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Analysis

Measuring environmentally sensitive productivity growth: An application to the urban water sector

Jayanath Ananda [a,c,*], Benjamin Hampf [b]

[a] School of Economics, La Trobe University, Albury-Wodonga Campus, Wodonga, VIC 3690, Australia
[b] Department of Law and Economics, Darmstadt University of Technology, Darmstadt, Germany
[c] School of Business and Law, Central Queensland University, 120, Spencer Street, Melbourne VIC 3000, Australia

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ABSTRACT

The energy use and greenhouse gas emissions in the provision of urban water and sewerage services have become an increasingly important issue in recent times. However, the impact of negative externalities such as greenhouse gas emissions on the productivity of urban water provision has received less attention in the literature. This paper applies the global Malmquist–Luenberger (GML) productivity index, which accounts for undesirable outputs in order to evaluate the productivity trends in the Australian urban water sector. Results indicate that the inclusion of greenhouse gas emissions significantly influences the productivity measurement. Findings also indicate that the conventional index, which disregards undesirable outputs, over-states the productivity growth. Despite a declining trend in greenhouse emissions over the period, the overall productivity trend of the urban water sector experienced a downward trend while accounting for bad output. This productivity decline occurs in a period of prolonged drought, water security concerns and increased reliance on desalinization and water recycling.

1. Introduction

Efficiency and productivity analysis of water utilities has traditionally focused on measuring desirable outputs relative to a set of inputs used in the production process. However, most production processes including the provision of urban water and sewerage services entail undesirable outputs such as greenhouse gas emissions (GHGs) and effluents. An increased concern about climate change and the introduction of GHG abatement policies have attracted attention on water-related emissions in recent times (Cook et al., 2012).

The urban water industry around the globe has been under pressure from an increasingly variable climate and escalating infrastructure costs to address the water supply security concerns. Consequently, water utilities have resorted to climate-independent water supply sources such as seawater desalinization and water recycling. The uptake of such options has further increased the energy use and associated GHGs in the urban water sector (Cook et al., 2012).[1]

In order to formulate urban water policies that are both economically efficient and sustainable, research on the relationship between economic efficiency and undesirable outputs is necessary. Traditional measures of productivity growth such as Malmquist, Törnquist and Fischer indices focus only on the production of desirable outputs and fail to consider harmful undesirable outputs such as GHGs. Ignoring undesirable outputs and their adverse environmental effects leads to biased measures of productivity (Chung et al., 1997) and sub-optimal policy outcomes. This is particularly important in regulatory decision making and best-practice benchmarking which is increasingly used in utility sectors. Best-practice benchmarking uses the top performing firms as a reference to all other similar firms in the industry. Therefore, failure to take into account 'bad' outputs as part of any comparative assessment of performance could give rise to poor decisions by regulators.

One possible approach to account for undesirable outputs in the productivity measurement is to modify traditional productivity indices so as to incorporate negative externalities (Yörük and Zaim, 2005). Various studies have internalized GHGs in the measurement of productivity growth Färe et al. (2012), Oh (2010a,b), Yörük and Zaim (2005), Zhang et al. (2011), Zhou et al. (2010, 2014). Among the methods that account for bad outputs in the measurement of productivity growth, the seminal work of Chung et al. (1997) stands out. Based on the Malmquist index (Caves et al., 1982), they developed the Malmquist–Luenberger (ML) productivity growth index which enabled the incorporation of undesirable outputs in the estimation of productivity indices without price information. In this study, we apply a modified version of the conventional ML index, the global ML index by Oh (2010a) and extended it to cover input orientation.

* Corresponding author at: School of Business and Law, Central Queensland University, 120, Spencer Street, Melbourne VIC 3000, Australia.
E-mail addresses: j.ananda@latrobe.edu.au, j.ananda@cqu.edu.au (J. Ananda).

[1] This incremental energy use involves a positive feedback in two systems: the energy sourced from the coal-fired electricity contributes to greenhouse emissions and the energy generation itself requires water (Cook et al., 2012).

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Despite the growing number of studies using the ML index, productivity studies that internalize negative externalities in the urban water literature are virtually non-existent. Our paper is the first attempt that accounts for bad outputs in the productivity growth measurement in the urban water sector. Using a panel data set covering the period 2006 to 2011, we model joint production of good output and bad output and apply it to analyze the productivity growth trends in the Australian urban water sector. We use the abovementioned global ML index of Oh (2010a) and the global Malmquist index of Pastor and Lovell (2005) to analyze the influence of GHGs on the productivity growth and to decompose the productivity growth into efficiency change and technical change components. Moreover, we apply the methodology by Simar and Wilson (1999) to correct for the bias in our nonparametric estimations of the productivity results.

The empirical results of our analysis indicate a declining trend of productivity growth over the study period. The productivity growth improved marginally from 2008 to 2009 but then fell rapidly since 2009. Despite declining greenhouse gas emissions, overall, we find that the sector experienced an average annual rate of 3.7% decline in productivity growth if GHG emissions are included in the analysis. Moreover, we find statistically significant differences between the productivity results if bad outputs are accounted for. The rest of the paper is organized as follows: The next section presents an overview of the methodology. Section 3 presents a description of data and the empirical model. Section 4 discusses the empirical results and Section 5 concludes.

2. Methodology

In this section, we present the methodology applied in our empirical analysis of Australian water utilities. We start by discussing the modeling of the production technology that accounts for the unintended by-production of pollutants as well as the measurement of efficiency using input distance functions. We then present the dynamic measurement of productivity changes as well as the decomposition into efficiency and technical changes.

2.1. Modeling the Technology and Estimating Efficiency

To model the technology accounting for environmental pollution consider a production process where m inputs $\boldsymbol{x} \in \mathbb{R}^m_+$ are used to produce k desirable outputs, $\boldsymbol{y} \in \mathbb{R}^k_+$. Moreover, r pollutants $\boldsymbol{u} \in \mathbb{R}^r_+$ result as an unintended consequence of the production of good outputs. The technology set of this production process is the collection of all technically feasible input–output combinations and can be formally defined as

$$T = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u})\} : \boldsymbol{x} \text{ can produce } (\boldsymbol{y}, \boldsymbol{u})\}. \tag{1}$$

Following the literature on production economics (Shephard, 1970), we assume that this technology set satisfies the following axioms (see Färe and Primont (1995) and Färe and Grosskopf (2004) for detailed discussions of these axioms):

1 Inactivity: $(0, 0, 0) \in T$.
2 No free-lunch: $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \notin T$ if $\boldsymbol{x} = 0$ and $(\boldsymbol{y}, \boldsymbol{u}) \geq (0, 0)$.[2]
3 Strong disposability of inputs: If $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in T$ and $\tilde{\boldsymbol{x}} \geqq \boldsymbol{x}$ then $(\tilde{\boldsymbol{x}}, \boldsymbol{y}, \boldsymbol{u}) \in T$.
4 Strong disposability of good outputs: If $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in T$ and $\tilde{\boldsymbol{y}} \leqq \boldsymbol{y}$ then $(\boldsymbol{x}, \tilde{\boldsymbol{y}}, \boldsymbol{u}) \in T$.
5 Weak disposability of bad outputs: If $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in T$ and $0 \leqq \rho \leqq 1$ then $(\boldsymbol{x}, \rho\boldsymbol{y}, \rho\boldsymbol{u}) \in T$.
6 Null-jointness of good and bad outputs: If $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in T$ and $\boldsymbol{u} = \boldsymbol{0}$ then $\boldsymbol{y} = \boldsymbol{0}$.
7 Convexity: T is a convex set.
8 Closeness: T is a closed set.

Axiom 1 ensures that "doing nothing" is technically feasible while axiom 2 excludes the possibility to produce positive amounts of outputs without using any inputs. We model inputs and good outputs as strong disposable factors. This means that given a combination of inputs and outputs within the technology, the same amount of outputs can be obtained using more inputs and the same amount of inputs can be used to produce less outputs. Thus, inefficiency is technically feasible. To ensure that the reduction of bad outputs is costly, we follow Färe et al. (1989) and include the pollutants as weakly disposable outputs. Hence, given an input–output combination within the technology, a reduction of bad outputs is only possible if the good outputs are reduced by the same factor ρ. The null-jointness assumption excludes the possibility to produce positive amounts of good outputs without producing any pollution. Therefore, the complete abatement of pollutants is not possible. Moreover, we assume that convex combinations of observations are feasible and that the technology is a closed set. This ensures that the boundary of the technology belongs to the technology set as well.

To estimate this technology set, we apply nonparametric methods (see e.g. Färe et al. (1985) for an overview). Given a sample of input–output combinations $(\boldsymbol{x}_i, \boldsymbol{y}_i, \boldsymbol{u}_i)$ for $i = 1, \ldots, n$ decision making units (DMUs), the estimation of the technology (data envelopment analysis, DEA) satisfying the above stated axioms reads as

$$\hat{T} = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) : \boldsymbol{x} \geqq \boldsymbol{X}\boldsymbol{\lambda},\ \boldsymbol{y} \leqq \boldsymbol{Y}\boldsymbol{\lambda},\ \boldsymbol{u} = \boldsymbol{U}\boldsymbol{\lambda},\ \boldsymbol{\lambda} \geqq \boldsymbol{0}\}. \tag{2}$$

In this formulation, $\boldsymbol{X}$ denotes the $m \times n$ matrix of inputs, $\boldsymbol{Y}$ denotes the $k \times n$ matrix of good outputs and $\boldsymbol{U}$ represents the $r \times n$ matrix of undesirable outputs (pollutants). $\boldsymbol{\lambda}$ denotes the $n \times 1$ vector of weight factors with the factors being non-negative but otherwise unrestricted indicating a constant returns to scale (CRS) technology. Moreover, while the inequality constraints on the inputs and good outputs ensure strong disposability, the equality constraint on the bad outputs indicates weak disposability. Since we assume a CRS technology, the scaling factor ρ can be set equal to one (see Färe and Grosskopf (2003)). This technology is null-joint in the good and the bad outputs if each bad output is produced by at least one DMU and each DMU produces at least one bad output (see Färe (2010)). Note that the conventional technology set ignoring the production of environmentally harmful pollutants can be obtained by removing the constraint on the bad outputs.

In our analysis, we follow previous studies on the efficiency of water utilities (see e.g. Saal et al. (2007)) and assume that the utilities do only have a limited choice in the amounts of produced outputs (e.g. due to regulation) but can control the inputs used to produce a given amount of outputs. Hence, we conduct an input-oriented measurement of the efficiency. To estimate the efficiency of a utility, we apply the Farrell (1957) input measure of technical efficiency which is defined as

$$\theta(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) = \min\{\theta : (\theta\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) \in T\}. \tag{3}$$

Given this measure of inefficiency, a utility is classified as efficient if $\theta(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) = 1$ and as inefficient if $\theta(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u}) < 1$. Moreover, $\theta(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{u})$ indicates the level to which a DMU can equiproportionately reduce all its inputs given a fixed amount of good and bad outputs.

Given the sample of input–output combinations, this measure can be calculated for a DMU i under evaluation by solving the linear programming problem,

$$\begin{aligned} &\min_{\theta,\boldsymbol{\lambda}} \theta \\ &s.t.\ \ \theta\boldsymbol{x}_i \geqq \boldsymbol{X}\boldsymbol{\lambda} \\ &\qquad \boldsymbol{y}_i \leqq \boldsymbol{Y}\boldsymbol{\lambda} \\ &\qquad \boldsymbol{u}_i = \boldsymbol{U}\boldsymbol{\lambda} \\ &\qquad \boldsymbol{\lambda} \geqq \boldsymbol{0}. \end{aligned} \tag{4}$$

[2] Following the usual notational convention ≥ implies that at least one element of a vector satisfies strict inequality while ≧ implies that all elements of the vector can satisfy equality.