Identifying efficient regulated firms with unobserved technological heterogeneity: A nested latent class approach to Norwegian electricity distribution networks

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Abstract

Since the 1990s many electricity distribution networks are incentive regulated. The regulators aim to identify utilities that can be used as "reference networks" for other (comparable) utilities in order to determine their relative efficiency. While the latent class stochastic frontier (LCSF) models are increasingly popular to account for technology heterogeneity among firms, Kumbhakar et al. (2013) have used the latent class structure to introduce a 'zero inefficiency stochastic frontier' (ZISF) model that allows researchers to distinguish between fully efficient and inefficient firms. In this paper we introduce a nested latent class (NLC) model where unobserved differences in performance are modeled using two ZISF models that are in turn nested in a latent class structure that aims to capture unobserved differences in technology or environmental conditions. This model allows researchers/regulators to identify reference networks that are persistently 100% efficient when the underlying technology is heterogeneous. We illustrate the proposed model with an application to the Norwegian distribution network utilities for the period 2004-2011. We find that the efficiency scores in both LCSF and ZISF models are biased, and that some firms in the ZISF model are wrongly labelled as inefficient. In addition, other firms are wrongly labelled as fully efficient by the ZISF model.

Keywords: latent class models, environmental conditions, electricity distribution, reference networks.

JEL: L15, L51, L94

1. Introduction

Since the worldwide reform of the electricity sectors since the 1990s many network utilities are incentive regulated. This reform trend coincided with some recent contributions to regulatory economics (Shleifer, 1985; Laffond and Tirole, 1993). The aim is to provide the firms with incentives to improve their operating and investment efficiency and to ensure that consumers benefit from the gains. The main methods used to achieve these objectives are incentive mechanisms, which provide the firms with financial rewards and penalties linked to their performance (Joskow, 2008). In many instances, the regulators aim to measure the firms' relative efficiency against those with best practice performance using parametric and non-parametric techniques (see Haney and Pollitt, 2013). In countries such as Germany, Norway, Switzerland, and Brazil the regulators normally identify more than one efficient benchmark as they have a large and diverse number of utilities in the sector.

Statistical benchmarking methods have been mainly used in electricity distribution networks to determine the relative efficiency of individual firms' operating costs and service quality compared to their peers.[1] All efficiency estimates are based on measuring the gap between the actual cost of the firm (production) and an optimal point on the cost (production) frontier, which is estimated from the available dataset. As regulators reward or punish firms according to their (in)efficiency level, the reliability of these scores is crucial for efficiency of the firms and credibility of the regulatory framework. Obtaining reliable (and fair) measures of firms' inefficiency requires controlling for the different environmental conditions under which each utility operates.[2] This is especially acute in benchmarking because of the financial implications that this analysis can have for the individual network, other network utilities, the whole sector, and ultimately the consumers. Errors in identifying the correct benchmark firms or measuring their efficiency has financial implications for all the less efficient firms against which they are compared.

Recently, latent class stochastic frontier (hereafter LCSF) models that combine the stochastic frontier approach with a latent class structure have appeared in the efficiency analysis literature to account for technology heterogeneity among the firms. Latent class models, also known as finite mixture models, have been used in several fields of research (see Beard et al., 1991; or Gropper et al., 1999; Orea and Kumbhakar, 2004; Greene, 2005, for some applications). A conventional LCSF model assumes that there is a finite number of technologies (classes) underlying the data and allocates probabilistically each firm in the sample to a particular technology. Once the benchmark technology of each firm is identified, its inefficiency in relation to that benchmark technology is measured from a specific distribution (e.g. half-normal) in which the parameters might differ.

Kumbhakar et al. (2013) have taken advantage of the latent class structure to introduce the so-called 'zero inefficiency stochastic frontier' (ZISF) model. This model

[1] Jamasb and Pollitt (2001) show the most commonly used approaches and provide a survey of benchmarking studies applied mainly in OECD countries. For a recent review of the applied literature on regulation of electricity distribution networks see for instance Kuosmanen (2012).

[2] The inclusion of environmental variables (also referred to as contextual variables or z-variables) in the model is contentious in the literature on efficiency analysis and has generated the development of several models (for a review of this topic in Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA), see for instance Johnson and Kuosmanen, 2012).

ignores the above-mentioned issue of unobserved differences in technology or contextual factors, but allows the researcher to distinguish between fully efficient and inefficient firms in the sample. The ZISF model is appealing in benchmarking, as it helps sector regulators to identify electricity distribution networks that can be used as "reference networks" for other (comparable) utilities.[3] The present paper proposes to use the ZISF approach to determine this reference network, while extending it this to also take into account the technological heterogeneity as well as geographical and weather conditions among the firms.

Kumbhakar et al. (2013) assume that there are only two types of firms (efficient and inefficient). While the inefficiency distribution for fully efficient firms is a point mass at 0, the degree of inefficiency for inefficient firms is captured by any of the array of standard one-sided distributions, such as half-normal, exponential, or truncated normal. However, they use the latent class structure to identify unobserved differences in performance, assuming the estimated technology to be the same for all firms. Consequently, they abstract from technological heterogeneity among the firms and focus exclusively on the distribution of inefficiency.

Therefore, the finite mixture models have traditionally been used to identify groups of firms that operate with different operating conditions or use different technologies. The issue here is that the presence of one technology or another is not directly observed by the researcher. At most, only partial technological or environmental indicators are available. If the underlying data generation process only involves two technologies and there are only two types of firms (efficient and inefficient), we could then estimate a latent class model with four classes in which both technological and efficiency parameters differ. As both sources of unobserved heterogeneity (i.e. behavioral and technological) are treated *symmetrically* in such model, it is not certain that the differences in performance are caused by differences in behavior or technology, and vice versa. In addition, it is not possible to distinguish between the probabilities of sharing the same technology (i.e. being comparable firms) and probabilities of sharing similar performances (i.e. being fully efficient or inefficient).[4]

The difference in the nature of behavioral and technological differences is not a semantic point. What is more, we take advantage of the difference in the nature of both of these sources of unobserved heterogeneity to develop a *nested* latent class model (hereafter NLC model) where the behavioral differences are modeled using two ZISF models that are in turn nested in a latent class structure that aims to capture unobserved differences in technology or environmental conditions. To our knowledge, the present study is the first to propose a *nested* latent class model. Hence, unlike Kumbhakar et al. (2013), we provide a framework to distinguish between the fully efficient and inefficient firms in the sample when the underlying technology is heterogeneous. In

[3] Several South American countries (e.g., Argentina, Chile, and Peru) use a rather similar concept, called "Model Company", to determine the allowed revenues, or allowed prices, of distribution companies (see Cossent, 2013). This approach relies on "building" an engineering bottom-up model of a network company as benchmarking reference for a set of real firms, which is characterized in terms of network assets and associated costs, overhead structure and commercial costs, and the density degree (urban vs. rural) of the sectors or areas operated by each firm.

[4] Kumbhakar et al. (2013, p. 67) state that "it is not clear from the finite mixture approach whether identifying a group of efficient firms is actually predicated on overfitting from allowing technological heterogeneity across the regimes".

addition, the present paper study is the first to introduce the zero-inefficiency approach in a regulatory context.

2. Empirical model

Let us first assume that there are J different technologies, and that each firm belongs to one and only one of these technologies. Next, we adapt in a panel data setting the ZISF model introduced by Kumbhakar et al. (2013) to identify behavioral differences among electricity distribution firms. Conditional on technology j (=1,…,J), the general specification of the ZISF model can be written as follows:

$$\ln y_{it} = f(x_{it}) + v_{it|j} - I(i) \cdot u_{it|j} \tag{1}$$

where i stands for firms, t for time, y_{it} is a measure of firms' cost or other performance, x_{it} is a vector of cost drivers, $v_{it|j}$ is a noise term that follows a normal distribution with zero mean and constant variance, and $u_{it|j}$ is a one-sided error term capturing firms' inefficiency. $I(i)$ is a behavioral indicator dummy that takes a zero value for fully efficient firms (and hence u_i=0 is assumed for these firms), while it is equal to unity for those firms that are inefficient (i.e. u_i>0).

The true value of $I(i)$ is not available to the researcher, and hence the probability of being efficient or inefficient should be estimated simultaneously alongside other parameters of the model. Note that $I(i)$ does not have a time subscript in equation (1). Therefore, we are interested in identifying firms that have persistently been fully efficient during the sample period. As it is customary, we parameterize the probability of being inefficient (i.e. $I(i)$=1) as a multinomial logit function:

$$\Pi_{i|j}(\gamma_j) = \frac{1}{T}\sum_{t=1}^{T} \frac{\exp(\gamma_j' z_{it})}{1+\exp(\gamma_j' z_{it})} \tag{2}$$

where z_{it} is a vector of firm-specific which influence whether a firm is inefficient or not. This probability is specified to be individual specific, but time invariant as in Greene (2005).[5]

The contribution of firm i to the *conditional* (on technology-class j) likelihood is:

$$LF_{i|j}\,(\theta_j) = LF_{i|j}^{SFA} \cdot \Pi_{i|j}(\gamma_j) + LF_{i|j}^{ZI}\left[1 - \Pi_{i|j}(\gamma_j)\right] \tag{3}$$

where θ_j encompasses all parameters associated with technology class j. $LF_{i|j}^{SFA}$ is the likelihood function of a SFA model with two random terms, which is the applicable likelihood function when firms are inefficient (i.e. $I(i)$=1), and $LF_{i|j}^{ZI}$ is the likelihood function of a normal random variable, which is the proper function when firms are fully efficient (i.e. $I(i)$=0). Following Greene (2005, eq. 35), we model these two likelihood functions as follows:

[5] Greene (2005) imposes the time invariance assuming that z_{it}=z_i. IF z_i is interpreted as an individual mean, both specifications are equivalent.

$$LF_{i|j}^{SFA} = \prod_{t=1}^{T} LF_{it|j}^{SFA} \tag{4}$$

$$LF_{i|j}^{ZI} = \prod_{t=1}^{T} LF_{it|j}^{ZI} \tag{5}$$

We next use the latent class structure to identify differences in technology among electricity distribution firms. The *unconditional* likelihood for firm *i* is obtained as the weighted sum of their technology-specific likelihood functions, where now the weights are probabilities of technology-class membership. That is:

$$LF_i(\theta,\delta) = \sum_{j=1}^{J} LF_{i|j}\left(\theta_j\right) P_{ij}\left(\delta_j\right), \quad 0 \le P_{ij}\left(\delta_j\right) \le 1, \quad \sum_{j=1}^{J} P_{ij}(\delta_j) = 1 \tag{6}$$

where, $\theta=(\theta_1,\ldots,\theta_j)$, $\delta=(\delta_1,\ldots,\delta_j)$ and the technology-class probabilities are parameterized again as a multinomial logit model:

$$P_{ij}\left(\delta_j\right) = \frac{1}{T}\sum_{t=1}^{T} \frac{\exp(\delta_j' q_{it})}{\sum_{j=1}^{J}\exp(\delta_j' q_{it})}, \qquad j = 1,\ldots,J, \qquad \delta_J = 0 \tag{7}$$

where q_i is a vector of firm-specific variables. Therefore, the overall likelihood function resulting from (2) and (7) is a continuous function of the vectors of parameters θ and δ, and can be written as:

$$ln\, LF\,(\theta,\delta) = \sum_{i=1}^{N} ln\, LF_i\,(\theta,\delta) = \sum_{i=1}^{N} ln\left\{\sum_{j=1}^{J} LF_{i|j}\left(\theta_j\right) P_{ij}\left(\delta_j\right)\right\} \tag{8}$$

Maximizing the above maximum likelihood function gives asymptotically efficient estimates of all parameters. The estimated parameters can then be used to compute (unconditional) posterior class membership probabilities for each technology, and (conditional) posterior class membership probabilities for both efficient and inefficient firms. The *unconditional* posterior probabilities can be first used to allocate each firm to a particular technology-class, and each firm can then be allocated to a fully-efficient or inefficient class *conditional* to the technology-class allocation.

3. Data

The data set used in this study is a balanced panel for the Norwegian distribution utilities for the years 2004 to 2011.[6] Norway presents a particularly suitable context and interesting case to implement the proposed methodology. First, Norway was among the first countries to introduce incentive-based regulation and efficiency benchmarking in 1997 (based on the DEA technique) in the electricity sector. Therefore, much of the managerial inefficiency of the networks has over time been removed. Second, Norway is the only country that explicitly incorporates quality of service in the form of the cost of non-delivered energy using estimated customer willingness-to-pay as an integrated part of the efficiency benchmarking exercise in incentive regulation of distribution networks. Third, unlike most countries, the Norwegian electricity sector consists of a

[6] Data for the period 2000-2003 is not used due to missing values in key variables, such as network size or cost of energy not supplied. Also, several firms were dropped due to lack of information on contextual variables. The data used is not a complete balanced panel because some observations still had unreasonable data, e.g. OPEX or CENS equal to zero, or negative values for new investment.

large, though slowly declining (due to mergers and acquisitions), number of network utilities which allows the use of more sophisticated analytical methods. Finally, the Norwegian energy regulator has systematically examined the effects of environmental factors such as geographic and weather conditions on cost and service quality performance of the utilities and has reflected these in the efficiency benchmarking models (see, e.g., Growitsch et al, 2012; Orea et al., 2012) . In particular, the regulator has analyzed (selected) a large (small) number of geographic and weather variables that might affect the firms' cost function.

We specify a simple cost model that uses, following the Norwegian benchmarking approach, *social costs* instead of total production costs as the dependent variable. In addition to operating expenses (OPEX), capital depreciation and its opportunity cost, our cost variable includes external quality costs. External quality costs i.e. cost of energy not supplied are calculated by multiplying the length of service interruptions with the estimated customer willingness-to-pay for an uninterrupted energy supply (CENS = cost of energy not supplied) plus the cost of network energy losses. All monetary variables are measured in 1000 NOK and in 2004 real terms.[7]

Regarding the cost drivers, our cost frontier includes three outputs (CUS = the number of final customers, NL = network length, and DE = delivered energy measured), and three input prices (PK = capital price. PE = energy price, and PL = labor price). While NL is measured in kilometers, DE is measured in megawatt-hours. On the other hand, whereas the labor price is the average salary in the electricity sector, and the price of capital is the sector regulator's (NVE) rent for cost of capital, the energy price is the average system price from NordPool Spot market. In addition to the economic variables we add a small number of environmental variables in our analysis. In particular, and following the Norwegian regulator, we include two weather variables (WIND = average reference wind, and WINDEX = average wind exposure), one geographic variable (DIS = distance to coast), and the percentage of overhead lines (OH) of total network length as additional cost drivers. As it is expected that the effect of environmental conditions on firms' costs might depend on the technological characteristics of the network, we have interacted the percentage of overhead lines with WIND, WINDEX and DIS.

The technological-class probabilities are also functions of OH in order to test whether other and unobserved technological differences are related to the percentage of overhead lines. Regarding firms' inefficiency, we use the percentage of overhead lines and network length variables (i.e. OH and NET) and the number of stations (ST) either as inefficiency determinants or determinants of being inefficient. The time trend is also included as a determinant of firms' inefficiency in order to check whether the Norwegian regulation system has been successful to promote gains in firms' performance.

[Insert Table 1]

4. Results

We estimate four alternative model specifications for empirical analysis. Table 2 shows the estimated coefficients of the cost models. The RSCFG model assumes that

[7] The consumer price index (CPI) has been used to deflate all monetary variables.

the inefficiency term follows a heteroscedastic half-normal distribution.[8] This empirical strategy not only allows us to get consistent estimates of both frontier coefficients and firm-specific inefficiency scores, but also to incorporate determinants of firms' inefficiency. The ZISF model is a panel-data and heteroscedastic version of the model introduced by Kumbhakar et al. (2013). Unlike these authors, the inefficiency term is again specified to be firm-specific. Although this model allows us to distinguish between fully efficient and inefficient utilities, it disregards the presence of unobserved differences in technology. In contrast, the LCSF model allows us to control for unobserved technological differences among firms. This model does not distinguish between fully efficient and inefficient utilities. In this sense, we hereafter state that the LCSF model does not control for unobserved behavioral differences among firms.[9] Finally, the NLC model takes into accounts both behavioral and technological differences among firms using the specification outlined in Section 2.[10]

As our results for firms technology and efficiency might depend on the empirical strategy followed to allow for unobserved differences in both technology and firms' performance, it is worth examining the goodness-of-fit of the four alternative specifications of our cost model. Given the estimated values of the likelihood function in Table 2, we can conclude that any model selection test (such the well-known AIC and BIC tests) would allow us to reject the RSCFG model in favour of the ZISF model. This implies that controlling for unobserved differences in firm inefficiency is important in our application. The RSCFG model would also be rejected in favour of the LCSF model, indicating that controlling for unobserved differences in firm technology and in the determinants of firm inefficiency is also important in our application. The previous three specifications would, in turn, be rejected in favour of the NLC model that allows us to include both types of unobserved heterogeneity. Based on these comparisons, we can conclude that the NLC model is preferred, and that results for firm technology and efficiency using the more restrictive RSCFG, LCSF and ZISF models should be interpreted with caution.

[Insert Table 2]

We estimate a (restricted) translog cost function that can be interpreted as a second-order approximation to the companies' underlying cost function. We therefore add the

[8] This model is labelled as RSCFG as it was introduced by Reifschneider and Stevenson (1991), Caudill and Ford (1993) and Caudill, Ford and Gropper (1995). The efficiency covariates in these papers are treated as determinants of the variance of inefficiency term.

[9] Here we are using an inaccurate language as the above statements are accurate when homoscedastic versions of the LCSF and ZISF models are estimated. In this case the LCSF only captures the unobserved differences in technology, whereas the ZISF model only captures unobserved differences in firm performance. We also estimated homoscedastic versions of our cost models, but the performed model selection tests rejected these more restrictive specifications in favor of their heteroscedastic counterparts, and results were robust to this issue.

[10] It should be noted that the heteroscedastic specification of the LCSF model allows estimation of the different coefficients associated with the determinant of the inefficiency term. In this sense, this model is able to control for unobserved differences in firms' performance as the ZISF model. However, while these differences in the LCSF model have only to do with the magnitude of the inefficiency term, the behavioral differences captured in the ZISF model have also to do with the existence or absence of this term. Therefore, our heteroscedastic ZISF model is able to capture two subtle aspects of firms' inefficiency. The common-technology assumption used in the ZISF model is in turn relaxed in the NLC model.

input prices to our cost function because they do not vary across utilities, but vary over time. This precludes using quadratic terms and interactions with these variables. As usual, homogeneity of degree one in prices is imposed by normalizing cost, labour price and capital price with the energy price. Each explanatory variable is measured in deviations with respect to its mean, such that the first-order coefficients in Table 2 can be interpreted as the cost elasticities/derivatives evaluated at the sample mean.

In general, all models perform quite well as all of the first-order coefficients have the expected sign and their magnitudes are also reasonable from a theoretical point of view. The first-order coefficients of all three outputs are positive and statistically different from zero. A similar observation can be made about the coefficients of input prices, which are also positive and statistically significant. The sum of the first-order coefficients of customer numbers and energy delivered is less than one, indicating that electricity distribution networks have natural monopoly characteristics when additional network is not required to meet additional demand.[11] The frontier coefficient of OH is negative and statistically significant in all models, indicating that the larger the percentage of overhead lines, the smaller is the total costs. This result indicates that, although underground cables are probably negatively correlated with CENS and reduce OPEX, they are more costly and increase the total costs. The LCSF and NLC models in turn indicate that the technology in this industry exhibits some heterogeneity. Although the output elasticities evaluated at the sample mean are similar in the two classes in both models, the technological heterogeneity can be particularly appreciated when we compare the second-order coefficients of the three outputs.

The estimated coefficients for the weather variables (WIND and WINDEX) and the distance to coast geographic variable (DIS) suggest that there are notable differences among the utilities in costs attributed to different environmental conditions. It is worth mentioning that most coefficients of OH interacting with these three contextual variables are statistically significant, indicating that the effect of any of the weather variables is larger when the importance of overhead lines increases. While the coefficients of WIND are negative (but rarely significant), the effect of WINDEX on firms' costs is mostly significant and positive indicating that a higher exposure to wind implies larger costs to the distribution networks. On the other hand, the coefficient of the distance to the coast is always negative. This might indicate that inland weather conditions are, as expected by the regulator, likely to be less severe than coastal weather conditions.

In addition to the frontier parameters, Table 2 displays the coefficients of the variables that are related to the inefficiency term, as determinants of either the inefficiency term ($u_{it|j}$) or the probability of being inefficient ($\Pi_{i|j}$). Several results, most of them common to the four alternative specifications of our cost model, are worth mentioning. First, the negative sign for the time trend also suggests, although not always significant, that the regulation system in Norway has been able to encourage firms to improve their performance during the sample period. The improvement in firms' performance is clear in Figure 1, where we depict the temporal evolution of the average efficiency scores that are obtained using our four specifications.[12]

[11] Also Salvanes and Tjøtta (1998) find evidence of natural monopoly characteristics in the Norwegian electricity distribution networks.

[12] This figure will be further examined later on.

[Insert Figure 1]

Second, we obtain a negative coefficient for NL in both RSCFG and LCSF models indicating that larger utilities tend to be more efficient than smaller utilities. In contrast, the positive coefficients of ST and OH indicate that it is more difficult to manage firms with many stations and longer overhead lines. It is interesting that, the aforementioned efficiency determinants do not appear to be significant in one of the classes of the LCSF model. Hence, we do not find evidence that these technology features make the operation of the distribution networks more costly. They are also not statistically significant when we move to the ZISF and NLC models that distinguish between inefficient and fully efficient firms.

While the technological variables included as efficiency determinants are still significant in the ZISF model, the probability of being inefficient does not depend on any covariate. This indicates that each firm has the same probability of being fully efficient, and they cannot use their size or other characteristics of their network as reason for not being 100% efficient. A similar comment can be made regarding one of the classes of the NLC model as the probability of being inefficient in this class does not depend on any covariate. In contrast, the probability of being inefficient in the other class decreases (increases) with network size (number of stations). These two outcomes therefore reinforce the previous results NL and ST were only included as determinants of firms' inefficiency.

We compare in Table 3 the sample partition using our preferred NLC model that controls for unobserved differences in technology and firm behaviour with those obtained using the more restrictive LCSF and ZISF models that only capture differences in one of the above-mentioned dimensions, and hence their sample partitions should be interpreted with caution as unobserved differences in technology might be labelled incorrectly as differences in behaviour, and vice versa. Compared to our preferred model that allocates a 40 and 60% of the observations to Class 1 and Class 2 respectively, the LCSF model slightly balances this allocation as the smaller (larger) class now includes a 44% (56%) of the sample. Note as well that, while all firms in the LCSF model are inefficient to some extent, the set of inefficient firms in the second class of the NLC model only represents a 43% of all observations allocated to this class.[13] Therefore, the efficiency scores of these firms in the LCSF model are expected to be seriously biased.

The ZISF model distinguishes between both types of firms. However, as it ignores the existence of unobserved differences in technology, it only identifies 42 firms as fully efficient firms that represent a 35% of the observations. The NLC model identifies a larger number of fully efficient firms (i.e. 48) that represent a 40% of the sample. In other words, in the ZISF model, some firms are wrongly labelled as inefficient because their inefficiency scores have been computed using a common cost frontier to all firms and common efficiency coefficients (two assumptions that are rejected in our application). In addition, other firms in the ZISF model are wrongly labelled as fully efficient as only 11 of the fully efficient firms of the ZISF model are identified as fully efficient using our preferred NLC model.

[13] This percentage increases up to 85% in the first class.

[Insert Table 3]

Figure 1 depicts the average efficiency scores of *all* firms in the case of the RSCFG and LCSF models - where there are no fully efficient firms - and the average efficiency scores of only those firms that are not fully efficient in the ZISF and NLC models. Our efficiency estimates are high, ranging from 87 to 97%. Similar figures are obtained in Miguéis et al. (2012) using a DEA method for the period 2004 to 2007, and in Growitsh et al. (2012) using a SFA approach for the 2001-2004 period. The latter authors also found that efficiency estimates strongly depend on the empirical strategy to control for observed and unobserved heterogeneity. The average efficiency level of the inefficient firms in the ZISF model is 87%. The estimated efficiency level of these firms in the RSCFG model is much higher, 97%, indicating that ignoring the existence of two types of firms (i.e. inefficient vs. fully efficient) tends to bias upwards the efficiency scores of those firms that are not fully efficient. The same comment can be made regarding the inefficient firms of the second class of the NLC model as their average efficiency level (91%) is far from that estimated (96%) using the RSCFG model.[14]

Table 4 shows the coefficients of correlation between pairs of efficiency scores obtained using our alternative specifications of the cost model. The table provides the coefficients of correlation using all observations in our sample or the observations allocated to particular technological or behavioural classes. The computed coefficients are often quite low, indicating that ignoring unobserved differences either in technology or in firms' behaviour might seriously bias the ranking of firms in accordance to their estimated efficiency levels. For instance, the coefficient of correlation between the RSCFG and LCSF models is only about 55% (49% using our preferred NLC model). This correlation declines up to 33% if we only use the observations belonging to the second class of the LCSF model. The correlation between LCSF and NLC models is relatively large, but far from 100% in the case of the second class. On the other hand, the coefficient of correlation between the ZISF model and other three models is lower than 50%. Regarding our preferred NLC model, the coefficient of correlation is only about 42%. This correlation drops up to 25% if we only use the observations belonging to the first class of this model.

[Insert Table 4]

5. Conclusions

In many countries, the electricity regulators aim to measure the network utilities' efficiency against best practice performance. Errors in identifying the correct benchmark firms or measuring their efficiency has important financial implications for all the less efficient firms against which they are compared. For this reason, obtaining reliable measures of firms' inefficiency often requires controlling for unobserved differences in the firms' technology or in the geographical and weather conditions under

[14] However, the average efficiency level of the inefficient firms in the first class of the NLC model is not seriously biased as the efficiency score using the RSCFG model is of similar magnitude on average.

which each utility operates. Several well-known latent class stochastic frontier models now allow researchers (and regulators) to account for the above-mentioned technology heterogeneity.

The regulators would also be interested in identifying the fully efficient network utilities that can be used as “reference networks” for other (comparable) utilities. The ‘zero inefficiency stochastic frontier’ model introduced recently by Kumbhakar et al. (2013) can be used to achieve this aim. However, this model does not control for unobserved differences in technology or environmental conditions.

The present paper extends the ZISF approach to take into account the heterogeneity in firms’ technology as well as in their environmental conditions. We take advantage of the differences in the nature of both sources of unobserved heterogeneity to develop a *nested* latent class (NLC) model. The behavioral differences are modeled using two ZISF models that are in turn nested in a latent class structure that aims to capture unobserved differences in technology or environmental conditions. To our knowledge, the present study is the first to propose a *nested* latent class model to distinguish between fully efficient and inefficient firms when the underlying technology is heterogeneous. The present paper study is also the first to introduce the zero-inefficiency approach in a regulatory context.

We illustrate the proposed models with an application to the Norwegian distribution network utilities for the period 2004-2011. Following the Norwegian benchmarking approach, four alternative specifications of a cost model are estimated, where a *social* measure of firms’ costs is used as dependent variable. In addition to the traditional output and input prices, we have added a number of relevant environmental variables as cost drivers in our analysis, as well as the percentage of overhead lines, i.e. the most important characteristic of firms’ networks.

In general, all models perform quite well as the cost elasticities evaluated at the sample mean have the expected signs and their magnitudes are quite reasonable from a theoretical point of view. However, based on the values of the estimated likelihood functions, we concluded that the NLC model is the preferred model, and that the results for the firms’ technology and efficiency using the more restrictive RSCFG, LCSF and ZISF models should be interpreted with caution.

Overall our results suggest the presence of notable differences among utilities in costs attributed to different weather conditions and locations. On the other hand, we have found that the regulation framework in Norway has been able to encourage firms to improve their performance during the sample period. We have also obtained evidence about the relationship between firms’ inefficiency and some characteristics of their networks. In particular, most of our specifications suggest that larger networks tend to be more efficient than smaller ones, and that it is more difficult to manage firms with more numerous stations and overhead lines.

We have found that our preferred model and the more restrictive LCSF and ZISF models split the sample into groups in rather different ways. Therefore, the efficiency scores in both LCSF and ZISF models are expected to be somewhat biased. We have also found that our NLC model identifies a larger number of fully efficient firms than the ZISF model, indicating that some firms in the ZISF model are wrongly labelled as inefficient. In addition, other firms are wrongly labelled as fully efficient by the ZISF model.

Our efficiency estimates are somewhat high and similar to those obtained in the literature using both parametric and non-parametric approaches. However, we have found that the efficiency scores of inefficient firms tend to be biased upwards if we do not distinguish between inefficient and fully efficient networks. The computed coefficients of correlation between pairs of efficiency scores are often quite small. Overall, our results indicate that the efficiency scores of our models not only might be biased if we ignore unobserved differences in technology (see previous literature), but also if we are not able to separate the fully efficient networks from the inefficient networks.

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Table 1. Descriptive statistics of the data.

	Mean	*St.Dev.*	*Min*	*Max*
COST	77700.02	132024.01	2343.05	793884.71
PK	0.06	0.01	0.05	0.08
PL	163.67	16.99	139	189.5
PE	331.02	73.94	234.6	436.3
CUS	16753.17	33229.86	348	182746
ST	809.9	1381.62	29	9428
DE	432406.39	875129.47	6915	5200000
NL	661.83	1036.34	30	6542
WIND	25.5	2.44	22	31
WINDEX	5.28	1.04	2.71	8.13
DISTANCE	53824.79	55649.33	190.96	196377
OH	0.68	0.19	0.14	0.97

Table 2. Parameter estimates.

	RSCFG		ZISF		LCM				NESTED LCM			
Parameters	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Cost frontier function					Class 1		Class 2		Class 1		Class 2	
Intercerpt	10.554	901.9	10.493	1923.6	10.454	699.5	10.623	1220.8	10.444	541.2	10.611	1313.2
lnCUS	0.335	9.963	0.377	18.741	0.329	10.227	0.370	15.851	0.373	6.744	0.384	11.380
lnNL	0.465	26.567	0.504	42.258	0.499	18.268	0.509	34.275	0.511	15.429	0.479	36.922
lnDE	0.116	3.988	0.063	3.392	0.132	4.199	0.087	4.188	0.093	2.232	0.088	2.854
$0.5 \cdot lnCUS^2$	0.176	1.067	0.268	2.486	-1.043	-3.327	0.035	0.227	-0.961	-1.942	0.007	0.053
$0.5 \cdot lnNL^2$	-0.004	-0.085	-0.108	-4.342	-0.246	-6.008	0.169	4.302	-0.254	-2.732	0.249	5.920
$0.5 \cdot lnDE^2$	0.071	0.884	0.088	1.784	-0.256	-1.115	0.018	0.151	-0.149	-0.434	0.007	0.061
lnCUS·lnNL	-0.041	-0.559	0.008	0.195	0.689	7.296	-0.018	-0.269	0.764	6.441	-0.070	-1.273
lnCUS·lnDE	-0.115	-1.007	-0.201	-2.648	0.580	2.233	0.045	0.352	0.473	1.152	0.084	0.711
lnNL·lnDE	0.047	0.775	0.081	2.309	-0.489	-6.537	-0.134	-2.449	-0.550	-6.112	-0.144	-2.975
lnPK	0.187	7.300	0.268	7.978	0.235	5.100	0.199	5.986	0.226	3.932	0.200	6.967
lnPL	0.764	17.398	0.670	9.470	0.678	8.895	0.769	11.898	0.687	7.743	0.771	12.301
OH	-0.289	-6.162	-0.352	-10.186	-0.442	-7.101	-0.443	-5.934	-0.470	-7.048	-0.202	-4.116
WIND	-0.005	-1.602	-0.003	-1.792	0.002	0.676	0.005	1.649	0.000	-0.039	0.002	0.568
WINDEX	0.019	2.620	0.021	4.720	-0.035	-4.963	-0.007	-1.071	-0.034	-3.323	0.000	0.008
lnDIS	-0.015	-3.741	-0.009	-3.938	-0.017	-5.127	-0.018	-5.502	-0.025	-4.401	-0.017	-3.865
OH·WIND	-0.094	-5.300	-0.108	-9.720	-0.116	-9.518	-0.170	-6.892	-0.140	-6.067	-0.128	-6.392
OH·WINDEX	0.225	6.241	0.248	11.359	0.292	8.545	0.413	5.169	0.344	7.260	0.340	4.239
OH·lnDIS	-0.101	-4.855	-0.105	-7.191	-0.032	-1.276	-0.047	-1.744	-0.014	-0.346	-0.022	-0.602
Random noise												
Intercept	-2.080	-82.14	-2.484	-77.23	-2.618	-65.87	-2.542	-66.31	-2.693	-49.031	-2.628	-62.49

Note: shadowed coefficients indicate they are significant at 10%.

Table 2. Parameter estimates (Cont.)

	RSCFG		ZISF		LCSF				NLC			
Parameters	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Inefficiency term												
Intercept	-1.743	-6.053	-1.696	-16.597	-1.355	-2.540	-3.567	-9.848	-1.242	-1.824	-1.978	-7.341
t	-0.538	-2.465	-0.020	-0.946	-0.607	-1.790	-0.040	-0.911	-0.511	-1.574	-0.057	-1.495
lnNL	-1.866	-1.947	-0.805	-4.900	-0.512	-0.653	-3.795	-3.884	0.036	0.031	0.125	0.140
lnST	1.950	1.990	0.678	3.911	0.682	0.894	2.538	3.283	0.218	0.191	-0.376	-0.490
OH	0.661	0.544	0.483	1.922	-0.282	-0.288	4.933	3.887	0.487	0.414	1.526	1.773
Zero inefficiency-class probabilities												
Intercept			0.664	2.151					2.537	0.700	-0.080	-0.120
lnNL			0.072	0.049					-3.305	-0.287	-8.110	-2.160
lnST			-0.419	-0.306					2.532	0.243	7.342	2.049
OH			-0.955	-0.522					-5.594	-0.468	-8.797	-1.598
Technology-class probabilities												
Intercept					-0.259	-1.326			-0.442	-2.230		
OH					-2.748	-1.706			-2.360	-1.354		
Obs.	957		957		957				957			
LF	612.761		730.02		931.018				971.594			
Mean LF	0.640		0.763		0.973				1.015			
Parameters	25		29		52				60			
AIC	-1175.52		-1402.06		-1758.04				-1823.19			
BIC	-1053.93		-1261.01		-1505.12				-1531.36			

Note: shadowed coefficients indicate significance at 10%.

Table 3. Sample partition

	NLC		LCSF		ZISF
	Class 1	Class 2	Class 1	Class 2	
SFA	327	249	422	535	623
ZI	56	325	0	0	334
SFA+ZI	383	574	422	535	957
All	957		957		957

Table 4. Efficiency scores. Coefficients of correlation

	RSCFG	**LCSF**	**ZISF**
LCSF			
All	0.55		
Class 1	(0.94)		
Class 2	(0.33)		
ZISF			
All	0.30	0.46	
SFA	(0.43)	(0.62)	
NLC			
All	0.49	0.77	0.42
Class 1 + SFA	(0.89)	(0.98)	(0.25)
Class 2 + SFA	(0.33)	(0.78)	(0.71)

Figure 1. Annual efficiency scores