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

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The ISEE 2016 Conference, Washington DC, USA, June. 26-29, 2016

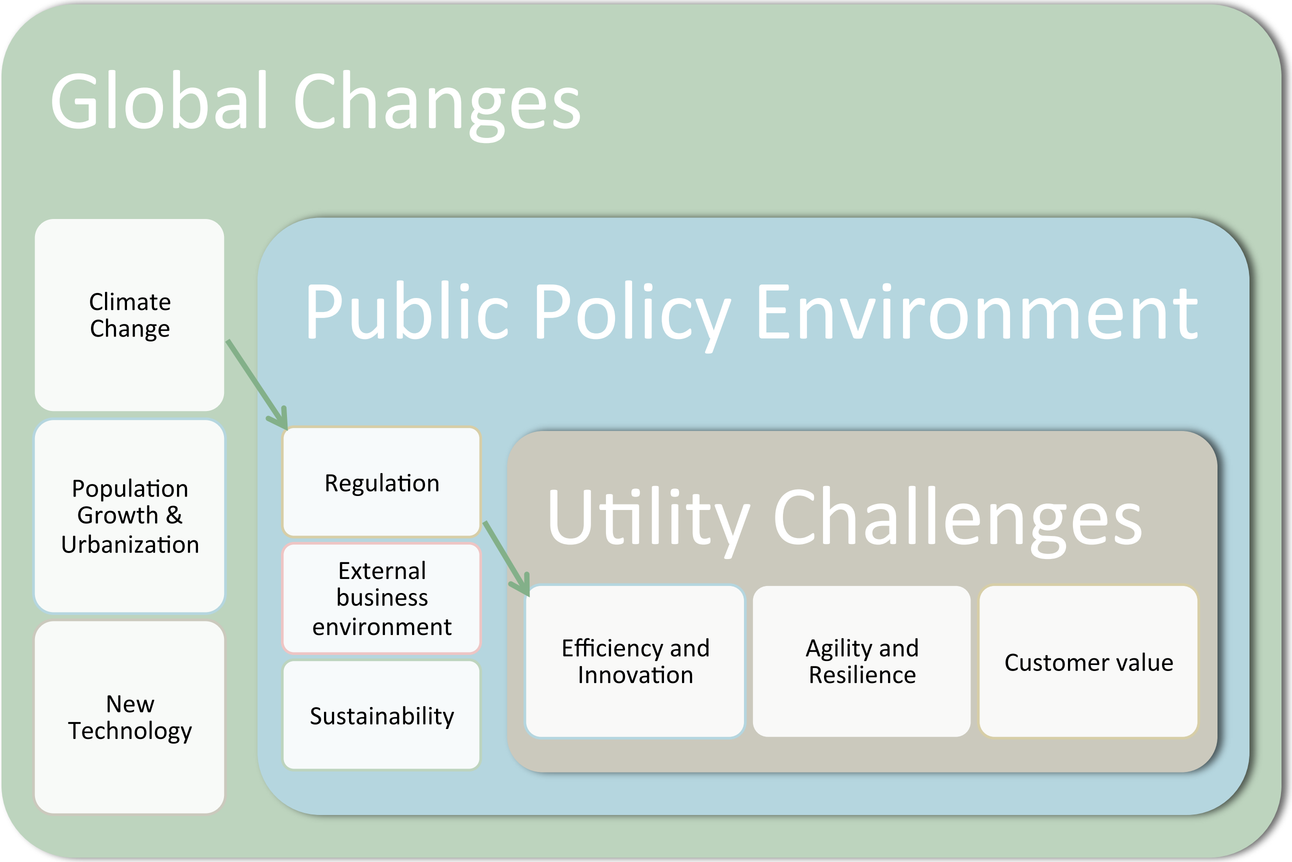
Outline

- 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



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 ***x***; to produce ***y*** desirable outputs and ***u*** pollutants .

- The technology set:

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

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

x

$$\text{If } (\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}) \in T \text{ and } 0 \leqq \rho \leqq 1 \text{ then } (\boldsymbol{x},\rho\boldsymbol{y},\rho\boldsymbol{u}) \in T. \qquad (2a)$$

$$\text{If } (\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}) \in T \text{ and } \tilde{\boldsymbol{y}} \leqq \boldsymbol{y} \text{ then } (\boldsymbol{x},\tilde{\boldsymbol{y}},\boldsymbol{u}) \in T. \qquad (2b)$$

$$\text{If } (\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}) \in T \text{ and } \boldsymbol{u} = \boldsymbol{0} \text{ then } \boldsymbol{y} = \boldsymbol{0}. \qquad (2c)$$

$$(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}) \notin T \text{ if } \boldsymbol{x} = \boldsymbol{0} \text{ and } (\boldsymbol{y},\boldsymbol{u}) \geq (\boldsymbol{0},\boldsymbol{0}). \qquad (2d)$$

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

$$\hat{T} = \{(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}): \boldsymbol{x} \geqq \boldsymbol{X}\lambda, \boldsymbol{y} \leqq \boldsymbol{Y}\lambda, \boldsymbol{u} = \boldsymbol{U}\lambda, \lambda \geqq 0\}. \qquad (3)$$

Modelling the production technology with bad outputs

- Following Farrell (1957) input measure of technical efficiency

$$\theta(\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}) = \min\ \{\theta : (\theta\boldsymbol{x},\boldsymbol{y},\boldsymbol{u}) \in T\}. \qquad (4)$$

- The above measure can be calculated by solving the LP problem:

$$\begin{aligned} &\min_{\theta,\lambda}\ \theta \\ &s.t.\ \theta\boldsymbol{x}_i \geqq \boldsymbol{X\lambda} \\ &\qquad \boldsymbol{y}_i \leqq \boldsymbol{Y\lambda} \\ &\qquad \boldsymbol{u}_i = \boldsymbol{U\lambda} \\ &\qquad \boldsymbol{\lambda} \geqq \boldsymbol{0}. \end{aligned} \qquad (5)$$

- 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, $\hat{T}$ 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)

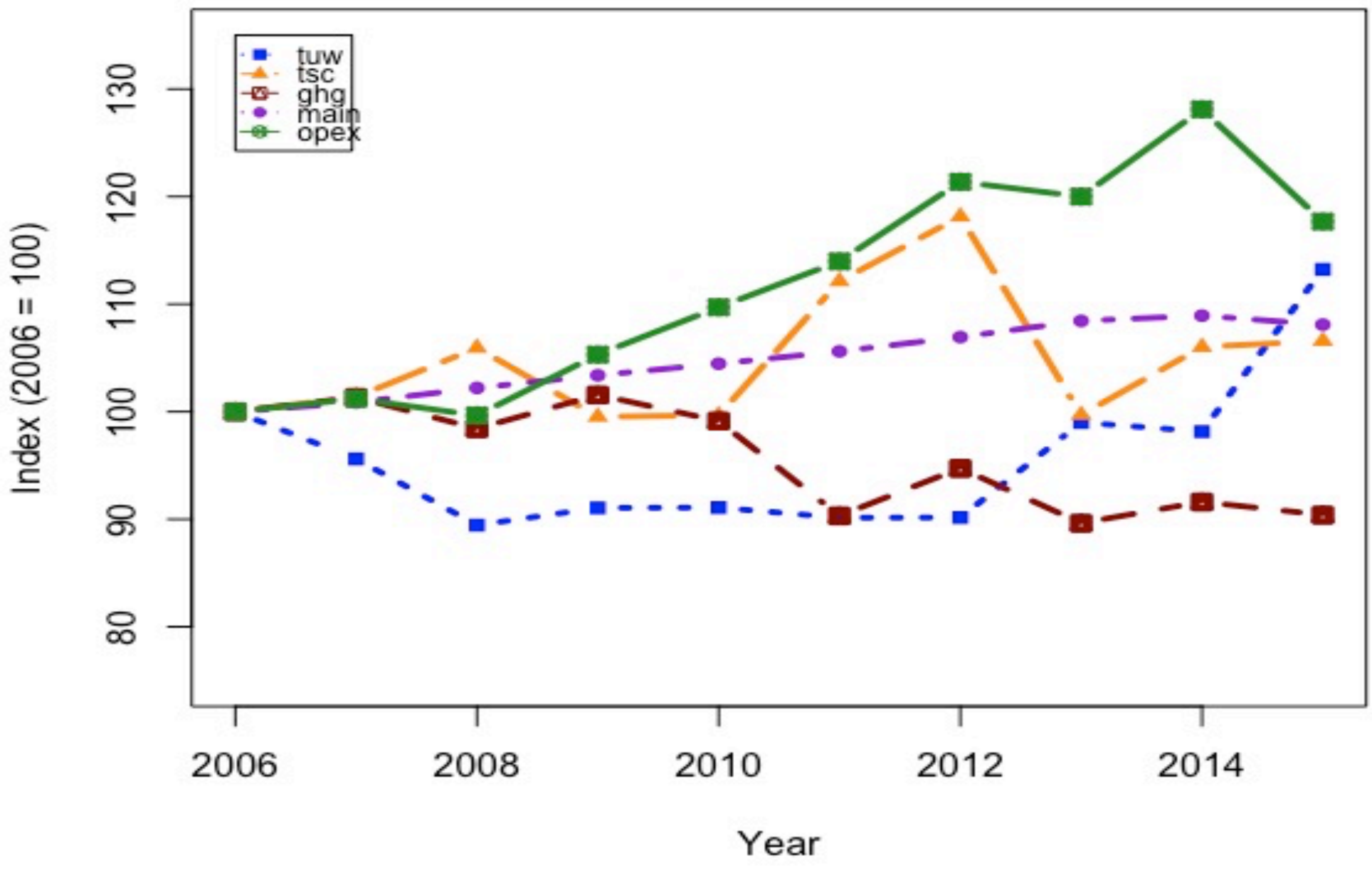
Data and model specification

- 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

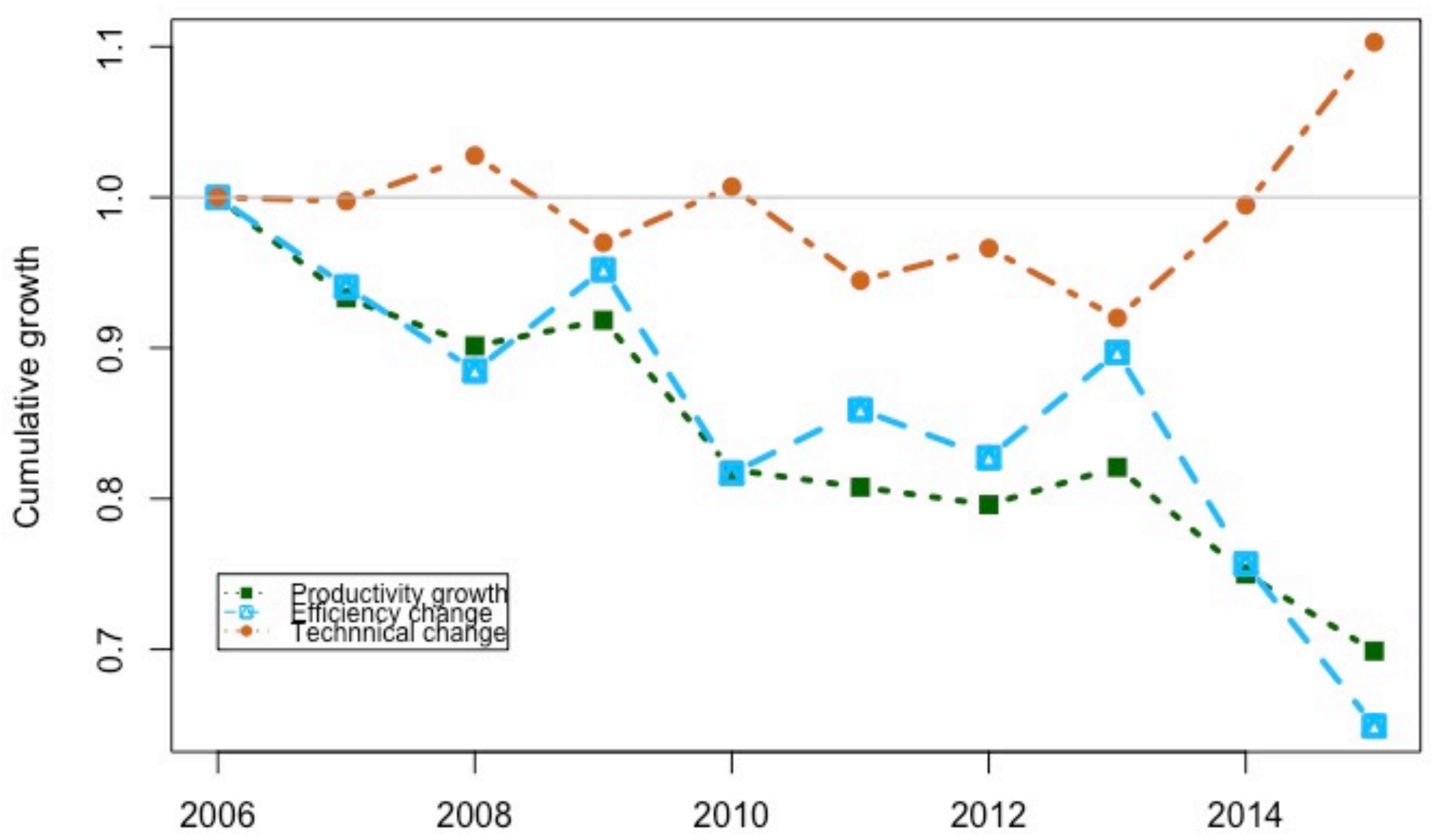
Descriptive statistics of data

Variable	Unit	Mean	Median	S.D.
Operational cost (opex)	A$/property	825.9	780.0	269.7
Water mains length	km	2385.5	962.5	3834.9
Water supplied (tuw)	ML	38681.7	10379.0	84448.7
Sewerage collected (tsc)	ML	28960.3	6741.5	75391.8
GHG emissions (ghg)	Tons CO_2 eq./1000 properties	437.9	408.0	247.9

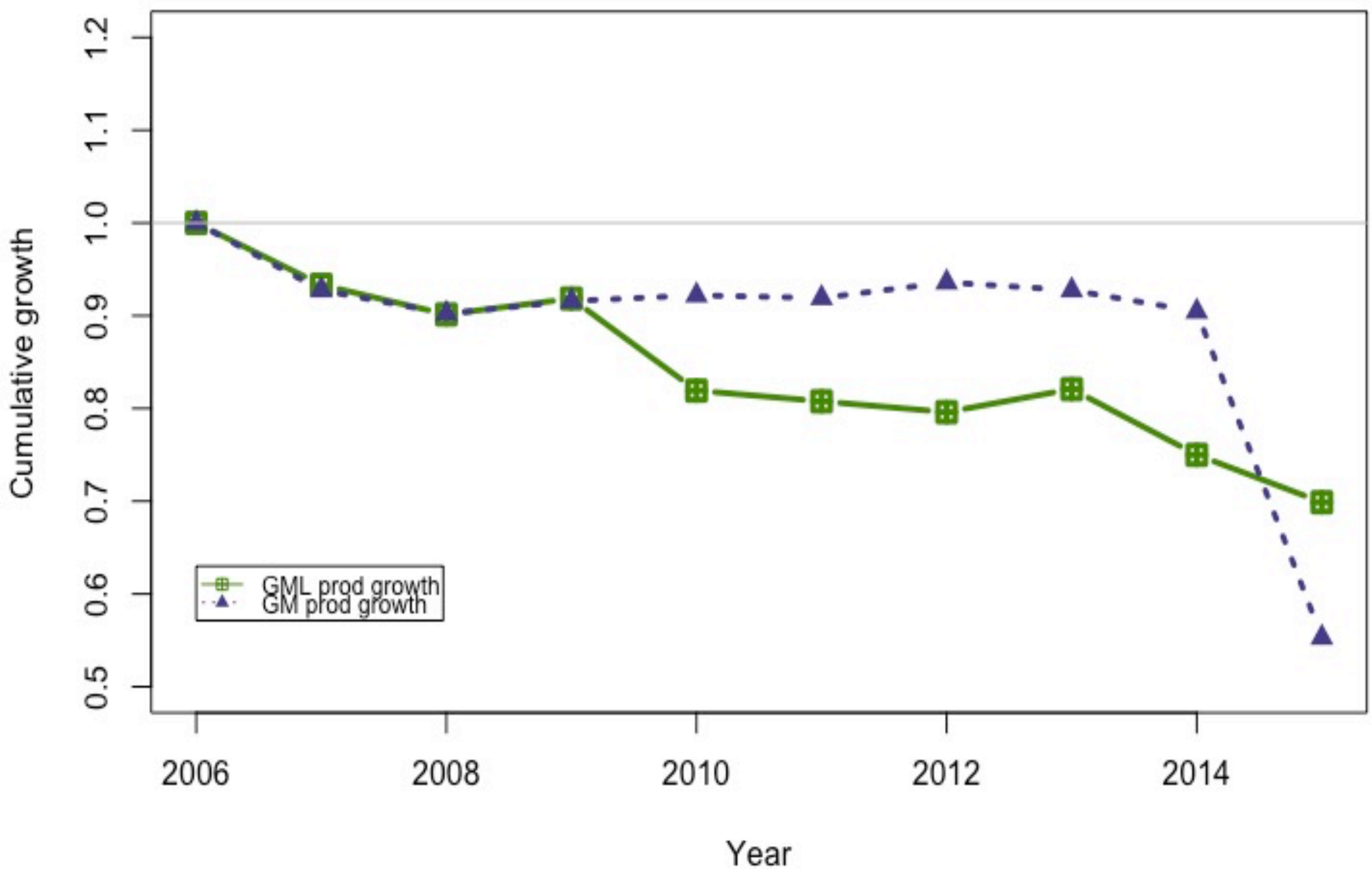
Temporal trends of variables



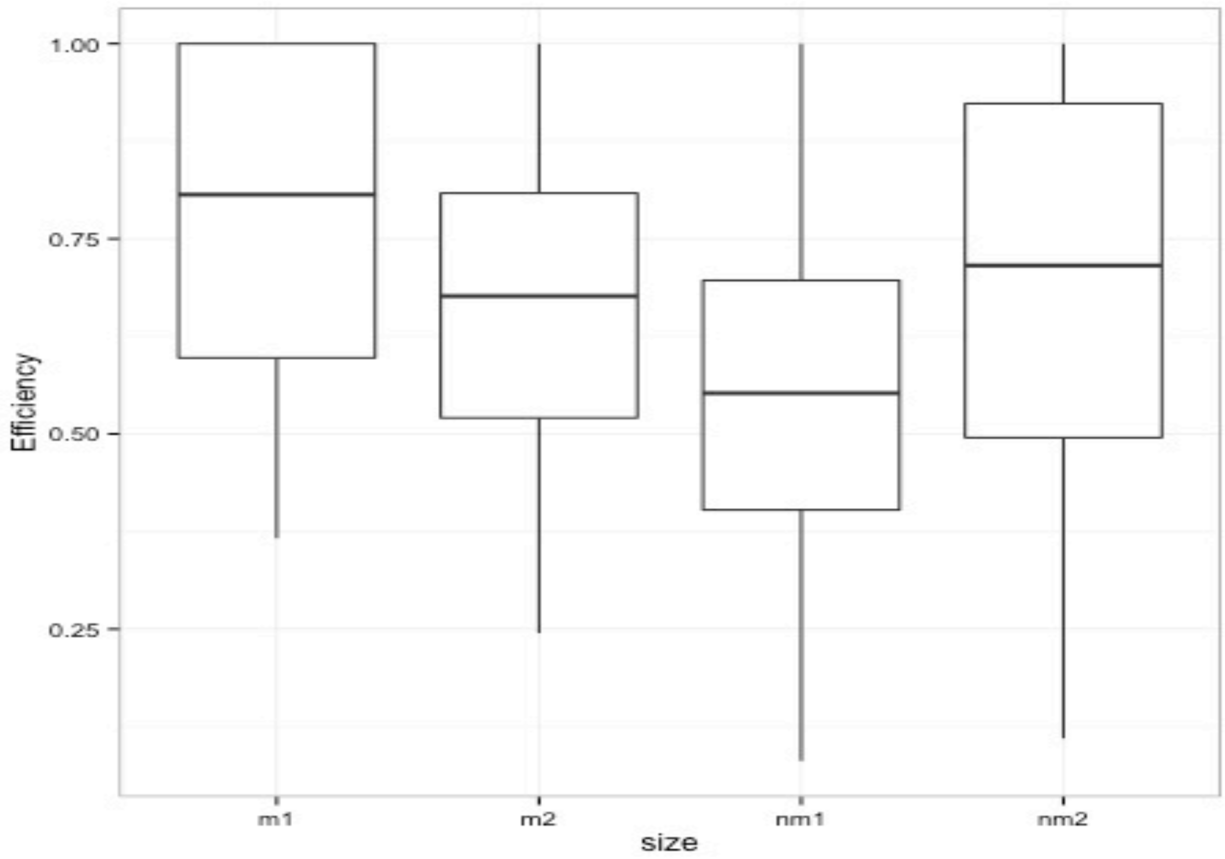
Results: Productivity change trends (bias-corrected)



Results: GML and GM comparison



Results: Technical efficiency by utility category



Exogenous variables affecting efficiency

Table 3: Truncated regressions and bootstrap model results

	Model 1 DEA Unadjusted	Model 2 DEA Bias Corrected	Model 3 DEA Bootstrap	Model 3 95% Confidence Intervals	
				L.B	U.B
Intercept	4.14231*** (0.000)	4.06165*** (0.000)	4.1132*** (0.000)	3.41605	4.70091
SURFACE	-0.18173* (0.045)	-0.1758* (0.031)	0.05079*** (0.000)	-0.2203	0.27146
RECYCLE	0.09387 (0.562)	0.10078 (0.508)	0.22994*** (0.000)	-0.1070	0.8551
GROUND	0.30375* (0.025)	0.22782 (0.054)	-0.2057*** (0.000)	-0.7247	-0.0661
TCP	-0.09405 (0.143)	-0.00535 (0.908)	-0.0198*** (0.000)	-0.0598	0.11752
CUSDEN	-0.0289*** (0.000)	-0.027410*** (0.000)	-0.0318** (0.000)	-0.0558	-0.0360
RESIDE	-0.08075 (0.814)	-0.11690 (0.710)	0.21677*** (0.000)	-0.8976	0.7568
LEAK	-0.0873* (0.044)	-0.06775 (0.067)	-0.0889*** (0.000)	-0.2684	-0.0536
PRODEN	-0.0020*** (0.000)	-0.00178*** (0.000)	-0.0019*** (0.000)	-0.0033	-0.0018

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

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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

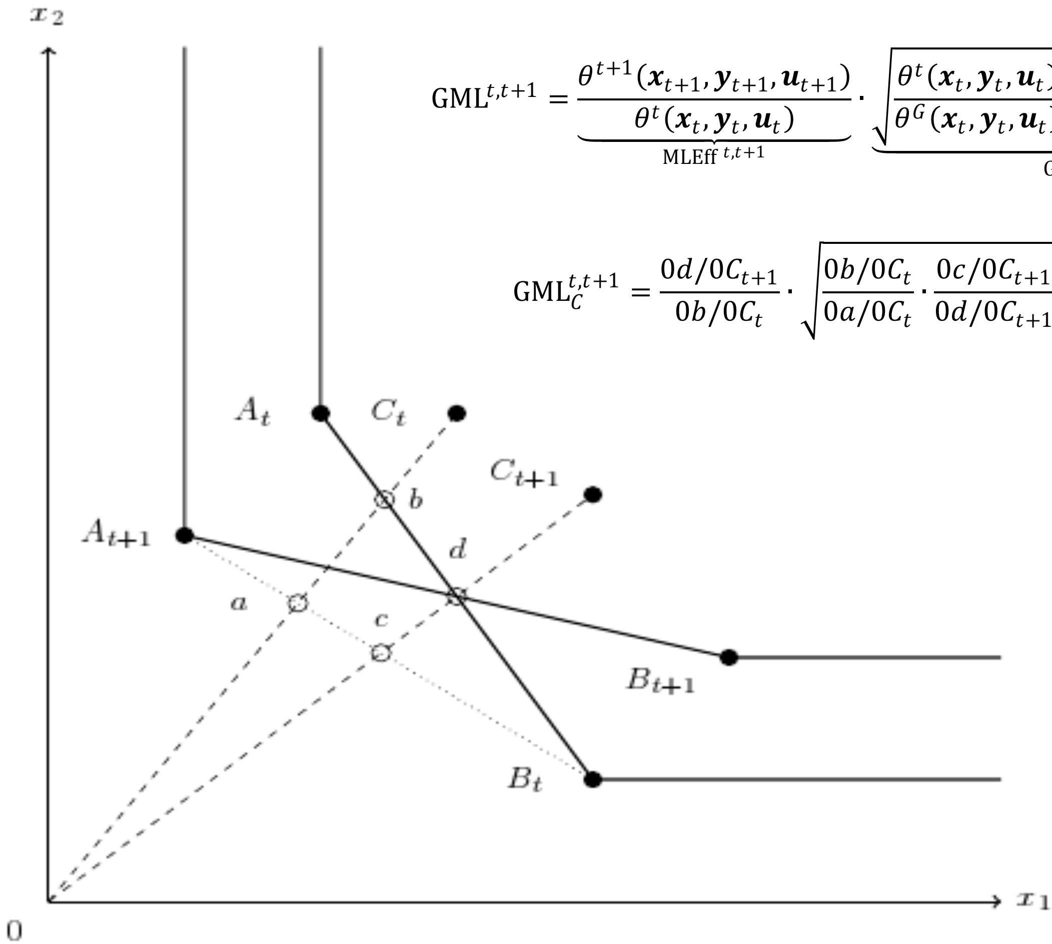
- Irrespective of the methodology, the productivity growth in the urban water sector has declined over the period
- Conventional Malmquist index over-states the productivity growth compared to GML index which accounts for GHGs
- Regulator must account for externalities such as GHGs in utility benchmarking 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

$$\mathrm{GML}^{t,t+1} = \underbrace{\frac{\theta^{t+1}(\boldsymbol{x}_{t+1},\boldsymbol{y}_{t+1},\boldsymbol{u}_{t+1})}{\theta^{t}(\boldsymbol{x}_{t},\boldsymbol{y}_{t},\boldsymbol{u}_{t})}}_{\mathrm{MLEff}^{\,t,t+1}} \cdot \underbrace{\sqrt{\frac{\theta^{t}(\boldsymbol{x}_{t},\boldsymbol{y}_{t},\boldsymbol{u}_{t})}{\theta^{G}(\boldsymbol{x}_{t},\boldsymbol{y}_{t},\boldsymbol{u}_{t})} \cdot \frac{\theta^{G}(\boldsymbol{x}_{t+1},\boldsymbol{y}_{t+1},\boldsymbol{u}_{t+1})}{\theta^{t+1}(\boldsymbol{x}_{t+1},\boldsymbol{y}_{t+1},\boldsymbol{u}_{t+1})}}}_{\mathrm{GMLTech}^{\,t,t+1}}$$

$$\mathrm{GML}_{C}^{t,t+1} = \frac{0d/0C_{t+1}}{0b/0C_t} \cdot \sqrt{\frac{0b/0C_t}{0a/0C_t} \cdot \frac{0c/0C_{t+1}}{0d/0C_{t+1}}} = \underbrace{\frac{0d/0C_{t+1}}{0b/0C_t}}_{<1} \cdot \sqrt{\frac{0b}{\underbrace{0a}_{>1}} \cdot \frac{0c}{\underbrace{0d}_{<1}}}$$



Analytical Framework