Energy Policy 65 (2014) 86–93

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Energy Conversion, Transportation/Transmission, and Storage

Scale economies and optimal size in the Swiss gas distribution sector

Mozhgan Alaeifar [a,*], Mehdi Farsi [b], Massimo Filippini [a,c]

[a] Center for Energy Policy and Economics (CEPE), Department of Management, Technology and Economics, ETH Zurich, Switzerland
[b] Faculty of Economics and Business, University of Neuchâtel, Switzerland
[c] Department of Economics, University of Lugano, Switzerland

HIGHLIGHTS

- Presence of unexploited scale economies for small and medium sized companies.
- Scale economies vary considerably with customer density.
- Higher density or greater complexity is associated with lower optimal size.
- Optimal size varies across the companies through unobserved heterogeneity.
- Firms with low density can gain more from expanding firm size.

ARTICLE INFO

Article history:
Received 3 October 2012
Received in revised form
30 August 2013
Accepted 7 September 2013
Available online 16 November 2013

Keywords:
Gas distribution
Unobserved heterogeneity
Scale economies
Optimal size

ABSTRACT

This paper studies the cost structure of Swiss gas distribution utilities. Several econometric models are applied to a panel of 26 companies over 1996–2000. Our main objective is to estimate the optimal size and scale economies of the industry and to study their possible variation with respect to network characteristics. The results indicate the presence of unexploited scale economies. However, very large companies in the sample and companies with a disproportionate mixture of output and density present an exception. Furthermore, the estimated optimal size for majority of companies in the sample has shown a value far greater than the actual size, suggesting remarkable efficiency gains by reorganization of the industry. The results also highlight the effect of customer density on optimal size. Networks with higher density or greater complexity have a lower optimal size.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

During past two decades, many industrial countries have started to reform their gas markets in order to lower costs and improve service quality and expand access to utility services. The EU gas directive, 1998/30/EC started a process of industry and market reform designed to produce a single, open and competitive market for natural gas across Europe (Thomas, 2005). The directive aimed to achieve this goal through the opening of third party access (TPA) for transport and storage of natural gas and by separating control of the main gas infrastructure from vertically integrated national and regional monopoly companies (Harris, 2008). The general idea is to introduce competition in the wholesale and retail markets, and to have a regulated natural monopoly in the transmission and distribution sectors. In the latter sectors we anticipate an increasing use of incentive schemes such as price-cap regulation, which is currently being used in UK and Argentina (Green, 1997).

Along with growing concerns about the performance of gas distribution companies, the productive efficiency of the sector can be questioned regarding economies of scale and the optimal size of local distributors. This issue is of particular importance in cases such as Switzerland, where the sector is characterized by relatively small operators. In fact, the natural gas distribution sector in Switzerland differs from most EU countries in its scale of operation. In many EU countries, gas distribution is either dominated by a few state-owned companies (e.g., France), or, in cases with a relatively large number of companies (e.g., Germany), the distributors are typically much larger than those operating in Switzerland, see Asche et al. (2001).

The Swiss gas distribution industry includes more than a 100 local small monopolists operating in relatively small to medium-size service areas with a strongly segmented structure. The size of a typical Swiss gas distributor is about 100th of that of a major

* Corresponding author. Tel.: +41 76 390 1347.
E-mail addresses: malaeifar@ethz.ch (M. Alaeifar), mehdi.farsi@unine.ch (M. Farsi), mfilippini@ethz.ch (M. Filippini).

0301-4215/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enpol.2013.09.038

Table 1
An overview of previous studies (gas distribution).

	Guldmann (1983)	Kim and Lee (1996)	Kim et al. (1999)	Fabbri et al. (2000)	Farsi et al. (2007)
Data	1979 (cross-section) U.S.	1987–1992 (panel data) Korea	1987–1995 (panel data) of 28 companies	1991–1992 (panel data) Italy	1996–2000 (panel data) Switzerland
Functional form (estimation)	Log linear OLS	Translog OLS, SUR	Translog OLS, FGLS SUR	Translog SUR	SFC-Cobb–Douglas GLS, GLS and Mundlack
Output	Residential and non-residential sales	Volume of gas delivered	Flow of natural gas	Volume of gas delivered	Volume of gas delivered
Output characteristics	Number of customers and population density	Customer density, average customer size and supply rate	–	Customer density, concentricity ratio and average altitude	Load factor, area size, customer density and terminal block
Factor prices	Omitted (considered to be constant)	Labor price, unit price of pipeline	Labor and administration price	Material and services, labor and capital price	Labor, capital and energy price
Economies of scale	Weak economies of scale	Weakly positive	Significant economies of scale	Very low	Weak
Economies of density	Significant economies of density	–	–	High	Strong

European company.[1] Considering the typical cases of EU countries with large dominant utilities, one can argue that the potential efficiency gains from the economies of scale are not considerable, so these are overlooked by the EU policy directives. However, given the relatively small size of Swiss gas distributors, such an approach does not apply to Switzerland's case. In Switzerland, and perhaps in other countries with similar market structures, an important policy question is to what extent the sector's productive efficiency can be improved through economies of scale. In these cases it can be argued that, for historical reasons related to the political organization of the economy,[2] the public utilities are organized in small units that are occasionally far from the optimal size. With globalization and the increasing integration of European natural gas markets, such historical grounds for small utilities appear to have lost relevance. In these circumstances, considerable efficiency gains may be achieved by reorganizing the industry in a more consolidated structure. Given this situation, economies of scale and optimal size are important policy issues especially for the case of Swiss natural gas distribution. In this study we focus on the issue of scale economies and its variation with output. Our main objective is to estimate the optimal size of the gas distribution companies and to study its possible variation with respect to network characteristics such as customer density.

This study estimates a total cost function via different panel data models using a panel of 26 gas distribution utilities in Switzerland over five years (1996–2000). As these utilities operate in environments characterized by strong heterogeneity, the omitted variables may have an important effect that can be better accounted for in panel data models. Due to the small size of the data set; statistical efficiency considered as a main issue to elaborate econometric specifications. Therefore, several econometric models, such as random effects and a system of equations with input share equations, are considered.

Finally, because of the strong heterogeneity of gas networks in both observed and unobserved characteristics, it is important to consider the variation of the economies of scale and optimal size across individual companies. For this reason two different approaches are considered in studying the variation of scale economies. In the first approach, economies of scale are studied for three hypothetical companies and in the second approach the economies of scale are estimated for four groups of companies based on the actual levels rather than on hypothetical values.

The rest of the study is organized as follows. In Section 2 we summarize the methodologies used in previous studies. The model specification and the concept of economies of scale are presented in Section 3. In Section 4 the estimation methods adopted here are discussed. Section 5 describes the data sets. The estimation results are presented in Section 6. The study ends with a summary of main results and policy conclusions.

2. Review of literature

Empirical contributions regarding cost and technology of gas distribution sector are not widely available in the literature. This can be partly explained by the lack of suitable data. In this section, some relevant studies are reviewed, focusing on the model specifications and econometric approaches suggested by different authors. A summary of these studies and their main results has been presented in Table 1. A special attention was given to the choice of flexible functional form and the necessity to account for unobserved heterogeneity in panel data set.

Guldmann (1983) proposed a multi-output cost function to model the structure of urban gas distribution. The cost of the system depends not only on the number of customers and the quantity sold to each but also on the population density. The results show the presence of weak economies of scale but significant economies of density. Guldmann's (1983) findings indicate that the economies of scale vary with the market size and territorial concentration of the customers. Hollas and Stansell (1988) analyzed the technical and allocative efficiencies of 64 US private gas distributors using a translog profit function. They include fuel and labor prices, customer density[3] and the fixed capital input[4] in the model. Hollas (1990), using the same data set, found that increasing the customer density has a statistically significant and negative effect on the cost of gas distribution.

Kim and Lee (1996) used a translog cost function to model the distribution technology of seven Korean gas distribution companies over the period 1987–1992. The explanatory variables include labor price, unit price of pipeline, customer density, customer size and supply rate.[5] Their results indicate that all the firms included in the sample are located in the increasing returns to scale region

[1] See Harris (2008) for statistics regarding major European companies.
[2] Federalism and the self-determination of relatively small communities.

[3] Defined as number of customers per mile of network.
[4] Measured in daily throughput capacity.
[5] These variables are defined as number of total customers/total pipe length, average consumption (total supply quantity/number of metering devices) and the number of total customer relative/number of total potential customers respectively.

in the early period and gradually exhausted scale economies in the later periods. The significance of output characteristics, especially customer density, has been underlined by the authors. Kim et al. (1999), estimated the total factor productivity growth in the natural gas industry based on an international comparison of 28 natural gas companies operating in the US, Belgium, Germany, Canada, France, Italy, Japan and Korea. All of the selected companies were engaged in both transmission and distribution, and their gas outputs were physically comparable with each other. A short-run translog variable cost function was adopted with one quasi-fixed input and two input variables. The results showed the presence of economies of scale for all the companies in the sample. Moreover, technological progress is considered as the main source of productivity growth in "mature" industrial countries. They concluded that the efficiency gains associated with the economies of scale are the main drivers of productivity growth in "premature" industries such as Korea.

In an empirical study involving 31 Italian gas distribution companies, Fabbri et al. (2000), estimated a long-term total cost function over 1991–1992. The specification includes customer density,[6] concentricity ratio,[7] the average altitude of the service area, and dummy variables for ownership differences and time effects. The analysis highlights the importance of customer density. Its coefficient is positive and statistically significant, suggesting a strong increase in the total cost when the density of customers decreases. Weak economies of scale and high economies of density characterize the nature of the technology. The results suggest a better performance for private operators. Fabbri et al. (2000) conclude that the privatization process in Italy's gas distribution should continue. They also highlight the benefits of having a large number of operators for a more effective regulation system, such as yardstick competition, and assert that, given the low degree of economies of scale in their data, these benefits outweigh the potential advantages of large utilities. It should be noted that the size of companies in their sample is about 7 times larger on average than that of the size of companies in our sample. This can explain the low degree of economies of scale in their data.

The data used in this study were analyzed in a previous study (Farsi et al., 2007) on the cost efficiency of the gas distribution utilities in Switzerland. The study used a stochastic cost frontier with various panel data specifications. A Cobb–Douglas total cost function was used as a function of output, input prices (including the price of labor), capital and energy (purchase price of natural gas), load factor, the number of terminal blocks, area size and customer density. Their results show the presence of considerable economies of (output) density but weak or insignificant economies of scale. This implies that distributors could decrease their average costs by increasing output as long as they use the same network, but the extension of networks does not result in any significant economies. By including spatial and network characteristics, Farsi et al. (2007) can distinguish between the economies of scale and density. However they used Cobb–Douglas functional form, because of the small size of the sample and the large number of parameters. The assessment of the potential variation of economies of scale and the estimation of optimal scale is not possible using the assumption of constant rate of economies of scale implied by Cobb–Douglas functional form. In this study, the authors consider a translog form and focus on the identification of the variations in the economies of scale and the optimal size. They find that the observed changes of output characteristics over the sample period do not show a variation at the same proportion as implicitly assumed in the definition of the scale economies. Their results suggest that the estimates of scale economies might be sensitive to the underlying assumptions on the proportions between different outputs. These findings indicate that the distinction between the economies of density and scale requires certain assumptions to which the estimation results might be sensitive. To the extent that these assumptions are not easily verifiable, it can be argued that a single measure of output could be equally appropriate for a general assessment of the variations of economies of scale with size, hence identifying the optimal scale. However, in the study by Farsi et al. (2007) the effect of unobserved heterogeneity has been considered; the choice of Cobb–Douglas cost function possesses the property of a constant elasticity of scale.

In addition, the choice of OLS in Kim and Lee (1996) and Kim et al. (1999), undermines the estimated results because of the problem of heterogeneity bias. The short panel used in the study by Fabbri et al. (2000), probably has not allowed the authors to account for unobserved heterogeneity, but the statistical efficiency of the results was improved using seemingly unrelated regression techniques. The current study extends the analysis conducted by Farsi et al. (2007) by using translog, a flexible functional form, in order to identify the variation in the economies of scale and also to define the optimal size of gas distribution utilities in Switzerland. Due to the issues concerning the small size of the sample, we highlight the importance of statistical efficiency in the estimation of optimal size. We argue that a parsimonious specification with a single measure of output can provide more realistic estimation of the optimal size than models with several output dimensions. It should also be noted that in practice deriving the optimal size from the optimality conditions over several output dimensions requires certain arbitrary assumptions. Therefore, the translog cost specification adopted includes a single output measure and the customer density along with input prices for capital, purchase price of natural gas and price of labor. Several econometric specifications, such as random effects and a system of equations with input share equations, are considered.

3. Model specification

Since this study evaluates cost elasticities to obtain economies of scale and the optimal size of gas distribution utilities, the volume of gas delivered has been taken as the output measure. Using a parsimonious specification three input prices, labor, energy and capital, and a measure of the characteristic of the service area are considered in the model. The translog form requires the underlying cost function to be approximated around a specific point, e.g., the sample mean or median. In this study the sample median is used as an approximation point. In addition, linear homogeneity in input prices is imposed by dividing total costs and input prices by labor price. If it is assumed that the firm minimizes cost and that the technology is convex, a total cost function can be written as

$$TC = f(Y, Pc, Pe, Pl, CUD) \tag{3.1}$$

where TC represents total costs; y is total volume of natural gas delivered measured in mWh, and Pc, Pe and Pl are the prices of capital, purchase price of natural gas and price of labor respectively. CUD represents the customer density, defined as number of clients per hectare of service area. Customer density should partially capture the impact on the costs of the heterogeneity of the service areas of the companies. In fact, differences in networks and environmental factors influence the production process and therefore the costs. Since the information is not available for all

[6] Ratio of network length to the number of customers.

[7] Share of the population resident in the inhabited areas of the municipalities.

network and environmental characteristics, we simply summarize the heterogeneity of the service area into one single variable.

The translog approximation of TC can be written as

$$\begin{aligned} Ln\left(\frac{TC_{it}}{P_{L_{it}}}\right) &= \alpha_0 + \alpha_Y \ln Y + \alpha_K \ln \frac{P_{K_{it}}}{P_{L_{it}}} + \alpha_E \ln \frac{P_{E_{it}}}{P_{L_{it}}} + \alpha_{CUD} \ln CUD_{it} \\ &+ \frac{1}{2}\alpha_{YY}(\ln Y_{it})^2 + \frac{1}{2}\alpha_{CDCD}(\ln CUD_{it})^2 + \frac{1}{2}\alpha_{KK}\left(\ln \frac{P_{K_{it}}}{P_{L_{it}}}\right)^2 \\ &+ \frac{1}{2}\alpha_{EE}\left(\ln \frac{P_{E_{it}}}{P_{L_{it}}}\right)^2 + \alpha_{YK} \ln Y_{it} \ln \frac{P_{K_{it}}}{P_{L_{it}}} + \alpha_{YE} \ln \frac{P_{E_{it}}}{P_{L_{it}}} \\ &+ \alpha_{YCUD} \ln Y_{it} \ln CUD_{it} + \alpha_{KE} \ln \frac{P_{K_{it}}}{P_{L_{it}}} \ln \frac{P_{E_{it}}}{P_{L_{it}}} \\ &+ \alpha_{KCUD} \ln \frac{P_{K_{it}}}{P_{L_{it}}} \ln CUD_{it} + \alpha_{ECUD} \ln \frac{P_{E_{it}}}{P_{L_{it}}} \ln CUD_{it} \end{aligned} \tag{3.2}$$

We define economies of scale (ES) as the relative increase in total costs resulting from a relative increase in output, holding all other factors constant at their sample median values. This is equivalent to the inverse of the elasticity of total cost with respect to output at the sample median.

$$ES = \frac{1/\partial \ln TC}{\partial \ln Y} \tag{3.3}$$

We will talk of economies of scale if ES is greater than 1, and accordingly, identifies diseconomies of scale if ES is below 1. In the case of $ES=1$ no economies or diseconomies of scale exist. Economies of scale exist if the average costs of a gas distribution company decrease as the volume of gas sold increases.[8]

Eq. (3.4) can be used to estimate the value of the economies of scale using the translog cost function (3.2) and by holding the input prices at their median values

$$ES = 1/(\alpha_Y + \alpha_{YY} \ln Y + \alpha_{YCUD} \ln CUD) \tag{3.4}$$

Here we can expect that the economies of scale decrease with respect to output and customer density, depending on the weight of the second-order coefficients (α_{YY}, α_{UCUD}) in Eq. (3.4).

Generally, the value of the economies of scale can be computed using the expression (3.3) for each company of the sample, for groups of similar companies of the sample or for some hypothetical companies. In this study we decided to calculate the economies of scale following the last two approaches.[9] In the first approach, the economies of scale are computed for three hypothetical companies, i.e., small, medium-sized and large companies.[10] Small companies are characterized by values of output and customer density that correspond to the first quartile of the sample distribution. Medium-sized companies are based on the median values of these variables, whereas large companies are based on the third quartile of the variables values of the sample distribution.

In the second approach, the economies of scale are estimated for four groups of companies based on actual levels of the variables rather than hypothetical values in order to be closer to the real situation. These groups are identified through a cluster analysis of all companies in the sample, and economies of scale are presented for these groups. This way of estimating the economies of scale is more attractive than the hypothetical analysis of scale economies because it reflects the real organization of the Swiss gas sector. Therefore, three different measures of complexity, including total cost, output and customer density are considered.[11]

3.1. Optimal size

Theoretically, optimal size in the cost structure is at the point with the least average cost or at the point when ES is equal to one

$$ES = 1 \tag{3.5}$$

By substituting Eq. (3.5) into Eq. (3.4) and rearranging, the following expression for the computation of the optimal size is obtained:

$$\ln Y^* = (1 - \alpha_Y - \alpha_{YCUD} \ln CUD^*)/\alpha_{YY} \tag{3.6}$$

In addition, with customer density at median optimal size is defined as follows:

$$\ln Y^* = (1 - \alpha_Y)/\alpha_{YY} \tag{3.7}$$

As can be seen, estimating optimal size Y^* requires an accurate estimation of α_{YY} as well as α_Y. If α_{YY} is not precisely estimated or significant, this procedure will lead to incorrect and counter-intuitive results and so is unsatisfactory. As we see later in the estimation results, α_{YY} is insignificant across all the models then the estimated optimal size based on Eq. (3.7), tends toward infinity. The importance of α_{YY} in the estimation is an argument why we prefer an alternative and arbitrary approach to defining optimal size.

For a typical U-shaped average cost, optimal quantity of output corresponds to minimum average cost where the slope is zero ($\Delta Ac/\Delta Y=0$). But in some industries such as the current study, the average costs always tend to decline over a period of time, thus even the largest companies might have cost advantages.[12] In this case, defining the optimal size is neither reasonable nor easy to find since every level of outputs seems to have a cost advantage over the lower level of outputs. For this reason in this study optimal size is defined practically at a point where the slope of average cost curve remains almost constant.[13] In order to give some precision to this notion, we calculate the slope of unit cost curve at the sample's first, median and third quartiles. It can be argued that companies might not be fully optimized at this point due to the decreasing nature of average cost. In fact this is true, but we can claim that at this point there is an opportunity for producers to exploit the considerable part of their unexploited scale economies.

A convenient approach is to present the average cost curve facing typical firms. The cost curve can be derived by evaluating the average cost function for a range of outputs while holding the customer density fixed at sample median (first and third quartile).

[8] In order to specify a parsimonious cost model we decided not to include the number of customers and the area size in model (3.1). For this reason, we are not able to estimate the economies of density such as Caves et al. (1985).

[9] By exploiting the fact that translog cost function is estimated at different approximation points, such as the sample's first and third quartiles, following Tjotta et al. (1994), it is possible to estimate several cost functions by varying the approximation point. Following this approach we have the possibility to obtain for each approximation point a value of the coefficients of Eq. (3.2) and, therefore, a value of the economies of scale. The idea is that for any given point of interest in the sample, the minimum approximation error can be achieved if the normalization is based on that point. This adjustment means that the estimated results at any given point are free from the estimation errors. In a preliminary analysis we also followed this approach. The values of the economies of scale obtained using this approach confirms the results presented in this paper using the other approaches. Therefore, in order to keep the paper readable we decided to not include in this paper this analysis.

[10] In the both approaches the factor prices are held constant at their median values.

[11] These results are obtained from an agglomerative hierarchical clustering technique based on the sample standard deviation (see Everitt et al., 2001).

[12] The industry tends naturally to become a monopoly. Natural monopolies tend to exist in industries with high capital costs and large networks in relation to variable costs, such as water supply and electricity supply.

[13] We set a threshold at a point, which exhibits the slope of average cost equal to $\Delta Ac/\Delta Y = 1 \times 10^{-6}$ and cost saving equal to 0.08%.

4. Estimation methods

The cost function (3.2) can be estimated as a single equation model or together with the input cost share equations as a system of equations.[14] Moreover, this cost function can be estimated using several econometric approaches for panel data that take the unobserved heterogeneity into account. Depending on assumptions made about intercept and error terms, for the estimation of a single equation regression using panel data it is possible to use a fixed effects or a random effects model. Another possible estimation method for single equation regressions is to pool the data and use OLS to estimate the model. The main drawback of the OLS model is that the panel structure of the data is completely ignored. On the other side, as discussed by Cameron and Trivedi (2005), when the within variation of some variables is relatively low, as in our case, the fixed effects model has a potential problem in statistical efficiency and the precision of the estimates. Therefore, in our case for the estimation of the single equation cost function (3.2) the most interesting econometric approach is the random effects model.

For the estimation of a system of equations composed of a cost function and the input cost share equations, a seemingly unrelated regression (SUR) can be used. The SUR approach improves the efficiency of ordinary least squares estimates by taking into account correlation in the disturbance terms between the cost and the various cost share equations (Zellner, 1962). Avery (1977) recognized that single equation panel data models could be extended by accounting for error correlations between systems of equations as in an SUR by including additional cross-equation variance terms in the covariance matrix of the error terms between equations. Unlike using Zellner (1962) on a time series or cross-section, GLS estimates for the system do not equal single-equation GLS estimates even with the same set of independent explanatory variables in the presence of cross equation correlated errors (Avery, 1977). To note, however, that the classical SUR approach used with panel data does not take into account the unobserved heterogeneity. Therefore, in this study we considered the inclusions of individual fixed or random effects in the SUR models. In the fixed-effect option we included firm-specific intercepts in the main equation, but no adjustment in share equations. In the random-effect option, following (Biørn, 2004) and (Nguyen, 2009), we included random effects in the main equation as well as share equations. However, as discussed previously, because of a large number of parameters and the low within variation of the variables, the fixed effects in a SUR framework could also suffer from the precision of the results. On the other side, in the random effects version of the SUR model it is very difficult to introduce cross-restrictions across equations as imposed from the micro-economic production theory. Therefore, the results obtained using this econometric approach may not be in line with economic theory.[15] Given this discussion concerning advantages and disadvantages of estimation approaches for single equations as well system equations, we decided to base our empirical analysis mainly on the results obtained from the estimation of the cost function using a RE model and to present the results obtained with simple SUR approach and SUR with fixed effects only for comparison purposes.

[14] Consisting of a cost function and input share equations obtained using Shephards's Lemma.

[15] Because the input share equations are obtained by differentiating the cost function, some of the coefficients of the cost function should be the same as the coefficients of the input share equations. Therefore, it is necessary to impose some cross restrictions on the coefficients. Unfortunately, Stata does not provide the possibility to impose cross restrictions within the SUR random effects framework. In a preliminary analysis, we used this approach and the obtained results confirm the results obtained with the estimation of the single equation cost model using a random effects model. However, because of the theoretical inconsistency we decided not to present these results.

5. Data

The data used in this paper is an unbalanced panel of 26 distribution companies for five years from 1996 to 2000.[16] These companies together, account for about 57% of the total gas consumption,[17] about a fifth of Swiss gas distributors and about 40% of the total length of the gas distribution network in Switzerland. This implies that many small gas distributors are underrepresented in the sample. Moreover, the average volume of distributed gas per network length in these companies is higher than the national average value. With regard to the service area, our sample covers 42% of all Swiss communities served with gas. Table 2 provides a descriptive summary of the main variables used in the analysis. Total costs (*TC*) are the total annual operating costs plus the gas purchases from the transmission sector. Tax expenditures and non-operating costs are excluded. Output (*Y*) is measured by the total amount of gas delivered to end-consumers and to downstream distributors.

Labor price (*PL*) is defined as the ratio of total annual labor costs, including social security costs, to the number of full-time-equivalent employees. The price of energy (*PE*) is the average unit price of the purchased gas. The capital price (*PC*) is calculated as the sum of expenditures other than labor expenses and gas purchases divided by the network length. These expenditures include interest payments and depreciation as well as material costs and other services included in operating costs. Capital stock includes the distribution network as well as other equipment such as monitoring and control systems and the final connections and metering equipment. In fact, lacking any other reliable measure of total capital stock, we assumed that the capital stock is more or less proportional to the network length. Moreover, as the network is the major part of the capital stock of a gas distributor, network length has been used as a proxy physical measure of capital in the calculation of capital prices. All costs and prices are adjusted for inflation using Switzerland's consumer price index and are measured in year 2000 Swiss Francs.

6. Results

Table 3 provides the regression results obtained using several econometric approaches. For the estimation of the system of equations composed of the cost function (3.2) and the relative input cost share equations, a simple SUR approach and SUR with fixed effects are applied. Further, in the last column we present the results obtained by a RE model.[18] The estimated cost functions are well behaved. Most of the parameter estimates are statistically significant and the coefficients of all models are relatively similar and have the expected signs.

As expected, all results obtained from the estimation of cost function together with the input cost shares using the SUR approach (Models I and II) show a higher number of significant coefficients in comparison to the estimation of a single-equation cost function using the RE approach (Model III). However, as previously discussed, the random effects version of the SUR model does not satisfy some conditions imposed by production theory. Furthermore, in the fixed effects version of the SUR approach

[16] The data for 1996 is not available for one company. Thus, the sample consists of 129 observations.

[17] None of the four regional companies are included.

[18] This RE model is estimated using GLS.

Table 2
Descriptive statistics (129 observations).

Variables	Mean	Std. deviation	Min	1st Quartile	Median	3rd Quartile	Max
Total annual costs TC (1000 CHF)	21,411	24,477	2592	8076	14,361	23,000	135,382
Annual output (*Y*) in mWh	548,515	729,301	58,000	164,700	398,890	541,515	4,174,000
Firm-average annual labor price (PL) CHF per employee	96,161	15,963	61,830	86,459	95,373	105,926	139,460
Firm-average annual capital price (PC) CHF per meter network length	29	11.00	12.53	20	27	34	75.78
Firm-average annual energy price (PE) 10^{-2} CHF/kWh	3	0.47	1.65	2	2	3	3.82
Number of customers per area size (CUD)	2	0.88	0.67	1.41	1.95	2.57	4.75
Energy cost share	0.58	0.09	0.38	0.54	0.59	0.65	0.78
Capital cost share	0.30	0.09	0.15	0.24	0.28	0.36	0.54

Note: All monetary values are in year 2000 Swiss Francs (CHF), adjusted by the consumer price index.

Table 3
Estimation results.

Coefficient	Model I. SUR	Model II. SUR (+fixed effects)	Model II IRE (random effects) single equation
a_y	**0.889**** (0.011)	**0.624**** (0.064)	**0.862**** (0.025)
a_{PK}	**0.294**** (0.006)	**0.291**** (0.0061)	**0.206**** (0.023)
a_{PE}	**0.594**** (0.006)	**0.595**** (0.0058)	**0.640**** (0.024)
a_{CUD}	**0.001** (0.026)	**0.504**** (0.097)	**0.107*** (0.063)
a_{yy}	−**0.001** (0.012)	−**0.081** (0.069)	−**0.024** (0.041)
a_{PKPK}	**0.142**** (0.014)	**0.102**** (0.015)	**0.018** (0.075)
a_{PEPE}	**0.209**** (0.016)	**0.143**** (0.020)	**0.150** (0.133)
a_{CDCD}	−**0.010** (0.055)	**0.345**** (0.16)	**0.118** (0.130)
a_{YPE}	**0.054**** (0.006)	**0.045**** (0.0065)	**0.067**** (0.031)
a_{YPK}	−**0.041**** (0.006)	−**0.037**** (0.0065)	−**0.029** (0.021)
a_{YCUD}	**0.064**** (0.020)	**0.117*** (0.066)	**0.163**** (0.048)
a_{PKPE}	−**0.164**** (0.010)	−**0.116**** (0.013)	−**0.154**** (0.060)
a_{PKCUD}	−**0.011** (0.014)	−**0.015** (0.0136)	**0.076** (0.059)
a_{PECUD}	**0.008** (0.013)	**0.009** (0.0133)	−**0.042** (0.057)
a_0	**0.121**** (0.012)	–	**0.129**** (0.031)

Standard errors are given in parenthesis.

* refers to significance of 90%.

** refers to significance of 95%.

(Model II), the coefficient of the second term of the output variable, which is very important for the computation of the economies of scale, is not significant. This result may be probably due to the low within variation of the variables and the large number of parameters to be estimated. Therefore, as discussed previously, we think that the single equation random effects model is the most appropriate model to use in our empirical analysis. However, for comparison, we will also present the estimated economies of scale obtained from all the above-mentioned models.

The cost function needs to satisfy some regularity conditions. These are that the cost function should be non-decreasing in input prices and output, linearly homogeneous in input prices, and concave. All models impose the linear homogeneity assumption by by normalizing costs and prices with the labor price.

As expected the results show that the output and input price coefficients are positive and highly significant across all models suggesting that the theoretical requirements of a cost function are fulfilled. Since total costs and all the continuous explanatory variables are in logarithms and normalized by their sample medians, the estimated first order coefficients can be interpreted as cost elasticity evaluated at the sample median. The output cost elasticity suggest that on average a 1% increase in the amount of gas delivered will increase total cost by about 0.6–0.9% depending on the specification adopted. The cost elasticities with respect to factor prices (α_{PK}, α_{PE}) and customer density (α_{CUD}) are positive and significant at the sample median. This indicates that a 1% increase in capital cost will affect total cost up to 0.3%, 1% increase in energy price will affect total cost up to 0.64% and 1% increase in customer density increases total costs up to 0.5%. These results are consistent with the actual data, which show a capital share of about 30% and energy share of about 60% for the sample median. Moreover, a majority of the second-order coefficients in particular a_{yy}, are insignificant in the random effect model as well as in SUR. This might put some risk on the estimation of optimal size, as we already discussed in Section 3.1.

The estimated scale economies based on the regression results and their confidence interval are given in Table 4. The estimated scale economies for the all three cases are significantly greater than one, suggesting that scale economies are not fully exploited in the majority of the companies. The high variation among different models indicates the sensitivity of the results to different assumptions. The variation also can be partially explained by the models' differences with respect to the unobserved network effects. The results obtained from the RE models (Models I and III) show that the unexploited scale economies are slightly greater in relatively small companies while results obtained from SUR model with fixed effects (Model II) show a different pattern. This difference is due to the fact that in the SUR model with fixed effects, the coefficient of the second term of the output variable is not significant.

Table 5 provides a description of four groups of companies that have been identified by cluster analysis of all companies in the sample. The table also lists the median value of average cost, output and customer density for each cluster along with a short description of each cluster. Group A contains 11 companies with high density and medium output, Group B has seven companies with low density and medium output, Group C has four companies with high density and small output and Group D contains three companies with large networks.

The estimated values of scale economies are represented in Table 6, within each one of the four clusters. These estimates are based on the average value of output and customer density for each cluster. As seen, the results estimated by the SUR models suggest the existence of scale economies for all groups in the sample, but the results by RE model suggest the existence of scale economies only for Groups A and B.

The results from the RE model show that the estimated scale economies for companies with high density are either small or not significantly different from one (Groups A, C and D). Moreover, companies with low density (Group B) are characterized by unexploited economies of scale. These results are almost consistent with previous results and confirm that the unexploited scale economies are greater in low-density companies. On the other hand, scale economies vary considerably with customer density.

As discussed previously, our preferred model is the RE model. Therefore the discussion of optimal size is based on the results obtained using this model. As resulted in the previous section, the majority of the companies in the sample have presented

Table 4
Economies of scale (approximated at sample median).

	Term	Model I SUR	Model II SUR(+fixed effects)	Model III RE (single equation)
1st Quartile	95% Conf. interval	1.15 (1.11, 1.19)	1.5 (1.27, 1.75)	1.2 (1.10, 1.30)
Median	95% Conf. interval	1.12 (1.09, 1.15)	1.6 (1.27, 1.92)	1.16 (1.05, 1.22)
3rd Quartile	95% Conf. interval	1.1 (1.07, 1.13)	1.58 (1.18, 1.95)	1.11 (1.04, 1.18)

Confidence intervals are given in parenthesis.

Table 5
Clusters.

Cluster	No. of firms	Network characteristic	Median output (mWh)	Median customer density (No. of customer per size of area)	Median average cost (CHF/mWh)
A	11	High density & medium output	455,007	2.32	41
B	7	Low density & medium output	223,339	1.04	43
C	4	High density & low output	98,838	2.17	44
D	3	high Density & high output	1,822,722	2.47	46

Table 6
Economies of scale for each cluster.

Cluster	SUR	SUR(+fixed effects)	RE (single equation)
A	**1.1** (1.07, 1.12)	1.59 (1.24, 1.94)	**1.14** (1.07, 1.20)
B	**1.14** (1.09, 1.18)	**1.71** (1.4, 2.02)	**1.3** (1.18, 1.42)
C	**1.09** (1.05,1.14)	**1.31** (0.99, 1.63)	**1.07** (0.94, 1.22)
D	**1.09** (1.05, 1.13)	**1.87** (0.88, 2.86)	**1.15** (0.98, 1.32)

Confidence intervals are given in parenthesis.

unexploited scale economies, implying that there are efficiency gains in expanding firm size for the majority of the companies in the sample. As discussed earlier,[19] optimal size is considered to be located on a relatively flat part of the average cost curve in which the slope of the unit cost curve remains almost constant for a large range of outputs. The average cost curves facing typical firms[20] are plotted in Fig. 1. Accordingly, the output levels which corresponding to ($\Delta Ac/\Delta Y = 1 \times 10^{-6}$) are also shown for all the three cases.

In addition, Table 7,[21] shows cost advantages of the typical companies for different points in the sample. In general, results confirm the small nature of Swiss gas distribution companies as they operate far from their optimal scale. It can be seen from the table, any output increase in low-density area corresponds to more cost advantages than high-density area. Moreover the results indicate that, in the process of doubling output, average cost falls drastically, suggesting a remarkable cost saving for low-density companies of doubled size. For instance, low-density companies would gain a 5.6% decrease in average cost for doubling size, while high-density companies only gain a 2.8% saving in average cost. These results suggest a better opportunity for cost saving by expanding outputs for small companies in the sample.

The results also highlight the effect of customer density on optimal size. Customer density is an important factor in this study because it is the only parameter that can capture the heterogeneity of service area. Moreover, the relationships between optimal size and customer density depend on the complexity of the network area and the environmental characteristics of each company. This can be seen by the results; optimal size varies across companies and lower optimal size can be seen for networks with higher density or greater complexity.

7. Conclusion and policy implications

This study uses a panel of 26 gas distribution utilities in Switzerland over five years. As these utilities operate in environments characterized by strong heterogeneity, the omitted variables may have an important effect that can be better accounted for in panel data models. A total cost function (translog) has been estimated via several econometrics models. Considering the small sample size, statistical efficiency is considered as a main consideration to elaborate econometric specifications. Therefore a parsimonious specification including few parameters[22] is preferred because it increases the statistical efficiency and precision of the estimation results. Thus, the variation of scale economies can be better estimated and more reasonable results can be expected for optimal size.

Among the panel data models used in this study, the single equation RE model seems to be the most appropriate. The results indicate the presence of unexploited scale economies for the majority of the companies in the sample. However, very large companies (in terms of output and density) and companies with a disproportionate mixture of output and density are exceptions. Such effects could be disguised by unobserved network characteristics that, if omitted from consideration, could lead to obtain inaccurate results. On the other hand, the estimated scale economies based on cluster analysis are almost consistent with previous results and confirm the presence of unexploited scale economies for low-density companies.

The results show that the estimated optimal size, for the majority of companies in the sample, is far greater than the actual size. This indicates the presence of remarkable efficiency gains by expanding the firm size. The estimated optimal size for a typical company shows that higher density or greater complexity is

[19] Section 3.1.
[20] With the customer density fixed at sample median, first and third quartile.
[21] Approximation point set at median.
[22] Only output and customer density.

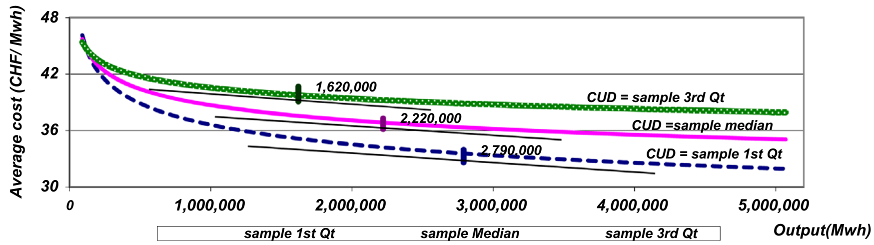

Fig. 1. Average cost curve.

Table 7
Cost advantages and optimal size of the typical companies.

Representative customer density	% Increase in output	% Cost saving (CHF/mWh)	Ad-hoc optimal size (mWh)
1st Quartile	10	1.5	2,790,000
	30	2.75	
	50	3.82	
	100	5.59	
Median	10	0.44	2,220,000
	30	1.6	
	50	2.55	
	100	4.07	
3rd Quartile	10	0.42	1,620,000
	30	0.98	
	50	1.62	
	100	2.76	

associated with lower optimal size, meaning that the optimal size varies considerably with customer density.

Therefore as a result, firms with low density can gain more from expanding firm size, and priority should be given to low-density companies in which considerable cost advantages exist, even for a little increase in output. Companies with high density and lower cost savings may receive the last attention. Generally, possible policy recommendations would be restructuring toward larger utilities by merging or joint ventures among small companies (particularly in low density areas), which would benefit more from cost advantages. It should be mentioned that an expansion policy appears to be bad advice for very large companies with increasing average cost or diseconomies of scale. In turn, an appropriate policy recommendation for these companies could be disintegration toward smaller utilities in order to lower average cost.

For a further study in Swiss gas distribution utilities, we recommend first to study the issue of economies of scope, since most of these companies are multi-utilities. These issues have a crucial importance in unbundling the integrated utilities into separate entities. Second, the strong heterogeneity among utilities operating in such different environments suggests that a cost function with random coefficients might be more reliable in analysis of scale economies than a constant coefficients model.

References

Asche, F., Osmundsen, L., Tveterås, R., 2001. Market integration for natural gas in Europe. International Journal of Global Energy Issues 16 (4), 300–312.
Avery, R.B., 1977. Error components and seemingly unrelated regressions. Econometrica 45, 199–209.
Biørn, X., 2004. Regression systems for unbalanced panel data: a stepwise maximum likelihood procedure. Journal of Econometrics 122, 281–291.
Cameron, A.C., Trivedi, P.K., 2005. Micro-econometrics Methods and Application. Cambridge University Press, Cambridge.
Caves, D.W., Christensen, L.R., Tretheway, M.W., Windle, R.J., 1985. Network effects and the measurement of returns to scale and density for US railroads. In: Daughety, A.F. (Ed.), Analytical Studies in Transport Economics. Cambridge University Press, Cambridge, pp. 97–120.
Everitt, B.S., Landau, S., Leese, M., 2001. Cluster Analysis, 4th edition Institute of Psychiatry, King College, London.
Fabbri, P., Fraquelli, G., Giandrone, R., 2000. Costs, technology and ownership of gas distribution in Italy. Managerial and Decision Economics 21, 71–81.
Farsi, M., Filippini, M., Kuenzle, M., 2007. Cost efficiency in the Swiss gas distribution sector. Energy Economics 29 (1), 64–78.
Green, R., 1997. Has price cap regulation of UK. Utilities been a success? Private Sector, No. 132.
Guldmann, J.M., 1983. Modeling the structure of gas distribution costs in urban areas. Regional Science and Urban Economics 13, 299–316.
Harris, N., 2008. Towards a true EU gas market. ⟨http://www.kingstonenergy.com/eugas0308.pdf⟩ (accessed 31.03.12).
Hollas, D.R., Stansell, S.R., 1988. Regulation, inter-firm rivalry, and the economic efficiency of natural gas distribution facilities. Quarterly Review of Economics and Business 28 (4), 21–37.
Hollas, D., 1990. Firm and interruptible pricing patterns: public versus private gas distribution utilities. Southern Economic Journal 57 (2), 371. (Available from Business Source Premier Database (accessed 23.04.09).
Kim, T.Y., Lee, J.D., 1996. Cost analysis of gas distribution industry with spatial variables. Journal of Energy and Development 20, 247–267.
Kim, T.Y., Lee, J.D., et al., 1999. International comparison of productivity and its determinants in the natural gas industry. Energy Economics 21, 273–293.
Thomas S., 2005. The European Union Gas and Electricity Directives. PSIRU-Report, Greenwich, ⟨www.psiru.org/reports/2005-10-E-EUDirective.pdf⟩ (accessed 31.12.2012).
Tjotta, S., Kjell, G., Salvanes, 1994. Productivity differences in multiple output industries: an empirical application to electricity distribution. Journal of Productivity Analysis 5, 23–43.
Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association 57 (298), 348–368.