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Abstract

Various government-owned businesses provide water supply services to Australian residents. With the advent of recent competition and regulatory reforms in infrastructure industries in Australia, more and more of these businesses are now facing new types of incentive-based regulatory regimes. This has led to a desire for more information on the performance of these businesses, both relative to each other and over time. In this study we use panel data on the 18 largest Australian water services businesses, observed over an eight-year period from 1995/6 to 2002/3, to measure the relative efficiency and productivity growth of these businesses. Data envelopment analysis (DEA) methods are used to obtain estimates of the multi-input, multi-output production technology. The potential use of these performance measures in price-cap regulation is discussed, where the effects of variable selection and data quality upon empirical results is emphasised.

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1. Introduction

The principal aim of this paper is to conduct an analysis of the performance of the urban water supply industry in Australia. This will involve the use of empirical techniques that can accommodate the multi-input, multi-output nature of the industry, which will be used to provide estimates of the relative efficiency, and historical productivity growth of each of the main urban water supply businesses in Australia. The main motivation for the study is to provide comprehensive performance information to help regulatory authorities set CPI-X price paths that encourage efficient performance. However, the paper contains considerable discussion of the data shortcomings that exist and hence the degree to which these measures should be used in a "light-handed" manner in any regulatory deliberations. Furthermore, we indicate that considerable work is required in improving the comparability of data, especially in the area of capital, before these types of measures can be used in a reliable manner.

Water users in Australia can be divided into two groups: (i) agricultural and (ii) residential and industrial. The businesses that supply water to the latter group of consumers can also be divided into two groups: (i) businesses that primarily supply water to small regional towns and rural communities, and (ii) larger businesses that generally supply water to the state capital cities and larger regional cities.

The latter group of large businesses are the focus of the present study. This is for two reasons. First, these large businesses are generally owned by state governments or territories and their prices tend to be regulated by independent regulatory agencies, while the smaller businesses are usually owned by local town councils, without formal independent price regulation.[1] Second, the larger businesses formed an industry association known as the Water Supply Association of Australia (WSAA) in 1995, and have subsequently been collecting high quality data for benchmarking purposes, which they make public in an annual publication known as *WSAAfacts* (see WSAA 2003). The members of WSAA are a significant part of the Australian water supply sector, supplying water to roughly two-thirds of the Australian population.[2]

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[1] Australia has three levels of government: (i) a federal government; (ii) states and territories; and (iii) local councils. There are six states (New South Wales, Victoria, Queensland, South Australia, Western Australia and Tasmania) and two territories (Northern Territory and Australian Capital Territory).

[2] From this point forward, when we refer to the *water supply industry* we will be specifically referring to these WSAA businesses.

A description of the history and current regulatory structure of the Australian water supply industry is difficult to provide, because it differs from one state to another. However the following description is applicable to the majority of businesses. First, these businesses have generally been government owned (i.e. either by a state government or a local council) for much of the 20th century, and still are.[3] Price levels have traditionally been set by the government. These prices have often been set so as to not cover all costs of production (ie. have been subsidised) and have generally been in the form of a fixed charge based upon the rated value of the property being connected. Thus, cross-subsidies have been common (King and Maddock, 1996, p20 and 26).

During the last decade a number of reforms have been implemented in the water sector, which mirror similar changes introduced in a number of infrastructure sectors in Australia. The businesses have been required to be more commercial in their operations and structure, while generally remaining in government ownership. This process has become known as "corporatisation". The key changes relate to: (i) introduction of a corporate structure of management; (ii) earning revenues which are sufficient for the business to earn a commercial rate of return on its capital investment; and (iii) an independent regulator is used to set prices at arms length from the government owner. For further detail see King and Maddock (1996, p21).

Each state and territory has a regulatory authority that is responsible for regulating prices charged for water by the major urban water supply businesses, plus other responsibilities (e.g. in the electricity and gas sectors). The different state regulators use similar but not identical methods in regulating water prices. For example, the NSW regulator, the Independent Pricing and Regulatory Tribunal (IPART), uses CPI-X regulation, via what is known as the "building blocks approach". This is a form of regulation that is a messy blend of incentive regulation and rate of return regulation, which is used by most regulatory authorities in Australia.

In CPI-X price regulation, the regulated business is permitted to increase its prices over a particular period (usually five years) by the change in the consumer price index (CPI) minus an X factor. The X factor is generally called a productivity offset, because it reflects the degree to which the regulator believes the business can improve its productivity (i.e.

[3] The one exception is in Adelaide where the assets remain government owned but the government has contracted a private company, United Water, to manage, maintain and operate the business over a 15-year contract period ending in 2010.

reduce its costs in real terms). However, the X factor can also incorporate other things, such as an allowance for the extra costs associated with required improvements in quality.[4]

The setting of the X factor value is always the subject of considerable debate. Most Australian regulators hire consultants to study the operations of each company and identify possible areas for cost savings. However, this approach is not without its criticisms. First, it is generally a fairly invasive process, because the consultants require a lot detailed information to make their assessments. Second, there is a perception that the conclusions made by the consultants are rather "black box" in nature because they are generally difficult to verify in a scientific manner. Third, information asymmetries tend to ensure that the business managers always know more about the true nature of the "efficient costs" of production, relative to the hired consultants. Fourth, the use of a business' own performance record to set an X factor may create incentives for the business to not attempt to improve its rate of productivity growth because of the danger that it will lead to a higher X factor in the next regulatory period.

These types of issues have encouraged some regulators to consider the use of industry benchmarks in the setting of X factors.[5] This generally involves the calculation of industry-level measures of average annual productivity growth using historical data, and/or the calculation of firm-level measures of relative efficiency, which are measured relative to an estimated production frontier, using a method such as data envelopment analysis (DEA) or stochastic frontier analysis (SFA). These methods have the advantage that they are less invasive and provide greater incentives for efficiency improvements. However, these methods have the disadvantage that it is often difficult to capture all aspects of a particular businesses' operating environment in a single production model, and hence the results of these methods need to be used in concert with additional information.

From our search of the published literature, we were unable to identify any studies that have applied these techniques to data on Australian water supply businesses. The best source of relative performance information currently available is WSSA (2003), which provides a range of partial productivity measures, such as operating costs per connection and per unit volume of water delivered, for each of its members over a number of years.

[4] For example, the UK water regulator, OFWAT, actually allowed prices to increase in real terms in its first price determination, because it required the UK businesses to make substantial investments in new capital to achieve newly mandated quality targets. See, Saal and Parker (2000) for discussion.

[5] For example, see the electricity supply case described in Diewert and Lawrence (2004).

However, WSAA (2003) does not attempt to calculate more comprehensive productivity measures for the industry.

Hence, as noted earlier, the main aim of this paper is to fill this gap by conducting a detailed analysis of the performance of the urban water supply industry in Australia, using empirical techniques that can accommodate the multi-input, multi-output nature of the industry, which can be used provide estimates of the relative efficiency and historical productivity growth of each of the main urban water supply businesses in Australia.

The remainder of the paper is organised into sections. In section 2 we provide a brief description of the Australian water supply industry and the factors that are likely to contribute to differences in production costs between businesses and over time. In section 3 we review some recent international analyses of water supply efficiency. In section 4 we describe the data envelopment analysis methods that are used in this paper, before presenting our empirical results in section 5, and making some concluding comments in the final section.

2. The Australian Water Supply Industry

The production process that is used to supply water to urban areas in Australia is fairly straight forward. One generally obtains raw water from a purpose built dam (or pumps it out of a river or groundwater aquifer), pipes it to a treatment plant for treatment, and then pipes it to households and businesses. However, comparisons of the relative efficiency of urban water supply businesses in Australia is a difficult exercise, because these firms operate in a wide variety of environments. Hence, cost comparisons are likely to be influenced by a number of factors that are not under the control of management.

Some information on the characteristics of the 18 businesses we consider in our empirical analysis is listed Table 1.[6] As can be seen, these businesses differ in various aspects, including the size of the business, the volumes of water delivered per customer, and the mix of residential and non-residential customers (i.e. commercial and industrial). Some of these and other factors that could influence the costs of production across these businesses are now discussed.

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[6] Note that the city of Melbourne is serviced by one wholesale water collection and treatment business (Melbourne Water Corporation) and three water distribution businesses (City West, South East and Yarra Valley). Thus the data listed for Melbourne Consolidated corresponds to these four businesses combined, while the cost data listed for the three water distribution businesses includes the costs of purchasing water from the wholesaler. Similarly, also note that Sydney, Brisbane and Gold Coast purchase bulk water from a wholesaler and that their costs include the costs of purchasing water from the wholesaler.

[Table 1 here]

A high *percentage of non-residential customers* is likely to be associated with higher costs per connection because these customers tend to consume higher volumes, but it is also likely to reduce costs per mega litre because of reductions in connection related costs and the fact that some industrial customers require lower levels of water treatment. From Table 1 we see that the percentage of non-residential customers is fairly uniform across the Australian businesses, with an average of 8.55%, however a few businesses do deviate to some extent, from a high of 12.24 in Goulburn Valley to a low of 4.62 in Gosford.

A high *percentage of water from non-catchment sources* (such as rivers and groundwater) is likely to be associated with lower capital costs (i.e. less dams needed) but conversely is likely to be associated with higher operating costs, due to larger amounts of pumping and treatment required. From Table 1 we see that these Australian water businesses derive less than 20% of their water from non-catchment sources (ie. pumping from rivers and groundwater), on average. However, three businesses derive over half of their water from non-catchment sources, namely Hunter, Perth and Barwon.

Higher *average rainfall* is likely to reduce the capital costs of water catchment because smaller dams are required since they are replenished more quickly. Average rainfall levels vary significantly across these businesses, from a low of 458mm in the Goulburn Valley in the south to a high of 1,953mm in Darwin in the tropical north.

Temperature differences can have a range of effects. Higher average temperatures can increase the demand for watering gardens and hence increase volumes per customer, while a wide range of temperatures over the year can result in a high peak to average flow ratio, the latter leading to larger capital costs per unit volume delivered, because the network needs to be built to accommodate the peak. Information on average maximum temperatures and peak to average flows are presented in Table 1, where we see that average maximum temperatures do not vary significantly, with all but Darwin (with 33 degrees Celsius) lying in the range from 19 to 26 degrees. The data on the ratio of peak to average flow is also fairly uniform, with most values lying in the range from 1.5 to 2.0. This is not a wide amount of variation, given that the numerator in this ratio depends upon water demand on a single day in the year.

A higher *network density* is likely to reduce costs associated with water distribution because less pipe infrastructure is needed per connection.[7] Information on the number of connections per km of mains pipeline is presented in Table 1. This shows a range of densities, from around 60 to 70 for most large cities to around 30 for those businesses that service the regional centres.

A large business *size* may result in lower costs because of scale economies, but if the large size is associated with serving a large city, then this may also increase the capital costs associated with collecting water, as discussed above. The data on number of connections in Table 1 shows that there is substantial size variation, from around 50 thousand properties for a number of the regional businesses to over 1.5 million in Sydney, the largest city in Australia.

A hilly *topography* can affect costs because of the extra pumping costs that are generally incurred. The data on electricity usage per connection (which is highly correlated with pumping activity) reported in Table 1, exhibits a wide range of values, from a low of 6 kw per connection for Yarra Valley, which receives all of its water supply from catchments up in the hills outside Melbourne, to a high of 332 for Adelaide, which needs to pump over 40% of its water from the Murray River.

The *soil type* can be important, with clay soils contributing to more pipe breakages, especially for the older terracotta pipe networks, and hence higher maintenance costs. However, clay soils can also mean a better seal on the dams and hence lower water losses contributing to lower water catchment capital costs. Information on soil type differences is not readily available, however it is known that cities such as Perth have a low clay content in their soils, relative to some other cities in Australia.

Differences in *demand management* policies (e.g. water use restrictions) can also influence costs via its effect on volumes per customer and also upon the ratio of peak to average flow. Once again, information on this factor is not readily available (nor easy to define), however it is known that these businesses have placed varying degrees of emphasis on demand management in recent years. For example, due to water catchment constraints, Gold Coast Water has been active in this area for some years, with the results of this activity reflected in their low peak to average ratio in Table 1.

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[7] This is a view that is commonly expressed by both regulators and regulated water businesses in Australia. However it is interesting to note that Feigenbaum and Teeples (1983, p674) hold the opposite view in that they expect the costs of US water companies to increase with density because of the need for "more hydrants, higher water pressure and greater peak capacities for fire protection".

Other differences in *local regulations and policies*, such as water pressure standards, minimum capacity standards (set by fire authorities), water quality standards and reliability standards, can also affect costs, however these are generally fairly uniform across Australia.

The above list of issues is not complete but does include some of the key cost drivers in this industry. What is clear from this discussion is that comparative performance measurement in the urban water supply industry in Australia is a challenging exercise. The model that we use in the empirical section of this paper will not be able to accommodate all of these factors completely, due to data constraints and degrees of freedom constraints. Hence the performance measures obtained should clearly be used carefully.[8]

3. Review of literature

In this section we review some studies that have conducted economic analyses of urban water supply businesses using empirical modelling techniques such as regression analysis, data envelopment analyses and stochastic frontier analysis. The review does not include any Australian studies because we were unable to find any Australian studies in the published literature.

US Studies

The question of the relative efficiency of public versus privately owned utilities led to a number of econometric analyses of water supply utilities in the USA in the late 1970's and 1980's. First, Crain and Zardkoohi (1978) estimate a Cobb-Douglas cost function and conclude that the public firms have significantly higher costs, relative to private firms. Their model involved a (logarithmic) regression of cost on output quantity, labour price, capital price and an ownership dummy variable. The output measure used was volume of water delivered while the cost measure was the sum of operating, maintenance and depreciation costs. This output measure can be criticised on the basis that it assumes a homogenous output, while the cost measure is also sub-optimal because it excludes the opportunity cost of capital.

A later study by Bruggink (1982) also comes to the same conclusions regarding the superiority of private firms using a similar approach. These two studies are then criticised in a subsequent study by Feigenbaum and Teeples (1983), who argue that the empirical work in

[8] This statement will be made even more strongly in later discussion where we discuss some of the data comparability issues, especially on the capital side of things.

these two previous studies is flawed because of: (i) the use of volume as the only output measure; (ii) the use of a simple functional form;[9] and (iii) the omission of relevant factor prices. They go on to specify a cost function model in which output is modelled using a hedonic function (which includes variables reflecting metering, treatment levels, density, capacity utilisation, customer size and water purchases); a more general translog functional form is specified; and an electricity price variable is included (in addition to labour and capital prices). They conclude that there are no significant differences in the costs of public and private firms. However, for some reason they exclude capital costs from their cost measure, which seems strange given that capital costs generally exceed operating costs in most network utilities.

Byrnes, Grosskopf and Hayes (1986) also address the private/public issue, but they instead decide to use the linear programming technique known as data envelopment analysis (DEA) to estimate levels of technical efficiency for each firm in the sample. They argue that their approach should be preferred to the cost function methods because of: (i) a lack of reliable data on (the economic notion of) capital costs; (ii) input quantity data being more reliable than input price data; (iii) no need to impose a function form; and (iv) the method produces estimates of best practice performance as opposed to average performance. They specify a production model with one output variable, volume of water delivered, and seven input variables: ground water, surface water, purchased water, part-time labour, full-time labour, length of pipeline and storage capacity. They conclude that there are no significant differences in the technical efficiency scores (nor the scale efficiency scores) of private versus public firms.

On face value, the Byrnes et al (1986) study could be criticised for not including more output indicators (as used in the Feigenbaum and Teeples study). However, as they point out, the input variables used are likely to control for a number of these differences in output characteristics. For example, the use of the three water source variables will ensure that firms with similar water source mixes will be benchmarked with each other,[10] while the use of two capital proxies (storage capacity and length of pipelines) should mean that firms with similar network densities will generally be benchmarked with each other.

[9] The Cobb-Douglas functional form is restrictive in the sense that it imposes constant input elasticities and elasticities of substitution which are equal to one (Coelli, Rao & Battese, 1998:201).

[10] This is because in output orientated DEA the method measures technical efficiency as the maximum amount by which output can be expanded, while holding the input quantities (and hence mixes) fixed.

Teeples and Glyer (1987) provide a comparison of the models of Crain and Zardkoohi (1978), Bruggink (1982) and Feigenbaum and Teeples (1983), using data on water utilities in California, and argue that the differing conclusions in these earlier papers can be put down to the model restrictions implicit in the earlier papers.

Interest in the issue of public versus private ownership of water supply companies in the US waned for a decade or so until another round of studies surfaced in the mid 1990's authored by Bhattarcharyya and colleagues: Bhattarcharyya, Parker and Raffie (1994) and Bhattarcharyya et al (1995a,b). These three studies also estimated econometric cost functions, but used more up-to-date data and looked at a number of alternative methodological approaches, such as (i) specifying a short run cost function (with capital quantity specified as a regressor); (ii) estimating the cost function in a system with first order equations; (iii) estimating a shadow cost system to reflect possible deviations from cost minimising behaviour; (iv) estimating the cost function using stochastic frontier techniques; (v) including quality variables such as system disruptions and water losses in the model, etc.

Lambert and Dichev (1993) also conducted a comparison of privately and publicly owned water utilities. They used data on 238 public and 32 private firms from a 1989 survey conducted by the American Water Works Association (AWWA) and measured technical, allocative and scale efficiency using DEA. The single output variable used was total water delivered, while the four input variables used inputs were: annual labour use in hours; British thermal units of energy used; value of material inputs used; and value of capital. The study finds that technical inefficiency is the main source of inefficiency and that there are no significant difference between private and public firms.

UK Studies

The 1990's also heralded the arrival of several studies using UK data, motivated by the privatisation moves in the early 1990's in the UK. These include the stochastic cost frontier analysis study by Lynk (1993); the comparison of DEA and regression methods in Cubbin and Tzanidakis (1998); the DEA studies of Thanassoulis (2000a,b) the cost function study of Ashton (2000); the Tornqvist total factor productivity (TFP) index study of Saal and Parker (2000) and the stochastic cost frontier study of Saal and Parker (2001).

In one of his SFA cost function models, Lynk (1993) studied the efficiency of 22 privately-owned water companies from 1984/85 to 1987/88. The dependent variable was operating cost, with the regressor variables being one output variable (water supplied); one input price variable (unit labour cost), and dummy variables for time and geography. The model was unusual in that it did not include a fixed capital variable, and did not attempt to accommodate the effects of customer size and network density.

Cubbin and Tzanidakis (1998) used 1994/95 UK water industry data to conduct a comparison of regression analysis (RA) and DEA. A measure of operating expenditure adjusted for factors outside the companies' control and unrelated to observable cost drivers was used as the sole input variable. Outputs were water delivered, length of mains and the proportion of water delivered to non-households. The results indicate differences in rankings, and the authors conclude that DEA is best used when large samples are available, although RA does not put individual weights on variables and as such may not be as fair to individual firms.

Thanassoulis (2000a and 2000b) undertook a data envelopment analysis of water distribution in the UK using data obtained from OFWAT. He included the input of operating expenditure, and argued for the exclusion of capital costs from the input(s) because OFWAT saw no convincing evidence that operating expenditure and capital expenditure were inversely related. Output measures used include number of properties connected, length of mains, volume of water delivered and pipe bursts. The choice of length of mains and pipe bursts as output variables are arguably controversial. The mains variable was included to attempt to capture the effects of network density. However, given that mains are a capital input, the use of mains as an output variable could perhaps signal to firms that more input is better. Mains bursts were included to attempt to reflect the fact that certain networks are more susceptible to bursts and hence require more reactive maintenance. However, one could alternatively argue that one would normally require a water company to attempt to minimise pipe bursts (through better maintenance) rather than maximise them. Once again, this output variable could send rather unusual incentive signals to the firm being assessed, in the medium term.

Other studies

In addition to these US and UK studies, a handful of additional studies have appeared in recent years. For example, the cost function study of French water supply businesses in Garcia and Thomas (2001); the SFA cost frontier study of water supply industries in Asian countries by Estache and Rossi (2002) and the DEA study of Mexican water supply businesses in Anwandter and Teofilo (2002). These papers tend to use similar methods to those discussed above.

4. Performance measurement methods

Simple ratio measures, such as water delivered per employee and operating costs per connection, are widely used performance measures. The popularity of these ratio measures, which we will call “partial productivity measures”, stems from the fact that they are easy to construct and also easy to interpret. However, in many cases these ratio measures are unreliable indicators of the “true productivity” of the business. This is because a particular business could have high operating costs per connection because it is poorly managed and wasteful, or it alternatively it could be due to factors not under the immediate control of the managers, such as (i) having high volumes per connection (due to a large proportion of non-residential customers or due to climatic factors); (ii) servicing an area with a low population density; (iii) owning assets which have a high average age and hence require more maintenance costs; (iv) being a small business and hence suffering from diseconomies of scale; and so on.

The key problem with this ratio measure of operating costs per connection is that it is a partial productivity measure, in that it does not include all information on the inputs and outputs used by the firm.[11] For example, it does not include output characteristics related to volumes per connection nor network density, and it ignores capital inputs, such as pipes and pumps. Furthermore, it does not take account of differences in the size of the business. These problems could perhaps be addressed by dividing the sample of firms up into a number of groups according to business size, and then according to volumes per customer, and then according to network density, and then according to capital intensity – but soon you would find that most cells in the four dimensional table would contain one firm or fewer, and hence a benchmarking exercise would not be sensible.

As an alternative to this, we use a method known as data envelopment analysis (DEA) in this study. This technique uses linear programming methods to build a piece-wise surface over data (on input and output quantities) for a sample of firms and then assesses the efficiency of each firm by measuring the distance that each data point lies below the best practice production frontier. This technique has the advantage that it can accommodate multiple inputs and multiple outputs, and produces information on “peer firms” for each of the inefficient firms. That is, those firms that have a similar input mix, output mix and scale of operation (to the particular inefficient firm), but are located on the frontier surface, and

[11] See related discussion of the gas supply industry in Carrington, Coelli and Groom (2002).

hence are producing the same output with fewer inputs. This method will be described in more detail shortly.

As is evident from the review of literature in the previous section, other techniques, such as ordinary least squares (OLS) regression, stochastic frontier analysis (SFA) and total factor productivity (TFP) indices calculated using price-based index numbers (PIN), have also been used in analyses of water industry performance in overseas studies. OLS methods are well known and easy to implement, however they could be criticised on the basis that they require the specification of a functional form for the production technology and they provide information on average performance rather than frontier performance.

SFA is an econometric technique that addresses this latter problem, by specifying a composed error term, with one part used to capture data noise and the other inefficiency. However SFA methods still require a functional form to be specified, plus distribution forms for its composed error structure. PIN methods, such as the popular Tornqvist TFP index, suffer from the problem that they require access to reliable price information (which is often difficult to obtain) plus they do not explicitly accommodate scale effects.

The DEA method used in this study is a frontier method that does not require specification of a functional form or a distributional form, and can accommodate scale issues. Hence it can address the above problems. However, DEA has the disadvantage that it does not explicitly accommodate the effects of data noise, while OLS and SFA methods do. On balance we have decided to use DEA methods here because we believe that data noise is less of an issue in an industry such as water supply, where accounting standards are high (relative to the case of small farmers in a developing country where SFA would be a wiser choice),[12] and because DEA is able to readily produce rich information on technical efficiency, scale efficiency and peers. However, in future work we plan to also use SFA methods to investigate the sensitivity of our results to the choice of methodology.[13]

Efficiency measurement using DEA

DEA uses linear programming (LP) to obtain the measures of technical efficiency (TE). The input-orientated DEA LP is set up so as to maximise the TE score of the i-th firm, subject to

[12] See Coelli (1995) for further discussion.

[13] See Coelli, Rao & Battese (1998) for further details regarding these various methods and their relative merits.

production remaining within the feasible set of production possibilities.[14] This involves the solution of the following LP problem.

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \\
&\text{st} \quad -y_i + Y\lambda \geq 0, \\
&\qquad \theta x_i - X\lambda \geq 0, \\
&\qquad \lambda \geq 0, \qquad (1)
\end{aligned}
$$

where y_i is a M×1 vector of outputs produced by the i-th firm, x_i is a K×1 vector of inputs used by the i-th firm, Y is the M×N matrix of outputs of the N firms in the sample, X is the K×N matrix of inputs of the N firms, λ is a N×1 vector of weights (which relate to the peer firms) and θ is a scalar measure of TE, which takes a value between 0 and 1 inclusive. This problem is be solved N times – once for each firm in the sample.[15]

The above DEA LP has become known as the constant returns to scale (CRS) DEA model because the resulting technology will be a CRS technology. Thus, the efficiency scores obtained from this DEA model will be influenced by scale effects, if they exist. This may not be desirable in some cases, since firms cannot always influence scale in the short run. The above CRS DEA LP can be adjusted in order to allow a variable returns to scale (VRS) DEA technology. This is done by adding a convexity constraint to the original problem, resulting in the following LP,

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \\
&\text{st} \quad -y_i + Y\lambda \geq 0, \\
&\qquad \theta x_i - X\lambda \geq 0, \\
&\qquad N1'\lambda=1 \\
&\qquad \lambda \geq 0, \qquad (2)
\end{aligned}
$$

where N1 is a vector of ones. This VRS LP produces technical efficiency scores that are either greater than or equal to those from the CRS problem. This means that the variable returns to scale specification gives "pure" technical efficiency scores, which are free of scale efficiency effects.

[14] DEA models can be either input or output orientated. In the input orientation the efficiency scores relate to the largest feasible proportional reduction in inputs for fixed outputs, while in the output orientation it corresponds to the largest feasible proportional expansion in outputs for fixed inputs. It is common practice to use an input orientation in analyses of network utilities because the firms are generally required to supply services to a fixed geographical area, and hence the output vector is essentially fixed. For example, see discussion in Coelli et al (2003, p41).

[15] The discussion here is based on that in Coelli, Rao & Battese (1998).

A scale efficiency (SE) score can be derived (for each firm) by dividing the CRS TE score by the VRS TE score. This SE score also takes a value between 0 and 1 inclusive.

Productivity measurement using DEA

If one has access to suitable panel data, Fare et al (1994) have shown that DEA frontier construction methods can be used to obtain estimates of Malmquist TFP index numbers. This approach also has an advantage relative to PIN TFP methods (e.g. Törnqvist TFP indices) that:

- price data are not required;
- the TFP indices obtained may be decomposed into components:
  - technical change (frontier-shift),
  - technical efficiency change (catch-up).

The one principal drawback of the Malmquist methods is that panel data are required, while the PIN methods may be calculated with only a single observation in each time period. However, this is not an issue in this study because we have panel data on 18 firms over an eight-year period.

The Malmquist TFP index measures the TFP change between two data points by calculating the ratio of the distances of each data point relative to a common technology. If the period t technology is used as the reference technology, the Malmquist (input-orientated) TFP change index between period s (the base period) and period t is can be written as

$$M_i^t(y_s, x_s, y_t, x_t) = \frac{d_i^t(y_t, x_t)}{d_i^t(y_s, x_s)}. \qquad (3)$$

Alternatively, if the period s reference technology is used it is defined as

$$M_i^s(y_s, x_s, y_t, x_t) = \frac{d_i^s(y_t, x_t)}{d_i^s(y_s, x_s)}. \qquad (4)$$

Note that in the above equations the notation $d_i^s(x_t, y_t)$ represents the distance from the period t observation to the period s technology. When t = s this distance is equivalent to the technical efficiency scores defined earlier. A value of M_i greater than one will indicate positive TFP growth from period s to period t while a value less than one indicates a TFP decline.

As noted by Färe, Grosskopf and Roos (1998), these two (period s and period t) indices are only equivalent if the technology is Hicks output neutral. That is, if the output distance functions may be represented as $d_i^t(x,y) = A(t)d_i(x,y)$, for all t. To avoid the necessity to either impose this restriction or to arbitrarily choose one of the two technologies, the Malmquist TFP index is often defined as the geometric mean of these two indices. That is,

$$M_i(y_s, x_s, y_t, x_t) = \left[\frac{d_i^s(y_t, x_t)}{d_i^s(y_s, x_s)} \times \frac{d_i^t(y_t, x_t)}{d_i^t(y_s, x_s)}\right]^{1/2}, \tag{5}$$

An equivalent way of writing this productivity index is

$$M_i(y_s, x_s, y_t, x_t) = \frac{d_i^t(y_t, x_t)}{d_i^s(y_s, x_s)}\left[\frac{d_i^s(y_t, x_t)}{d_i^t(y_t, x_t)} \times \frac{d_i^s(y_s, x_s)}{d_i^t(y_s, x_s)}\right]^{1/2}, \tag{6}$$

where the ratio outside the square brackets measures the change in the input-oriented measure of Farrell technical efficiency between periods s and t. That is, the efficiency change is equivalent to the ratio of the Farrell technical efficiency in period t to the Farrell technical efficiency in period s. The remaining part of the index in equation 5 is a measure of technical change. It is the geometric mean of the shift in technology between the two periods, evaluated at x_t and also at x_s. Thus the two terms in equation 6 are:

$$\text{Efficiency change} = \frac{d_i^t(y_t, x_t)}{d_i^s(y_s, x_s)} \tag{7}$$

and

$$\text{Technical change} = \left[\frac{d_i^s(y_t, x_t)}{d_i^t(y_t, x_t)} \times \frac{d_i^s(y_s, x_s)}{d_i^t(y_s, x_s)}\right]^{1/2} \tag{8}$$

The four distance measures in equation 5 are calculated by solving four DEA-like linear programming (LP) problems. The required LPs are:[16]

$$\begin{aligned} d_i^t(y_t, x_t) &= \min_{\theta,\lambda} \theta, \\ \text{st} \quad & -y_{it} + Y_t\lambda \geq 0, \\ & \theta x_{it} - X_t\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{9}$$

[16] Note that these are CRS DEA models. CRS is required to ensure that the TFP index includes scale effects. For further discussion see Coelli et al (1998).

$$d_i^s(y_s, x_s) = \min_{\theta,\lambda} \theta,$$
$$\begin{aligned} \text{st} \quad & -y_{is} + Y_s\lambda \geq 0, \\ & \theta x_{is} - X_s\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{10}$$

$$d_i^t(y_s, x_s) = \min_{\theta,\lambda} \theta,$$
$$\begin{aligned} \text{st} \quad & -y_{is} + Y_t\lambda \geq 0, \\ & \theta x_{is} - X_t\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{11}$$

and

$$d_i^s(y_t, x_t) = \min_{\theta,\lambda} \theta,$$
$$\begin{aligned} \text{st} \quad & -y_{it} + Y_s\lambda \geq 0, \\ & \theta x_{it} - X_s\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{12}$$

These four LP's must be solved for each firm in the sample. Thus when there are 18 firms and two time periods, 74 LP's must be solved. As extra time periods are added, one must solve an extra three LP's for each of the 18 firms (to construct a chained index for each firm). Thus we need to solve 74+3*18*6=398 LP's in this instance.

5. Data and empirical results

Data

The data used in this exercise is taken from WSAAfacts (2003, 2001). The data produced in these WSAAfacts publications is very detailed and comprehensive. However, since the data was not collected with this study specifically in mind, we do note that some of the variables we use are clearly sub-optimal, and hence our results should be viewed with caution and should only be viewed as preliminary in nature.

Two data sets are used in this section. The first is annual data on the 18 firms from the 2002/03 financial year. This is the most recent available information and hence will be used to calculate the technical efficiency and scale efficiency scores. The second data set is panel data, containing data on these 18 firms over an eight-year period from 1995/96 to 2002/03. When discussing this latter data set the issue of the selection of appropriate price deflators becomes important.

The selection of the input and output variables that are to be included in a DEA model is a complicated exercise. The decision process in this study is guided by our discussion of the cost drivers in the industry; our review of the overseas literature; our knowledge of the available data in WSAAfacts; and by the degrees of freedom constraints that we face when using such a small sample size. We have decided to limit our attention to models that involve no more than four variables, due to our degrees of freedom constraints.

We have chosen two output variables:

- number of properties connected (PROP), and
- volume of water delivered (WDEL),

and two input variables:

- operating expenditure (OPEX), and
- capital (CAP).

This set of output indicators is a set that is often used in network industries, such as water, electricity and gas. They are included to ensure that firms with similar average customer sizes are benchmarked with each other.[17] The other main output attribute, network density, is accommodated indirectly in this model by ensuring that the input set contains both a capital and a non-capital variable. Given that the capital intensity of these firms is primarily determined by their network density (ie. sparse networks tend to have higher amounts of pipeline capital relative to OPEX because their customers are further apart) this will tend to ensure that high density firms are benchmarked with similar firms and vice versa.

Some previous studies have broken up OPEX in to smaller variables, such as labour and non-labour measures. This allows one to use physical measures of labour if available. Since we had no data on the labour input, this was not a choice that was available to us. Furthermore, given the amount of outsourcing that is prevalent in many of these firms, the distinction between labour and non-labour OPEX would be rather arbitrary. In addition, given our degrees of freedom constraints, the inclusion of an additional variable in the model would not be wise in any case.

The choice of an appropriate measure of capital input is always a challenge in empirical analyses such as this. Major water supply asset groups include pipes, pumps, treatment plants and storage, plus other groups such as vehicles, buildings and equipment. Given that detailed and comparable data on these various groups were not available and given

[17] An alternative set of output indicators could be to have volume delivered to small customers and volume delivered to large customers. However, such data was not available to us, and would be unlikely to provide a better fit if available.

our degrees of freedom constraints, the obvious option was for us to find a monetary measure that could provide a reasonable proxy for the aggregate quantity of capital used. Our first choice was a depreciation measure, but none was available in WSAAfacts. Hence we considered using the capital stock variable: “written down current cost of fixed assets”. This could be a reasonable measure of capital consumption if each firm had a portfolio of assets with similar average asset lives and hence the stock of capital would be roughly proportional to the consumption of capital. However the measure we finally decided to use was capital (CAP) equal to “total expenditure” (TOTEX) minus OPEX. This was because TOTEX was calculated as OPEX plus capital costs, where capital costs were equal to depreciation plus 4% of the written down current cost of fixed assets. This measure is clearly designed to be more a capital cost measure as opposed to a capital quantity measure, however it has the advantages that it will be affected by average asset lives and it is also the measure which WSAA members are familiar with.

This capital measure is not without a number of problems. First, it is based on a depreciated (written down) capital stock measure and hence if a firm has an average asset age lower than the average firm, they will appear to be using more capital, even though the service potential of “a kilometre of pipe” is likely to be quite similar across the firms. Second, different companies use different valuation methods, which is likely to introduce noise into this measure. Third, the firms tend to do one-off asset revaluations in certain years (eg. every 5 years or so) and then use the consumer price index (CPI) to revalue their assets in the intervening years. Given that changes in asset construction costs often deviate from the CPI (see discussion below), this can mean that a firm which has done a recent revaluation of assets may appear to be using substantially more (or less) capital relative to the average firm, depending on the relationship between these two price indices.

The above discussion of the capital measure does not make for happy reading. Hence, as a robustness check, we have also used the “total length of mains” (MAINS) as an alternative capital measure in some models. This measure will also be sub-optimal because it implicitly assumes that the quantities of other capital items (pumps, plants etc.) are used in proportion to pipeline capital.

When we use data from 1995/96 through to 2002/03 to calculate productivity growth over time we must also consider how we are going to convert our monetary measures (OPEX and CAP) into real measures, because they are meant to be proxies for the quantities of inputs used. In WSAAfacts this issue is dealt with by the use of the CPI. However, the CPI (reflecting price movements in food, housing, etc.) may be a poor measure of price movements in water supply variable inputs (eg. labour, chemicals, electricity) and water supply assets (eg. pipes, pumps, construction services, etc.). To investigate this issue we searched for some more appropriate price index deflators. Unfortunately, we could find none that were specific to the water industry, nor to network industries in general. The best indices we could identify were:

- ABS Catalogue 5204.0, Australian System of National Accounts, Table 8, EXPENDITURE ON GDP, Implicit Price Deflators, Final Consumption Expenditure, General Government, State and Local, and
- ABS Catalogue 5204.0, Australian System of National Accounts, Table 8, EXPENDITURE ON GDP, Implicit Price Deflators, Public Gross Fixed Capital Formation, Public Corporations, State and Local,

for OPEX and CAP, respectively.[18]

These two indices, which we will call the OPEX deflator (OD) and the CAP deflator (CD) are plotted in Figure 1, along with the CPI. Note that the new OPEX price deflator follows a similar pattern to the CPI, but at a higher level, increasing by 25% as opposed to 18%. The new CAPEX price deflator, however, is well below these two indices, and in fact falls slightly, by 6%. The flat nature of the new CAPEX price deflator is most likely a reflection of productivity savings in capital construction over this period.

[Fig 1 here]

To illustrate the effect of the use of these alternative deflators upon the OPEX and capital measures, we have plotted indices of the various measures (aggregate for the industry) in Figure 2. The variables involving the CPI deflator are called OPEX and CAP, while those involving the new deflators are called OPEXN and CAPN. It is interesting to note that when the CPI is used, the CAP index has no net change over the eight year period, while when the new capital deflator is used CAPN increases by 25%. Given that the number of connections has increased by 14% and the water quality requirements have increased over this period, the CAPN measure is likely to be closer to the "truth" relative to the CAP measure. However,

[18] For details, see the ABS web site http://www.abs.gov.au/.

when we observe that the length of mains have only increase by 5%, we begin to suspect that some number in the middle of 0% and 25% is likely to be closer to the mark.[19]

[Fig 2 here]

Efficiency scores

Given the above discussion, we have decided to use length of mains as a capital proxy in our preferred DEA model. Thus it contains two output variables, WDEL and CONN, and two input variables, OPEX and MAINS. Technical efficiency (TE), scale efficiency (SE) and CRS technical efficiency (CRSTE=TE×SE) scores are listed in Table 2 and plotted in Figure 3. The mean TE score is 0.904, which indicates that the average firm could reduce input usage by 9.6% and still produce the same output level.[20] Seven firms have TE scores of 1, indicating that they are on the DEA frontier: Brisbane, City West, Gosford, Goulburn Valley, Melbourne, Darwin and Sydney.

The location of a firm such as Darwin on the DEA frontier may come as a surprise to some, given that it traditionally has high costs per connection (see for example WSAA, 2001). But it should be kept in mind that Darwin has a high WDEL/CONN ratio relative to most firms, and hence is likely to be located near the fringe of the DEA frontier, with few other peers to compare with. Similar comments could be made with regard to other firms in the sample that are especially unique in some aspects. For example, if the are especially large firms, such as Sydney and Melbourne, relative to the remainder of the sample. Thus, the DEA method can be a bit too generous to these types of “fringe firms”.[21]

One way in which the study could be amended to attempt to address this problem associated with “fringe firms” is to include data on extra businesses from other countries, as is done in the Carrington et al (2001) gas supply study. The inclusion of data on firms from other countries can also be important for those firms in the “centre” of the data set if the local firms are as a group inefficient relative to world’s best practice.[22] However, this can be a

[19] This discussion emphasises the questionable nature of all the available capital measures, and indicates that substantially better data would need to be collected before this type of analysis could provide input to a regulatory discussion.

[20] Keeping in mind all previous comments about data quality and model simplifications.

[21] Parametric methods, such as SFA, are less susceptible to this type of problem, because the parametric frontier does not have the degree of local flexibility that a DEA frontier has.

[22] For example, see the international benchmarking study of Australian electricity supply in BIE (1996, p96), where it was found that the performance of the Australian electricity supply industry (measured using a total factor productivity index) was approximately 30% below the US electricity supply industry in the early 1990’s.

challenging exercise, with data comparability issues generally becoming more complex, as discussed in Coelli et al (2003, p94).

The mean SE score in Table 2 is 0.903, indicating that the average firm should be able to reduce input use (per unit of output) by 9.7% if it was able to change its scale of operation. However, it should be kept in mind that the size of many of these firms is determined by geographical factors, and hence the option of changing scale is not available. The final column in Table 2 provides information on the nature of scale economies, from which we note that all 12 firms that have scale inefficiency do so because of their small size. That is, they are located on the increasing returns to scale (IRS) portion of the DEA frontier. The small firms from regional Victoria, Barwon, Central Gippsland, Central Highlands, Coliban and Goulburn Valley, have the lowest SE scores in the sample.

When we look at the CRSTE scores, which equal the product of the TE and SE scores, we observe that the CRSTE scores are quite low for these small regional firms. This is also evident in many of the commonly reported partial productivity measures, such as OPEX/WDEL and OPEX/CONN, and emphasises the point that these partial ratios can be quite misleading because they do not account for scale economies.

[Table 2 here]

[Figure 3 here]

Given the concerns that we have with our capital measure, we decided that it would be wise to repeat the DEA analysis with our MAINS measure replaced with CAP. The results obtained were reassuringly similar, with the exception of some small changes for Brisbane and Hunter. The TE scores for the two models are plotted in Figure 4 for ease of comparison.

[Figure 4 here]

Another test of the worth of our DEA model is to run a second-stage regression of the TE scores upon various factors that we know are not explicitly accounted for in the model and hence may be influencing the TE scores obtained. Hence, using the TE scores from Table 2 and information on percentage of non-residential connections; percentage of water from non-catchment sources; average annual rainfall (mm); average maximum temperature (degrees C); peak to average flow; and electricity consumption per connection (all from Table 1) we ran a second-stage regression. None of these factors had estimated coefficients that were significant at the five percent or ten percent levels. Hence, we can be reasonably confident in the quality of our DEA model.

Productivity Growth

In the above efficiency analysis we consider two different models because of our concerns with the capital measure. In our analysis of productivity growth we have the additional complexity of the choice of price deflators. As a result, we have chosen to calculate four different sets of Malmquist DEA TFP measures. The technical efficiency change (TEC), technical change (TC) and TFP change (TFPC) from these four models are summarised in Table 3. The first set of results relate to the preferred model where MAINS are used to proxy capital and the new deflator is used to deflate OPEX. For this model we see that average annual TFP change over these 18 firms over 8 years is equal to a 1.2% decline per year. This measure can be decomposed into a 2.2% technical regress per year and 1.2% increase in technical efficiency per year.[23]

[Table 3 here]

The other three sets of results in Table 3 are within 0.6% of the above TFP change measures. The second model, involving MAINS and the CPI deflator, obtains TFP change of minus 1.5% per year. This is slightly below the preferred model results, because the smaller CPI deflator suggests that OPEX is growing at a faster real rate. The third model, involving CAPN and the new deflators, obtains TFP change of minus 1.7% per year. This again is slightly below the preferred model results, because the CAPN measure grows at a faster rate relative to MAINS, suggesting greater capital input usage. Finally, The fourth model, involving CAP and the CPI deflator, obtains TFP change of minus 0.6% per year. This is slightly above the preferred model results, because the CAP measure grows at a slower rate relative to MAINS, suggesting less capital input usage.

More detailed results for the preferred model involving MAINS and the new deflator are provided in Table 4, where the time-wise patterns are listed, and in Table 5, where the firm-

[23] These figures do not add to zero because of rounding.

level results are provided. The average annual TFP changes vary from plus 3.6% to minus 5.1%, while the average firm-level changes vary from plus 1.6% to minus 5.0%.

[Table 4 here]

[Table 5 here]

The negative measures of TFP change obtained warrant further comment. First, the price deflators used are approximate, and hence these could be influencing things. Second, during this period, demand management strategies were put in place in many firms, which would have had a dampening effect upon WDEL and hence upon the aggregate output measure. Third, quality improvement strategies were put in place in many firms during this period, which would be reflected in higher input use, but not in higher output production, because the quality of the services provided are not explicitly reflected in the DEA model used. Fourth, we note that some of the smallest companies in the sample have the lowest productivity growth. That is, Barwon, Central Highlands, Coliban, Goulburn Valley and Darwin have the lowest TFP growth. Thus our unweighted measure of TFP growth is likely to understate the aggregate TFP growth in the industry. Lastly, the largest reduction in TFP growth occurred in the final year of the sample. If we had finished our sample one year earlier, the average TFP growth would have been almost one percentage point higher.

With reference to some of the above comments, we conducted a few extra calculations to gauge the sensitivity of our results to some of these factors. First, we calculated the weighted average TFP growth for the industry using CONN as the weight, and found that the aggregate TFP change measure increased from minus 1.2% to 0.0%, reflecting the better performance of the larger firms in the sample. Second, we reran the preferred model with WDEL omitted from the output set, to attempt to adjust for the possible effects of demand management initiatives, and obtained an average TFP growth of plus 0.4% per year. Furthermore, when we applied the above firm weights to these new scores we obtained an average TFP growth of plus 1.1% per year. However, this measure could potentially overstate the rate of TFP growth because it does not reflect the fact that WDEL/CONN is reducing over time, which should imply less cost per connection.

Use in price regulation

How might a regulator use these efficiency and productivity growth results in implementing price-cap regulation? Given that the regulator is reasonably confident in the data that is used in the study (which would not be the case in this particular case), we provide the following illustrative example.

In most cases, price caps are set over a five-year term. The regulator will allow firms to increase prices each year by CPI-X, where X is a measure of the expected productivity improvements. The value of X is usually based upon a measure of previous TFP growth in the industry. Also, if the regulator believes some firms are more inefficient than other firms it will ask the more inefficient firms to achieve higher X factors.

The regulator may require all firms to achieve the weighted mean annual productivity growth of 1.1 % we obtained from the TFP model where WDEL was omitted (assuming that demand management policies are likely to continue over the next five years). Furthermore, it could require firms with DEA technical efficiency scores below one to catch up 50% of the way to the frontier over the next five years. This is a conservative request, designed to account for the fact that the technical efficiency scores are measured with error, and also to reflect the fact that some firms will find it difficult to make efficiency savings if they face constraints, such as having excess capacity in areas where projected growth is low, etc.

We have used the above rules to construct illustrative X factors for the 18 WSAA firms. We have taken the TE scores from Table 2 and produced X factors for each firm, which are reported in Table 6. To illustrate how the X factor values in Table 6 were calculated, consider the first listed firm, Canberra, which has a TE score of 0.755. It would be required to catch up (1-0.755)/2=0.123 or 12.3% over the five year period. Which is $(1.16)^{1/5}$=1.023 or 2.3% compounded catch-up per year. Thus its X factor would be 1.1+2.3=3.4% per year.

The X factors in Table 6 range from 1.1% per year for the frontier firms, to 4.6 % per year for Central Highlands, the firm with the lowest technical efficiency score (0.627). The average X factor is 2.0 % per year. An X factor of 2.0 % implies that the firm must reduce unit costs in real terms by 2.0 % per year.

However, it should be emphasised that these types of X factors, derived from a process such as this, should not be used in a prescriptive or mechanical manner. The numbers should ideally be used as a "starting point" for discussions between the regulator and the regulated. For example, Adelaide, which has an illustrative X factor of 2.6, that is above the average value of 2.0, may wish to argue that the DEA model has not properly taken account of the fact that it must pipe almost half of its water from the Murray river, which results in higher pumping costs and treatment costs (due to silt and salt) relative to a firm such as Sydney which derives almost all its water from catchment sources. Adelaide may wish to attempt to cost out the extra expenses involved and then make a case to the regulator for a reduced X factor on this basis.

[Table 6 here]

We should also reiterate our earlier comments regarding data quality. The above illustrative X-factors are based upon a DEA model that used length of mains as a proxy for the capital input. This is a sub-optimal measure, which was used because we had even less faith in the reliability of the capital measures, which were based upon a variety of valuation techniques in different businesses, including (i) a detailed replacement cost valuation of each item in the asset register, (ii) using the CPI to scale an asset valuation made some years before, and (iii) in some cases simply scaling the historical cost valuation by a "ball-park" factor, such as 1.5.

The capital valuation issue is not our only concern. In addition we note that all of these businesses also supply wastewater services to their customers. To our knowledge, it is unlikely that all businesses are using the same set of overhead cost allocation rules. Thus it is possible that some firms may putting more (or less) overhead costs into the "water supply costs bucket" versus the "wastewater services bucket", relative to the industry average. If this is the case, the water supply efficiency measures will be biased.

Furthermore, it should be noted that our initial plan in this study was to attempt to measure the efficiency of the water distribution business alone. That is, with the wholesale part of the business (water collection and treatment) removed so we could have a better chance of comparing like with like, because the wholesale activities are the ones that are most heavily affected by differing local environmental conditions. However, the published data did not allow us to do this. This is one avenue that regulators could consider in the future, when collecting data for exercises such as these.

While on the topic of differing environments, it is worth noting that some observers have expressed concerns regarding the fact that the above (illustrative) X-factors are based upon a TE score from a particular year, and that these TE scores can be significantly affected by annual climatic differences in a country such as Australia, where a large percentage of water is used on gardens. One possible solution to this problem is to use an average of TE scores over recent years. However, this could disadvantage those firms who have had TE scores that are trending upwards in recent years. A preferable option could be to use some form of smoothing on the volume data, such as using a three-year moving average in the DEA model, and then simply use the TE score from the final period.

6. Conclusions

In this study we provide (to our knowledge) the first published set of comprehensive performance measures for the Australian water supply industry. We use DEA to provide measures of technical efficiency and scale efficiency for each of the 18 WSAA businesses in 2002/03. We also provide TFP change measures for each firm over the eight-year period from 1995/96 to 2002/03. Our results indicate that the average firm has a technical efficiency score of 90.4% and has annual average TFP growth of between minus 1.7 % and plus 1.1%, depending upon the measures used in each DEA TFP model.

The above range of TFP measures illustrate the importance of the choice of data used in these studies. Our analysis has highlighted a number of data related issues that warrant further attention before the results of a study such as this could be considered for use in aiding the decision making process in the price regulation of water supply businesses. In particular, the available data on capital needs improvement. WSAA firms are using capital valuation methods that satisfy the relevant accounting standards. However, the variety of methods used means that the available data is not comparable across firms. Furthermore, a lack of appropriate water industry price deflators for use in the TFP calculations is an additional concern. The ABS deflators used in this study were an improvement over the use of the CPI, but much work remains to be done in this area.

It should be emphasised that these data problems would apply equally if we were to use a less sophisticated performance measurement technique, such as OPEX per ML of water delivered. However, the DEA methods used here have advantages over this type of partial productivity ratio in that they are able to make adjustments for scale of operations, average customer size and density, so as to allow more appropriate comparisons of performance.

This study represents our first attempt at the calculation of comprehensive performance measures for this industry. Various avenues for further work remain. First and foremost, the analysis should be repeated once better data is obtained (on capital value, price deflators, etc.). Second, the work could be repeated using stochastic frontier methods (SFA) to judge the sensitivity of results to the choice of methodology. Third, this study has focussed on water supply activities. One could repeat the exercise for the wastewater activities of these businesses, to obtain an indication of the overall performance of the urban water services industry in Australia.

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Table 1: Descriptive Statistics

Business	number of connections ('000)	volume per connection (kL)	connections per km of mains	percentage of non-residential connections	percentage of water from non-catchment sources	average annual rainfall (mm)	average maximum temperature (degrees C)	peak to average flow ratio	electricity consumption per connection (kW)
Canberra	133	422	44.87	6.77	0.00	584	21	2.27	18
Barwon	118	351	35.79	9.32	99.47	496	20	2.01	19
Brisbane	403	411	68.39	8.19	0.00	1014	25	2.34	264
Central Gippsland	57	360	29.95	10.53	20.08	744	21	3.00	236
Central Highlands	53	336	25.99	9.43	3.68	616	19	1.98	31
City West M	286	424	75.56	10.14	0.00	598	21	1.81	*
Coliban	60	436	31.07	10.00	0.35	476	22	2.21	*
Gold Coast	197	293	69.49	5.08	0.00	1215	26	1.45	85
Gosford	65	256	69.44	4.62	32.83	1268	24	2.00	197
Goulburn Valley	49	621	29.66	12.24	5.10	458	22	2.04	215
Hunter	205	375	46.44	7.80	57.04	1114	22	1.79	169
Melbourne Cons	1472	325	67.49	8.36	0.00	598	21	1.81	*
Darwin	42	838	34.20	11.90	6.90	1953	33	1.52	292
Adelaide	481	372	55.32	5.61	43.67	555	23	2.24	332
South East M.	572	297	70.37	8.22	0.00	598	21	1.93	12
Sydney	1638	388	79.93	7.08	1.36	1186	23	1.51	99
Perth	621	342	52.50	10.95	50.19	781	25	1.73	167
Yarra Valley M	614	306	71.03	7.65	0.00	598	21	1.88	6
Average	**393**	**397**	**53.19**	**8.55**	**17.82**	**825**	**23**	**1.97**	**143**

1. A "*" indicates missing values.
2. All data from 2002/03 except for rainfall and temperature which are 10 year averages and non-catchment, peak and electricity which are from 2000/01.
3. Business names have been altered to more clearly reflect the cities they serve.

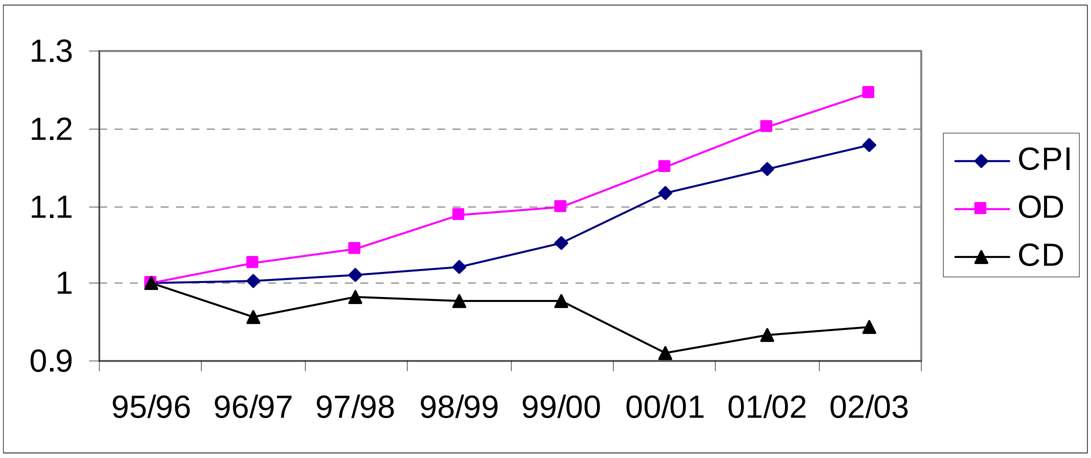

Figure 1: Alternative Price Indices, 1995/96 to 2002/03

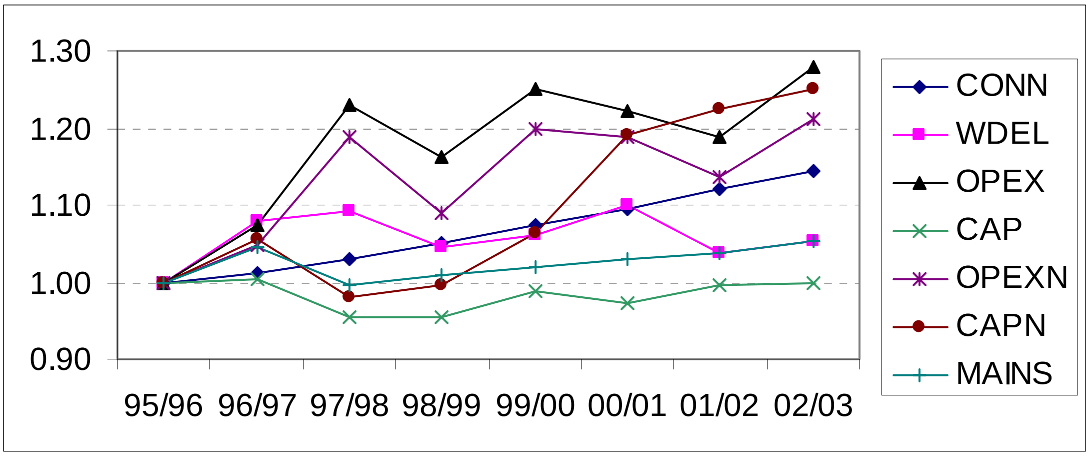

Figure 2: Industry-level Inputs and Outputs, 1995/96 to 2002/03

Table 2: DEA efficiency scores, 2002/03

firm	TE-CRS	TE	SE*	scale**
Canberra	0.708	0.755	0.937	irs
Barwon	0.618	0.826	0.748	irs
Brisbane	1.000	1.000	1.000	-
Central Gippsland	0.459	0.760	0.604	irs
Central Highlands	0.371	0.627	0.591	irs
City West M	1.000	1.000	1.000	-
Coliban	0.600	0.849	0.707	irs
Gold Coast	0.978	0.999	0.979	irs
Gosford	0.934	1.000	0.934	irs
Goulburn Valley	0.841	1.000	0.841	irs
Hunter	0.749	0.797	0.939	irs
Melbourne Cons	1.000	1.000	1.000	-
Darwin	1.000	1.000	1.000	-
Adelaide	0.847	0.847	1.000	-
South East M.	0.971	0.976	0.995	irs
Sydney	1.000	1.000	1.000	-
Perth	0.832	0.846	0.984	irs
Yarra Valley M	0.984	0.989	0.995	irs
mean	**0.827**	**0.904**	**0.903**	

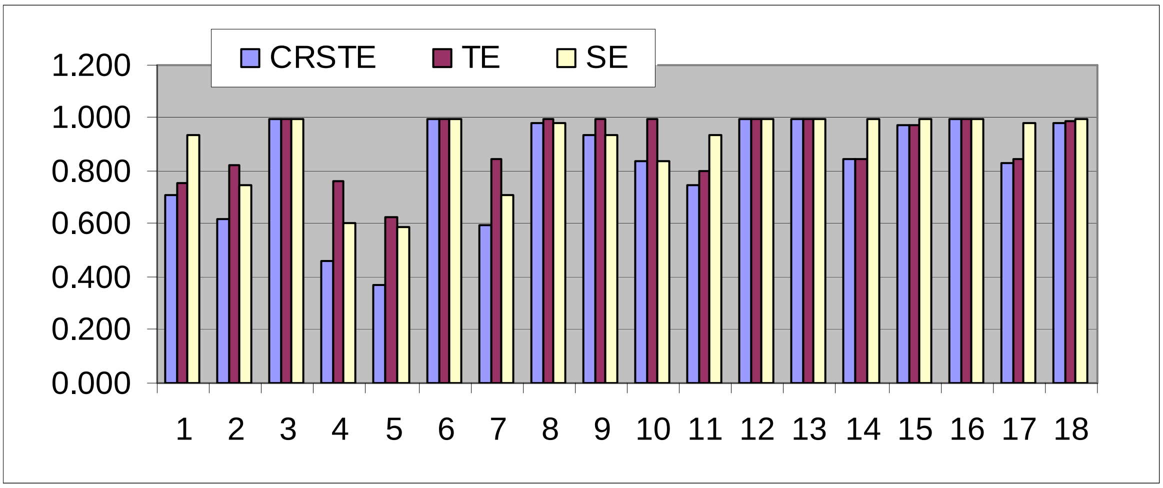

Figure 3: DEA efficiency scores, 2002/03

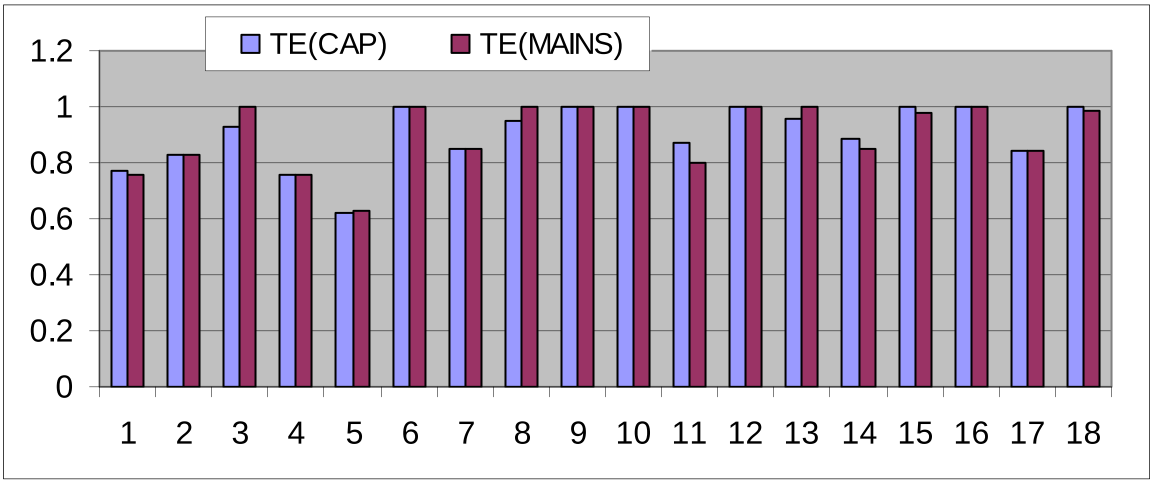

Figure 4: Comparison of DEA efficiency scores from models using CAP versus MAINS, 2002/03

Table 3: Summary of results for four TFP models, 1995/96 to 2002/03

Model	TEC	TC	TFPC
MAINS & new deflators	1.011	0.978	0.988
MAINS & CPI	1.010	0.975	0.985
CAP & new deflators	0.992	0.991	0.983
CAP & CPI	0.991	1.002	0.994

Table 4: Annual average TFP results, 1995/96 to 2002/03

year	TEC	TC	TFPC
1996/97	0.997	1.039	1.036
1997/98	1.123	0.88	0.988
1998/99	0.993	0.979	0.972
1999/00	0.955	1.01	0.964
2000/01	1.024	1.005	1.029
2001/02	0.991	0.993	0.984
2002/03	1	0.949	0.949
mean	**1.011**	**0.978**	**0.988**

Table 5: Annual average firm-level TFP results, 1995/96 to 2002/03

firm	TEC	TC	TFPC
Canberra	1.040	0.960	0.998
Barwon	1.005	0.963	0.968
Brisbane	1.021	0.974	0.995
Central Gippsland	1.011	0.989	1.000
Central Highlands	0.960	1.016	0.975
City West M	1.000	0.977	0.977
Coliban	1.007	0.943	0.950
Gold Coast	1.008	0.982	0.990
Gosford	1.021	0.986	1.007
Goulburn Valley	0.992	0.962	0.954
Hunter	1.024	0.963	0.986
Melbourne Cons	1.007	0.991	0.998
Darwin	1.000	0.971	0.971
Adelaide	1.039	0.969	1.007
South East M.	1.012	0.996	1.009
Sydney	1.018	0.998	1.016
Perth	1.029	0.968	0.996
Yarra Valley M	0.998	1.001	0.998
mean	**1.011**	**0.978**	**0.988**

Table 6: Illustrative calculation of X factors

firm	TE	TFPC	catch up	X factor
Canberra	0.755	1.1	2.3	3.4
Barwon	0.826	1.1	1.7	2.8
Brisbane	1.000	1.1	0.0	1.1
Central Gippsland	0.760	1.1	2.3	3.4
Central Highlands	0.627	1.1	3.5	4.6
City West M	1.000	1.1	0.0	1.1
Coliban	0.849	1.1	1.5	2.6
Gold Coast	0.999	1.1	0.0	1.1
Gosford	1.000	1.1	0.0	1.1
Goulburn Valley	1.000	1.1	0.0	1.1
Hunter	0.797	1.1	2.0	3.1
Melbourne Cons	1.000	1.1	0.0	1.1
Darwin	1.000	1.1	0.0	1.1
Adelaide	0.847	1.1	1.5	2.6
South East M.	0.976	1.1	0.2	1.3
Sydney	1.000	1.1	0.0	1.1
Perth	0.846	1.1	1.5	2.6
Yarra Valley M	0.989	1.1	0.1	1.2
mean	**0.904**	**1.1**	**0.9**	**2.0**