t, y^t) = 1$. Given that the biased input-oriented plant capacity utilisation measures $DF_i^t(x_f^t, x_v^t, 0) \leq 1$ are always smaller than unity, this leads to this particular result. Second, only for the periods $2009-2010$ and $2012-2013$ the biased and unbiased capacity utilisation indices are larger than unity, indicating an improvement, while for all other periods these deteriorate under both C and NC. Third, the average frontier change (part (iii)) is minimal in period $2009-2010$, improves till period $2012-2013$, and then decreases. Also, the average frontier change is larger than the average changes in parts 1 and 2 for all periods, except for periods $2009-2010$ under C and NC.

Note that under NC the number of computational infeasibilities for the frontier change is much higher than under C. While the NC frontier technology leads to a closer fit with the data and results in a more precise measurement of local technical change, this precision comes at the cost of an increased possibility of infeasibilities (see also Kerstens and Van de Woestyne (2014)).

Table 5 reports the Spearman rank correlation coefficients for component of the input-oriented MPI (25). This table is structured in a similar way to Table 3. First, components on the diagonal (in bold) depict the rank correlation between the C and NC cases. Second, the components under the diagonal show the rank correlation between NC components, and the components above the diagonal show the rank correlation between the C components.

Table 5: Spearman rank correlations for the input-oriented MPI (25) and its components

		Part (i)	Part (ii) (inverse)	Part (iii)	MPI
Part (i)	Correlation Coefficient	**0.179***	0.901**	0.238**	0.179*
	N	**149**	248	149	149
Part (ii) (inverse)	Correlation Coefficient	*1.000***	**0.892****	0.158	0.086
	N	*248*	**248**	149	149
Part (iii)	Correlation Coefficient	*-0.096*	*0.096*	**0.442***	0.819**
	N	*21*	*21*	**21**	149
MPI	Correlation Coefficient	*-0.096*	*0.096*	*1.000***	**0.181**
	N	*21*	*21*	*21*	**21**

The following three conclusions emerge from studying Table 5. First, for the C results, one can observe that part (iii) and MPI have a very high rank correlation and part (i) and inverse of part (ii) have the highest rank correlation among all components of the input-oriented MPI. Second, for the NC results, part (iii) and the input-oriented MPI have a unity rank correlation while also part (i) and inverse of part (ii) have a unity rank correlation. Third, comparing C and NC results, the highest rank correlations are for Part (ii) followed by part (iii) and then the other components.

5.3 Comparing Output- and Input-Oriented Malmquist Productivity Indices and Some Further Results

To compare output- and input-oriented Malmquist productivity indices, one can deduce the following conclusions. First, the output-oriented MPI moves inverse to the input-oriented MPI in all periods except for the two last ones under C. Thus, there is agreement on the same pattern of growth and decline, except for the two last periods under C. This inverse relationship is somewhat mitigated under NC: only in the 3 periods $2011 - 2012$ till $2013 - 2014$ this inverse relation holds true. Thus, there is less agreement on patterns of growth and decline under NC. Thus, overall output- and input-oriented MPI do not necessarily measure the same things. Second, the frontier change component (part (iii)) moves in an inverse way when comparing both MPI indices under C for almost all periods except the last one, while it moves in an inverse way only for the periods $2011 - 2012$ till $2013 - 2014$ under NC. Thus, there is less agreement on patterns of frontier change under NC. Overall, output- and input-oriented frontier change do not necessarily measure the same things all the time. Third, the plant capacity utilisation change (part (ii)) moves in an inverse way when comparing both MPI indices under C for the periods $2011 - 2012$ and $2012 - 2013$; while it moves in an inverse way only for the periods $2008 - 2009$ under NC. Thus, there is less agreement on patterns of plant capacity utilisation change under NC. Thus, output- and input-oriented plant capacity utilisation change are not necessarily measuring things exactly the same all the time.

Table 6: Spearman rank correlations among components of output- and input-oriented MPI (23) and (25)

		Part (i)	Part (ii)	Part (iii)	MPI
Convex	Correlation Coefficient	-0.113	-0.088	0.945**	0.952**
	N	248	248	141	141
Nonconvex	Correlation Coefficient	-0.092	-0.092	0.044	0.044
	N	248	248	20	20

Table 6 reports the Spearman rank correlation coefficients among the components of the output- and input-oriented MPI under C and NC separately. To calculate this Spearman rank correlation coefficients, we ensure that all components of the input-oriented MPI (15) and output-oriented MPI (10) have the same interpretation. Therefore, we invert the second part of the output-oriented MPI (10) such that all output-oriented components have the same interpretation. Furthermore, we invert the input-oriented MPI (15) as well as its first and third components such that these are in line with the second component. Thus, all output- and input-oriented MPI and components now are interpreted as follows: when any of these components is larger (smaller) than unity, this indicates an improvement (deterioration) in the corresponding component.

The following two conclusions emerge from studying Table 6. First, for the C results, one can observe that the highest rank correlations are for output- and input-oriented MPI followed by part (iii). Second, for the NC results, all components of the output- and input-oriented MPI experience very low rank correlations.

In most of the literature computing Malmquist productivity indices, it is simply assumed that the observed components are somehow statistically significant. However, the hotel industry is a service sector and there are some a prior indications that the quaternary sector of the economy may suffer from Baumol's cost disease: a rise of salaries in jobs that experience no or low increase of (labour) productivity. Furthermore, the hotel sector is rather sensitive to the business cycle. Finally, some hotel studies like Assaf and Barros (2011) do report overall close to stagnant productivity growth: for a sample of 31 hotel chains over the period 2006 to 2008 about half experience productivity decline, while the other half benefits from productivity growth. A glance at our own Tables 2 and 4 suffices to see that the MPI hovers very closely around unity.

Therefore, it can be meaningful to perform a t-test to evaluate whether the average

MPI as well as its components are significantly different from unity or not. We report the corresponding p-values in Table 7. If the p-value is greater than 0.05, then it means that we cannot reject the null hypothesis that the population average equals unity at the 5% significance level. If the p-value is less than or equal to 0.05, then it means that we reject this same null hypothesis at the 5% significance level: the average MPI differs from unity.

Table 7: T-test whether MPI and its components differ from unity

			Part (i)	Part (ii)	Part (iii)	MPI
Convex	$M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$	t-test	-0.497	2.193	2.4	2.057
		p-value	0.62	0.029	0.017	0.041
		N	248	248	230	230
	$M_i^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$	t-test	-1.811	3.954	2.85	2.836
		p-value	0.071	0	0.005	0.005
		N	248	248	149	149
Nonconvex	$M_o^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$	t-test	-0.054	1.312	-0.442	-0.442
		p-value	0.957	0.191	0.659	0.659
		N	248	248	228	228
	$M_i^{t,t+1}(x^t, y^t, x^{t+1}, y^{t+1})$	t-test	-1.715	3.777	1.362	1.362
		p-value	0.088	0	0.188	0.188
		N	248	248	21	21

Based on the results of Table 7, we can infer two conclusions. First, for the convex input- and output-oriented MPI and their components, the p-value of the t-test are less than 0.05, except for part (i). This indicates that under convexity for both input- and output-oriented MPIs, the average MPIs, and their parts (ii) and (iii) differ from unity. Thus, there is obvious improvement or deterioration in productivity. Second, for the nonconvex input- and output-oriented MPI and their components, the p-value of the t-test is bigger than 0.05, except for part (ii) of the input-oriented MPI. This indicates that under nonconvexity for both input- and output-oriented MPIs, the average MPI, and their components do not differ from unity. Thus, there is no obvious improvement or deterioration in productivity. Overall, it is interesting to observe that the precise conclusion seems to be very much conditioned on the convexity axiom.

In a first attempt to provide some external validation for the different PCU notions used in this contribution, we compare these with a more traditional non-frontier capacity utilisation measure in the hotel industry. The only relevant information available to us is the average occupancy rate. This average occupancy rate equals the number of rooms (nights) actually sold divided by the number of rooms (nights) available within the relevant time period at the provincial level. Table 8 contains the Spearman rank correlations between the average occupancy rate and the levels of the output- and input-oriented PCU notions under both convexity and nonconvexity.

The Spearman rank correlations between output- and input-oriented PCUs on the one hand and average occupancy rate on the other hand for each separate year are reported in the first nine rows of Table 8. In the two last lines we report the Spearman rank correlations when we consider on the one hand all observations over all years listed above and on the other hand an intertemporal frontier (amalgamating all observations over all years in one frontier). While the year by year frontiers are needed for the MPI and its decomposition, the intertemporal frontier is solely computed for the purpose of comparing the PCUs with the average occupancy rate.

Table 8: Spearman rank correlations among components of output- and input-oriented PCU and average occupancy rate

	Convex		Nonconvex	
Periods	$PCU_o(x, x_f, y)$	$PCU_i(x, x_f, y)$	$PCU_o(x, x_f, y)$	$PCU_i(x, x_f, y)$
2008	0.329	0.293	0.266	0.281
2009	-0.098	0.189	0.054	0.191
2010	0.217	0.572**	0.253	0.554**
2011	0.288	0.567**	0.289	0.552**
2012	0.228	0.513**	0.229	0.502**
2013	0.516**	0.688**	0.227	0.685**
2014	0.427**	0.667**	-0.022	0.636**
2015	0.491**	0.714**	-0.027	0.723**
2016	0.344	0.748**	0.882	0.72**
Union of all year-by-year frontier estimates	0.324**	0.539**	0.173**	0.525**
Intertemporal frontier estimates	0.113	0.531**	0.125*	0.493**

Several conclusions emerge from looking at Table 8. First, a bit surprisingly the input-oriented PCU notion correlates slightly better than the output-oriented PCU notion with average occupancy rate. Second, the NC results have slightly lower rank correlations than the C results. Third, when we consider the union of all year-by-year frontier estimates, there is a significant relation among all PCU notions with the average occupancy rate. However, one can observe that the input-oriented plant capacity notion correlates better than the output-oriented plant capacity notion with average occupancy rate under both C and NC cases. Finally, when we consider the intertemporal frontier, there is a significant relation between average occupancy rate with all PCU notions, except the convex output-oriented PCU notion. Thus, the results show that the input-oriented PCU notion, similar to the year-by-year frontiers, correlates better than the output-oriented PCU notion with the average occupancy rate under both C and NC cases. Overall, this indicates that these PCU notions do have some substantial relation with a more traditional non-frontier capacity utilisation measure in the hotel industry.

5.4 Robustness Check

To investigate the sensitivity of our findings, we perform a bootstrap on the four possible cases (i.e., input- vs output-oriented combined with convex vs nonconvex). For the convex cases, we follow the procedure described in Simar and Wilson (1999), but suitably adapted to our short-run sub-vector efficiency measures and the accompanying MPI components mentioned in (23) and (25). Since these components are new, no existing bootstrapping software can be employed. Therefore, the bootstrap routines have been developed from scratch in Python.

For the technical details about the original procedure, we refer the interested reader to Simar and Wilson (1999) for all details. But, bootstrapping according to these authors can -roughly speaking- be summarized as follows. Using the variation present in the efficiency measures derived from the available observations combined with a kernel estimator based on the bivariate normal density function, create perturbed inputs (outputs) for the input-oriented (output-oriented) case. This is done a number of B times: we consider the customary $B = 2000$ used in a lot of other bootstrap studies. Since the data at hand consists of panel data, there are serial correlations that must be preserved when creating these perturbations. For each of these perturbed inputs and outputs, sequences of the required efficiency measures and related MPI components are then computed (i.e., the bootstrap sequences). Finally, the median is taken of these B bootstrap sequences and a 95% confidence interval can be obtained by using the percentile method among others (i.e., by considering the interval with boundary points the minimum and maximum of the ordered bootstrap sequence after cutting off 2.5% at both sides). Since this process has to be repeated for all observations and all time periods, it is rather computationally challenging.

For the nonconvex cases, to the best of our knowledge no satisfying bootstrap methods have been described in the literature. Only Jeong and Simar (2006) develop a method to bootstrap nonconvex efficiencies, but it requires a type of Delaunay triangulation (i.e., the multidimensional counterpart of linear interpolation). Given the complexity of the procedure and the fact that it convexifies a nonconvex technology to some extent, we opt not to go down this road. But, simply applying the same strategies developed for the convex cases effectively does not yield meaningful results in the nonconvex cases either. The main obstacle is the lack of variation in the efficiency measures obtained from the original observations. In fact, for some of the available years, all observations are (sub-vector) efficient which leads to no variations at all and consequently a vanishing variance-covariance matrix.[6]

[6] Even for the convex case, this issue can occur if the number of observations is rather small compared to the number of inputs and outputs: this is known as the *curse of dimensionality*.

To overcome this issue for our sample, we have opted for a pragmatic approach and we use the variations obtained in the convex models to create perturbed inputs and outputs from which the corresponding nonconvex efficiency measures are derived: MPI components can then be obtained. In terms of comparing convex and nonconvex results, this pragmatic approach makes sense since the perturbations in the underlying inputs and outputs are kept very similar so that possible differences in results can be attributed solely to differences in technology.

Table 9 reports the difference (ΔMPI) between the geometric mean of the MPI estimates reported in Tables 2 and 4 on the one hand and the geometric mean of the MPI bootstrap estimates over all observations on the other hand. Table 9 also reports the average lower (MPI_{lb}) and upper (MPI_{ub}) bounds of the 95% confidence intervals obtained from the bootstrap results. For the other components, the results are presented in Table C.1 in Appendix C.

For the output-oriented model under convexity, the bootstrapped MPI values are larger than the original MPI values with nearly all deviations being negative. For all other models, we observe an opposite result with most deviations being positive. This implies that the tourism productivity index as calculated by traditional method tends to be overestimated in most cases while the output-oriented model underestimates tourism performance under the convexity assumption. Based on the confidence intervals, it is apparent that the deviations between the upper and lower bounds are relatively small: this highlights the small scope for change in China's regional tourism efficiency. Only the change in productivity in 2009-2010 is significantly different from unity under all assumptions. More precisely, for the output-oriented MPIs the improvement or deterioration in productivity is confirmed between 2008-2012 under the convexity assumption, but the same conclusion is supported only for 2008-2009 under the nonconvexity assumption. For the input-oriented MPIs, there is an obvious productivity deterioration between 2009-2010, but the improvement in MPI lasts only between 2012-2014 under the convexity assumption. By contrast, we observe an input-oriented MPI improvement between 2014-2015 under the nonconvexity assumption. The conclusions from these bootstrapping results confirm our main findings from the t-test in Table 7. The statistical significance of the Malmquist productivity indices varies according to our assumptions on the convexity axiom. The results show that the impact of the convexity assumption in performance measurement is non-negligible in empirical applications.

Table 9: MPI deviations and confidence intervals

	Convex								NonConvex							
	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016
Output-Oriented																
ΔMPI	0.0002	-0.0016	-0.0005	0.0004	-0.0063	-0.0004	-0.0004	-0.0004	0.0298	0.0059	0.0026	0.0013	0.0023	-0.0017	-0.0013	0.0056
MPI_{lb}	1.0894	1.0329	1.0006	1.0042	0.8581	0.9607	0.9833	0.9910	1.0779	0.8249	0.9502	0.8973	0.7521	0.9356	0.9572	0.9409
MPI_{ub}	1.1467	1.0763	1.0446	1.0548	0.9043	1.0094	1.0165	1.0243	1.2078	0.9364	1.0537	1.0100	0.8668	1.0625	1.0699	1.0603
Input-Oriented																
ΔMPI	0.0005	0.0035	0.0018	0.0013	-0.0022	-0.0008	0.0008	0.0012	0.0163	-0.0132	0.0009	0.0342	-0.0300	-0.0111	0.0088	0.0127
MPI_{lb}	0.9517	0.9328	0.9414	0.9556	1.1667	1.0198	0.9808	0.9783	0.9712	0.7887	0.9299	0.8884	0.9991	0.9988	1.0196	0.9579
MPI_{ub}	1.0133	0.9915	1.0055	1.0168	1.2593	1.0902	1.0311	1.0303	1.1540	0.9438	1.0725	1.0660	1.1992	1.1855	1.1338	1.0914

6 Conclusions

Starting from the seminal theoretical proposal to include an output-oriented plant capacity utilisation notion within an output-oriented MPI (De Borger and Kerstens (2000)), this contribution has made two new proposals: a first is to include an attainable output-oriented plant capacity utilisation concept within the output-oriented MPI, and a second is to integrate an input-oriented plant capacity utilisation measure within the input-oriented MPI.

Our empirical application on a balanced panel of Chinese hotels has served to empirically illustrate the above extended decompositions of the MPI. The final comparison of output- and input-oriented MPI has shown that there is some overall agreement on the same patterns of growth and decline, but that there also exist some substantial exceptions The same conclusions were found for the frontier change component (part (iii)), and for the plant capacity utilisation change (part (ii)). Overall, output- and input-oriented MPI as well as their decomposition partially measure similar things, but these MPI and components also measure things differently in their own right.

Being among the first in the tourism literature to test for the significance of the observed patterns of the MPI, we interestingly observe that the change in MPI and its components is mainly significantly different from unity under convexity, while it is mainly not significantly different from unity under nonconvexity. Furthermore, to the best of our knowledge we offer the first perspective on some external validation for the different PCU notions by comparing these with the average occupancy rate. Our empirical results reveal that the input-oriented PCU notion correlates better than the output-oriented PCU notion with the average occupancy rate under both C and NC. Thus, these PCU notions are somehow related to this more traditional non-frontier capacity utilisation measure in the hotel industry.

Avenues for eventual future research include the following. First, one could try to combine a graph-based Malmquist productivity index (see Zofío and Lovell (2001)) with a graph-based plant capacity notion (see Kerstens, Sadeghi, and Van de Woestyne (2020)). Furthermore, it may be attractive to try to develop suitable plant capacity indicators that could be used to extend the existing decompositions of the Luenberger productivity indicator. In a similar vein, it may be useful to search how to include plant capacity components into the Hicks-Moorsteen TFP index and the Luenberger-Hicks-Moorsteen TFP indicator. Also an external validation for the different plant capacity notions discussed in this contribution remains a hot topic: our aggregate level provincial results should ideally be complemented with firm level results. As to the choice of fixed inputs, while we relied on economic tradition, from an empirical point of view it could be worthwhile to see how the number of employees as a second fixed input would affect our empirical results. Finally, one may consider a second stage regression of MPI change and its components on a series of explanatory variables when these would be available, or using lagged values to forecast future MPI values.

References

Anderson, R., M. Fish, Y. Xia, and F. Michello (1999): "Measuring Efficiency in the Hotel Industry: A Stochastic Frontier Approach," *International Journal of Hospitality Management*, 18(1), 45–57.

Assaf, A., and C. Barros (2011): "Performance Analysis of the Gulf Hotel Industry: A Malmquist Index with Bias Correction," *International Journal of Hospitality Management*, 30(4), 819–826.

Assaf, A., and K. Cvelbar (2011): "Privatization, Market Competition, International Attractiveness, Management Tenure and Hotel Performance: Evidence from Slovenia," *International Journal of Hospitality Management*, 30(2), 391–397.

Assaf, A., and M. Tsionas (2018): "The Estimation and Decomposition of Tourism Productivity," *Tourism Management*, 65, 131–142.

Balk, B. (2003): "The Residual: On Monitoring and Benchmarking Firms, Industries and Economies with Respect to Productivity," *Journal of Productivity Analysis*, 20(1), 5–47.

Banker, R., and R. Morey (1986): "Efficiency Analysis for Exogenously Fixed Inputs and Outputs," *Operations research*, 34(4), 513–521.

Barros, C. (2005): "Measuring Efficiency in the Hotel Sector," *Annals of Tourism Research*, 32(2), 456–477.

Barros, C., P. Dieke, and C. Santos (2010): "Heterogeneous Technical Efficiency of Hotels in Luanda, Angola," *Tourism Economics*, 16(1), 137–151.

Barros, C., N. Peypoch, and B. Solonandrasana (2009): "Efficiency and Productivity Growth in Hotel Industry," *International Journal of Tourism Research*, 11(4), 389–402.

Bjurek, H. (1996): "The Malmquist Total Factor Productivity Index," *Scandinavian Journal of Economics*, 98(2), 303–313.

Blake, A., M. Sinclair, and J. Soria (2006): "Tourism Productivity: Evidence from the United Kingdom," *Annals of Tourism Research*, 33(4), 1099–1120.

Bosetti, V., M. Cassinelli, and A. Lanza (2007): "Benchmarking in Tourism Destinations; Keeping in Mind the Sustainable Paradigm," in *Advances in Modern Tourism Research: Economic Perspectives*, ed. by A. Matias, P. Nijkamp, and P. Neto, pp. 165–180. Physica, Heidelberg.

Bosetti, V., and G. Locatelli (2006): "A Data Envelopment Analysis Approach to the Assessment of Natural Parks' Economic Efficiency and Sustainability. The Case of Italian National Parks," *Sustainable Development*, 14(4), 277–286.

Botti, L., O. Goncalves, and H. Ratsimbanierana (2012): "French Destination Efficiency: A Mean-Variance Approach," *Journal of Travel Research*, 51(2), 115–129.

Botti, L., N. Peypoch, E. Robinot, B. Solonadrasana, and C. Barros (2009): "Tourism Destination Competitiveness: The French Regions Case," *European Journal of Tourism Research*, 2(1), 5–24.

Briec, W., and K. Kerstens (2004): "A Luenberger-Hicks-Moorsteen Productivity Indicator: Its Relation to the Hicks-Moorsteen Productivity Index and the Luenberger Productivity Indicator," *Economic Theory*, 23(4), 925–939.

Caves, D., L. Christensen, and W. Diewert (1982): "The Economic Theory of Index Numbers and the Measurement of Inputs, Outputs and Productivity," *Econometrica*, 50(6), 1393–1414.

Cesaroni, G., K. Kerstens, and I. Van de Woestyne (2017): "A New Input-Oriented Plant Capacity Notion: Definition and Empirical Comparison," *Pacific Economic Review*, 22(4), 720–739.

Cesaroni, G., K. Kerstens, and I. Van De Woestyne (2019): "Short-and Long-Run Plant Capacity Notions: Definitions and Comparison," *European Journal of Operational Research*, 275(1), 387–397.

Chambers, R. (2002): "Exact Nonradial Input, Output, and Productivity Measurement," *Economic Theory*, 20(4), 751–765.

Chambers, R., R. Färe, and S. Grosskopf (1996): "Productivity Growth in APEC Countries," *Pacific Economic Review*, 1(3), 181–190.

Cracolici, M., P. Nijkamp, and P. Rietveld (2008): "Assessment of Tourism Competitiveness by Analysing Destination Efficiency," *Tourism Economics*, 14(2), 325–342.

De Borger, B., and K. Kerstens (2000): "The Malmquist Productivity Index and Plant Capacity Utilization," *Scandinavian Journal of Economics*, 102(2), 303–310.

Devesa, M., and L. Peñalver (2013): "Size, Efficiency and Productivity in the Spanish Hotel Industry - Independent Properties versus Chain-Affiliated Hotels," *Tourism Economics*, 19(4), 801–809.

Diewert, W., and K. Fox (2017): "Decomposing Productivity Indexes into Explanatory Factors," *European Journal of Operational Research*, 256(1), 275–291.

Färe, R., S. Grosskopf, B. Lindgren, and P. Roos (1995): "Productivity Developments in Swedish Hospitals: A Malmquist Output Index Approach," in *Data Envelopment Analysis: Theory, Methodology and Applications*, ed. by A. Charnes, W. Cooper, A. Lewin, and L. Seiford, pp. 253–272. Kluwer, Boston.

Färe, R., S. Grosskopf, and C. Lovell (1994): *Production Frontiers*. Cambridge University Press, Cambridge.

Färe, R., S. Grosskopf, and P. Roos (1996): "On Two Definitions of Productivity," *Economics Letters*, 53(3), 269–274.

Färe, R., S. Grosskopf, and V. Valdmanis (1989): "Capacity, Competition and Efficiency in Hospitals: A Nonparametric Approach," *Journal of Productivity Analysis*, 1(2), 123–138.

Fousekis, P., and A. Papakonstantinou (1997): "Economic Capacity Utilisation and Productivity Growth in Greek Agriculture," *Journal of Agricultural Economics*, 48(1), 38–51.

HACKMAN, S. (2008): *Production Economics: Integrating the Microeconomic and Engineering Perspectives*. Springer, Berlin.

HATHROUBI, S., N. PEYPOCH, AND E. ROBINOT (2014): "Technical Efficiency and Environmental Management: The Tunisian Case," *Journal of Hospitality and Tourism Management*, 21, 27–33.

HU, J.-L., C.-N. CHIU, H.-S. SHIEH, AND C.-H. HUANG (2010): "A Stochastic Cost Efficiency Analysis of International Tourist Hotels in Taiwan," *International Journal of Hospitality Management*, 29(1), 99–107.

HUANG, C.-W., C.-T. TING, C.-H. LIN, AND C.-T. LIN (2013): "Measuring Non-Convex Metafrontier Efficiency in International Tourist Hotels," *Journal of the Operational Research Society*, 64(2), 250–259.

HUANG, Y., H. MESAK, M. HSU, AND H. QU (2012): "Dynamic Efficiency Assessment of the Chinese Hotel Industry," *Journal of Business Research*, 65(1), 59–67.

HULTEN, C. (1986): "Productivity Change, Capacity Utilization, and the Sources of Efficiency Growth," *Journal of Econometrics*, 33(1–2), 31–50.

——— (2001): "Total Factor Productivity: A Short Biography," in *New Developments in Productivity Analysis*, ed. by C. Hulten, E. Dean, and M. Harper, pp. 1–47. University of Chicago Press, Chicago.

JEONG, S.-O., AND L. SIMAR (2006): "Linearly Interpolated FDH Efficiency Score for Nonconvex Frontiers," *Journal of Multivariate Analysis*, 97(10), 2141–2161.

JOHANSEN, L. (1968): "Production functions and the concept of capacity," Discussion Paper [reprinted in F. R. Førsund (ed.) (1987) Collected Works of Leif Johansen, Volume 1, Amsterdam, North Holland, 359–382], CERUNA, Namur.

KERSTENS, K., J. SADEGHI, AND I. VAN DE WOESTYNE (2019): "Plant Capacity and Attainability: Exploration and Remedies," *Operations Research*, 67(4), 1135–1149.

——— (2020): "Plant Capacity Notions in a Non-parametric Framework: A Brief Review and New Graph or Non-Oriented Plant Capacities," *Annals of Operations Research*, 288(2), 837–860.

KERSTENS, K., AND Z. SHEN (2021): "Using COVID-19 Mortality to Select Among Hospital Plant Capacity Models: An Exploratory Empirical Application to Hubei Province," *Technological Forecasting and Social Change*, 166, 120535.

Kerstens, K., Z. Shen, and I. Van de Woestyne (2018): "Comparing Luenberger and Luenberger-Hicks-Moorsteen Productivity Indicators: How Well is Total Factor Productivity Approximated?," *International Journal of Production Economics*, 195, 311–318.

Kerstens, K., and I. Van de Woestyne (2014): "Comparing Malmquist and Hicks-Moorsteen Productivity Indices: Exploring the Impact of Unbalanced vs. Balanced Panel Data," *European Journal of Operational Research*, 233(3), 749–758.

Last, A.-K., and H. Wetzel (2010): "The Efficiency of German Public Theaters: A Stochastic Frontier Analysis Approach," *Journal of Cultural Economics*, 34(2), 89–110.

Mairesse, F., and P. Vanden Eeckaut (2002): "Museum Assessment and FDH Technology: Towards a Global Approach," *Journal of Cultural Economics*, 26(4), 261–286.

McMahon, F. (1994): "Productivity in the Hotel Industry," in *Tourism: The State of the Art*, ed. by A. Seaton, pp. 616–625. Wiley, New York.

Morey, R., and D. Dittman (1995): "Evaluating a Hotel GM's Performance: A Case Study in Benchmarking," *Cornell Hotel and Restaurant Administration Quarterly*, 36(5), 30–35.

Moriarty, J. (2010): "Have Structural Issues Placed New Zealand's Hospitality Industry beyond Price?," *Tourism Economics*, 16(3), 695–713.

Morrison, C. (1985): "Primal and Dual Capacity Utilization: An Application to Productivity Measurement in the U.S. Automobile Industry," *Journal of Business & Economic Statistics*, 3(4), 312–324.

Morrison Paul, C. (1999): *Cost Structure and the Measurement of Economic Performance: Productivity, Utilization, Cost Economics, and Related Performance Indicators*. Kluwer, Boston.

Nishimizu, M., and J. Page (1982): "Total Factor Productivity Growth, Technological Progress and Technical Efficiency Change: Dimensions of Productivity Change in Yugoslavia, 1965-78," *Economic Journal*, 92(368), 920–936.

Núñez-Serrano, J., J. Turrión, and F. Velázquez (2014): "Are Stars a Good Indicator of Hotel Quality? Assymetric Information and Regulatory Heterogeneity in Spain," *Tourism Management*, 42, 77–87.

Ouellette, P., and V. Vierstraete (2004): "Technological Change and Efficiency in the Presence of Quasi-Fixed Inputs: A DEA Application to the Hospital Sector," *European Journal of Operational Research*, 154(3), 755–763.

Peypoch, N., and B. Solonandrasana (2008): "Aggregate Efficiency and Productivity Analysis in the Tourism Industry," *Tourism Economics*, 14(1), 45–56.

Ritchie, J., and G. Crouch (2003): *The Competitive Destination: A Sustainable Tourism Perspective*. CABI, Wallingford.

Russell, R. (2018): "Theoretical Productivity Indices," in *The Oxford Handbook on Productivity Analysis*, ed. by E. Grifell-Tatjé, C. Lovell, and R. Sickles, pp. 153–182. Oxford University Press, New York.

Sellers-Rubio, R., and J. Nicolau-Gonzálbez (2009): "Assessing Performance in Services: The Travel Agency Industry," *Service Industries Journal*, 29(5), 653–667.

Sena, V. (2001): "The Generalised Malmquist Index and Capacity Utilization Change: An Application to Italian Manufacturing, 1989-1994," *Applied Economics*, 33(1), 1–9.

Simar, L., and P. Wilson (1999): "Estimating and Bootstrapping Malmquist Indices," *European Journal of Operational Research*, 115(3), 459–471.

Sun, J., J. Zhang, J. Zhang, J. Ma, and Y. Zhang (2015): "Total Factor Productivity Assessment of Tourism Industry: Evidence from China," *Asia Pacific Journal of Tourism Research*, 20(3), 280–294.

Wober, K., and D. Fesenmaier (2004): "A Multi-Criteria Approach to Destination Benchmarking: A Case Study of State Tourism Advertising Programs in the United States," *Journal of Travel & Tourism Marketing*, 16(2–3), 1–18.

Zhang, L., L. Botti, and S. Petit (2016): "Destination Performance: Introducing the Utility Function in the Mean-Variance Space," *Tourism Management*, 52, 123–132.

Zofío, J. (2007): "Malmquist Productivity Index Decompositions: A Unifying Framework," *Applied Economics*, 39(18), 2371–2387.

Zofío, J., and C. Lovell (2001): "Graph Efficiency and Productivity Measures: An Application to US Agriculture," *Applied Economics*, 33(11), 1433–1442.

Appendices: Supplementary Material

A Mathematical Programming Problems

We treat the computational issues surrounding the three Malmquist index decompositions (23), (24), and (25) in sequence and componentwise.

Starting with the Malmquist index decomposition (23), the short-run output-oriented radial technical efficiency measure $DF_o^t(x_f^t, y^t)$ (numerator of part (i)) when DMU_p is under evaluation can be obtained by solving the following mathematical programming problem:

$$\begin{aligned} \max_{\theta,z} \quad & \theta \\ s.t. \quad & \sum_{k=1}^{K} z_k y_k^t \geq \theta y_p^t, \\ & \sum_{k=1}^{K} z_k x_{fk}^t \leq x_{fp}^t, \\ & \theta \geq 0, z \in \Gamma, \end{aligned} \tag{A.1}$$

where we allow for both the cases of a convex Γ^{C} and a non-convex Γ^{NC} technology following (6). The short-run output-oriented radial technical efficiency measure $DF_o^{t+1}(x_f^{t+1}, y^{t+1})$ (denominator of part (i)) is computed analogously by replacing the time index t by $t+1$ in model (A.1).

The numerator of $PCU_o^t(x^t, x_f^t, y^t)$ in part (ii) of the above decomposition $DF_o^t(x^t, y^t)$ (see (16)) is solved by the following mathematical programming problem:

$$\begin{aligned} \max_{\theta,z} \quad & \theta \\ s.t. \quad & \sum_{k=1}^{K} z_k y_k^t \geq \theta y_p^t, \\ & \sum_{k=1}^{K} z_k x_k^t \leq x_p^t, \\ & \theta \geq 0, z \in \Gamma. \end{aligned} \tag{A.2}$$

The numerator of $PCU_o^{t+1}(x^{t+1}, x_f^{t+1}, y^{t+1})$ in part (ii) of the above decomposition $DF_o^{t+1}(x^{t+1}, y^{t+1})$ is obtained in an analogous way by replacing the time index t by $t+1$ in model (A.2).

Turning to part (iii) of the above decomposition, the mathematical programming problems of the same period output-oriented radial technical efficiency measures $DF_o^t(x^t, y^t)$ and $DF_o^{t+1}(x^{t+1}, y^{t+1})$ have been dealt with in model (A.2). It now suffices to discuss the adjacent period output-oriented radial technical efficiency measures $DF_o^t(x^{t+1}, y^{t+1})$ and $DF_o^{t+1}(x^t, y^t)$. The adjacent period output-oriented radial technical efficiency $DF_o^t(x^{t+1}, y^{t+1})$ is solved by the following mathematical programming problem:

$$\begin{aligned} \max_{\theta,z} \quad & \theta \\ s.t. \quad & \sum_{k=1}^{K} z_k y_k^t \geq \theta y_p^{t+1}, \\ & \sum_{k=1}^{K} z_k x_k^t \leq x_p^{t+1}, \\ & \theta \geq 0, z \in \Gamma. \end{aligned} \tag{A.3}$$

The output-oriented radial technical efficiency measure $DF_o^{t+1}(x^t, y^t)$ can be computed analogously by replacing the time index t on the left-hand side of the inequalities by $t+1$ and by doing the reverse for the right-hand side of the inequalities in model (A.3).

Turning to the Malmquist index decomposition (24), the short-run attainable output-oriented radial technical efficiency measure $ADF_o^t(x_f^t, y^t, \bar{\lambda})$ (numerator of part (i)) can be simply obtained by solving the following mathematical programming problem:

$$\begin{aligned} \max_{\theta,z,x_v} \quad & \theta \\ s.t. \quad & \sum_{k=1}^{K} z_k y_k^t \geq \theta y_p^t, \\ & \sum_{k=1}^{K} z_k x_{fk}^t \leq x_{fp}^t, \\ & \sum_{k=1}^{K} z_k x_{vk}^t \leq x_v, \\ & x_v \leq \bar{\lambda} x_{vp}^t, \\ & \theta \geq 0, x_v \geq 0, z \in \Gamma. \end{aligned} \tag{A.4}$$

The short-run attainable output-oriented radial technical efficiency measure $ADF_o^{t+1}(x_f^{t+1}, y^{t+1}, \bar{\lambda})$ (denominator of part (i)) is computed analogously by replacing the time index t by $t+1$ in model (A.4).

The numerator of $APCU_o^t(x^t, x_f^t, y^t, \bar{\lambda})$ in part (ii) of the above decomposition $DF_o^t(x^t, y^t)$ (see (18)) is solved as in model (A.2). The numerator of $APCU_o^{t+1}(x^{t+1}, x_f^{t+1}, y^{t+1}, \bar{\lambda})$ in part (ii) of the above decomposition $DF_o^{t+1}(x^{t+1}, y^{t+1})$ is obtained in an analogous way by replacing the time index t by $t+1$ in model (A.2).

Focusing on part (iii) of the above decomposition, the mathematical programming problems of the same period output-oriented radial technical efficiency measures $DF_o^t(x^t, y^t)$ and $DF_o^{t+1}(x^{t+1}, y^{t+1})$ have been dealt with in model (A.2). The adjacent period output-oriented radial technical efficiency $DF_o^t(x^{t+1}, y^{t+1})$ and $DF_o^{t+1}(x^t, y^t)$ have been dealt with in model (A.3).

Finally, looking at the Malmquist index decomposition (25), the short-run input-oriented efficiency measure reducing variable inputs evaluated relative to the input set with a zero output level $DF_i^t(x_f^t, x_v^t, 0)$ (numerator of part (i)) is computed by solving the following mathematical programming problem:

$$\begin{aligned} \min_{\lambda,z} \quad & \lambda \\ s.t \quad & \sum_{k=1}^{K} z_k y_k^t \geq 0, \\ & \sum_{k=1}^{K} z_k x_{fk}^t \leq x_{fp}^t, \\ & \sum_{k=1}^{K} z_k x_{vk}^t \leq \lambda x_{vp}^t, \\ & \lambda \geq 0, z \in \Gamma. \end{aligned} \tag{A.5}$$

The short-run input-oriented radial technical efficiency measure $DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, 0)$ (denominator of part (i)) is computed analogously by replacing the time index t by $t+1$ in model (A.5).

The numerator of $PCU_i^t(x^t, x_f^t, y^t)$ in part (ii) of the above decomposition $DF_i^t(x_f^t, x_v^t, y^t)$ (see (21)) is solved by the following mathematical programming problem:

$$\begin{aligned} \min_{\lambda,z} \quad & \lambda \\ s.t \quad & \sum_{k=1}^{K} z_k y_k^t \geq y_p^t, \\ & \sum_{k=1}^{K} z_k x_{fk}^t \leq x_{fp}^t, \\ & \sum_{k=1}^{K} z_k x_{vk}^t \leq \lambda x_{vp}^t, \\ & \lambda \geq 0, z \in \Gamma. \end{aligned} \tag{A.6}$$

The numerator of $PCU_i^{t+1}(x^{t+1}, x_f^{t+1}, y^{t+1})$ in part (ii) of the above decomposition $DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, y^{t+1})$ is obtained in an analogous way by replacing the time index t by $t+1$ in model (A.6).

Looking at part (iii) of the above decomposition, the mathematical programming problems of the same period short-run input-oriented radial technical efficiency measures $DF_i^t(x_f^t, x_v^t, y^t)$ and $DF_i^{t+1}(x_f^{t+1}, x_v^{t+1}, y^{t+1})$ have been dealt with in model (A.6). We now can limit ourselves to discuss the adjacent period short-run input-oriented radial technical efficiency $DF_i^t(x_f^{t+1}, x_v^{t+1}, y^{t+1})$ and $DF_i^{t+1}(x_f^t, x_v^t, y^t)$. The adjacent period short-run input-oriented radial technical efficiency $DF_i^t(x_f^{t+1}, x_v^{t+1}, y^{t+1})$ is solved by the following mathematical programming problem:

$$\begin{aligned}
\min_{\lambda,z} \quad & \lambda \\
s.t \quad & \sum_{k=1}^{K} z_k y_k^t \geq y_p^{t+1}, \\
& \sum_{k=1}^{K} z_k x_{fk}^t \leq x_{fp}^{t+1}, \\
& \sum_{k=1}^{K} z_k x_{vk}^t \leq \lambda x_{vp}^{t+1}, \\
& \lambda \geq 0, z \in \Gamma.
\end{aligned} \tag{A.7}$$

The short-run input-oriented radial technical efficiency measure $DF_i^{t+1}(x_f^t, x_v^t, y^t)$ can be computed analogously by replacing the time index t on the left-hand side of the inequalities by $t+1$ and by doing the reverse for the right-hand side of the inequalities in model (A.7).

B Empirical Approach to Determining Input Fixity

We have also calculated the change of all inputs measured in absolute percentage points over the successive years. Table B.1 lists these absolute percentage point changes over the years and also reports the average and standard deviation over the whole period.

Two observations stand out. First, these absolute percentage point changes vary quite a bit over time. Second, it turns out that all of the four inputs remain somewhat volatile over the period under investigation. But, on average the first and fourth inputs turn out to be the least volatile. Therefore, from an empirical point of view the number of employees (I1) is least volatile followed by the fixed input of fixed assets (I4). Hence, from an empirical point of view the number of employees (I1) can also be considered as quasi-fixed along with the fixed assets (I4).

While our choice of taking only fixed assets as a fixed input mainly relies on a priori economic arguments, it can from an empirical point of view also be relevant to test the impact of adding the number of employees as another fixed input. This remains to be done in future work.

Table B.1: Inputs Change in Absolute Percentage Points over Time

	I1	I2	I3	I4
2008-2009	4.8	15.92	12.05	29.08
2009-2010	7.64	26.46	26.28	11.95
2010-2011	5.16	22.49	22.1	9.67
2011-2012	9.37	24.41	14.92	10.19
2012-2013	11.32	19.24	15.41	9.88
2013-2014	5.18	13.81	8.67	9.64
2014-2015	4.07	8.99	8.12	7.14
2015-2016	4	12.08	8.71	7.2
Average	6.44	17.92	14.53	11.84
St. Dev.	13.24	16.33	13.13	11.04

C Bootstrapping Results for all MPI Components

Table C.1: Inputs Change in Absolute Percentage Points over Time

	Convex								**NonConvex**							
	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016
Output-Oriented																
ΔPart(i)	0.2568	0.1032	0.0999	0.0521	-0.1341	-0.0682	-0.0087	0.0216	0.1479	-0.1933	-0.0965	-0.2380	-0.4142	-0.5157	-0.2225	-0.2696
Part(i)$_{lb}$	0.6805	0.8554	0.8408	0.9267	1.0452	0.9385	0.9377	0.9088	0.7741	1.0874	0.9850	1.1040	1.2772	1.3325	1.0578	1.1151
Part(i)$_{ub}$	0.7874	0.9695	0.9430	1.0433	1.1910	1.0731	1.0250	1.0452	0.9639	1.3311	1.1857	1.3603	1.6187	1.6848	1.3322	1.3886
ΔPart(ii)(inverse)	0.2556	0.1100	0.0988	0.0518	-0.1298	-0.0679	-0.0136	0.0226	0.1437	-0.1963	-0.0959	-0.2376	-0.4234	-0.5084	-0.2230	-0.2726
Part(ii)(inverse)$_{lb}$	0.7908	0.9770	0.9491	1.0527	1.1987	1.0745	1.0336	1.0491	0.9556	1.3312	1.1779	1.3543	1.6190	1.6553	1.3304	1.3883
Part(ii)(inverse)$_{ub}$	0.6814	0.8544	0.8363	0.9245	1.0359	0.9216	0.9350	0.9095	0.7887	1.0790	0.9944	1.1130	1.2619	1.3270	1.0782	1.1239
ΔPart(iii)	-0.0021	0.0035	-0.0019	-0.0006	-0.0001	0.0000	-0.0052	0.0000	0.0249	0.0050	0.0038	0.0020	-0.0008	0.0026	-0.0024	0.0039
Part(iii)$_{lb}$	1.0715	1.0136	0.9885	0.9839	0.8351	0.9312	0.9639	0.9611	1.0746	0.8233	0.9496	0.8920	0.7488	0.9323	0.9622	0.9420
Part(iii)$_{ub}$	1.1635	1.0956	1.0603	1.0815	0.9346	1.0309	1.0439	1.0560	1.2076	0.9450	1.0589	1.0222	0.8674	1.0615	1.0758	1.0684
ΔMPI	0.0002	-0.0016	-0.0005	0.0004	-0.0063	-0.0004	-0.0004	-0.0004	0.0298	0.0059	0.0026	0.0013	0.0023	-0.0017	-0.0013	0.0056
MPI$_{lb}$	1.0894	1.0329	1.0006	1.0042	0.8581	0.9607	0.9833	0.9910	1.0779	0.8249	0.9502	0.8973	0.7521	0.9356	0.9572	0.9409
MPI$_{ub}$	1.1467	1.0763	1.0446	1.0548	0.9043	1.0094	1.0165	1.0243	1.2078	0.9364	1.0537	1.0100	0.8668	1.0625	1.0699	1.0603
Input-Oriented																
ΔPart(i)	0.0017	-0.0068	-0.0016	0.0004	0.0188	-0.0034	-0.0114	0.0024	0.0015	-0.0068	-0.0016	0.0004	0.0187	-0.0034	-0.0113	0.0027
Part(i)$_{lb}$	0.8039	1.0416	0.9276	0.7730	0.9056	0.8631	0.9070	0.8376	0.8040	1.0294	0.9327	0.7715	0.9056	0.8566	0.9078	0.8419
Part(i)$_{ub}$	1.0206	1.2271	1.0100	0.9529	1.1538	1.0364	1.0270	1.0317	1.0212	1.2190	1.0231	0.9529	1.1540	1.0323	1.0315	1.0334
ΔPart(ii)(inverse)	-0.0003	-0.0080	-0.0019	-0.0012	0.0139	-0.0052	-0.0044	-0.0002	0.0077	-0.0037	-0.0032	0.0045	0.0202	-0.0091	-0.0096	0.0039
Part(ii)(inverse)$_{lb}$	1.0571	1.2251	1.0188	0.9759	1.1620	1.0571	1.0372	1.0274	1.1174	1.2191	1.0277	1.0094	1.1894	1.0616	1.0424	1.0396
Part(ii)(inverse)$_{ub}$	0.8073	1.0210	0.9118	0.7660	0.8941	0.8642	0.8906	0.8335	0.8122	0.9933	0.9192	0.7639	0.8829	0.8470	0.8810	0.8262
ΔPart(iii)	-0.0012	0.0030	0.0025	-0.0031	-0.0080	-0.0015	0.0099	-0.0014	0.0138	0.0242	-0.0157	0.0525	-0.0585	0.0108	0.0008	-0.0164
Part(iii)$_{lb}$	0.9489	0.9178	0.9358	0.9418	1.1222	1.0018	0.9590	0.9560	1.0234	0.7504	0.9425	0.8856	1.0274	0.9743	1.0266	0.9823
Part(iii)$_{ub}$	1.0556	0.9983	1.0158	1.0477	1.2636	1.1157	1.0506	1.0509	1.1859	0.9013	1.0901	1.0561	1.2310	1.1621	1.1402	1.1215
ΔMPI	0.0005	0.0035	0.0018	0.0013	-0.0022	-0.0008	0.0008	0.0012	0.0163	-0.0132	0.0009	0.0342	-0.0300	-0.0111	0.0088	0.0127
MPI$_{lb}$	0.9517	0.9328	0.9414	0.9556	1.1667	1.0198	0.9808	0.9783	0.9712	0.7887	0.9299	0.8884	0.9991	0.9988	1.0196	0.9579
MPI$_{ub}$	1.0133	0.9915	1.0055	1.0168	1.2593	1.0902	1.0311	1.0303	1.1540	0.9438	1.0725	1.0660	1.1992	1.1855	1.1338	1.0914

Table C.1 contains the basic MPI bootstrapping results reported in Table 9 as well as the results for the other components. Again, as obtained from Table 7, the statistical significance of the different components varies for different years and models, and whether or not convexity is assumed. For example, components Part(i) and Part(ii) (inverse) are almost all significantly distinct from unity for the nonconvex output-oriented MPI contrary to the convex output-oriented and nonconvex input-oriented MPIs where these two parts are not significantly different from unity for several periods. As for the observed deviations between the original and the bootstrapped estimations, Part(i) and Part(ii) (inverse) results for the output oriented MPI under nonconvexity, Part(iii) for output oriented MPI and Part (ii) (inverse) for input oriented MPI under convexity are mainly negative. For other models, we observe similar patterns as for the MPIs discussed in the main text: the deviations are mainly positive implying an overestimation of tourism performance by the traditional methods. Overall, the bootstrap corrected values on different components confirm again our main findings from Tables 7 and 9 that the results are very much conditioned by the convexity axiom.