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Evaluating the X-Factor: A Brief Overview of Methodologies and Best Practices

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Abstract

Regulators and policymakers evaluating total factor productivity studies that inform the X-factor in price or revenue cap regulation face key challenges in determining the appropriateness of and potential bias from methodologies and assumptions selected by utilities in developing their performance-based regulation cases. This paper helps regulators overcome these challenges by providing an overview of common methodologies, assumptions, and their potential biases, as well as recommendations for improving the evaluation of total factor productivity studies. This article focuses on the aspects of developing the X-factor by bringing together all the components used to develop an appropriate X-factor value. The most common approach to TFP measurement is the index method. To accurately estimate TFP, appropriate data and sample selection, output measurement, input measurement and index weighting must occur. A sample period of at least 10 years is recommended. One area of bias occurs when the productivity trends are not representative of the productivity trend for the industry. Different output measures such as sales volume or customer count can create bias that requires using a mix of output measures to address different causes of trends in output, e.g., volume growth can increase revenues while energy efficiency can cause a negative bias. Input biases can be caused by inappropriate indices for measuring changes in labor, capital and O&M. Inappropriately choosing the benchmark year can bias the capital index.

Keyword: Incentive regulation

1 Introduction

Performance-based regulation (PBR) can improve upon cost-of-service regulation if utilities face similar performance incentives to those in competitive markets. One approach to strengthen performance incentives in price- or revenue-cap regulation is to index prices or revenues to a macroeconomic inflation indicator such as the Gross Domestic Product Price Index (GDPPI), which is adjusted by a productivity offset: the X-factor. We focus on total factor productivity (TFP) studies that inform the X-factor and adjust the macroeconomic inflation indicator to better reflect actual price or revenue growth in the electric industry.

When an external benchmark (such as the rest of the economy) is used to recreate the pressures of a competitive market, the X-factor sums the difference in TFP growth rates between the electric industry and the rest of the economy and the difference in input price growth rates between the rest of the economy and the electric industry (Bernstein and Sappington, 1999). Although TFP is simply the difference in growth rates between a company's physical outputs and physical inputs, there are a variety of approaches to estimate TFP, each with their benefits and drawbacks, and many challenges in the accurate measurement of outputs and inputs in the electric sector.

We provide a brief overview of TFP measurement approaches, including frontier, non-frontier, parametric, and non-parametric methods, focusing on index number methodologies which are the most commonly used approach in North American TFP studies of the electricity sector. We also summarize key challenges for TFP measurement including the measurement of outputs and inputs (especially the concept of capital), as well as data issues and weighting methods.

We bring together in this paper the requirements and methods used to evaluate the X-factor submissions through examination of the literature and recent TFP studies used in X-factor determinations for PBR. In doing so we scrutinize the potential biases introduced into TFP measurement, methods to reduce the bias, identify best practices in addressing key challenges, and provide recommendations for regulators and policymakers for evaluating TFP studies.

2 Common Approaches for Estimating Total Factor Productivity

TFP measures the difference in growth rates between a firm's physical outputs and physical inputs. Assume firm i at time t produces an output, Q, using a production technology $F(\cdot)$, and a vector of inputs, X. Letting A represent differences in productivity among firms, a firm's production function is

$$Q_{it} = A_{it}F_{it}(X_{it}). \quad (1)$$

TFP studies estimate the parameter A_{it}, which is typically unobservable. By letting $k \in \{it, j\tau\}$ specify the underlying production technology, taking logarithms, and rearranging the production function, Van Biesebroek (2007) shows that TFP studies aim to estimate how much extra output firm i can produce at time t compared to firm j at time τ, conditional on their use of inputs (X_{it} and $X_{j\tau}$) and underlying production technology $F_k(\cdot)$ as shown in equation 2:

$$ln\left(\frac{A_{it}}{A_{j\tau}}\right)_k = ln\left(\frac{Q_{it}}{Q_{j\tau}}\right) - ln\left(\frac{F_k(X_{it})}{F_k(X_{j\tau})}\right). \quad (2)$$

Methodologies to estimate TFP differ in how the ratio of aggregated input is determined. Common TFP methodologies can be categorized into frontier or non-frontier, parametric or non-parametric, as shown in Table 1. Frontier methodologies compare firms to the most efficient (best practice) firms, whereas non-frontier methodologies compare firms to the average firm (Mahadevan, 2003). Frontier methodologies also differentiate between movements toward the production frontier (technical efficiency) and outward shifts of the production frontier (technological change). Non-frontier methodologies assume firms are technically efficient and any change in TFP is due to technological change. Frontier methods have the disadvantages that benchmarking firms against best practice firms may set an unrealistic target, and these methods are sensitive to data errors or omissions. Whereas non-frontier methods may set too low a target (Lawrence and Diewert, 2004).

Both frontier and non-frontier methods can be estimated parametrically and non-parametrically. With parametric methods, a functional form for the production technology is specified, and parameters are estimated using econometric analysis of input and output data. Because the production technology must be specified, these methods are sensitive to the chosen functional form. Non-parametric methods do not require the functional form of the production technology but have the drawback that they cannot be validated by statistical tests (Mahadevan, 2003).

Table 1 provides an overview of common TFP estimation methodologies which include index number methods, ordinary least squares and other econometric methods, data envelopment analysis, and stochastic frontier methods. Index number methods are the most used approach for estimating TFP to inform the X-factor in North American PBR. However, a brief overview of other methodologies is provided in the Appendix – Alternative Methods to Estimate Total Factor Productivity including econometric methods, data envelopment analysis, and stochastic frontier methods.

Table 1. Total Factor Productivity Estimation Methodologies

	Non-Frontier	**Frontier**
Non-Parametric	Index Number Methods	Data Envelopment Analysis
Parametric	Ordinary Least Squares and Other Econometric Methods	Stochastic Frontier Methods

2.1 Index Number Methodologies

Index number methods combine diverse outputs and inputs into changes in total output and total input by taking a weighted average (Lawrence and Diewert, 2004). With the economic approach, index number properties are related to properties of underlying production functions and economic theory. This approach begins with the pioneering work of Solow (1957), which provided an index number approach to estimate the Solow residual – the growth in outputs not explained by the growth of inputs – or TFP (Hulten, 2001).

As the Solow (1957) model had several limiting assumptions, Jorgensen and Griliches (1967) introduced several measurement innovations, derived from a Törnqvist index approach. The Törnqvist index replaces Solow's (1957) continuous time shares of labor and capital with average, between-period shares of labor and capital, and continuous time growth rates with differences in natural logarithms of output quantity (Q) and input quantity (L, K) variables:

$$lnA_{it} - lnA_{it-1} = ln\frac{Q_{it}}{Q_{it-1}} - \left(\frac{s_{it}^L + s_{it-1}^L}{2}\right) ln\frac{L_{it}}{L_{it-1}} - \left(\frac{s_{it}^K + s_{it-1}^K}{2}\right) ln\frac{K_{it}}{K_{it-1}}. \quad (3)$$

With information on output, labor, and capital quantities, as well as relative shares of wages, s^L, and capital rents, s^K, for the ith firm at times t and $t-1$, TFP growth can be calculated. Further innovations by Diewert (1976), Caves et al. (1982a), and Caves et al. (1982b), showed that the Törnqvist index could be used for multilateral productivity comparisons by comparing firm i to a hypothetical firm derived from average log of output ($\overline{lnQ_t}$), labor ($\overline{lnL_t}$) , and capital ($\overline{lnK_t}$) from a representative sample of firms,

$$\overline{lnA_t} = \left(lnQ_{it} - \overline{lnQ_t}\right) - \widetilde{s^{L}}_{\iota t}\left(lnL_{it} - \overline{lnL_t}\right) - \widetilde{s^{K}}_{\iota t}\left(lnK_{it} - \overline{lnK_t}\right), \tag{4}$$

where $\widetilde{s^{L}}_{\iota t} = \frac{s_{it}^{L}+s_{t}^{L}}{2}$ and $\widetilde{s^{K}}_{\iota t} = \frac{s_{it}^{K}+s_{t}^{K}}{2}$. This multilateral Törnqvist index allows comparisons of firms that are both bilateral and transitive (Caves et al, 1982b).[1]

Index number approaches have many benefits including that many outputs and inputs can be incorporated, and that the underlying production technology can vary among firms. Their main limitations are due to underlying assumptions of firm behavior and market structure (perfect competition in output and factor markets, and optimizing behavior), as well as the assumption that data is measured without error (Van Biesebroeck, 2007). Although constant returns to scale is an underlying assumption, an additional factor can be included to address the effect of scale, and methodologies have been developed for estimating factor prices when there are increasing returns to scale (Van Biesebroeck, 2007; Diewert and Fox, 2010). The Törnqvist index number approach is widely used in TFP studies for the electricity sector.

3 Total Factor Productivity Measurement: Key Challenges, Potential Biases, and Best Practices

There are two important elements for designing incentives for PBR programs: 1) de-linking a utility's costs from its allowed prices or revenues, and 2) linking a utility's allowed prices or revenues with costs of comparable utilities (Bell, 2002). In practice, this is accomplished by allowing output prices to rise at the rate of macroeconomic inflation ($\dot{P}^{E}$) with an offset for the X-factor, which sums the difference in TFP growth rates for the electric industry and the rest of the economy, $\left[\dot{T} - \dot{T^{E}}\right]$, and the difference in input price growth rates between the rest of the economy and the electric industry $\left[\dot{W^{E}} - \dot{W}\right]$.[2]

$$\dot{P} = \dot{P}^{E} - \left[\dot{T} - \dot{T^{E}}\right] + \left[\dot{W^{E}} - \dot{W}\right], \tag{5}$$

where the X-factor is

$$X = \left[\dot{T} - \dot{T^{E}}\right] + \left[\dot{W^{E}} - \dot{W}\right]. \tag{6}$$

To estimate TFP, output and input prices and quantities must be determined. Key challenges for the electricity sector include addressing potential issues with data and sample selection, output measurement, input measurement (especially the concept of capital), and overall index weighting methods. In the following section, we will discuss potential biases and best practices for each of these key challenges based on the literature and recent TFP studies for the electricity sector.

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[1] See also Christensen et al. (1973) for discussion on the theoretical properties of the Törnqvist index when the production function has the translog form.

[2] See Bernstein and Sappington (1999) for the derivation of the X-factor. This formulation assumes the use of a macroeconomic inflation indicator, if an industry input inflation measure is used, the X-factor is $X = \dot{T}$.

3.1 Data, Sample Selection, and Length of Study

The data, sample selection and length of study period for developing the X-factor are critical to providing a usable value. Bias in the data must be addressed. The characteristics of the sample are important as is the length of the sample period in determining an appropriate and equitable X-factor.

3.1.1 Data

Index methods are sensitive to measurement error (Van Biesebroeck, 2007), with the direction and magnitude of potential biases depending on the underlying measurement error. To address potential measurement error concerns, publicly available, standardized datasets, such as those available from government agencies are desirable. If measurement error is a significant concern, econometric approaches to TFP measurement can be used.

Key questions regulators need to answer: (1) are data sources reputable and do they suffer from measurement error, and (2) are data sources and any procedures to change the data clearly documented.

3.1.2 Sample Selection

Price or revenue caps de-link a utility's costs from its allowed prices or revenues, but to link a utility's costs to those of comparable firms requires selecting an appropriate sample of comparison firms. In North America, the X factor is often determined from a representative sample of firms for the electric industry. Potential biases can occur if productivity trends are driven by a handful of utilities, not representative of the productivity trend for the electric industry.

Heterogeneity across firms is less of a concern when the metric is TFP growth, as heterogeneity largely vanishes, and the largest possible sample of firms can be used. However, if heterogeneity persists, a restricted sample of more comparable firms can be used, as long as exogenous factors that drive productivity differences across firms are accounted for, such as external business conditions (Weisman, 2018).

In practice, based on review of several TFP studies and expert opinions, the Alberta Utilities Commission concluded that a TFP study sample could be based on all companies in the electric industry for which good data are available, or on a subset of those companies if the sub-sample is large enough to provide reliable estimates (AUC, 2012).

Two key questions for regulators and policymakers with respect to sample selection are: (1) does the peer group selected facilitate a meaningful comparison to the firm in question, and (2) how exogenous differences between heterogeneous utilities are accounted for (Weisman, 2018). TFP can also be calculated with different sub-sections of samples to understand the impact of particular sample choices.

3.1.3 Length of study

The X-factor can be calibrated to reflect long- or short-run trends, depending on the length of the study period selected. While short-run trends can be more volatile due to fluctuations in demand or input prices, long run trends can smooth these effects, but cause financial stress for utilities if there is input price volatility (Lowry and Getachew, 2009). Makholm (2018) recommends using the longest time period available to uncover the underlying productivity growth trend of the industry, rather than the underlying trend of a business cycle. Best practices are to use a length of study that is long enough to smooth volatility in outputs and costs, while remaining representative of the TFP growth trend that is likely to occur during the PBR period.

In practice, the Alberta Utilities Commission found that, based on expert opinion, a sample period of at least 10 years was sufficient for determining long-run industry TFP (AUC, 2012). Similarly, the Massachusetts Department of Public Utilities has approved TFP estimates based on samples which are better indicators of future expectations, with sample lengths of 15 years for both Eversource and National Grid (MDPU, 2017; MDPU, 2019).

Key questions regulators need to understand include: (1) is the TFP growth trend reasonable for the PBR period, and (2) if long-term growth trends are suspected to be unstable, to request statistical tests evidencing a structural break.

3.2 Output Measurement

The choice of output measure(s) can also affect TFP growth rates as TFP reflects the difference in growth rates between a firm's physical outputs and inputs. Output is typically measured from the perspective of demand or supply. A common demand measure is the amount and value of energy distributors provide to customers, often measured by volume of sales and total revenue. Supply measures consider the availability and condition of infrastructure, which is another important service in supplying electricity to customers. Common supply measures include quality and quantity of electricity supplied, as well as coverage and capacity of the system, often measured by number of customers and system capacity (Lawrence and Diewert, 2004; Lawrence, 2009).

Other factors that affect the choice of output measure are whether the PBR is a price cap or revenue cap. With a price cap, how much energy is sold directly affects a company's revenues, and volumetric measures of output such as volume of sales or peak demand are common. With a revenue cap or a revenue-per-customer cap, the number of customers may be more important drivers of a firm's revenue given their importance in driving utility costs (Lowry and Makos, 2018). Yet, many practitioners recommend several output measures to reflect changes in output trends. Lawrence and Diewert (2004) recommend an output measure comprised of energy throughput, system capacity, and customers to incorporate both customer- and sales-density variables. Makholm (2018) recommend a mix of output measures (number of customers, line miles, peak usage, etc.) to reflect changing trends in output due to the changing nature of electricity distribution, where an increase in inputs may not necessarily lead to an increase in output (such as investments in advanced metering infrastructure which aim to reduce demand).

When combining several outputs into an aggregate, total output measure, index number methods require a weight be allocated to each output. A commonly used weight is the share of revenue for each output, however if prices are not explicitly available, an econometric cost function is often used to determine cost shares (Lawrence and Diewert, 2004). Table 2 provides some common output measures for recent TFP studies, all of which used a Törnqvist index methodology.

Table 2. Summary of Output Measurement for Recent TFP Studies

Study	Price/Revenue Cap or Other	Output	Weights
Lowry et al., 2020	Revenue cap	Number of customers, ratcheted maximum peak demand, mid-year generation capacity, generation volume, mid-year transmission line miles	Cost shares were computed with an econometric cost model
Meitzen, 2018	Revenue cap	Number of customers (total number of retail customers served)	Number of customers was the sole output measure
Meitzen, 2017	Revenue cap	Number of customers (total number of retail customers served)	Number of customers was the sole output measure
Brown and Carpenter, 2016	Rate (price) cap for electric distribution companies	Volume (MWh) (residential, commercial, industrial, and public sales)	Revenue-based weights
Meitzen, 2016	Rate (price) cap for electric distribution companies	Volume (MWh) (residential, commercial, industrial, and public sales)	Revenue-based weights
Lowry, 2016	Rate (price) cap for electric distribution companies	Number of customers (total number of retail customers served)	Number of customers was the sole output measure
Kaufmann et al., 2013	Price cap	Customer numbers (other than street lighting, sentinel lighting, and unmetered scattered loads), total kWh deliveries, and system capacity peak demand	Cost shares were computed with an econometric cost model
Makholm and Ros, 2010; Makholm and Ros, 2012	Rate (price) cap for electric distribution companies	Residential, commercial, industrial, and public sales volume (MWh)	Revenue-based weights
Makholm et al., 2010	Other: TFP analysis for the U.S. Electric Industry (1972–2009)	Sales volume (MWh)	Revenue-based weights

Biases created by different output measures (such as sales volume or customer count) depend on the trend captured by the output measure. For example, if volumetric charges are high, volume growth can increase revenues more than costs, creating a positive bias. Alternatively, volume growth can be slowed by energy efficiency and demand response programs, creating a negative bias. Best practices point to using a mix of output measures to address these and other changing output trends in the electricity industry. A key question regulators need to understand is the sensitivity of TFP to changes in various output measures, which can be uncovered by requesting sensitivity analyses.

3.3 Input Measurement

Input indexes are typically comprised of multiple inputs and are used to capture both growth in input quantities and growth in input prices. Distribution systems typically include input categories of operations and maintenance expenditure and capital expenditure, with operations and maintenance separated into labor, and materials and services in North America (Lawrence, 2009). Weights are typically determined by the relative cost share of each input, with capital subindexes having the heaviest weight in capital-intensive distribution systems (Lowry and Makos, 2018).

3.3.1 Labor, Materials and Services

Labor, and materials and services quantities are either measured directly, when data permits, or indirectly by deflating the value of relevant costs (Lawrence, 2009). An example of a direct measure of labor quantity is the number of full-time employees. An example of an indirect measure of labor quantity is labor costs (measured by salary and wage expenses) deflated by labor price indexes (measured by a relevant salary and wage price index).

Table 3 provides some common input measures for recent TFP studies, all of which used a Törnqvist index methodology.

Table 3: Common Assumptions for Measuring Labor, Materials, and Services Quantities and Prices

Study	Input	Quantity Measurement	Price Measurement
Meitzen, 2018	Labor	Obtained by deflating the cost of labor (direct payroll distribution, plus a share of administrative and general and customer accounts and sales labor, FERC Form 1) by the price of labor	U.S. Bureau of Labor Services (BLS) Employment Cost Index for utility industry wages and salaries
	Materials	Obtained by deflating the cost of materials (O&M net of payroll distribution, plus a share of administrative and general and customer accounts and sales O&M, FERC Form 1) by the price of materials	GDPPI
Meitzen, 2017	Labor	Obtained by deflating the cost of labor (direct payroll distribution, FERC Form 1) by the price of labor	BLS Employment Cost Index for utility industry wages and salaries
	Materials	Obtained by deflating the cost of materials (O&M net of payroll distribution, FERC Form 1) by the price of materials	GDPPI
Brown and Carpenter, 2016	Labor	Estimate of full-time equivalent (FTE) employees	Distribution salaries from FERC Form 1
	Materials	Obtained by deflating the cost of materials (O&M net of distribution labor cost) by the GDPPI	GDPPI
Meitzen, 2016	Labor	Estimate of FTEs. FTEs are multiplied by the ratio of distribution salaries to total salaries to obtain distribution employee quantity	Distribution salaries from FERC Form 1

Study	Input	Quantity Measurement	Price Measurement
	Materials	Obtained by deflating the cost of materials (O&M net of distribution labor cost) by the GDPPI	GDPPI
Lowry, 2016	Labor	Salary and wage expenses (O&M salaries, wages, pensions, and other benefits) deflated by a regionalized salary and wage labor price index	Regionalized salary and wage labor price index
	Materials and Services (M&S)	Power distribution and meter reading, plus a sensible share of administrative and general expenses (exclusive of pension expenses) deflated by an M&S price index developed from BLS producer price indexes	M&S price index
Kaufmann et al., 2013	Operation, Maint. & Admin. (OM&A)	Distribution OM&A expenses deflated by an index of OM&A prices.	Non-labor prices were measured with GDP-IPI, an index that applies to all final domestic demand in Canada
Makholm and Ros, 2010; Makholm and Ros, 2012	Labor	Estimate of FTEs	Calculated by dividing Direct Payroll to Electric Distribution by FTEs attributed to Distribution
	Materials, Rents and Services (MRS)	Obtained by deflating the cost of materials (O&M net of distribution labor costs) by the GDPPI	GDPPI
Makholm et al., 2010	Labor	Estimate of FTEs	Calculated by dividing Direct Payroll to Electric Distribution by FTEs attributed to Distribution
	MRS	O&M net of labor expenses from FERC Form 1. MRS expense is deflated by dividing MRS expense by the GDPPI to obtain a measure of the MRS quantity input	GDPPI

Most debate in PBR proceedings over labor measurement are with respect to the accurate measurement of labor quantity (such as number of full-time employees, which may be difficult to ascertain with contracted labor) or selection of relevant price indexes. Whereas most debate in materials and services measurement is with respect to which expense categories are included, how joint expenses are allocated, and selection of relevant price indexes. Regulators need (1) methods that are transparent and replicable, and (2) to know the sensitivity of TFP to various methods or inclusion/exclusion of expense categories.

3.3.2 Capital

Capital quantity is decomposed into consistent capital quantity and price indexes. Capital quantity measures the flow of services from the acquired capital assets, and capital price measures what would be earned in a competitive market for rental of capital services (Lowry and Makos, 2018).

Capital quantity can be measured directly (for example, with line length or transformer capacity), or indirectly with the deflated asset value method (Lawrence and Diewert, 2004; Lawrence 2009). For example, with the indirect method, utility plant value is often deflated using a construction cost index (Lowry, 2019).

A practitioner typically observes new capital (I_t) added to capital stock (K_t) each year, but not total capital stock, requiring total capital stock to be inferred from past and current additions (Hulten, 1991). Because older capital may be less productive, depreciation must also be considered. One method for adding capital additions to capital stock is the perpetual inventory method, where investment (I_t) from all surviving capital vintages is weighted by a number (ϕ) between zero and one to allow for older capital to be less productive than newer capital, and summed to equal total capital stock: $K_t = \phi_0 I_t + \phi_1 I_{t-1} + \cdots + \phi_t I_{t-T}$, where $\phi_0 = 1$ and $t - T$ is the date of the oldest surviving vintage (Hulten, 1991). Because ϕ is rarely observed, it is common to assume it follows an observable pattern – a depreciation profile (Hulten, 1991).

Three depreciation patterns are commonly chosen in electricity TFP studies: one-hoss-shay, straight-line, and geometric decay, as shown in Figure 1.

With one-hoss-shay, the asset is assumed to be fully efficient ($\phi = 1$) over its service life ($t = 0, 1, 2, \dots, T$) and the asset falls apart when the service life ends (efficiency is then equal to zero). With the straight-line efficiency pattern, efficiency declines linearly until the asset is retired, although efficiency decays in equal increments ($1/T$) each year ($\phi_{T-1} = 1 - \left(\frac{T-1}{T}\right)$) for the service life of the asset. With the geometric decay efficiency pattern, the productive capacity of the asset decays at a constant rate, $\delta = \frac{\phi_{t-1} - \phi_t}{\phi_{t-1}}$, giving an efficiency sequence, $\phi_t = (1 - \delta)^t$, which is characterized by the decay rate δ rather than the service life of the asset (Hulten and Wykoff 1996).

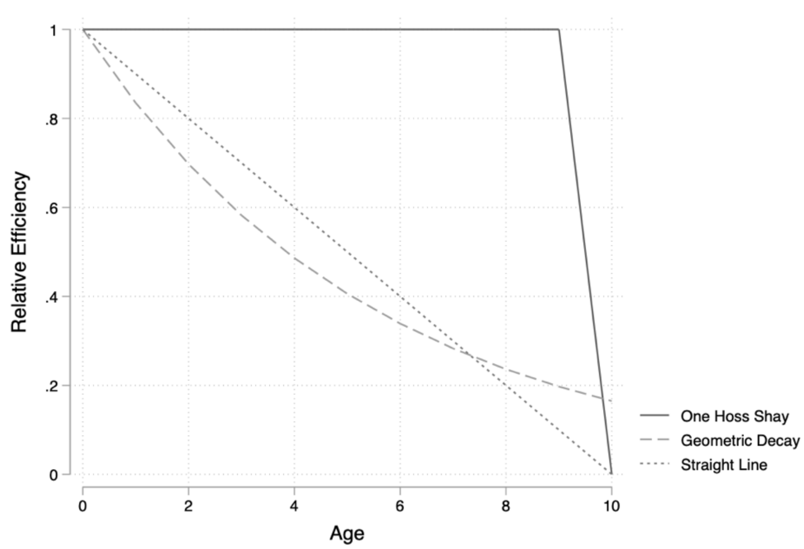

Figure 1: Depreciation Profiles for One Hoss Shay, Geometric Decay (at 16.5%), and Straight Line

Capital cost can also be measured directly by applying a constant percentage reflecting depreciation, the opportunity cost of capital, and the rate of capital gains to the assets' value, or indirectly as the residual from revenue minus operating costs.

The direct approach requires a "user cost" (reflecting depreciation, the opportunity cost of capital, and capital gains) be applied to the assets' value (Lawrence, 2009). Assuming an asset is purchased and used for one period, the user cost (U_t) is for a t years old asset is equal to its purchase price (P_t) minus the discounted end of period price one year in the future, $(1+r)^{-1}P_{t+1}$, where the real interest rate is r: $U_t = P_t - (1+r)^{-1}P_{t+1}$.

As an example, with one-hoss-shay depreciation, the gross capital stock model is appropriate for aggregating capital stock K over the current (I_0) and prior ($N-1$) period investments:

$$K = I_0 + I_1 + \ldots + \ I_{N-1}. \tag{7}$$

The user cost for a new asset with price P_0, real interest rate r, and useful life N, is then

$$U_0 = P_0 r(1+r)^{-1}[1-(1+r)^{-N}]^{-1}. \tag{8}$$

With geometric decay depreciation, the net capital stock model is appropriate for aggregating capital stock K, over current (I_0) and prior period (I_t) investments, where t indicates investment occurring t periods ago:

$$K = I_0 + (I-\delta)I_1 + (1-\delta)^2 I_2 + \cdots + (1-\delta)^t I_t. \tag{9}$$

The user cost for a new asset with price P_0, real interest rate r, and constant rate of depreciation δ is

$$U_0 = (1+r)^{-1}(r+\delta)P_0 \tag{10}$$

For further reading and an application of these methods to straight-line depreciation, see Diewert and Lawrence (2000). Table 4 provides examples of capital quantity and price methodologies in recent TFP studies, all of which used a Törnqvist index methodology.

Table 4: Common Assumptions Used in Measuring Capital Input Quantities and Prices

Study	Input	Quantity Measurement	Price Measurement
Meitzen, 2018	Capital	Perpetual inventory method with one-hoss-shay depreciation assumption	Price is the dual to the one-hoss-shay capital quantity
Meitzen, 2017	Capital	Perpetual inventory method with one-hoss-shay depreciation assumption	Price is the dual to the one-hoss-shay capital quantity
Brown and Carpenter, 2016	Capital	Perpetual inventory method with one-hoss-shay depreciation assumption	Price is the dual to the one-hoss-shay capital quantity
Meitzen, 2016	Capital	Perpetual inventory method with one-hoss-shay depreciation assumption	Price is the dual to the one-hoss-shay capital quantity
Lowry, 2016	Capital	Perpetual inventory method with geometric decay depreciation assumption	Price is the dual to the geometric decay capital quantity

Study	Input	Quantity Measurement	Price Measurement
Kaufmann et al., 2013	Capital	Perpetual inventory method with geometric decay depreciation assumption	Price is the dual to the geometric decay capital quantity
Makholm and Ros, 2010; Makholm and Ros, 2012	Capital	Perpetual inventory method with one-hoss-shay depreciation assumption	Price is the dual to the one-hoss-shay capital quantity
Makholm et al., 2010	Capital	Perpetual inventory method with one-hoss-shay depreciation assumption	Price is the dual to the one-hoss-shay capital quantity

Most debate in PBR proceedings over capital measurement is with respect to underlying assumptions that inform the capital quantity index. The choice of benchmark year affects the starting capital cost and quantity and can create positive or negative bias in TFP estimates. Using the net plant value (when the gross plant value is appropriate) can create downward bias in TFP estimates if net plant value underestimates capital quantity. Although the literature is clear that the gross plant value is appropriate for one-hoss-shay, and the net plant value for geometric decay (Diewert and Lawrence, 2000), in practice both net or gross plant value are used with both depreciation assumptions. Further, different depreciation assumptions can result in different capital quantity and price valuations.

Best practices are to have a benchmark year that allows for many years of plant additions to minimize measurement error, a depreciation assumption that best reflects the underlying depreciation profile of the asset, and that quantity and price indexes should be consistent (reflect the same depreciation assumptions). Key recommendations for regulators are to consider whether the benchmark year allows for sufficient capital additions to minimize measurement error, to request sensitivity analyses if it is believed the choice of gross or net plant value is overstating or understating capital quantity, and to determine if the depreciation assumption reflects the underlying depreciation profile of the asset. Sensitivity analyses to capital quantity and price assumptions can be requested.

3.4 Overall Index Weighting Methods

Other important areas for consideration are that index weights can be chained or multilateral, and the overall averaging of TFP trends. With a chain-weighted index, weights are calculated for consecutive periods (Equation 3) whereas with a multilateral index, weights are calculated relative to the average firm (Equation 4). A simple numerical example is provided in the Appendix. Although either method is appropriate for TFP growth, with TFP levels, only the multilateral method (Equation 4) is appropriate. Regulators and policy makers can request sensitivity analyses to various weighting methods as necessary. TFP trends can also be averaged as a simple arithmetic average or as a weighted average, with more weight given to more similar firms. Again, regulators can request sensitivity analyses to understand the extent to which the averaging method for TFP trends affects the TFP measure.

4 Discussion and Conclusion

Performance based regulation provides incentives for utilities like those faced by companies in competitive markets to encourage operational efficiency and cost reductions. However, regulators and policymakers face key challenges in determining the appropriateness of and potential bias from methodologies and assumptions used by utilities to inform the X-factor, which escalates prices or revenues, in PBR cases. Based on the literature and best practices from TFP studies that inform the X-factor, we develop the alternatives and requirements to undertake the complete analysis of performance-based submissions that use the index method to help regulators overcome these challenges. To accurately estimate TFP, appropriate data and sample selection, output measurement, input measurement and index weighting must occur. We find that although TFP measurement does not have a one-size-fits-all approach, as methodologies and assumptions depend on the unique circumstances of individual utilities, we highlight underlying factors which may bias TFP studies and provide recommendations to identify and address potential biases.

Key takeaways are that study methodologies and assumptions should be transparent enough that the study could be reproduced, and sensitivity analysis of key assumptions can be undertaken to show the sensitivity of TFP to changing those key assumptions. We found several points that regulators should address when evaluating TFP calculations. They included the reputability of data sources and their measurement error; the procedures used to change the data along with the transparent and clear documentation; whether peer groups selected made for meaningful comparisons; how the exogenous difference between heterogeneous utilities was accounted for; and whether the length of the study period accounted for TFP growth reasonably (at least 10 years in length) and whether statistical tests were undertaken to determine structural breaks. Similar points need to be addressed for input and output measurement. Methods to measure inputs need to be transparent and replicable with the sensitivity of the measures known. Several approaches for calculating capital were described. The approach chosen needs to minimize measurement error and requires sensitivity analysis to understand the measurement error. Input biases can be caused by inappropriate indices for measuring changes in labor, capital and O&M. Inappropriately choosing the benchmark year can bias the capital index. Different output measures such as sales volume or customer count can create bias that requires using a mix of output measures to address different causes of trends in output, e.g., volume growth can increase revenues while energy efficiency can cause a negative bias. One area of bias occurs when the productivity trends are not representative of the productivity trend for the industry.

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Appendix – Alternative Methods to Estimate Total Factor Productivity

Three methods to calculate the relative productivity of the individual firm to the efficiency frontier are discussed in this appendix: econometric methods, data envelopment analysis, and stochastic frontier methods. Econometric methods can use generalized method of moments, semi-parametric estimators, and stochastic frontier methods to evaluate the relative efficiency of the firm. Data envelopment is a linear programming technique that identifies the efficiency frontier and compares identified firms to the frontier. The stochastic frontier method constructs the efficiency frontier from known best practices firm and compares firms to the frontier. A simple numerical example of a Törnqvist index approach is also provided.

A Econometric Methods

Two prominent econometric methods for estimating TFP are (1) estimating the parameters of the production function, or (2) assuming firms exhibit profit-maximizing or cost-minimizing behavior, deriving cost or demand functions (Abbott, 2005). Both are parametric methods. As an example, by taking the natural logarithm of a Cobb-Douglas production function, an econometrician estimates

$$q_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \omega_{it} + \epsilon_{it}, \qquad \text{(A1)}$$

where q is the output of firm i at time t, l is labor, and k is capital. Because ω represents productivity differences among firms, and is unobservable, it must be estimated. However, because ω could be correlated with input choices, it could create simultaneity bias if estimated with ordinary least squares. Recommended methods include generalized method of moments (GMM), semi-parametric estimators, and stochastic frontier methods to address this issue. See Van Biesebroeck (2007) and Van Beveren (2012) for further reading.

Once potential biases are addressed, productivity growth can be estimated as

$$lnA_{it} - \overline{lnA_t} = (q_{it} - \overline{q_t}) - \widehat{\alpha_l}\left(l_{it} - \overline{l_t}\right) - \widehat{\alpha_k}\left(k_{it} - \overline{k_t}\right). \qquad \text{(A2)}$$

using the estimated parameters for labor ($\widehat{\alpha_l}$) and capital ($\widehat{\alpha_k}$).

B Data Envelopment Analysis

Data envelopment analysis (DEA) is a linear programming technique that identifies the most efficient (best practice) firms by fitting a frontier over the sampled firms. Firm efficiency is measured as the ratio of total outputs to total inputs, and less efficient firms are measured relative to the frontier (Abbot, 2005).

Van Beisebroeck, 2007, shows that in practice, the efficiency, θ, of a firm-year unit is the ratio of a linear combination of outputs (Q) to a linear combination of inputs (L, K), where weights on outputs (v_q) and inputs (u_l, u_k) are chosen to maximize efficiency for the unit under consideration. A linear-programming problem is solved separately for each unit ($i = 1 \ldots N$).

$$\max_{v_q, u_l, u_k} \theta_1 = \frac{v_q Q_1 + v^*}{u_l L_1 + u_k K_1} \qquad \text{B.1)}$$

$$\text{subject to} \frac{v_q Q_i + v^*}{u_l L_i + u_k K_i} \leq 1 \quad i = 1 \ldots N$$
$$v_q, u_l + u_k > 0, u_l, u_k \geq 0$$
$$v^* \geq 0 \quad (v^* = 0 \text{ for constant returns to scale})$$

If another unit produces more output with the same amount of input using identical input weights, unit 1 is considered dominated, and weights have sign restrictions so that the efficiency of each firm cannot exceed 100% when using the same weighting scheme. Efficiency is then the productivity difference between unit i and the most efficient unit, $\theta_i = A_i/A_{max}$, said otherwise, DEA estimates

$$lnA_{it} - \overline{lnA_t} = ln\theta_{it} - \frac{1}{N}\sum_{j=1}^{N_t} ln\,\theta_{jt}. \qquad \text{B.2)}$$

Because DEA is a non-parametric method, it can be used when the production technology varies across firms. It also has the advantage of better identifying potential efficiency improvements as technological change can be separated from technical efficiency. However, DEA is sensitive to the weights chosen as well as sensitive to outliers, as measurement error can affect all estimates (Frayer et al., 2016).

C Stochastic Frontier Methods

Stochastic frontier methods are similar to DEA in that a production frontier is constructed from best practice firms. However, it differs in the assumptions used to separate the distribution of the unobserved firm productivity parameter (ω_{it}) from the random error.

The productivity parameter, ω_{it}, is modeled using assumptions about the distribution of productivity in the sample of firms and is interpreted as the inefficiency of firm i at time t relative to the best practice firms in the sample. Battese and Coelli (1992) show that by assuming the productivity of each firm can vary over time and is drawn from a truncated normal distribution with mean, γ, and variance, σ^2, the productivity parameter can be modeled as

$$\omega_{it} = e^{-\eta(t-T)}\omega_i \qquad \text{with } \omega_i \sim N^+(\gamma, \sigma^2) \qquad \text{C.1)}$$

For a sample of *N* firms over T time periods. Efficiency increases (decreases) over time if η is positive (negative). The parameter ω is usually estimated using maximum likelihood methods (see Coelli, 1992; and Greene, 2010) where technical efficiency is

$$TE_{it} = E(e^{-\omega_{it}} | \omega_{it} + \epsilon_{it}). \qquad \text{C.2)}$$

The stochastic frontier method produces accurate TFP levels if output is measured accurately, firms share the same technology, and productivity differences among firms do not change that much over time (Van Biesebroeck, 2007). However, the methodology does require specification of the production technology.

D Törnqvist Index Numerical Example

To provide a brief numerical example of Equation (3), suppose we have a firm that produces two outputs *A* and *B* from two inputs, *X* and *Y*. The prices and quantities of outputs and costs and quantities of inputs are given in Table D1.

Table D1. Törnqvist Index Example – Output and Input Prices and Quantities

	Prices and Quantities of Outputs				Costs and Quantities of Inputs			
Time	P_A	Q_A	P_B	Q_B	C_X	Q_X	C_Y	Q_Y
$t-1$	3	5	3	5	2	7	3	7
t	3	6	4	6	4	6	4	11

From price and quantity or cost and quantity data in Table D1, one can compute revenue or cost shares for outputs and inputs, as shown in Table D2.

Table D2. Törnqvist Index Example – Revenue and Cost Share Calculation

	(1) Revenue from A	**(2) Revenue from B**	**(3) Total Revenue**	**(4) s^A**	**(5) s^B**	**(6) Cost of X**	**(7) Cost of Y**	**(8) Total Cost**	**(9) s^X**	**(10) s^Y**
Time	$P_A \times Q_A$	$P_B \times Q_B$	$(1)+(2)$	$(1) \div (3)$	$(2) \div (3)$	$C_X \times Q_X$	$C_Y \times Q_Y$	$(6)+(7)$	$(6) \div (8)$	$(7) \div (8)$
$t-1$	15	15	30	0.5	0.5	14	21	35	0.4	0.6
t	18	24	42	0.429	0.571	24	44	68	0.353	0.647

From this data we can compute the Törnqvist index, which shows a 4% decrease in productivity, as shown in column (7) of Table D3.[3]

[3] Note that Törnqvist index numbers are exponentiated in Table D3.

Table D3. Törnqvist Index Example – Calculation of Output, Input, and Productivity Indexes

	(1)	(2)	(3) Törnqvist Output Index	(4)	(5)	(6) Törnqvist Input Index	(7) Productivity Index
Time	$\frac{s_t^A + s_{t-1}^A}{2} \ln \frac{Q_{A,t}}{Q_{A,t-1}}$	$\frac{s_t^B + s_{t-1}^B}{2} \ln \frac{Q_{B,t}}{Q_{B,t-1}}$	$e^{(1)+(2)}$	$\frac{s_t^X + s_{t-1}^X}{2} \ln \frac{Q_{X,t}}{Q_{X,t-1}}$	$\frac{s_t^Y + s_{t-1}^Y}{2} \ln \frac{Q_{Y,t}}{Q_{Y,t-1}}$	$e^{(4)+(5)}$	$(3) \div (6)$[4]
$t-1$	0 (The base year is normalized so that $\frac{Q_{A,t}}{Q_{A,t-1}} = 1$)	0	1	0	0	1	1
t	0.085	0.098	1.2	-0.058	0.281	1.25	0.96

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[4] Equivalent to $e^{[(1)+(2)]-[(4)+(5)]}$.

Vitae

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