Urban water services and greenhouse emissions: Towards an environmentally sensitive regulatory approach

Jay Ananda, PhD.
School of Business and Law, CQUUniversity Melbourne, Australia

Outline

• Background and aims
• Analytical framework
• Data and model specifications
• Results
• Conclusions
Background

• Environmental efficiency of utility industries
• Joint production of good and bad outputs
• Growing environmental concerns, climate change and GH emissions
• Traditional utility regulation – Cost benchmarking, price monitoring, price caps

• Criteria for alternative regulatory approaches
  • Economic efficiency
  • Transparency
  • Sustainability and resilience
Utility industry challenges

Global Changes
- Climate Change
- Population Growth & Urbanization
- New Technology

Public Policy Environment
- Regulation
- External business environment
- Sustainability

Utility Challenges
- Efficiency and Innovation
- Agility and Resilience
- Customer value
Objectives of the research

1. Incorporate GHG emissions (bad output) into the productivity analysis in the Australian urban water sector;
2. Compare the results ignoring GHG emissions;
3. Identify sources of inefficiency and implications for utility regulation.
Analytical Framework

• Data Envelopment Analysis (DEA)

• Efficiency and productivity analysis – the traditional focus has been on the production of outputs from a set of inputs

• Including bad outputs in the efficiency and productivity analysis is not new (Fare et al. 2001; Fare et al. 2004; Ball et al. 2005)

• Internalising bad outputs in productivity studies using DEA approaches (Färe et al., 2001; Yörük and Zaim, 2005; Zhou et al., 2010; Oh, 2010; Zhang et al., 2011; Färe et al., 2012).
Modelling the production technology with bad outputs

• Consider a production process where:

  inputs $\mathbf{x}$; to produce $\mathbf{y}$ desirable outputs and $\mathbf{u}$ pollutants.

• The technology set:

  \[ T = \{ (\mathbf{x}, \mathbf{y}, \mathbf{u}) : \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{u}) \} \]  

  (1)

• Following Färe and Primont (1995) and Färe and Grosskopf (2004), the technology set satisfies the following axioms:

  \[ \begin{align*}
  (2a) & \quad \text{If } (\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T \text{ and } 0 \leq \rho \leq 1 \text{ then } (\mathbf{x}, \rho \mathbf{y}, \rho \mathbf{u}) \in T. \\
  (2b) & \quad \text{If } (\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T \text{ and } \mathbf{y} \leq \mathbf{\tilde{y}} \text{ then } (\mathbf{x}, \mathbf{\tilde{y}}, \mathbf{u}) \in T. \\
  (2c) & \quad \text{If } (\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T \text{ and } \mathbf{u} = \mathbf{0} \text{ then } \mathbf{y} = \mathbf{0}. \\
  (2d) & \quad (\mathbf{x}, \mathbf{y}, \mathbf{u}) \notin T \text{ if } \mathbf{x} = \mathbf{0} \text{ and } (\mathbf{y}, \mathbf{u}) \geq (0, 0).
  \end{align*} \]

• Given the input-output combinations for DMUs, the non-parametric estimation of the technology reads as:

  \[ T^* = \{ (\mathbf{x}, \mathbf{y}, \mathbf{u}) : \mathbf{x} \geq X\lambda, \mathbf{y} \leq Y\lambda, \mathbf{u} = U\lambda, \lambda \geq 0 \}. \]  

  (3)
Modelling the production technology with bad outputs

- Following Farrell (1957) input measure of technical efficiency
  \[
  \theta(x, y, u) = \min \{\theta : (\theta x, y, u) \in T\}. \tag{4}
  \]

- The above measure can be calculated by solving the LP problem:
  \[
  \begin{align*}
  \min_{\theta, \lambda} & \quad \theta \\
  \text{s.t.} & \quad 0x_i \geq X\lambda \\
  & \quad y_i \leq Y\lambda \\
  & \quad u_i = U\lambda \\
  & \quad \lambda \geq 0.
  \end{align*} \tag{5}
  \]

- To analyze dynamic changes, we apply the Malmquist index which is based on distance functions (Caves et al., 1982)

- To include bad outputs, Chung, Fare & Grosskopf (1997) extended this index to calculate Malmquist-Luenberger index (Fare et al. 2001; Yoruk and Zaim 2005; Zhang et al. 2011)

- To overcome infeasibility issues, Oh (2010) developed a Global Malmquist-Luenberger index (GML) (Pastor & Lovell, 2005)
Bias-correction of GML index

- Estimated technology set, $T'$ is a subset of true but unknown technology set, $T$
- Distance functions and the GML estimates are biased
- Simar and Wilson (1999) bias-correction procedure applied to GML index and its components ($B=2000$)
Data and model specification

- Panel data set containing 490 observations constituting 49 water utilities over 10 years (2005-06 to 2014-15)
- Output variables are exogenously determined for urban water utilities and thus input-orientation chosen (Saal et al., 2007)
- OPEX – Labour costs, chemical and material costs, bulk water charges
- Capital expenditure problematic:
  - Capital investments tend to be ‘lumpy’
  - Differing valuation methods (‘Fair value’ versus historical value)
- Length of the network as a capital proxy
- Greenhouse Gas Emissions (GHGs) as bad output; Total water delivered as and sewerage collected as good outputs
## Descriptive statistics of data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Median</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operational cost (opex)</td>
<td>A$/property</td>
<td>825.9</td>
<td>780.0</td>
<td>269.7</td>
</tr>
<tr>
<td>Water mains length</td>
<td>km</td>
<td>2385.5</td>
<td>962.5</td>
<td>3834.9</td>
</tr>
<tr>
<td>Water supplied (tuw)</td>
<td>ML</td>
<td>38681.7</td>
<td>10379.0</td>
<td>84448.7</td>
</tr>
<tr>
<td>Sewerage collected (tsc)</td>
<td>ML</td>
<td>28960.3</td>
<td>6741.5</td>
<td>75391.8</td>
</tr>
<tr>
<td>GHG emissions (ghg)</td>
<td>Tons CO₂ eq./1000 properties</td>
<td>437.9</td>
<td>408.0</td>
<td>247.9</td>
</tr>
</tbody>
</table>
Temporal trends of variables
Results: Productivity change trends (bias-corrected)
Results: GML and GM comparison
Results: Technical efficiency by utility category
Exogenous variables affecting efficiency

Table 3: Truncated regressions and bootstrap model results

<table>
<thead>
<tr>
<th></th>
<th>Model 1 DEA Unadjusted</th>
<th>Model 2 DEA Bias Corrected</th>
<th>Model 3 DEA Bootstrap</th>
<th>Model 3 95% Confidence Intervals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.14231***</td>
<td>4.06165***</td>
<td>4.1132***</td>
<td>3.41605 4.70091</td>
</tr>
<tr>
<td>SURFACE</td>
<td>-0.18173*</td>
<td>-0.1758*</td>
<td>0.05079***</td>
<td>-0.2203 0.27146</td>
</tr>
<tr>
<td>RECYCLE</td>
<td>0.09387</td>
<td>0.10078</td>
<td>0.22994***</td>
<td>-0.1070 0.8551</td>
</tr>
<tr>
<td>GROUND</td>
<td>0.30375*</td>
<td>0.22782</td>
<td>-0.2057***</td>
<td>-0.7247 -0.0661</td>
</tr>
<tr>
<td>TCP</td>
<td>-0.09405</td>
<td>-0.00535</td>
<td>-0.0198***</td>
<td>-0.0598 0.11752</td>
</tr>
<tr>
<td>CUSDEN</td>
<td>-0.0289***</td>
<td>-0.027410***</td>
<td>-0.0318**</td>
<td>-0.0558 -0.0360</td>
</tr>
<tr>
<td>RESIDE</td>
<td>-0.08075</td>
<td>-0.11690</td>
<td>0.21677***</td>
<td>-0.8976 0.7568</td>
</tr>
<tr>
<td>LEAK</td>
<td>-0.0873*</td>
<td>-0.06775</td>
<td>-0.0889***</td>
<td>-0.2684 -0.0536</td>
</tr>
<tr>
<td>PRODEN</td>
<td>-0.0020***</td>
<td>-0.00178***</td>
<td>-0.0019***</td>
<td>-0.0033 -0.0018</td>
</tr>
</tbody>
</table>

Note: n = 306; p-values are in brackets; *** Significant at 1% level, ** at 5% and * at 10%.
Discussion

• Recycling including desalinisation typically increases the energy footprint and GHGs

• Groundwater has low treatment costs compared to surface water from dams

• Efficiency and productivity decline
  • Drought effects and the increased effort towards water security may be affecting the productivity
  • Water OPEX has risen (30%) which includes high energy costs (NWC, 2012)
  • Recent changes to water quality standards in some jurisdictions
  • Impact of regulation + behavioural changes due to outdoor water restrictions and water conservation (Cahill & Lund, 2013)
Conclusions

• Irrespective of the methodology, the productivity growth in the urban water sector has declined over the period

• Conventional Malmquist index over-states the productivity growth compared to GML index which accounts for GHGs

• Regulator must account for externalities such as GHGs in utility benchmarking to ensure sustainability:
  • Incentives for top performers
  • Support to improve energy efficiency for the weak performers

• Further research to better understand the water-energy nexus on operational efficiency and productivity
Thank you
Input-oriented GML index

\[
\text{GML}^{t+1} = \frac{\theta^{t+1}(x_{t+1}, y_{t+1}, u_{t+1})}{\theta^t(x_t, y_t, u_t)} \cdot \frac{\theta^t(x_t, y_t, u_t)}{\sqrt{\theta^G(x_t, y_t, u_t) \cdot \theta^{t+1}(x_{t+1}, y_{t+1}, u_{t+1})}}
\]

\[
\text{GML}^{t+1} = \frac{0d/0C_{t+1}}{0b/0C_t} \cdot \frac{0b/0C_t}{0d/0C_{t+1}} \cdot \frac{0c/0C_{t+1}}{0a/0C_t} \cdot \frac{0b/0C_{t+1}}{0d/0C_{t+1}} \cdot \frac{0a}{0b} \cdot \frac{0d}{0c}
\]