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# Productivity growth and incentive regulation in Austria's gas distribution

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ABSTRACT

The projected rate of productivity growth is the critical determinant of the price cap in incentive regulation. However, the regulatory authorities generally lack sophisticated industry TFP studies to set an optimal cap. We thus estimate productivity growth in the Austrian gas distribution sector in a translog cost function framework. A key feature is our unique panel database on costs and outputs of regulated utilities for the period 2002–2013, covering six years prior and during incentive regulation as introduced in 2008. We find a modest TFP growth rate in the early sample years, followed by a decline to zero or even slightly negative rates in recent years. We also find a significant potential for returns to scale, which is left unexploited, indicating that utilities could significantly save on costs by merging. As essential investments have already been undertaken in the past, opportunities for technological progress seem to be limited in recent years.

## 1. Introduction

Since the rise of *incentive-based regulation* of network industries (see e.g., Baumol, 1982; Crew and Kleindorfer, 1986; Littlechild, 1983; Laffont and Tirole, 1993), many regulatory authorities across the world have applied price (or revenue) caps, which define the annual rate at which conceded output prices of natural monopoly firms have to decrease. The price cap is usually called "the general X-factor" (X-gen).[1] The idea is to mimic a competitive market environment in the regulated industry, where any changes in firms' costs stemming from changes in productivity or input prices are entirely passed on to consumers (Bernstein and Sappington, 1999).[2] This system intends to provide incentives for efficiency improvements, as any cost savings beyond the price cap enter as profits. *Productivity growth* is generally assumed to be the most crucial component of the price cap (Lowry and Getachew, 2009), and in many jurisdictions it is the only determinant, whereas changes in input prices are often disregarded.

As we argue in this paper, regulators generally have only a vague idea about the optimal choice of the price cap, due to a lack of sophisticated studies on TFP growth for the respective regulated industries. Thus its value is often the result of a political decision-making process (e.g. Baker et al., 2002; Baldwin and Cave, 1999; Schmitt and Stronzik, 2015) that lacks scientific rationale. However, it is essential to determine an *optimal* value of the price cap for the proper functioning of the regulatory system. A too stringent price cap below the theoretical optimum endangers firms' financial viability and may cause under-investment as well as poor service quality, whereas a cap above the optimum risks monopoly profits with high price mark-ups for consumers and a general public mistrust in regulation.

Given a lack of evidence about the TFP potential of regulated gas distributors in Austria, we are the first to estimate productivity growth (and its source components) at the firm level based on the econometric estimation of a translog multi-output cost function. From a methodological point of view, the parametric estimation of a cost function bears many advantages compared to non-parametric methods, as we are able to exploit the panel dimension of the data by including individual fixed

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[1] From now on, we do not make a distinction between price and revenue caps but simply refer to both terms as "price caps". The price cap is usually called "the general X-factor". In some jurisdictions (such as Austria), the general X-factor applies to *all* regulated firms, and for *individual firms* a "stretch factor", which is determined through benchmarking, is added to address individual inefficiency (see also Lowry and Getachew, 2009).

[2] In many jurisdictions (such as Austria), this implies that for a pre-specified regulatory period (e.g. five years), the granted costs or revenues of regulated companies are reduced by the price cap on an annual basis after being valorized by a general price index, such as consumer prices. In this case, this form of regulation is called "CPI minus X" (or "RPI minus X″) regulation going back to Stephen Littlechild in the 1980s.

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effects (to capture time-invariant unobserved firm heterogeneity) as well as a stochastic error term (to capture random shocks).[3] Moreover, our approach allows for non-constant returns to scale, and for decomposing TFP growth into its components in conjunction with their statistical significance. In Appendix B, we also add potentially important control variables (e.g. to further account for firm heterogeneity), to provide robustness.

A distinct feature compared to other studies is our rich and unique panel database on expenditures and network characteristics of regulated Austrian gas distributors over the period 2002–2013, covering six years before and after the introduction of incentive regulation in 2008. Our data are specifically for the *gas distribution* segments of these companies (as many firms also serve other segments, e.g. electricity). Despite data confidentiality,[4] reliability is assured, as the Austrian regulatory authority, E-Control, cross-checked our data for plausibility according to their own data collection, which is used for regulatory decisions (e.g. benchmarking analyses, determination of granted costs, etc.).

Eventually, our estimates of TFP growth allow for deducting the optimal value of the price cap.[5] So far, the Austrian regulatory authority has gauged the price cap based on external evidence from TFP studies of other countries and sectors, negotiations with industry representatives, and crude estimates from publicly available index numbers (for the *whole electricity* sector). Hence, and as we argue later in more detail, TFP growth rates seem to be rather arbitrarily chosen, emphasizing the need for a sophisticated productivity analysis of the Austrian gas distribution sector.

We find that average productivity growth gradually declined from an initial rate of 1.4% in 2013 to zero or even slightly negative rates in recent years. The TFP decomposition shows that there is a significant (latent) potential for returns to scale, especially for small utilities, which is, nevertheless, left unexploited. Realized scale economies are essentially zero throughout the sample period. Hence, technical change is the main source of TFP growth for Austrian gas distributors. It seems that important investments have already been undertaken in the past, resulting in a limited and fading potential for technological opportunities in recent years.

The remainder of the paper is structured as follows. Section 2 discusses the related literature on TFP measurement and econometric cost models. Section 3 introduces the regulatory regime in Austria's gas distribution sector. In Section 4, we discuss the measurement and decomposition of productivity growth, while the data for the underlying cost function estimation are presented in Section 5. Our main results of the productivity estimation and several robustness checks are presented in Section 6. Section 7 concludes and offers policy recommendations.

## 2. Literature

In this section, we first discuss various methods as applied in the literature to measure the productivity of gas and electricity distribution companies; secondly, we focus on relevant studies that parametrically estimate cost functions or cost frontiers.

Due to data limitations (e.g. firm-level panel data on specific segments), it is often not possible to parametrically estimate industry productivity. Instead, many studies apply non-parametric methods (see e.g. Del Gatto et al., 2011; Diewert, 1981) such as index number approaches (Laspeyres, Paasche, Fisher), non-parametric indices (e.g. Malmquist or Törnqvist), or other non-parametric approaches (e.g. growth accounting, data envelopment analysis). The advantage of econometric estimation over non-parametric methods is that random noise in the data or (unobserved) firm heterogeneity can be addressed more precisely by error components (random error, fixed effects), additional control variables, or functional form. Also, estimates of TFP growth and its source components can be attributed with statistical significance (Heshmati and Kumbhakar, 2011). Econometric estimation is "data hungry" since it requires firm-level panel data over a reasonable period. To our knowledge, only few relevant econometric cost-based studies exist that utilize firm-level panel data to infer about productivity growth for gas distribution, while there is more literature for electricity distribution.

There are a few studies of productivity or efficiency performance in *gas distribution*. Hammond et al. (2002) apply data envelopment analysis (DEA) for the U.K. in 1937 and find higher efficiency of gas utilities under the basic price system relative to those subject to the sliding scale system or maximum price system. Hollas et al. (2002) apply DEA and find that productivity performance has not been affected by the restructuring of the U.S. gas distribution industry during 1975–1994. Waddams Price and Weyman-Jones (1996) apply the Malmquist-index method and show that productivity in the UK gas industry increased after privatization in 1986. Non-parametric productivity studies in related industries are, e.g. Arocena and ContínHuerta, (2002, Törnqvist for electricity, oil, and gas in Spain), Førsund and Kittelsen (1998, Malmquist for Norway's electricity distribution), and Hjalmarsson and Veiderpass (1992, Malmquist for Sweden' electricity distribution).

More recently, some studies emerged that *econometrically* analyze productivity growth in a cost function or cost frontier framework to estimate cost savings over time unrelated to output or input price variation (and other control variables).[6] In a recent study, Casarin (2014) estimates a multi-output translog variable cost function for eight Argentinian gas distributors covering two cycles of incentive regulation over 1993–2001. Technical change is measured by a standard time trend model and by a time index approach allowing for "non-smooth" yearly jumps and estimated at slightly *negative* annual rates of −0.18% and −0.83%, respectively. Not only is the limited productivity potential in line with our findings, but also the technical change (and capacity utilization) explains most of the TFP performance, while scale effects (and other factors) are of minor importance. In contrast to Casarin (2014), our study takes individual fixed effects into account (controlling, among other time-invariant factors, for time-invariant inefficiency, which turns out to be the major source of inefficiency).[7]

In a closely related article, Lowry and Getachew (2009) estimate a translog cost function for 36 major U.S. gas distributors (including gas storage and gas transmission in their operations) during 1994–2004 to propose a "TFP target" (which reflects X-gen under the assumption that

[3] This paper intends to estimate TFP growth (i.e. the shift of the cost frontier), not firm specific inefficiency (i.e. the distance to the cost frontier). Hence, to disentangle productivity from inefficiency, it would be ideal to apply stochastic frontier analysis (SFA). However, the maximum likelihood function for SFA did not converge (which is a common problem with this method; for more details, see the discussion provided in Section 2). From this perspective, estimating a cost function with *fixed effects* seems particularly important in our case, as fixed effects capture time-invariant inefficiency at the firm level. As we show in Section 4, a test confirms that the major part of total inefficiency in our sample is time-invariant inefficiency (as captured by firm fixed effects), whereas time-varying inefficiency is statistically negligible.

[4] Actual cost data (as opposed to costs granted by the regulatory authority) are generally only available confidentially. To the best of our knowledge, there is no other study that incorporates such panel data on utilities' costs and outputs at the firm level over such a long period.

[5] Many regulatory authorities set the value of X-gen equal to TFP growth in the regulated industry. However, we also provide a derivation of X-gen according to the theoretically well-founded Bernstein-Sappington (1999) differential formula.

[6] Alternatively, it is possible to employ a production function/frontier, which represents the dual to the cost approach, to measure productivity growth as the increase in output unrelated to changes in inputs.

[7] Casarin uses exogenous cost shifters, such as load factor, residential to total gas deliveries, customer density, distribution area, and customers per kilometer of pipeline to control for heterogeneity.

productivity is its sole determinant) for two major gas companies in Ontario between 1.51% (excluding business conditions) and 1.87% (including business conditions). In line with our results, realized scale economies are rather low at 0.37%, while technical change lies at a modest 1.13%. Their multi-output translog cost function controls for business conditions yet does not include a second-order trend term or output-trend interactions (to meet regularity conditions), which, in contrast, we do. Individual fixed effects are also not taken into account. From a methodological viewpoint, our fully specified translog cost functions with all second-order and interaction terms and individual fixed effects may be more accurate.

The only related study using a *stochastic frontier* framework is Farsi et al. (2007) for 26 Swiss gas distributors for the period 1996–2000. However, in contrast to our general functional form of a translog cost function including all second-order terms, Farsi et al. (2007) restrict their cost function to a Cobb–Douglas specification to avoid the many parameters of a translog specification given only 129 observations. The authors assume inefficiency to be constant over time but include control variables to address firm heterogeneity and find the average inefficiency of 6–7.5% relative to an efficient firm. The assumption of invariant inefficiency conforms with our finding that the major part of inefficiency in our sample is time-invariant and thus captured by individual fixed effects. Also, no evidence of realized scale economies is in line with our findings. In a related study, Aleifar et al. (2014) find unexploited scale economies for Swiss gas distributors.

In another recent article, yet for *electricity* distribution, Dimitropoulos and Yantchew (2017) measure productivity for 73 electricity distributors located in Ontario for the period 2002–2012 based on both an econometric estimation of a multi-output translog cost function and a non-parametric Törnqvist index. The annual TFP growth rate is found to be *negative* at around −1%, though no statistical significance levels are provided. Moreover, technical change range from about 0% at the beginning of the sample to around −1.5% at the end and explains almost the entire variation in TFP, while scale economies are roughly zero and hardly change over time. These results support our findings of declining TFP growth over time towards zero (and even negative) growth in the gas distribution sector (as a comparable industry to electricity distribution) in Austria covering nearly the same period (2002–2013). Also, we find almost no realized scale economies throughout the sample period and a higher rate of technical change in the early sample years, which fades over time. In contrast to their translog cost function, having only a linear time trend, we apply a more flexible functional form by adding a quadratic trend term and trend interactions with factor prices and outputs allowing for non-neutral technical change and scale effects.

Another related paper on TFP estimation based on a translog cost function is Goto and Sueyoshi (2009) for nine utilities in the Japanese electricity distribution sector. The authors find, as in other related studies, a negative TFP growth in the rage of −1.2% to −1.8% over the sample period 1984–2003, which is mainly driven by the negative rate of technical change, while realized scale economies are of minor importance. Unfortunately, no significance levels are provided for the productivity estimates. Also, the paper makes use of a random coefficients model, but not of fixed effects.[8] Similarly, Oh (2015) estimates TFP and its source components of technical change and scale economies of Korean fossil-fuel generation firms for the period 2001–2012 based on a translog cost function. The authors find a negative TFP growth rate of −0.7% over the sample period, which is even lower in recent years (−2.8% in 2012). The analysis, however, bears limitations: it only employs one output; it omits interaction terms between outputs, input prices and the time trend; despite having estimated a fixed-effects model, the authors favor the random effects model to measure TFP; many parameter estimates are insignificant.

Overall, the related literature on econometric cost-based approaches in gas and electricity distribution indicates that historical TFP growth rates were higher and have significantly declined to around zero or even negative TFP growth in recent years. Compared to related econometric TFP studies, which either restrict the translog cost function to a limited set of higher-order terms or neglect trend interactions, or confine their functional form to a Cobb–Douglas specification, our approach bears a more general functional form (i.e. translog cost function with all second-order terms and trend interactions). Still, many papers struggle with statistically insignificant coefficients when estimating a cost function, due to a limited number of observations and many parameters to estimate. Most studies focus on the estimation of cost functions rather than on cost frontier models, which are designed to tackle inefficiency. A likely explanation may be that, as in our study, the convergence of the maximum likelihood function of a cost frontier approach may not be achieved. This problem becomes especially pronounced for industry studies of only a few gas or electricity distribution utilities and, thus, a limited number of observations). Firm-fixed effects, which are mostly neglected in related papers, are therefore a way to control for time-invariant inefficiency when estimating a cost function. In our case, a test confirms that firm fixed effects are sufficient to take out inefficiency, which is mainly driven by its time-invariant part (see the discussion in Section 4), so that our estimate of TFP growth is not biased by inefficiency. Finally, we extend the limited availability of econometric industry TFP studies that are much needed for policy recommendations, such as, in our case, on setting an appropriate price cap in incentive regulation. Given that actual cost data of firms are hardly accessible to researchers, there are only few related studies. Thus, even though our analysis builds on a limited data sample (i.e. 17 utilities, 185 observations), it represents a natural extension of the literature.

## 3. Regulatory environment

Before the introduction of incentive regulation in 2008, the Austrian gas distribution sector was regulated on a cost-plus basis, in which any expenditures associated with the network operations of the regulated utilities are granted by the regulator. Hence, under cost-plus, regulated utilities may not have an incentive for cost-efficient behavior. In 2008, an incentive regulation regime was introduced to encourage higher efficiency among the regulated natural monopoly firms and make them operate as if they operated in a competitive environment. Under perfect competition, firms are price takers and thus pass on any cost savings from productivity growth or input price reductions directly to end-users via price adjustments. Hence, an optimal price cap would make sure that firms reduce their final prices in accordance with predicted productivity gains (see Bernstein and Sappington, 1999).

Since February 2008, gas distribution firms have been subject to a general price cap, the general X-factor, of 1.95% annually, implying that granted costs are reduced by this percentage each year.[9] Under price-cap regulation, firms are residual claimants on any additional cost savings over the regulatory period, providing an incentive to save on costs. Moreover, Austria's regulatory system exhibits other vital features: regulation of total costs (TOTEX); regulatory period of five years[10]; elevation of granted costs by a network input price index;

[8] The assumption of the random coefficient model is that the individual error components ($\mu^i$) are random and uncorrelated with independent variables. However, the second assumption hardly applies.

[9] This holds for "100%-efficient" firms as determined in the benchmarking. "Inefficient" firms must, in addition, catch up and become "efficient" over a period of 10 years. This is achieved by applying the so-called "X-ind", i.e. an individual efficiency factor, which depends on the efficiency score attained at the benchmarking. In this study, we only focus on the general price cap (X-gen), which is why we do not provide more details on the individual "stretch factor".

[10] The first regulatory period was from February 2008 until December 2012; the second period started in January 2013 and lasted until December 2017.

benchmarking of gas distribution companies to calculate individual (in) efficiency factors.

There might be a problem with our approach to productivity measurement if firms anticipated the introduction of incentive regulation and acted strategically in the years before its introduction. The introduction of incentive regulation in gas distribution was announced in 2007, one year before its actual introduction (see e.g. E-Control, 2008). While consultation processes started earlier, the actual and precise design of incentive regulation was not clear before the year 2007. Moreover, and very importantly in our context, productivity measurement based on firm-level data of costs and firm characteristics was applied for the first time in the year 2017 for the upcoming regulatory period starting in 2018. For the first two regulatory periods 2008–2012 and 2013–2018 (that overlap with our sample period), the regulatory authority gauged TFP growth from 23 international empirical TFP studies of various regulated industries, such as electricity and gas, but also telecommunications, water supply, seaports, and airports from several countries and for different sample periods (see, e.g. E-Control, 2013, p. 15).[11] Hence, as the predicted rate of TFP growth from exogenous TFP studies from other countries and industries, firms could not have had incentives to act strategically to influence TFP growth in Austria's gas distribution sector.[12]

The price cap represents the central element in incentive regulation. Hence, its magnitude set by the regulatory authority is of utmost importance. On the one hand, a price cap set *too stringent* creates the risks that current consumers underpay for the services and that regulated companies are put under undue strain from not being able to earn the opportunity cost of capital, with possible adverse side effects, such as under-investment, under-provision of quality or outright bankruptcy. On the other hand, under a price cap set *too loose*, current consumers overpay for the services and regulated companies earn excessive monopoly profits (market power rents), with additional possible adverse side effects, such as a general public mistrust of regulation (Bernstein and Sappington, 2000). In spite of the theoretical relevance of the price cap, its practical implementation by regulatory authorities remains cumbersome because of a lack of sophisticated (empirical) analyses of productivity growth in the regulated industry. As a result, regulators often have only a vague idea of how to set the price cap.

Schmitt and Stronzik (2015) provide a discussion on the role of the price cap (i.e. the general X-factor) in different regulatory regimes. Regarding Germany's incentive regulation regimes of electricity and gas distribution, the authors state that the determination of the general X-factor for the first and second regulatory periods of 1.25% and 1.50%, respectively, appeared to be the result of a political decision, rather than being based on empirical evidence—most likely due to a lack of reliable data for a sophisticated scientific analysis. This is relevant because Germany's regulatory regime is comparable with Austria's and often serves as a reference for regulatory decisions.

Similarly, Casarin (2014) states that, after restructuring the Argentinean gas industry in 1992, the regulatory authority set a price cap of zero and then increased it to 4.8–4.4% (individualized by firm) in 1998, which in both cases seemed like an arbitrary decision rather than a decision based on expected productivity gains derived from economic analysis. Baker et al. (2002, p. 6) investigate incentive regulation in the UK's regulated industries (and in particular the water industry) and conclude that "(a) higher degree of transparency, and agreed methods for developing and applying the productivity and input price assumptions in setting X, would help avoid mistakes and help provide companies with sound efficiency incentives." Baldwin and Cave (1999, p. 247) stress that regulators have only very limited information regarding the "true productive potential of the firms they regulate" and that "regulators have to rely, in making projections of productivity growth, on the accumulation of a variety of disparate data and, ultimately, on judgement." Overall, we find evidence of positive values of the price caps set by regulatory authorities across countries and industries,[13] which may indicate public pressure on regulatory authorities to set high price caps, which depart from an economic optimum (based on empirical estimation).

Concerning Austria's gas distribution industry (and also electricity distribution), due to a lack of adequate information regarding productivity growth based on sophisticated economic studies, the regulatory authority had to set the price cap based on "vague" information. On the one hand, a set of 23 international productivity studies regarding various regulated industries (i.e. gas and electricity distribution, airports, seaports, telecommunications, water supply) and different sample periods served as the basis of the regulatory decision about an interval of possible values of X-gen. On the other hand, direct negotiations with the interest group of the gas distribution companies as well as other stakeholders (e.g. social parties) eventually resulted in a value of 1.95% for the first two regulatory periods (2008–2012 and 2013–2017). It is, therefore, the goal of this paper to deduct a rigorous estimate of TFP growth in Austria's gas distribution on transparent and scientific grounds.

## 4. Methodology

We aim at estimating productivity growth of Austrian gas distributors for the time periods before and after the introduction of incentive regulation in 2008. The starting point of our productivity analysis is a general multi-output logarithmic cost function with $m$ outputs ($Y$), $n$ factor prices ($P$), and a time trend ($T$):

$$\ln C = f(\ln Y_1, \ldots, \ln Y_m, \ln P_1, \ldots, \ln P_n, T). \tag{1}$$

To allow for a *flexible* functional form of the actual unknown long-run cost function, we apply a translog cost function, which represents a second-order Taylor expansion for the approximation point of the mean values of the variables[14]

$$\begin{aligned}\ln C_{it} = &\sum_{k=1}^{m} \alpha_k \ln Y_{kit} + \sum_{h=1}^{n} \beta_h \ln P_{hit} + \frac{1}{2}\sum_{k=1}^{m}\sum_{l=1}^{m} \gamma_{kl} \ln Y_{kit} \ln Y_{lit} \\ &+ \frac{1}{2}\sum_{h=1}^{n}\sum_{j=1}^{n} \delta_{hj} \ln P_{hit} \ln P_{jit} + \sum_{k=1}^{m}\sum_{h=1}^{n} \zeta_{kh} \ln Y_{kit} \ln P_{hit} \\ &+ \sum_{k=1}^{m} \eta_{kT} \ln Y_{kit} T_{it} + \sum_{h=1}^{n} \theta_h \ln P_{hit} T_{it} + \mu_T T + \frac{1}{2}\mu_{TT} T^2 + X_{it}'\chi \\ &+ \upsilon_i + \varepsilon_{it}\end{aligned} \tag{2}$$

where $i$ and $t$ denote firms and years respectively. $X$ represents a vector of control variables, which we include in our robustness specifications. Individual fixed effects ($\upsilon_i$) capture time-invariant firm-specific cost effects. That is, we include an individual constant for each firm to address firm-specific characteristics that do not vary with time, such as the geographic area, the topography of the service region, etc., but also

[11] In detail, only two *gas* studies are included (one is a TFP study of gas transmission), whereas 9 telecommunication studies, 4 studies of electricity distribution system operators, 1 study of the whole electricity sector (incl. electricity production), 1 water supply study, 3 airport studies, 3 sea ports studies. The period of the utilized TFP studies spans over 1935–2007, which strongly deviates from our sample frame 2002–2013 that is a more suitable estimation period for TFP developments in the near future.

[12] The first benchmarking to estimate individual inefficiencies was carried out in the year 2007 using firm level data but just for one year. Thus, one cannot rule out strategic behavior of firms to influence their *relative* positions.

[13] Ernst & Young provides an international comparison of regulated electricity and gas distribution industries in selected European countries subject to different regulation regimes and show that efficiency factors are positive in any incentive regulation regime. http://www.ey.com/Publication/vwLUAssets/Mapping_Power_and_Utilities_Report_2013/$FILE/EY%20European%20Power%20regulatory%20report%20FINAL%200513.pdf, 12.06.2017.

[14] See also Berndt (1991), chap. 9; Caves et al. (1981); Martínez-Budría et al. (2003); Triebs et al. (2016).

**Table 1**
Descriptive statistics.

| Variable | Description | Mean | Median | StD. |
|---|---|---|---|---|
| TOTEX | Total expenditures of distribution activities (tEUR) | 34,767.96 | 19,233.70 | 50,340.87 |
| KM | Network length (KM) | 2370.98 | 1897.00 | 2934.98 |
| MP | Metering points (#) | 85,334.63 | 28,869.00 | 172,737.20 |
| GW | Installed capacity (GW) | 1025.54 | 323.77 | 1370.83 |
| Pc | Price of capital (%) | 14.34 | 13.17 | 4.43 |
| Pl | Price of labor (tEUR) | 70.73 | 68.35 | 21.45 |
| IndShare | Share of industrial and large business customers (%) | 5.86 | 5.83 | 2.97 |
| CustDens | Customer density (MP/KM) | 31.15 | 19.32 | 36.66 |

Notes: The sample consists of 185 firm-year observations. "StD." is standard deviation.

time-invariant inefficiency. Indeed, a test of inefficiency, as suggested by Kumbhakar et al. (2015, p. 155), reveals a statistically significant right skewness of the residuals, indicating the presence of inefficiency when the model is estimated without fixed effects. Conversely, the estimation, including fixed effects, does not yield a statistically significant right skewness, indicating that total inefficiency seems to be rather constant over time and is captured by our fixed effects. In other words, given that fixed effects appear to be sufficient to take out inefficiency (i.e. it becomes statistically indistinguishable from zero), time-variant inefficiency seems to be statistically negligible. $\varepsilon_{it}$ is the stochastic error term.

We impose symmetry in the parameters, $\gamma_{kl} = \gamma_{lk}$, $\delta_{hj} = \delta_{jh}$. A well-behaved cost function also requires linear homogeneity in factor prices. A Wald test of $\sum_i \beta_h = 1$ does not reject the null hypothesis of linear homogeneity (see the regression output in Table 2). Moreover, we apply Shephard's Lemma to (2) to obtain cost shares:

$$s_h = \frac{\partial \ln C(.)}{\partial \ln P_h} = \beta_h + \sum_j \delta_{hj} \ln P_{jit} + \sum_k \zeta_{kh} \ln Y_{kit} + \theta_h T_{it}. \tag{3}$$

Equation (3) augments the efficiency of the model by adding the cost shares as additional information to (2) without imposing any additional parameters. Hence, we jointly estimate a system of equations of the translog cost function together with the cost shares with iterative nonlinear seemingly unrelated regression (SUR; Zellner, 1962).

We follow Denny et al. (1981) [15] and measure the growth rate of TFP as the sum of technical change and changes in scale economies:

$$\dot{TFP}_{it} = \dot{TC}_{it} + \left(1 - \frac{1}{RTS_{it}}\right) \cdot \sum_k \frac{\partial \ln C_{it}}{\partial \ln Y_{kit}} \dot{Y}_{kit} \cdot RTS_{it}, \tag{4}$$

where $\dot{Y}_k$ denotes the growth rate of output k. *Technical change* (TC), the first term of (4), represents the negative derivation of the cost function with respect to the time trend:

$$\dot{TC}_{it} = -\frac{\partial \ln C_{it}}{\partial T_{it}} = -\left(\sum_k \eta_{kT} \ln Y_{kit} + \sum_h \theta_h \ln P_{hit} + \mu_T + \mu_{TT} T_{it}\right). \tag{5}$$

In other words, the time trend captures changes in costs, which cannot be explained by changes in the right-hand-side variables (i.e. outputs, input prices, fixed effects, control variables), and are thus thought of as technological change (or 'manna from heaven').

The second term of (4) is the *scale effect* (SE), which measures variations in costs concerning changes in outputs. Given that the cost elasticity of output k is $\varepsilon_k = \frac{\partial \ln C_{it}}{\partial \ln Y_{kit}} = (\alpha_k + \sum_l \gamma_{kl} \ln Y_{lit} + \sum_h \zeta_{kh} \ln P_{hit} + \eta_{kT} T_{it})$ and that inverse returns to scale (RTS) are $\frac{1}{RTS_{it}} = \sum_k \varepsilon_k$ representing the opportunity for incremental scale economies, we can reformulate the scale effect as (see also

[15] See also Casarin (2014) and Dimitropoulos and Yantchew (2017) for applications to gas distribution and electricity distribution, respectively.

**Table 2**
Main results: NLSUR estimates of the translog cost function.

| | Model (1) | | | |
|---|---|---|---|---|
| Variable | Coef. | Estimate | SE | P-val. |
| ln *KM* | $\alpha_1$ | 1.0007 | (0.858) | (0.243) |
| ln *MP* | $\alpha_2$ | 0.4068 | (1.289) | (0.752) |
| ln *GW* | $\alpha_3$ | 0.9770 | (0.270) | (0.000) |
| ln *Pl* | $\beta_1$ | 0.1397 | (0.166) | (0.401) |
| ln *Pc* | $\beta_2$ | 0.7730 | (0.130) | (0.000) |
| $0.5 \ln KM^2$ | $\gamma_{11}$ | −0.4545 | (0.168) | (0.007) |
| $0.5 \ln MP^2$ | $\gamma_{22}$ | −0.0769 | (0.147) | (0.600) |
| $0.5 \ln GW^2$ | $\gamma_{33}$ | 0.0602 | (0.053) | (0.255) |
| ln *KM* ln *MP* | $\gamma_{12}$ | 0.1956 | (0.124) | (0.114) |
| ln *MP* ln *GW* | $\gamma_{23}$ | −0.0770 | (0.049) | (0.116) |
| ln *KM* ln *GW* | $\gamma_{13}$ | −0.0246 | (0.066) | (0.710) |
| $0.5 \ln Pl^2$ | $\delta_{11}$ | −0.0066 | (0.040) | (0.867) |
| $0.5 \ln Pc^2$ | $\delta_{22}$ | −0.0128 | (0.033) | (0.701) |
| ln *Pl* ln *Pc* | $\delta_{12}$ | −0.0713 | (0.017) | (0.000) |
| ln *KM* ln *Pl* | $\zeta_{11}$ | 0.0029 | (0.020) | (0.883) |
| ln *MP* ln *Pl* | $\zeta_{21}$ | 0.0764 | (0.014) | (0.000) |
| ln *GW* ln *Pl* | $\zeta_{31}$ | −0.0785 | (0.015) | (0.000) |
| ln *KM* ln *Pc* | $\zeta_{12}$ | 0.1525 | (0.023) | (0.000) |
| ln *MP* ln *Pc* | $\zeta_{22}$ | −0.1016 | (0.012) | (0.000) |
| ln *GW* ln *Pc* | $\zeta_{32}$ | −0.0074 | (0.014) | (0.593) |
| ln *KM*·*T* | $\eta_{1T}$ | −0.0065 | (0.008) | (0.423) |
| ln *MP*·*T* | $\eta_{2T}$ | 0.0110 | (0.007) | (0.096) |
| ln *GW*·*T* | $\eta_{3T}$ | 0.0041 | (0.004) | (0.328) |
| ln *Pl*·*T* | $\theta_{1T}$ | −0.0029 | (0.003) | (0.273) |
| ln *Pc*·*T* | $\theta_{2T}$ | −0.0122 | (0.002) | (0.000) |
| *T* | $\mu_T$ | −0.0674 | (0.036) | (0.062) |
| $0.5T^2$ | $\mu_{TT}$ | 0.0025 | (0.002) | (0.120) |
| Firm fixed effects | | yes | | |

Notes: Dependent variable is ln(TOTEX). Standard errors are robust to heteroscedasticity.

Heshmati, 2003)

$$\dot{SE}_{it} = \left(1 - \sum_k \varepsilon_k\right) \cdot \sum_k \frac{\varepsilon_k}{\sum_m \varepsilon_m} \dot{Y}_{kit}. \tag{6}$$

The intuition is that in the presence of increasing (decreasing) returns to scale, an increase in all outputs leads to an under-proportional (over-proportional) change in total costs so that a firm can save on costs when augmenting its size. In a network-bound industry like gas distribution, which is characterized by local natural monopolies, we expect increasing RTS. However, even in the presence of increasing RTS, realized scale economies depend on the actual changes in outputs ($\dot{Y}_k$), which have been stagnant or even negative for Austrian gas distribution companies according to our data Fig. A1-A3.[16]

A few words are in order about how we derive the significance levels of $\dot{TFP}$ and its source components. For the productivity analysis, we utilize all required parameter estimates (as given in equations (4)–(6)) as obtained from the regression of the cost function, irrespective of their

[16] Appendix Figures A1–A3 show percentage variations in outputs by utility. For many utilities we observe investments in the pipeline network, whereas for some firms reductions are observable in some years (e.g. due to displacement of outdated pipes). Most utilities face reductions in metering points over the sample period, indicating a trend away from gas heating systems or better building insulation. However, few firms face up-and-down movements or constant increases, which may be due to moving of customers. Billed capacity, which is based on peak load, hinges strongly on extreme weather and climate conditions, as well as on consumer demand, and thus varies across firms and years. In electricity distribution, a related industry, Dimitropoulos and Yantchew (2017) also discuss the observed slowdown in load growth and aging of infrastructure.

statistical power. Thus, the linear and non-linear combinations of the coefficient estimates together with the levels of the included variables determine the statistical significance of the productivity estimates. In other words, the statistical significance levels of the productivity estimates hinge not only on the statistical power of the respective coefficient estimates but also on the magnitudes of the included variables in the calculation of the productivity components.

## 5. Data

Our data originate from a database developed in the course of a study on behalf of the Austrian Association of Gas and Heating Companies, which was gratefully provided for further academic research under the condition that individual data points about firms are not made publicly available. Our underlying survey regarding the collection of the data closely followed the surveys by the Austrian regulatory authority collecting data for cost reviewing processes and regulatory decisions (e.g. benchmarking analyses, determination of granted costs). Fortunately, the Austrian regulatory authority cross-checked our data for plausibility according to their own data collections, ensuring the high validity of our dataset. Our database, thus, represents a fundamental feature because reliable and detailed information at the firm level about actual expenditures and outputs (i.e. technical characteristics of the network) is hardly available to researchers. This unique dataset allows for the empirical estimation of a cost function to obtain TFP growth estimates.

Our underlying dataset comprises of 19 out of 20 regulated Austrian gas distributors; however, the estimation sample reduces to 17 firms due to missing data on factor prices for two relatively small utilities.[17] The sample period 2002–2013 covers six years before and six years after the introduction of incentive regulation on February 1, 2008. The dependent variable, total costs, is calculated as the sum of operating and capital expenditures that are directly related to the distribution operations of the firms.[18] For the appropriate choice of relevant output variables that are under the control of the utility and determine costs, we take output measures from the relevant literature into consideration.[19] Outputs that are available in our dataset and that often appear in the literature (see Casarin, 2014; Farsi et al., 2007; Lowry, Getachew, 2009; Rossi, 2001) are the network length (KM), metering points (MP, i.e. customers), and accounted and billed capacity (MW). According to conversations with industry representatives and the regulatory authority,[20] these variables are the most plausible output-related cost drivers because they are under the immediate control of the firms,[21] whereas the distributed volumes (GWh) are determined by demand.

Concerning factor prices, the price of labor (Pl) is calculated as labor expenses divided by the number of full-time equivalent employees. However, we lose one firm due to outsourcing (i.e. zero values for labor expenditures and number of employees) and another firm due to missing information regarding their employees. It was difficult to calculate an adequate price of capital given the data available. The measurement of the cost of capital is a general problem. Ideally, one would want to measure opportunity costs, which are not available in balance sheets or cash flow statements. For example, Farsi et al. (2007) calculate the price of capital as the network length relative to expenses other than for labor and gas, which is far from ideal. We calculate the price of capital (Pc) by dividing capital expenditures by the regulatory asset base. A more substantial value captures an increased cost of capital but may also capture more significant investment opportunities or differential capital stock age profiles (younger capital stock) across firms. We acknowledge these difficulties but can only correct econometrically as much as possible, for example, by including other control variables and firm-fixed effects.

A few data points are missing because some companies could not research data points from long ago. Altogether, this leaves us with an unbalanced panel of 185 observations in 17 utilities. Table 1 provides summary statistics of our regression sample. The average sample firm has total expenditures (TOTEX) of 34.8 million euros and operates a gas network of 2371 km with 85,335 metering points, and has 1026 GW of billed peak load capacity. The price of capital is, on average, 14.34%, and the price of labor is about 71 thousand euros. The significant differences between means and medians of costs and outputs indicate considerable sample skewness arising from firm heterogeneity. Two major firms in our sample mainly drive this skewness; their cost shares are 37% and 17%, respectively, relative to the total aggregated costs in 2013. Moreover, most standard deviations are large relative to their mean values pointing to substantial heterogeneity across firms. This underlines the importance of including firm-fixed effects to account for unobserved firm-level heterogeneity, which cannot be captured by observable cost drivers (i.e. outputs, factor prices, and control variables).

## 6. Results

In this section, we present our productivity decomposition based on estimates of a translog cost function, as presented in equation (2), jointly estimated with its input shares as given in equation (3), in a nonlinear seemingly unrelated regression (SUR) framework. To provide robustness, Appendix B also presents regressions with additional variables to control further for firm heterogeneity and evaluate productivity growth. All regressions include heteroscedasticity-robust standard errors.

The estimates of the main specification of the translog cost function, as given in Table 2, are the foundation of our productivity analysis. Despite the statistical insignificance of the estimated coefficients of the network length (*KM*), the metering points (*MP*), and the price of labor (*Pl*), many of their interaction terms are statistically significant and thus legitimize their inclusion.[22] Notably, the coefficient of the time trend

[17] The two small firms that get truncated because of missing data on factor prices account for only 0.86% in total costs in the year 2013.

[18] TOTEX are the sum of OPEX (personnel expenses, material expenses, other expenses, cost allocations, Adjustment – internally produced and capitalized assets and higher upstream network costs) and CAPEX (financing costs = WACC * Regulatory Asset Base). Regulatory Asset Base is book value (immaterial and tangible fixed assets), adjustment of book values to 40 years (according to E-Control's calculations), subsidies for building costs, and adjustments of subsidies for building costs to 40 years (according to E-Control's calculations).

[19] Farsi et al. (2007) also provide a summary of measures used in the empirical literature on cost functions in gas distribution.

[20] The Austrian regulatory authority (E-Control, 2008, p. 38) applies similar measures, yet KM are weighted by different gas grid layers (GL) to reflect their different impacts on costs (exact weights: GL1 < 300 mm: 1.94, GL1 > 300& < 600 mm: 3.17, GL1 > 600: 4.22, GL2 < 300 mm: 1.00, GL2 > 300& < 600: 1.36, GL2 > 600: 1.36); MP refers to residential and small business customers; MW refers to large business and industry customers. Applying these measures we obtain comparable estimates for ΔTFP.

[21] Austrian gas distributors have no supply obligations, so they have full control over their network length, metering points, and billed capacity.

[22] Given the limited number of observations and the large number of parameter estimates of the translog cost function with firm fixed effects, insignificant point estimates are allegeable. A low within-variation of the variables may also be blamed for a limited statistical power. Appendix Figures A1–A3 show percentage changes of the outputs for each sample utility indicating that there is within-variation. Multi-collinearity issues may also lead to insignificant parameter estimates (see e.g. Ray, 1982). Unconditionally, our three output variables show high correlations, as given in Appendix Table A1, panel a. However, we include firm fixed-effects in our regressions, which take out the mean of each sample firm. Correlations of the demeaned outputs, as given by Appendix Table A1, panel b, which correspond with the actual correlations in the fixed-effects regressions, show that multi-collinearity is less worrisome, though.

**Table 3**
Productivity decomposition.

| Sample mean | TFP (%) | p-val. | TC (%) | p-val. | SE (%) | p-val. | *1/RTS* | *p-val.* |
|---|---|---|---|---|---|---|---|---|
| 2003 | 1.430 | (0.123) | 1.421 | (0.126) | 0.009 | (0.012) | *0.640* | *(0.002)* |
| 2004 | 1.087 | (0.065) | 1.076 | (0.068) | 0.011 | (0.010) | *0.694* | *(0.011)* |
| 2005 | 0.940 | (0.090) | 0.932 | (0.094) | 0.008 | (0.046) | *0.728* | *(0.032)* |
| 2006 | 0.778 | (0.068) | 0.774 | (0.070) | 0.004 | (0.078) | *0.764* | *(0.086)* |
| 2007 | 0.776 | (0.053) | 0.774 | (0.054) | 0.003 | (0.083) | *0.771* | *(0.096)* |
| 2008 | 0.728 | (0.042) | 0.725 | (0.043) | 0.003 | (0.343) | *0.841* | *(0.322)* |
| 2009 | 0.491 | (0.175) | 0.489 | (0.177) | 0.002 | (0.350) | *0.849* | *(0.346)* |
| 2010 | 0.219 | (0.612) | 0.217 | (0.177) | 0.002 | (0.389) | *0.849* | *(0.347)* |
| 2011 | −0.147 | (0.788) | −0.150 | (0.784) | 0.003 | (0.441) | *0.848* | *(0.344)* |
| 2012 | −0.285 | (0.671) | −0.285 | (0.672) | 0.000 | (0.878) | *0.859* | *(0.384)* |
| 2013 | −0.589 | (0.470) | −0.592 | (0.468) | 0.002 | (0.446) | *0.860* | *(0.389)* |
| Mean | 0.508 | (0.123) | 0.504 | (0.127) | 0.003 | (0.169) | *0.797* | *(0.159)* |
| **Sample median** | **TFP (%)** | **p-val.** | **TC (%)** | **p-val.** | **SE (%)** | **p-val.** | ***1/RTS*** | ***p-val.*** |
| 2003 | 1.719 | (0.064) | 1.713 | (0.065) | 0.006 | (0.000) | *0.577* | *(0.000)* |
| 2004 | 1.804 | (0.027) | 1.788 | (0.029) | 0.016 | (0.001) | *0.586* | *(0.000)* |
| 2005 | 1.302 | (0.074) | 1.291 | (0.077) | 0.011 | (0.000) | *0.583* | *(0.000)* |
| 2006 | 1.092 | (0.090) | 1.084 | (0.093) | 0.008 | (0.001) | *0.593* | *(0.000)* |
| 2007 | 0.888 | (0.125) | 0.884 | (0.127) | 0.003 | (0.026) | *0.601* | *(0.001)* |
| 2008 | 0.715 | (0.206) | 0.707 | (0.211) | 0.008 | (0.019) | *0.601* | *(0.001)* |
| 2009 | 0.514 | (0.385) | 0.508 | (0.392) | 0.006 | (0.009) | *0.611* | *(0.001)* |
| 2010 | 0.155 | (0.807) | 0.152 | (0.811) | 0.003 | (0.456) | *0.614* | *(0.001)* |
| 2011 | −0.188 | (0.792) | −0.191 | (0.788) | 0.003 | (0.460) | *0.616* | *(0.001)* |
| 2012 | −0.416 | (0.614) | −0.415 | (0.615) | −0.001 | (0.496) | *0.624* | *(0.001)* |
| 2013 | −0.694 | (0.463) | −0.696 | (0.461) | 0.002 | (0.032) | *0.632* | *(0.001)* |
| Mean | 0.626 | (0.219) | 0.621 | (0.224) | 0.005 | (0.002) | *0.609* | *(0.001)* |

Notes: TFP is the growth rate of total factor productivity; SE is the growth rate of realized scale economies; 1/RTS is the inverse of returns to scale and reflects the potential for scale economies; TC is the rate of technical change. The period starts in 2003 because the estimation of SE includes a first difference (annual changes in outputs) leading to the loss of the year 2002. The p-values are given for the following $H_0$:.TFP = 0, SE = 0, TC = 0, and 1/RTS = 1.

($T$) is statistically significant and its squared term's ($0.5T^2$) significance is at the margin with a p-value of 0.12.

Table 3 presents productivity estimates evaluated at the sample mean and median.[23] We decompose TFP growth into TC and realized SE but also report the (latent) potential for RTS (i.e. 1/RTS), which may be exploited by significant output increases (e.g. through a merger). In line with related papers (Casarin, 2014; Dimitropoulos and Yantchew, 2017; Farsi et al., 2007; Lowry and Getachew, 2009) we find no evidence of realized SE for the average or the median-sized firm. However, there is a significant potential for RTS. We find statistically significant inverse RTS of 0.80 for the average-sized firm over the full sample period, meaning that if all outputs are increased by 10%, costs disproportionately increase by only 8%. The potential for RTS is even larger for median sized (i.e. smaller) utilities at 0.61. Large potential gains from RTS seem plausible for the gas distribution network representing the natural monopoly part of the gas industry. Moreover, our finding of vast but unexploited potentials for RTS bear policy relevance as it indicates that utility mergers would bring about substantial cost savings, which is especially pronounced for small utilities (since the potential gains are more substantial at the median than the mean).

Technical change, evaluated at the sample mean, lies at a relatively modest rate of 0.51% (statistically marginally significant with a p-value of 0.12) for the entire sample period 2003–2013. However, the year-by-year estimates show that technical change was substantially higher in the early sample years with rates of around 1% (2004 and 2005) or higher (1.4% in 2003), followed by a gradual decline to slightly negative (but statistically insignificant) rates during the most recent sample years (2011–2013). At the sample median, the rates are slightly more pronounced with a rate of TC of 1.7% in 2003 falling towards −0.6% (but statistically not different from zero) in 2013.

Since realized scale economies are roughly zero percent throughout our sample period, TFP growth essentially follows the rate of technical change. We thus observe higher TFP growth rates in the early sample years and subsequently lower rates until TFP growth turns negative (but statistically indistinguishable from zero) in the most recent years. Fig. 1 gives kernel densities of the estimated productivity components. Evidently, TFP growth rates vary between firms in a reasonable range of −5% to +4% and are thus not driven by extreme outliers.

The falling TFP growth over time, with even negative but statistically insignificant rates in the later sample years, suggests that there may hardly be potential for technological opportunities in the near future. This is foremost attributed to a regress in TC. As discussed earlier, studies on TFP growth in gas (Casarin, 2014) and electricity distribution (Dimitropoulos and Yantchew, 2017) support the notion of declining TFP growth with declining TC and low realizations of scale economies.[24]

[23] Please note that the estimates of the productivity components exclude the year 2002, as the rate of SE is based on a first difference leading to the loss of one year.

[24] Negative TFP growth is possible for several reasons. For example, if there is competitive pressure from other sources of energy than gas, e.g. from oil, electricity or from energy saving investments (e.g. thermal insulation), TFP growth from changes in scale economies may become negative, particularly in the short run, when the presence of fixed inputs limits the incumbent supplier's ability to reduce inputs at the same rate that outputs decline (see Bernstein and Sappington, p.21, 1999). Recently, Bloom et al. (2017) persuasively show that research productivity sharply declines within each product group.

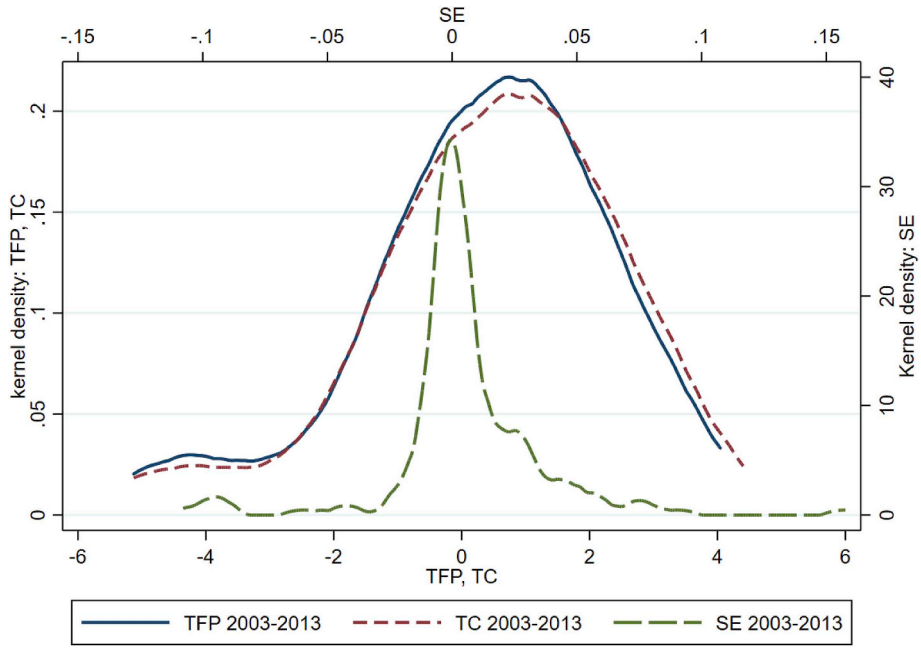


**Fig. 1.** Kernel densities: TFP, SE, TC
*Note: For better visibility, Fig. 1b disregards one outlier for which SE is -3.05.*

We can think of three possibilities for a low rate of TC in Austria's gas distribution sector in recent years: (1) anticipation effects such that technological opportunities have been exploited before the introduction of incentive regulation in 2008; (2) the period of incentive regulation may have sent sub-optimal investment incentives (see Cullmann and Nieswand, 2016) that have manifested in unexploited technological opportunities; or (3) fading potential for technological progress. Since in our data, there is no discernible indication for a significant change in investment behavior around the year 2008 when incentive regulation was introduced, and moreover firms had no incentive to act strategically in the years before it was introduced (see above), anticipation effects seem less likely. Of course, one can never rule out adverse incentive effects of regulatory measures; however, under the notion of exogenous technological change, firms cannot – at least not for a very long period – tweak their actual costs to resemble granted costs. Thus, what we measure should be realized TC. Firms remain residual claimants[25] during incentive regulation and should have an incentive to achieve their potential.

It rather seems that technological opportunities and the potential for cost savings due to technological progress have faded over time. Given the sunk cost nature of investments in the industry, this appears plausible. Network investments (CAPEX), once undertaken, cannot be reversed, and ex-post (after investments have been made) technological progress may only be achieved by reducing operating costs (OPEX). Since OPEX make up only around 65% of total costs (35% CAPEX), ex-post technological opportunities are constrained.

Indeed, from expert discussions with industry representatives, we were told that, during the late 1980s and 1990s, critical investments, such as the replacement of grey iron pipelines by cast steel pipelines or the electronic monitoring of pipelines, brought about productivity gains. During the late 1990s and early 2000s, some utilities have tried to erode inefficiencies from overstaffing, for example through outsourcing of labor or mergers of the gas and electricity grids. This may partly explain why we observe higher TFP growth rates during the early sample years. However, once these investments have been carried out, the potential for achieving significant productivity gains vanishes over time, supporting our findings of a declining rate of technological progress. Also, the realization of SE seems limited, as metering points are on average shrinking, foremost due to better building insulation paralleled by a trend away from gas heating systems. This also limits the scope for expanding the pipeline network. For the time being, mergers would represent a genuine way of improving productivity through the realization of the significant potential for returns to scale.

## 7. Conclusion and policy implications

We focus on Austria's gas distribution industry to estimate productivity growth parametrically as derived from a flexible translog cost function. Moreover, we can decompose TFP growth into its source components (technical change and scale economies). Our data represent a unique collection of expenditures and network characteristics in a panel of gas distribution utilities subject to incentive regulation, which was introduced in 2008, for the sample period 2002–2013.

From a methodological perspective, our study extends the related literature by putting the TFP estimation to empirical scrutiny based on a flexible functional form of the long-run translog cost function with all second order and interaction terms (including the trend interactions) and individual fixed effects. In contrast, related studies usually apply more restrictive functional forms (e.g. omitting some higher-order interaction terms, omitting the squared time trend, restricting the cost function to a Cobb–Douglas specification, investigating a short-run cost function, etc.). Moreover, in our case, the inclusion of individual fixed effects essentially takes out individual inefficiency, which is thus mainly driven by its time-invariant part. Hence, although we are not able to explicitly address individual inefficiency (as in an SFA framework), our estimations of TFP and technical change (i.e. “frontier shift”) do not suffer from bias due to inefficiency. Moreover, our estimations are subject to a rich and unique panel data on actual costs and firm characteristics, which are fully reliable as they were cross-checked for plausibility by the regulatory authority. Such data are usually not available to the public.

Our study bears strong policy relevance as regulatory authorities

[25] That is, any cost savings beyond the regulatory price cap enter as firm profits.

usually lack sophisticated industry productivity estimates and, thus, only have a vague idea about how to optimally set the price cap in incentive regulation. As we outline in this study, regulators face severe limitations regarding their information on the productive potential of the regulated firms, mostly because of missing adequate data for scientific TFP analysis. Moreover, price cap values in practice appear to be the result of a political decision-making process and public pressure on the regulatory authorities to set the cap at a stringent rate. Hence, our study helps to fill the void of missing empirical evidence on TFP potential in Austria's gas distribution on a transparent and scientific basis.

Our results imply that the rate of TFP fell gradually over the sample period, from an initially high growth of 1.4% in 2003 to a negative but statistically insignificant rate of −0.6% in 2013, evaluated at the sample mean. The productivity estimates are even more pronounced, when evaluated for the smaller median-sized sample firm, of 1.7% in 2003, steadily falling to −0.7% in 2013. These findings are mainly driven by technical change, whereas the contribution of scale economies is essentially zero. That is, utilities have not been able to exploit the relatively high potential for cost savings from returns to scale (e.g. through mergers).

Moreover, it seems that important investments have been carried out in the past (and during the early sample years, which may explain higher TFP growth rates) so that technological opportunities fell over time. If the regulatory authority set X-gen according to the TFP potential in the near future (e.g. the forthcoming 5 years) against the estimated productivity progress from this analysis, a high positive value does not seem to be justified.[26] We show that low TFP performance during recent sample years deviate from relatively high historic X-gen values in the Austrian gas distribution industry.

Naturally, our study faces some limitations. Our analysis is subject to a limited number of observations of few regulated gas distribution utilities (which, nonetheless, reflect *all* but one minor regulated gas distributors in Austria). However, given that there are few related TFP studies, because actual cost data of utilities are hardly accessible, we believe that our analysis is an add-on to the literature. Moreover, we are not able to apply a stochastic cost frontier model to analyze inefficiency explicitly, and thus cannot make claims about the individual "stretch factor" that may incentivize inefficient utilities to catch up with frontier-utilities. Still, we apply individual fixed effects, which, in our case capture inefficiency, so that our estimate of TFP is not biased by individual changes in inefficiency.

Although Austria's gas distribution sector represents a small case for international comparison, it bears external validity because of its similarities with other regulated sectors in other countries, such as comparable technological opportunities as in electricity distribution, sunk capital investments as in most regulated network-bound sectors, and incentive regulation for more than a decade.

## Declarations of interest

The data employed in this study were collected in the course of a project on behalf of the Austrian Association of Gas- and District Heating Supply Companies (FGW). These data have been gratefully provided for this academic study under the condition that individual firm observations are not made publicly available. It is possible to replicate all estimations, tables, and figures as presented in this paper based on the confidential dataset via a local desktop at the University of Kaiserslautern and upon signing a confidentiality agreement. However, access to individual firm-level data is restricted. The authors have no financial or other benefits from this academic study.

## Appendix A. Additional Tables and Figures

Table A1
Output correlations

| *a) Unconditional output correlations* | | | |
|---|---|---|---|
| | KM | MP | MW |
| KM | 1 | | |
| MP | 0.520 | 1 | |
| MW | 0.804 | 0.692 | 1 |

| *b) Demeaned output correlations* | | | |
|---|---|---|---|
| | KM | MP | MW |
| KM | 1 | | |
| MP | 0.426 | 1 | |
| MW | 0.229 | 0.026 | 1 |

[26] If the regulator followed the well-founded regulatory formula set out by Bernstein and Sappington (1999), the optimal value of X-gen should also take the TFP growth of the economy as well as input price variations of the regulated industry and the economy into account. Our calculations (see Appendix C) suggest an optimal value of X-gen close to zero for the near future.

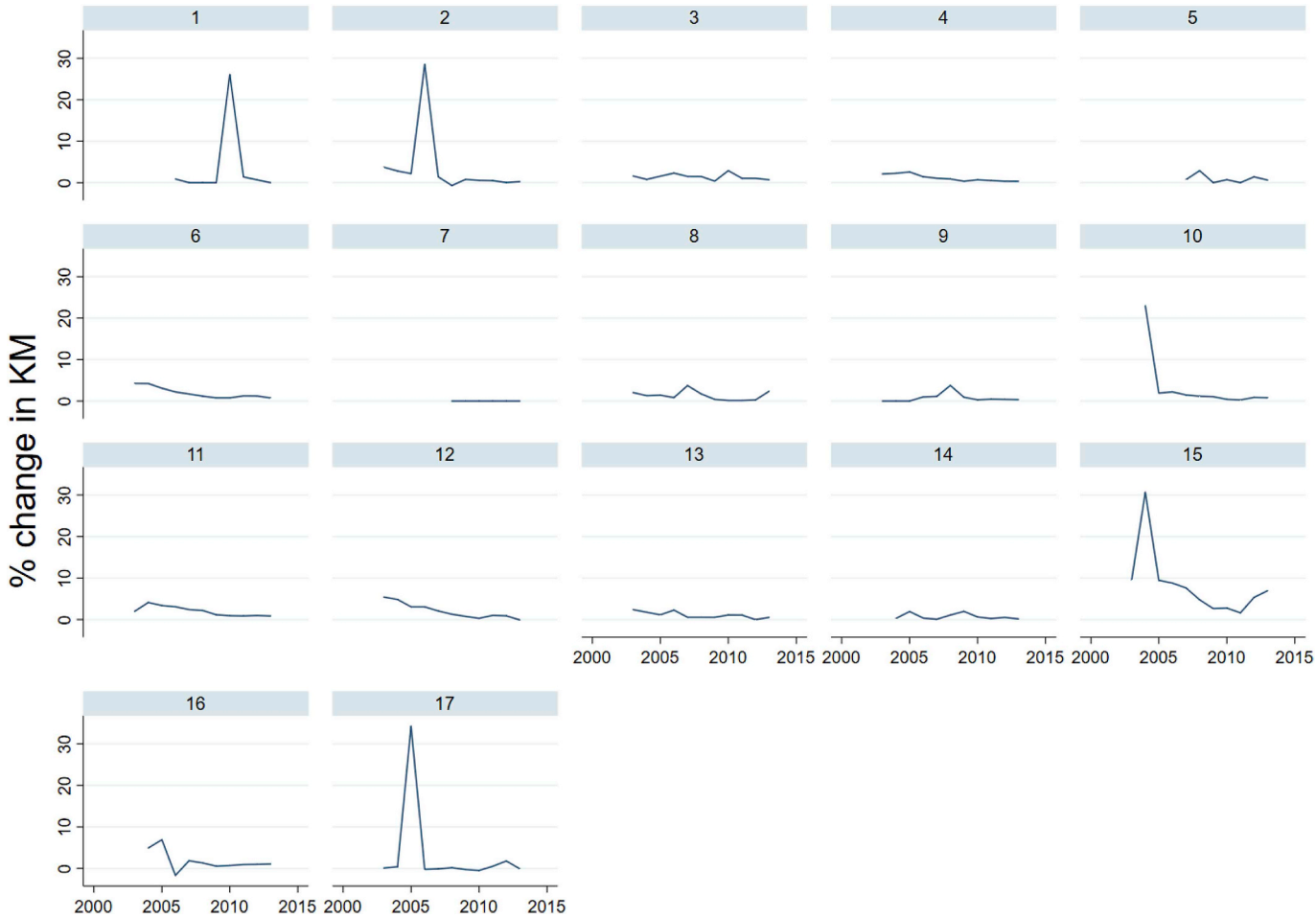


**Fig. A1.** Percentage changes in pipeline length by utility


**Fig. A2.** Percentage changes in metering points by utility


**Fig. A3.** Percentage changes in peak load by utility

## Appendix B. Robustness of empirical results

To further address firm heterogeneity and the impact of incentive regulation on firm performance, we add additional control variables (i.e. a dummy for the period of incentive regulation, the share of industrial customers, and customers per pipeline kilometer) to our main specification, as shown in Table B1. We find that the coefficient estimates of the main specification of the cost function stay very robust against the inclusion of the additional control variables. What is more, neither the individual inclusion of the control variables nor their compound inclusion leads to a significant increase in the within model fit (within $R^2$) over to the main specification. Table B2 presents the respective estimates for TFP growth. Again, the TFP growth rates as estimated from the robustness specifications support our findings as presented in the main text.

Model (2) extends the main specification by a binary indicator *IncReg* with a value of one for the period of incentive regulation from 2008 to 2013, and zero for the years 2002–2007. In discussions with the regulatory authority and industry representatives, we were told that, in the course of the introduction of incentive regulation, regulated utilities faced a one-off cut in *granted* costs by around 8%.[27] As opposed to *actual* costs, *granted* costs refer to costs that the regulatory authority indeed recognizes as costs related to the subject of regulation (i.e. gas distribution activities). Nevertheless, a cut in granted costs may bring about reductions in actual costs. The intention for the required one-time cost reduction by the regulatory authority was to erode accumulated inefficiencies of the firms previous to the introduction of incentive regulation. However, the estimated coefficient of *IncReg* turns out statistically insignificant.

Table B1
Robustness: NLSUR estimates of the translog cost function.

| | | Model (2) | | | Model (3) | | | Model (4) | | | Model (5) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coef. | Estimate | SE | P-val. | Estimate | SE | P-val. | Estimate | SE | P-val. | Estimate | SE | P-val. |
| ln *KM* | $\alpha_1$ | 1.032 | (0.865) | (0.23) | 0.966 | (0.855) | (0.26) | 1.842 | (2.052) | (0.37) | 1.698 | (2.032) | (0.40) |
| ln *MP* | $\alpha_2$ | 0.400 | (1.270) | (0.75) | 0.292 | (1.310) | (0.82) | −0.369 | (2.212) | (0.87) | −0.373 | (2.227) | (0.87) |
| ln *GW* | $\alpha_3$ | 0.988 | (0.271) | (0.00) | 0.973 | (0.267) | (0.00) | 0.991 | (0.280) | (0.00) | 0.996 | (0.277) | (0.00) |
| | | 0.142 | (0.166) | (0.40) | 0.139 | (0.166) | (0.40) | 0.140 | (0.166) | (0.40) | 0.141 | (0.166) | (0.40) |

(*continued on next page*)

[27] On average, the regulator cut 8% of granted costs. However, the cost reductions included firm-specific components, so that the cuts varied across firms.

Table B1 (*continued*)

| | | Model (2) | | | Model (3) | | | Model (4) | | | Model (5) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Coef. | Estimate | SE | P-val. | Estimate | SE | P-val. | Estimate | SE | P-val. | Estimate | SE | P-val. |
| ln *Pl* | $\beta_1$ | | | | | | | | | | | | |
| ln *Pc* | $\beta_2$ | 0.773 | (0.131) | (0.00) | 0.771 | (0.130) | (0.00) | 0.773 | (0.131) | (0.00) | 0.771 | (0.131) | (0.00) |
| 0.5 ln $KM^2$ | $\gamma_{11}$ | −0.463 | (0.170) | (0.01) | −0.448 | (0.168) | (0.01) | −0.187 | (0.655) | (0.78) | −0.232 | (0.655) | (0.72) |
| 0.5 ln $MP^2$ | $\gamma_{22}$ | −0.076 | (0.146) | (0.61) | −0.067 | (0.149) | (0.65) | 0.200 | (0.664) | (0.76) | 0.167 | (0.662) | (0.80) |
| 0.5 ln $GW^2$ | $\gamma_{33}$ | 0.062 | (0.053) | (0.24) | 0.057 | (0.052) | (0.27) | 0.061 | (0.053) | (0.25) | 0.059 | (0.053) | (0.26) |
| ln *KM* ln *MP* | $\gamma_{12}$ | 0.197 | (0.124) | (0.11) | 0.196 | (0.124) | (0.11) | −0.082 | (0.658) | (0.90) | −0.035 | (0.655) | (0.96) |
| ln *MP* ln *GW* | $\gamma_{23}$ | −0.080 | (0.050) | (0.11) | −0.073 | (0.049) | (0.13) | −0.081 | (0.051) | (0.12) | −0.079 | (0.051) | (0.12) |
| ln *KM* ln *GW* | $\gamma_{13}$ | −0.023 | (0.067) | (0.73) | −0.027 | (0.065) | (0.68) | −0.022 | (0.067) | (0.75) | −0.024 | (0.067) | (0.72) |
| 0.5 ln $Pl^2$ | $\delta_{11}$ | −0.007 | (0.040) | (0.86) | −0.007 | (0.040) | (0.87) | −0.007 | (0.039) | (0.86) | −0.007 | (0.040) | (0.85) |
| 0.5 ln $Pc^2$ | $\delta_{22}$ | −0.012 | (0.034) | (0.73) | −0.012 | (0.033) | (0.71) | −0.013 | (0.033) | (0.70) | −0.011 | (0.034) | (0.74) |
| ln *Pl* ln *Pc* | $\delta_{12}$ | −0.072 | (0.017) | (0.00) | −0.071 | (0.017) | (0.00) | −0.071 | (0.017) | (0.00) | −0.071 | (0.017) | (0.00) |
| ln *KM* ln *Pl* | $\zeta_{11}$ | 0.003 | (0.020) | (0.88) | 0.003 | (0.020) | (0.88) | 0.003 | (0.020) | (0.88) | 0.003 | (0.020) | (0.88) |
| ln *MP* ln *Pl* | $\zeta_{21}$ | 0.077 | (0.014) | (0.00) | 0.076 | (0.014) | (0.00) | 0.077 | (0.013) | (0.00) | 0.077 | (0.013) | (0.00) |
| ln *GW* ln *Pl* | $\zeta_{31}$ | −0.079 | (0.015) | (0.00) | −0.079 | (0.015) | (0.00) | −0.079 | (0.015) | (0.00) | −0.079 | (0.015) | (0.00) |
| ln *KM* ln *Pc* | $\zeta_{12}$ | 0.152 | (0.023) | (0.00) | 0.152 | (0.023) | (0.00) | 0.152 | (0.023) | (0.00) | 0.152 | (0.023) | (0.00) |
| ln *MP* ln *Pc* | $\zeta_{22}$ | −0.101 | (0.012) | (0.00) | −0.102 | (0.012) | (0.00) | −0.102 | (0.012) | (0.00) | −0.102 | (0.012) | (0.00) |
| ln *GW* ln *Pc* | $\zeta_{32}$ | −0.007 | (0.014) | (0.61) | −0.007 | (0.014) | (0.59) | −0.007 | (0.014) | (0.60) | −0.007 | (0.014) | (0.61) |
| ln *KM·T* | $\eta_{1T}$ | −0.006 | (0.008) | (0.44) | −0.007 | (0.008) | (0.40) | −0.006 | (0.008) | (0.49) | −0.006 | (0.009) | (0.47) |
| ln *MP·T* | $\eta_{2T}$ | 0.011 | (0.007) | (0.09) | 0.011 | (0.007) | (0.09) | 0.010 | (0.007) | (0.13) | 0.011 | (0.007) | (0.11) |
| ln *GW·T* | $\eta_{3T}$ | 0.004 | (0.004) | (0.37) | 0.004 | (0.004) | (0.31) | 0.004 | (0.004) | (0.31) | 0.004 | (0.004) | (0.33) |
| ln *Pl·T* | $\theta_{1T}$ | −0.003 | (0.003) | (0.28) | −0.003 | (0.003) | (0.27) | −0.003 | (0.003) | (0.27) | −0.003 | (0.003) | (0.27) |
| ln *Pc·T* | $\theta_{2T}$ | −0.012 | (0.002) | (0.00) | −0.012 | (0.002) | (0.00) | −0.012 | (0.002) | (0.00) | −0.012 | (0.002) | (0.00) |
| *T* | $\mu_T$ | −0.066 | (0.036) | (0.07) | −0.068 | (0.036) | (0.06) | −0.064 | (0.036) | (0.08) | −0.064 | (0.036) | (0.07) |
| $0.5T^2$ | $\mu_{TT}$ | 0.002 | (0.002) | (0.15) | 0.003 | (0.002) | (0.11) | 0.003 | (0.002) | (0.12) | 0.003 | (0.002) | (0.14) |
| *IncReg* | $\chi_1$ | −0.018 | (0.021) | (0.41) | | | | | | | −0.018 | (0.021) | (0.40) |
| *IndSh* | $\chi_2$ | | | | 0.002 | (0.004) | (0.57) | | | | 0.003 | (0.004) | (0.54) |
| *CustDens* | $\chi_3$ | | | | | | | −0.004 | (0.009) | (0.66) | −0.003 | (0.009) | (0.72) |
| Firm fixed effets | | | | yes | | | yes | | | yes | | | yes |

Notes: Dependent variable is ln(TOTEX). All regressions are based on 185 observations. Standard errors are robust to heteroscedasticity. ***, **, * denote significance at the 99%, 95%, and 90% level, respectively.

Model (3) adds the share of industrial and large business customers, *IndSh*, to the main specification. Customer heterogeneity may have substantial effects on utilities' costs. The estimated coefficient is positive but insignificant, indicating that industrial customers may have a positive effect on costs, which are, however, statistically not distinguishable from zero.

Model (4) includes the customer density measured as the number of metering points per kilometer of the pipeline network (*CustDens*). In line with expectation, the sign of the estimated coefficient is negative – a higher density of consumers along the pipeline network is associated with lower costs – yet statistically indistinguishable from zero.

Finally, Model (5) includes the control variables *IncReg*, *IndSh*, and *CustDens* altogether. Again, none of their estimated coefficients turns out statistically significant, while the point estimates of the coefficients of the remaining variables stay robust to the estimates of the main specification as given in Table 2. From these robustness checks, we conclude that the regression estimates stay robust to the inclusion of several additional potentially relevant variables and that firm heterogeneity is already well addressed by the main specification.

Table B2
Productivity estimates of robustness specifications

| Sample mean | (2) TFP (%) | (3) TFP (%) | (4) TFP (%) | (5) TFP (%) |
|---|---|---|---|---|
| 2003 | 1.831 | 2.190 | 2.005 | 1.803 |
| 2004 | 1.714 | 2.059 | 1.880 | 1.675 |
| 2005 | 1.194 | 1.521 | 1.349 | 1.145 |
| 2006 | 0.839 | 1.092 | 0.990 | 0.779 |
| 2007 | 0.674 | 0.906 | 0.812 | 0.601 |
| 2008 | 0.483 | 0.691 | 0.608 | 0.396 |
| 2009 | 0.227 | 0.411 | 0.339 | 0.127 |
| 2010 | −0.071 | 0.084 | 0.023 | −0.187 |
| 2011 | −0.363 | −0.234 | −0.285 | −0.494 |
| 2012 | −0.564 | −0.459 | −0.500 | −0.709 |
| 2013 | −0.787 | −0.705 | −0.737 | −0.946 |
| Mean | 0.439 | 0.646 | 0.561 | 0.351 |

Notes: TFP is the growth rate of total factor productivity based on the regression models (2)–(5) as presented in Table B1.

## Appendix C. Calculating the General X-factor

In the main text, for simplicity we assumed TFP growth to be the only determinant of the price cap, as applied in many jurisdictions worldwide. However, a seminal paper by Bernstein and Sappington (1999; BS) shows that the general X-factor, as the most crucial element of price cap regulation, reflects not only TFP growth but also input price variations, and that the regulated sector should be assessed against the benchmark of the remainder economy.

BS show that in a *competitive* economy ($E$), any changes in costs stemming from changes in productivity ($\Delta TFP$) and/or variations in input prices ($\Delta w$) are passed on to consumers via price changes ($\Delta P$)[28]: $\Delta P^E = \Delta w^E - \Delta TFP^E$. Hence, incentive regulation via a price cap wants to simulate a competitive environment in the regulated sector ($R$) by adjusting prices with the general X-factor (X-gen): $\Delta P^R = \Delta P^E - X_{gen} = \Delta P^E - [(\Delta TFP^R - \Delta TFP^E) + (\Delta w^E - \Delta w^R)]$. This yields the BS differential formula[29]

$$X_{gen} = (\Delta TFP^R - \Delta TFP^E) + (\Delta w^E - \Delta w^R). \tag{C1}$$

In what follows, we utilize external data sources and suggestions from the related literature to create measures for $\Delta TFP^E$, $\Delta w^E$, and $\Delta w^R$ (see Table C1) and combine these data with our empirical estimates of $\Delta TFP^R$ to calculate X-gen. We subject the calculation of X-gen to the sample period of incentive regulation 2008–2013 because recent sample years predict the coming regulatory period better than data points from long ago. Bernstein and Sappington (1999, p. 10) support this argument, stating that predictions of performance levels should be based on "updated, current measures of relevant variables."

The OECD provides yearly TFP growth rates for Austria ($\Delta TFP^E$), with an average rate of 0.07% for 2008–2013 (and 0.64% for 2002–2013). To calculate the growth in input prices in the regulated gas distribution sector ($\Delta w^R$), we follow the regulatory authority (E-Control, 2013, p. 25) and calculate the yearly change of the Network Input Price Index (NPI), which calculates as $\Delta w_t^R = \Delta NPI_t = 0.4 * \Delta BPI_t + 0.3 * \Delta BWI_t + 0.3 * \Delta CPI_t$, where $BPI$ is the Building Price Index, $BWI$ is the Index for Basic Wages, $CPI$ is the Consumer Price Index, and $t$ denotes the year of observation.[30] For the period 2008–2013, we calculate an average growth rate of input prices of 2.74% (2.40% for 2002–2013).

There is no standardized measure for the growth rate of input prices in the total economy ($\Delta w^E$). We follow Stronzik and Wissner (2013) and utilize two input factors, labor and capital, for which we utilize the measures of the Index for Basic Wages ($BWI$) and the Deflator for Gross Fixed Capital Formation ($\Delta$GFCF). We weight these measures by the Wage Ratio ($l$), which measures the share of labor income (including social expenditures by the employers) relative to the primary income of the total economy[31]: $\Delta w_t^E = l * \Delta BWI_t + (1 - l) * \Delta GFCF_t$. This yields an average annual input price growth rate for Austria's economy of 2.56% for the period 2008–2013 (2.47% for 2002–2013). Finally, Austria's output price inflation ($\Delta P^E$) is measured by the change in the CPI, which is 2.21% for the period 2008–2013 (2.04% for 2002–2013). Table C2 summarizes the measures for $\Delta TFP^E$, $\Delta w^E$, and $\Delta w^R$ and their underlying indices for calculation.

Table C2 calculates values of X-gen according to the BS formula as given in (C1), based on our index numbers for $\Delta TFP^E$, $\Delta w^E$, and $\Delta w^R$ and estimates for $\Delta TFP^R$. Taking the recent six-year period, 2008–2013, as the most adequate predictor of TFP growth in the forthcoming regulatory period, we calculate a value of X-gen of −0.17% (row 1 of Table C2). Since there are no statistical significance levels available for the respective index numbers, we cannot make a more precise qualification of this number. However, it seems plausible that the value of X-gen may not be statistically different from zero. Moreover, once we focus on the full sample period 2002–2013 (row2 of Table C2), we calculate a value of X-gen of essentially zero (i.e. 0.01%). Hence, calculating X-gen according to the BS differential formula for Austria's regulated gas distribution sector using our TFP estimates and external data for the remaining components (i.e. $\Delta TFP^E$, $\Delta w^E$, $\Delta w^R$), we calculate a value of X-gen close to zero for the near future.

Table C1
Index numbers

| | $\Delta TFP^E$ (%) | $\Delta w^R$ (%) | $\Delta w^E$ (%) | ΔBWI (%) | ΔCPI (%) | ΔBPI (%) | ΔGFCF (%) | Wage ratio (l) |
|---|---|---|---|---|---|---|---|---|
| 2002 | 0.80 | 1.54 | 1.99 | 2.50 | 1.76 | 0.67 | 0.83 | 0.69 |
| 2003 | −0.30 | 1.44 | 2.01 | 2.20 | 1.36 | 0.93 | 1.59 | 0.69 |
| 2004 | 1.30 | 2.03 | 2.07 | 2.00 | 2.06 | 2.03 | 2.21 | 0.67 |
| 2005 | 1.50 | 2.10 | 2.36 | 2.30 | 2.37 | 1.74 | 2.47 | 0.67 |
| 2006 | 2.10 | 2.31 | 2.81 | 2.70 | 1.46 | 2.65 | 3.00 | 0.64 |
| 2007 | 1.90 | 2.91 | 3.02 | 2.50 | 2.12 | 3.82 | 3.95 | 0.64 |
| 2008 | −0.30 | 3.84 | 3.14 | 3.00 | 3.23 | 4.92 | 3.40 | 0.64 |
| 2009 | −1.60 | 2.50 | 2.98 | 3.40 | 0.56 | 3.28 | 2.08 | 0.68 |
| 2010 | 1.10 | 2.56 | 1.87 | 1.60 | 1.76 | 3.89 | 2.42 | 0.67 |
| 2011 | 0.60 | 2.87 | 2.08 | 2.00 | 3.30 | 3.21 | 2.23 | 0.67 |
| 2012 | 0.40 | 2.72 | 2.94 | 3.30 | 2.43 | 2.50 | 2.18 | 0.68 |
| 2013 | 0.20 | 1.92 | 2.38 | 2.60 | 2.00 | 1.34 | 1.89 | 0.69 |
| ∅ 2008–2013 | 0.067 | 2.736 | 2.565 | 2.650 | 2.214 | 3.191 | 2.365 | 0.672 |
| ∅ 2002–2013 | 0.642 | 2.396 | 2.470 | 2.508 | 2.035 | 2.582 | 2.354 | 0.670 |

Notes: $\Delta w_t^R = \Delta NPI_t = 0.4 * \Delta BPI_t + 0.3 * \Delta BWI_t + 0.3 * \Delta CPI_t$. $\Delta w_t^E = l * \Delta BWI_t + (1 - l) * \Delta GFCF_t$. BWI is the Index for Basic Wages, CPI is the Consumer Price Index, BPI is the Building Price Index, ΔGFCF is the Deflator for Gross Fixed Capital Formation.

[28] In a competitive environment, firms have no market power and are, thus, price takers.

[29] In regulatory practice, alternative versions of (7) appear, mostly due to simplifying procedures and limiting data requirements. Replacing $(\Delta w^E - \Delta TFP^E)$ by $\Delta P^E$ yields $X_{gen} = \Delta P^E - \Delta w^R + \Delta TFP^R$, which only requires three instead of four terms, and $\Delta P^E$ can easily be measured by the output inflation rate. Moreover, some regulatory authorities (e.g. the Austrian regulator) set the X-gen equal to the "frontier shift": $X_{gen} = \Delta TFP^R$ (and simultaneously compensate firms by a Network Input Price Index (NPI) instead of an output price index). However, the BS formula represents the state-of-the-art in setting X-gen.

[30] BPI, BWI, and CPI are obtained from Statistics Austria: https://www.statistik.at/web_en/statistics/Economy/Prices/consumer_price_index_cpi_hcpi/index.html, September 26, 2017.

[31] We gratefully acknowledge that Statistics Austria provided the data for the wage ratio and the ΔGFCF upon email request on May 9, 2017.

Table C2
Calculation of X-gen

| $\Delta TFP^R$(%) | Explanation | $X = (\Delta TFP^R - \Delta TFP^E) + (\Delta w^E - \Delta w^R)$ | X-gen (%) |
|---|---|---|---|
| 0.07 | ∅TFP 2008–2013 | X = 0.07–0.07 + 2.57–2.74 | −0.17 |
| 0.58 | ∅TFP 2003–2013 | X = 0.58–0.642 + 2.47–2.40 | 0.01 |

## References


Aleifar, M., Farsi, M., Filippini, M., 2014. Scale economies and optimal size in the Swiss gas distribution sector. Energy Policy 65, 86–93.

Arocena, P., Contín, I., Huerta, E., 2002. Price regulation in the Spanish energy sector: who benefits? Energy Policy 30, 885–895.

Baker, B., Williamson, B., Lay Jung, H., 2002. The General Efficiency Assumption: Setting X in RPI-X: A Report for Water UK. NERA Economic Consulting.

Baldwin, R., Cave, M., 1999. Understanding Regulation: Theory, Strategy and Practice. Oxford University Press.

Baumol, W.J., 1982. Productivity incentive clauses and rate adjustment for inflation. Public Util. Fortn. 110 (2), 11–18.

Berndt, E.R., 1991. The Practice of Econometrics: Classic and Contemporary. Addison-Wesley Publishing Company, Reading, Massachusetts.

Bernstein, J.I., Sappington, D.E.M., 1999. Setting the X Factor in price-cap regulation plans. J. Regul. Econ. 16 (1), 5–25.

Bernstein, J.I., Sappington, D.E.M., 2000. How to determine the X in RPI-X regulation: a user's guide. Telecommun. Policy 24, 63–68.

Bloom, N., Jones, C.I., Van Reenen, J., Webb, M., 2017. Are Ideas Getting Harder to Find? NBER Working Paper 23782.

Casarin, A.A., 2014. Productivity throughout regulatory cycles in gas utilities. J. Regul. Econ. 45, 115–137.

Caves, D., Christensen, L., Swanson, J., 1981. Productivity growth, scale economies, and capacity utilization in U.S. Railroads, 1955–74. Am. Econ. Rev. 71 (5), 994–1002.

Crew, M., Kleindorfer, P., 1986. The Economics of Public Utility Regulation. MIT Press, Cambridge.

Cullmann, A., Nieswald, M., 2016. Regulation and investment incentives in electricity distribution: an empirical assessment. Energy Econ. 57, 192–203.

Del Gatto, M., Di Liberto, A., Petraglia, C., 2011. Measuring productivity. J. Econ. Surv. 25 (5), 952–1008.

Denny, M., Fuss, M., Waverman, L., 1981. The substitution possibilities for energy. In: Berndt, E.R., Field, B.C. (Eds.), Modelling and Measuring Natural Resource Substitution. MIT Press, Cambridge, MA.

Diewert, W.E., 1981. In: Cowing, T.G., Stevenson, R. (Eds.), The Theory of Total Factor Productivity Measurement in Regulated Industries. Academic Press, New York, pp. 17–44.

Dimitropoulos, D., Yantchew, A., 2017. Is productivity growth in electricity distribution negative? An empirical analysis using Ontario data. Energy J. 38 (2), 175–200.

E-Control, 2008. Erläuterungen zur Verordnung der Energie-Control Kommission, mit der die Tarife für die Systemnutzung in der Gaswirtschaft bestimmt werden (Gas-Systemnutzungstarife-Verordnung 2008. GSNT-VO 2008). https://www.e-control.at/documents/20903/-/-/67bac8b8-895f-4182-af9f-c8ea2c5a0d75.

E-Control, 2013. Regulierungssystematik für die zweite Regulierungsperiode GAS, 1.1.2013–31.12.2017. https://www.e-control.at/documents/20903/-/-/10bba9e5-c533-441c-8500-2c83689e9fa4.

Farsi, M., Filippini, M., Kuenzle, M., 2007. Cost efficiency in the Swiss gas distribution sector. Energy Econ. 29, 64–78.

Førsund, F.R., Kittelsen, S.A.C., 1998. Productivity development of Norwegian electricity distribution utilities. Resour. Energy Econ. 20, 207–224.

Goto, M., Sueyoshi, T., 2009. Productivity growth and deregulation of Japanese electricity distribution. Energy Policy 37, 3130–3138.

Hammond, C.J., Johnes, G., Robinson, T., 2002. Technical efficiency under alternative regulatory regimes: evidence from the inter-war British gas industry. J. Regul. Econ. 22 (3), 251–270.

Heshmati, A., 2003. Productivity growth, efficiency and outsourcing in manufacturing and service industries. J. Econ. Surv. 17 (1), 79–112.

Heshmati, A., Kumbhakar, S.C., 2011. Technical change and total factor productivity growth: the case of Chinese provinces. Technol. Forecast. Soc. Chang. 78, 575–590.

Hjalmarsson, L., Veiderpass, A., 1992. Productivity in Swedish electricity retail distribution. Scand. J. Econ. 94, 193–205.

Hollas, D.R., Macleod, K.R., Stansell, S.R., 2002. A data envelopment analysis of gas utilities efficiency. J. Econ. Financ. 26 (2), 124–137.

Kumbhakar, S.C., Wang, H., Horncastle, A.P., 2015. Stochastic Frontier Analysis Using Stata. Cambridge University Press, New York.

Laffont, J., Tirole, J., 1993. A Theory of Incentives in Procurement and Regulation. The MIT Press, Cambridge.

Littlechild, S., 1983. Regulation of British Telecommunications' Profitability. Department of Industry, London.

Lowry, M., Getachew, L., 2009. Econometric TFP targets, incentive regulation and the Ontario gas distribution industry. Rev. Netw. Econ. 8 (4), 325–345.

Martínez-Budría, E., Jara-Díaz, S., Ramos-Real, F.J., 2003. Adapting productivity theory to the quadratic cost function. An application to the Spanish electric sector. J. Prod. Anal. 20 (2), 213–229.

Oh, D., 2015. Productivity growth, technical change and economies of scale of Korean fossil-fuel generation companies, 2001–2012: a dual approach. Energy Econ. 49, 113–121.

Ray, S., 1982. A translog cost function analysis of U.S. Agriculture, 1939–77. Am. J. Agric. Econ. 64 (3), 490–498.

Rossi, M.A., 2001. Technical change and efficiency measures: the post-privatization in the gas distribution sector in Argentina. Energy Econ. 23, 295–304.

Schmitt, S., Stronzik, M., 2015. Die Rolle des generellen X-Faktors in verschiedenen Regulierungsregimen. (The role of the general productivity factor in different types of incentive regulations for energy networks). WIK Diskussionsbeitrag Nr. 399.

Stronzik, M., Wissner, M., 2013. Genereller Produktivitätsfaktor Österreichischer Stromverteilnetzbetreiber. (General Productivity Factor of Austrian Electricity Distributors). WIK-Consult on behalf of E-Control Austria.

Triebs, T., Saal, D.S., Arocena, P., Kumbhakar, S.C., 2016. Estimating economies of scale and scope with flexible technology. J. Prod. Anal. 45, 173–186 (published online).

Waddams Price, C.W., Weyman-Jones, T., 1996. Malmquist indices of productivity change in the UK gas industry before and after privatization. Appl. Econ. 28 (1), 29–39.

Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and test of aggregation bias. J. Am. Stat. Assoc. 57 (298), 348–368.


## Further reading


Burns, P., Weyman-Jones, T., 2008. The Long-Run Level of X in RPI-X Regulation: Bernstein and Sappington Revisited. Working Paper.