Using Spatial Econometrics to Mitigate Omitted Variables in Stochastic Frontier Models: An Application to Norwegian Electricity Distribution Networks *

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Abstract

An important methodological issue in efficiency analysis for incentive-based regulation of utilities is to account for the effect of unobserved cost drivers such as environmental factors. We combine a spatial econometric approach with stochastic frontier analysis to control for unobserved environmental conditions when measuring efficiency of electricity distribution utilities. Our empirical strategy relies on the geographic location of firms as a source of information that has previously not been explored in the literature. The underlying idea is to utilise data from neighbouring firms that can be spatially correlated as proxies for unobserved cost drivers. We illustrate our approach using a dataset of Norwegian distribution utilities for the 2004-2011 period. We find that the lack of information on weather and geographic conditions can be compensated with data from surrounding firms. The methodology can also be used in efficiency analysis and regulation of other utilities sectors where unobservable cost drivers (such as environmental variables) are important, e.g. gas, water, agriculture, fishing.

Keywords: spatial econometrics, stochastic frontier models, environmental conditions, electricity distribution networks.

JEL classification: D24, L51, L94.

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1. Introduction

Since the 1990s many network utilities are incentive regulated with the aim of improving their operating and investment efficiency as well as ensuring that consumers benefit from the gains. 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). As regulators reward or penalise firms using relative efficiency measures, obtaining reliable (and fair) measures of firms' efficiency requires controlling for the different environmental conditions under which each utility operates. This is particularly important in the case of incentive regulation and benchmarking of electricity, gas, and water networks where the results of efficiency analysis have important financial implications for the firms.

However, there are many characteristics of the utilities sector (e.g., geography, climate or network characteristics) that affect production costs but which are unobserved. Statistical methods have recently been developed to address this issue. For instance, the True Fixed/Random Effects models introduced by Greene (2005) capture the unobserved heterogeneity through a set of firm-specific intercepts. This approach only uses the temporal (i.e. within) variation contained in the data to estimate the coefficients of other cost drivers. As we will show later, this is quite problematic in our application because many important determinants of utility costs such as the energy delivered or number of customers, are persistent or slow changing variables. On the other hand, possible differences among utilities associated with their use of different technologies are also often addressed using simple sample selection procedures, latent class models, random coefficients models, or semiparametric models.

In this paper we advocate using a different empirical strategy to account for the unobserved differences in environmental conditions among electricity distribution networks based on their geographic location. The latter presents an invaluable source of information that has been ignored in the literature which up to now was dedicated only to estimating network technology or the measurement of their relative inefficiency. Indeed, as many unobservable variables are likely to be spatially correlated, an alternative empirical strategy emerges. Our spatial model is prompted from the fact that any (relevant) unobservable cost driver should be correlated with firms' costs, a variable that is observable by the researcher/regulator. The underlying idea of our empirical proposal is to use (surrounding) firms' costs as proxies of the *unobserved* cost drivers that are likely to be spatially correlated, such as weather and geographic conditions, population structure, electricity demand patterns, input prices, etc.

Regarding other popular approaches in the SFA literature to deal with omitted variables such as panel data, random coefficient and latent class models, it is surely out of the scope of the paper to compare our approach with all other possible methods. As all approaches have advantages and disadvantages and rely on different assumptions, the results obviously differ in the same fashion as a latent class model provides different results than a random coefficients model or a panel data estimator. Note that a common feature of the above approaches is that they ignore the spatial structure of the data. This distinctive feature makes the paper relevant for researchers working in energy economics and other network industries. Moreover, our spatial-based approach can be used in panel data settings. Indeed, as they utilise different (spatial vs. temporal) dimensions of our data, they can be viewed as *complementary* approaches to deal with unobserved variables. In this sense, we also examine whether there are spatial spillovers once we control for firm-specific but time-invariant effects using the true fixed and random effects stochastic frontier models introduced by Greene (2005) and Mundlak (1978)-type specifications of our pooled SFA model.

The main contribution of this paper is to link efficiency analysis methods addressing unobserved heterogeneity with spatial econometrics methods commonly employed to examine spatial interactions across regions.[1] To the best of our knowledge, our paper is among the first to apply spatial econometrics in efficiency analysis using firm level data. There are no major systemic economic or technical reasons that the conditional cost of a firm (i.e. given its own output and price variables), is affected by those of adjacent firms to any significant degree.[2] In this context, the estimated spillover effects in our model are expected to be spurious, i.e. only caused by omitted variables. This in turn implies that our spatial specification introduces constraints on the parameters, instead of the traditional spatial model. Moreover, the spatial econometric models are used (interpreted) here as a means to control for unobserved heterogeneity in a standard SFA model measuring firms' inefficiency.[3]

Empirical analysis of efficiency of distribution utilities have, since the deregulation and unbundling of the electricity sector, led to a number of studies. Such studies initially focused on international comparisons of efficiency and productivity

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[1] Since the seminal contribution by Anselin (1988) introducing the spatial effects to econometric models, researchers have developed several spatial econometric models and estimation methods (see, e.g, Kelejian and Prucha, 1998, 2010 and Baltagi and Liu, 2011). For comprehensive reviews of this literature, see Arbia (2014) and Elhorst (2014). Regarding our spatial approach, it should be pointed out that this literature uses spatial information not only to examine economic-based (causal) spatial spillovers, but also to deal with omitted variables that are spatially correlated (see, e.g., LeSage and Pace, 2009). As Elhorst (2010) point out a model with spatial autocorrelation in not observable variables (the so-called SEM) can be expressed as a Spatial Durbin Model (SDM) with constraints, which is the idea behind our proposal. In our case, we do not expect causal spatial spillovers and the unobservable spatial spillovers can be estimated using a constrained Spatial Durbin Model.

[2] We are thankful to the NVE staff in charge of network regulation who could confirm this point.

[3] See Glass et al (2016) for a recent application with spatial effects in SFA settings.

(e.g., Hattori et al., 2005) then later extended their focus to include quality of service in the analysis (e.g., Yu et al., 2009). More recently the scholarly focus has been on the efficiency and productivity development of the networks under regulation (Dimitropoulos and Yatchew, 2017) and how to take the heterogeneity among the firms into consideration (Kumbhakar and Lien, 2017; Orea and Jamasb, 2017).[4] The present paper falls into latter category of studies.

The geographic/weather variables might either have a direct effect on costs of firms if a deterioration in the environment technically requires the use of more (expensive) inputs to provide the same level or quality of service, or an indirect effect on firms' cost through inefficiency if, for instance, it is more difficult to operate in regions with adverse weather conditions. Regardless of whether they have a direct or indirect effect on costs, firms operating in regions with unfavourable weather conditions should not be penalised for their relative poor performance because of environmental conditions that are beyond their control.

Therefore, some regulators control for these conditions in benchmarking or revenue cap exercises and often use simpler empirical strategies than in the present paper as they also aim to gain acceptance from stakeholders. For instance, cost data of firms is often purged by regulators (e.g., by Ofgem in the UK) in order to control for the effect of adverse environmental conditions prior to using them in benchmarking exercises. Also, the Norwegian regulator uses advanced econometric analysis of the data in order to enhance their understanding of the features of the firms and the sector prior to benchmarking analysis.

[4] See also Kopsakangas-Savolainen and Svento (2011), Growitsch et al (2012), and Kumbhakar et al (2015).

Other regulators directly examine in DEA or SFA frontier models the role and significance of variables related to cables, connections and meters, substations and transformers, towers, decentralized generation, injection points, population changes, soil types, altitude differences, urbanization, areas etc. The Norwegian regulator has used environmental variables such as forest, snow and wind/coast as additional outputs in first-stage DEA analysis followed by second-stage analyses to correct the calculated DEA efficiency scores for three environmental factors: interfaces, islands and distributed generation (see Frontier Economics, 2012). The German energy regulator undertakes an extensive second-stage analyses to determine whether some of more than 200 non-included variables should be included in the analysis. The second-stage analyses are typically conducted by regressing the first-stage efficiency scores on environmental factors in stage two, or simply using graphical inspection or non-parametric tests for ordinal differences (see Agrell and Bogetoft, 2013). It is noteworthy that these methods require collecting costly environmental data, while our spatial-based approach uses the already available cost data.

The next section presents the spatial econometric model that allows to use data from surrounding firms as proxies for the omitted, but spatially correlated, cost drivers. Section 3 summarizes the empirical strategy used in this paper to estimate a SFA model that includes a generated variable as an additional regressor. Section 4 dwells on the data used in the empirical analysis and its sources. In Section 5 we estimate a spatial econometric model to compute a proxy variable that will stand in for spatially correlated omitted variables. We then estimate a standard SFA model to estimate the inefficiency of the firms and to conduct a robustness analyses using the available environmental data and panel data estimators. Finally, Section 6 presents the conclusions.

2. A Cost Model with (Unobserved) Spatially Correlated Variables

This section develops a micro-level spatial econometric model that allows us to control for unobserved environmental conditions that are likely to be spatially correlated when we use a cost function to estimate the firms' technology. Let us first assume that the firms' cost can be modelled entirely by using the following cost equation:

$$lnC_{it} = \beta X_{it} + Z_{it} + v_{it} + u_{it} \tag{1}$$

where *i* stands for firms, *t* stands for periods, C_{it} is a measure of firms' cost, and X_{it} is a vector of *k* observable cost drivers such as the number of customers, energy delivered, network length, and labour and capital prices and Z_{it} represents the *unobserved* cost drivers. This equation includes two error terms, v_i and u_i. While the former term is a symmetric error term measuring pure random shocks, the latter term is a non-negative error term measuring firms' inefficiency.

As is often the case with observed data,[5] some unobserved cost drivers are also likely to be spatially correlated. In line with the literature on spatial econometrics, the spatial correlation can be modelled as follows:

$$Z_{it} = \lambda W_i Z_t \tag{2}$$

Here Z_t is a vector of Nx1 unobserved cost drivers, W_i is a known 1xN spatial weight vector with elements that are equal to zero if a particular firm j is not a neighbour of firm i and equal to one if the two firms are neighbours – i.e. the service

[5] For illustration purposes, we show several auxiliary regressions in Appendix A where we use equation (2) to examine the degree of spatial correlation for some of our observed cost drivers. As expected, we find that all variables are spatially correlated to some extent. Therefore, it is reasonable to expect some degree of spatial correlation also in unobserved determinants of firms' costs.

areas of the electricity distribution utilities are adjacent. The term λ is a coefficient that measures the degree of spatial correlation between the unobserved cost drivers.

Equation (1) cannot be *directly* estimated as Z_{it} is an omitted variable that, if ignored, will bias our efficiency scores because it will be captured by the noise or inefficiency terms. We thus propose using an *indirect* approach to estimate (1). The underlying idea behind our proposal is that we could use the (purged) costs of surrounding firms as proxies for Z_{it} if the unobserved cost drivers are spatially correlated. Hence, our empirical strategy takes advantage of the spatial proximity of the networks.

First, we proceed to replace Z_{it} in equation (1) with equation (2). Thus, equation (1) can be alternatively rewritten as follows:

$$lnC_{it} = \beta X_{it} + \lambda W_i Z_t + v_{it} + u_{it} \tag{3}$$

This equation again cannot be estimated as the vector Z_t is not observed. However, note that, by rearranging equation (1), we can obtain:

$$Z_{it} = lnC_{it} - \beta X_{it} - v_{it} - u_{it} \tag{4}$$

This equation simply indicates that, if β and both errors terms were observable, Z_{it} should be correlated with a purged cost measure. In this sense, the purged costs can be interpreted as an “observable” counterpart of Z_{it}. We then replace Z_t in equation (3) with its “observable” counterpart, obtaining the following model:

$$lnC_{it} = \beta X_{it} + \lambda W_i lnC_t - \lambda\beta W_i X_t + \varepsilon_{it} \tag{5}$$

where

$$\varepsilon_{it} = h_{it} + v_{it} + u_{it} \tag{6}$$

and

$$h_{it} = -\lambda W_i(v_t + u_t) \tag{7}$$

$C_t = (C_{1t}, C_{2t}, \ldots, C_{Nt})$ is an Nx1 vector of the observed costs of the firms, $X_t = (X_{1t}, X_{2t}, \ldots, X_{Nt})$ is an Nx1 vector of firms' explanatory variables, and v_t and u_t are again Nx1 vectors of the firms' random terms.

Several comments are in order with respect to this specification of the firms' cost. First, if we compare the original model in (1) and the new specification in (5)-(7), we notice that:

$$Z_{it} = \hat{Z}_{it} + h_{it} \tag{8}$$

where

$$\hat{Z}_{it} = \lambda W_i lnC_t - \lambda\beta W_i X_t \tag{9}$$

Equation (8) simply shows that the unobserved cost driver Z_{it} can be decomposed into a *predictable* component $\hat{Z}_{it}$ (i.e. the portion of Z_{it} that can be predicted with the data of surrounding firms), and an *unpredictable* component h_{it}. The latter term can in turn be interpreted as a measurement error term. As the inefficiency term is non-negative, h_{it} is negative on average, and hence our predicted $\hat{Z}_{it}$ tends to *overestimate* the true value of the omitted variable Z_{it}.

Second, in contrast to equation (1), equation (5) is a cost model that now includes a set of spatially lagged variables, i.e. $W_i lnC_t$ and $W_i X_t$. Therefore, equation (5) resembles a conventional spatial econometric model. However, in our model, only one additional coefficient is estimated, and the coefficient of the spatially lagged dependent variable should not be interpreted as the effect of neighbours' costs on the cost of a particular firm. Rather, λ is measuring the spatial correlation between the unobserved or omitted variables in our sample. Our empirical strategy relies on the statistical significance of this coefficient as we are unable to use the data of surrounding firms to obtain a proxy for Z_{it} if λ =0. Therefore, it is important for our empirical strategy to test whether this parameter is statistically significant.

On the other hand, it is worth mentioning that our spatial specification of firms' costs in equation (5) is similar to the Durbin Stochastic Frontier (SDF) model introduced recently by Glass et al. (2016) in which they propose estimating the following model:

$$lnC_{it} = \beta X_{it} + \lambda W_i lnC_t + \theta W_i X_t + \tilde{\varepsilon}_{it} \tag{10}$$

where $\tilde{\varepsilon}_{it} = v_{it} + u_{it}$. It is easily observable that our spatial model in (5)-(7) and the SDF model differ in two important aspects. First, the set of parameters θ in the SDF model is not restricted to be equal to $-\lambda\beta$. In this sense, our spatial model in (5) is nested in the SDF model. However, no spatially correlated omitted (random) variables are explicitly modelled in the SDF model. Although Glass et al. (2016) state that their approach can be "easily adapted to develop a spatial error stochastic frontier model", they do not include a spatial structure in the error term. In terms of our spatial model, this is equivalent to using a zero h_{it} term. The mentioned differences simply indicate that our spatial model and the SDF model are non-nested. This is because the spatial spillovers in both models are of different nature. While the spatial spillovers in Glass et al. (2016) have an economic or causal interpretation, the spatial spillovers in our spatial model are simply associated with the omitted variables. Hence the spatial effects estimated in our model lack an economic interpretation as they are completely "spurious".

We next discuss how to estimate our spatial SFA model taking into account that ε_{it} includes two spatially correlated error terms (see equations 6 and 7). If the spatial error correlation involves a one-sided error term, this does not prove to be an easy task.

In order to gain an idea of this, we rewrite again our spatial model in equations (5)-(7) as follows:

$$lnC_{it} = [\beta X_{it} + \lambda W_i lnC_t - \lambda\beta W_i X_t] + \Delta v_{it} + \Delta u_{it} \tag{10}$$

where

$$\Delta v_{it} = v_{it} - \lambda W_i v_t$$

$$\Delta u_{it} = u_{it} - \lambda W_i u_t$$

It should be pointed out that while Δv_{it} follows a complex multivariate normal distribution, the distribution of Δu_{it} (i.e. the difference of, say, two independent one-sided error terms) is not known, and this prevents using a ML estimator (see Wang, 2003; and Wang and Ho, 2010). As a fully ML specification of the model is not feasible in our case, in the next section we propose a simple procedure that includes $\hat{Z}_{it}$ as an additional regressor, and controls for h_{it} by using a linear function of its determinants.[6]

3. Stochastic Frontier Model with Generated Regressor

Our estimation strategy uses a two-step procedure, advocated for various models in Kumbhakar and Lovell (2000). In the first step, equation (5) are estimated ignoring the (spatial and frontier) structure of the error term, ε_{it}. The degree of spatial correlation of omitted variables (i.e. parameter λ) and other coefficients of the cost frontier are estimated using the Generalized Method of Moments (GMM) because the spatially lagged dependent variable is endogenous. It is worth noting that, as in previous literature on both spatial and SFA models using two-stage procedures, the first-step

[6] Areal et al (2012) proposed a comprehensive Bayesian procedure involving the use of a Gibbs sampler and two Metropolis-Hastings steps to estimate the spatial dependence of firms' efficiency.

GMM residuals are not used here to estimate the *complete* structure of the overall term ε_{it} because its distribution is not known. Instead, the first-step estimates aim to obtain a prediction of Z_{it} that is used in a second regression as an additional explanatory variable.

In the second step, the following specification of firms' cost in equation (1) is estimated:

$$lnC_{it} = \beta X_{it} + \gamma_{it}\hat{Z}_{it} + v_{it} + u_{it} \tag{11}$$

where

$$\gamma_{it} = \frac{Z_{it}}{\hat{Z}_{it}} = \frac{\hat{Z}_{it}+h_{it}}{\hat{Z}_{it}}, \tag{12}$$

In order to obtain (11), we have replaced the original omitted variable in (1) with its predicted counterpart using equation (9). The ratio γ_{it} can be interpreted here as a firm-specific and time-varying coefficient, that tends to be less than unity because h_{it} is on average less than zero. In our empirical application, we will first estimate a common γ value for all firms, so that the final cost model estimated in our paper is:

$$lnC_{it} = \beta X_{it} + \gamma\hat{Z}_{it} + v_{it} + u_{it} \tag{13}$$

where the common γ coefficient can now be interpreted as the average value of γ_{it}. The fact that h_{it} does not appear in (13) does not imply that we are (completely) ignoring the spatial part of the composed error term ε_{it} in (10) because h_{it} is roughly captured (at least its average value) by an estimate of γ that will depart from the theoretical value of unity.

It should be pointed out, however, that γ_{it} is a function of h_{it}, which on average depends on the number of adjacent firms (i.e. W_i) and the inefficiency level of adjacent firms (i.e. the magnitude of u_t). Therefore, more accurate estimates can be obtained if we model γ_{it} as a linear function of the number of adjacent firms (N_i) and, if the SFA model is heteroskedastic, the spatial lags of all determinants of firms' inefficiency ($W_i q_{it}$), that is:

$$\gamma_{it} = \gamma_0 + \gamma_1 N_i + \gamma_2 W_i q_{it} \tag{14}$$

Therefore, our preferred specification of the second-step model is:

$$lnC_{it} = \beta X_{it} + (\gamma_0 + \gamma_1 N_i + \gamma_2 W_i q_{it})\hat{Z}_{it} + v_{it} + u_{it} \tag{15}$$

Finally, note that, conditional on $\hat{Z}_{it}$, our new specification of firms' cost has the structure of a conventional SFA model, so it can be estimated using MLE techniques once the distributional assumptions concerning the noise and inefficiency terms are made. As is common in the SFA literature, we will assume that $v_{it} \sim N(0, \sigma_v)$ and the inefficiency term are independently distributed across firms and over time, and follows a half-normal distribution, i.e. $u_{it} \sim N^+(0, \sigma_u)$.[7] As anticipated above, this model can accommodate heteroskedastic inefficiency terms simply by making the variance of σ_u functions of some exogenous variables (q_{it}). Regardless of whether the model is homoscedastic or not, efficiency scores are estimated for each firm using the conditional distribution of u_{it} given v_{it}+ u_{it} introduced by Jondrow et al. (1982).

4. Data

We apply our empirical strategy to a balanced set of panel data for the Norwegian distribution utilities over the years 2004 to 2011. The data used in this study was obtained from the sector regulator, the Norwegian Water Resources and Power Directorate (NVE). We specify a simple cost model that uses, in line with the Norwegian benchmarking approach, *social costs* (SCOST) as the dependent variable. In

[7] The stochastic frontier model can accommodate heteroskedastic inefficiency terms simply by making the variance of σ_u functions of some exogenous variables.

addition to operating expenses (OPEX), capital depreciation and its opportunity cost, the social costs variable also includes the cost of network energy losses, and the cost of energy not supplied (CENS) to different user groups due to service interruptions. The cost of network energy losses is obtained by multiplying the units of network energy losses with the average system price in NordPool wholesale market in a given year. CENS is calculated by multiplying the energy not supplied (KWh) during a specific interruption with a unit cost (NOK/KWh) that depends on customer type, duration, and whether the interruption was planned or not.

We follow the previous literature to select the main cost drivers. In particular, all of our estimated cost functions include three outputs (CUS=number of customers; NL=network length; and DE=delivered energy),, and three input prices (PK= capital price, regulated return of capital; PE = energy price, reference system price in NordPool Spot; PL= labour price, a wage dominated index).[8] We also use the percentage share of overhead lines (OH) of the total network length as an additional cost driver. This variable is employed to represent the main technical feature in this industry as firms' decisions on, for example, investment and maintenance of overhead and underground lines, are different.

Regarding firms' inefficiency, we follow Orea and Jamasb (2017) and use the percentage of overhead lines (OH), the network length variable (NL) and the number of transformer stations (ST) as inefficiency determinants. We include ST and OH as efficiency determinant to examine whether it is costlier to manage firms with more stations and with higher share of overhead lines. These can also be viewed as measures of complexity of networks something that regulatory benchmarking models are

[8] Energy Price is used to impose linear homogeneity. Therefore, it will not explicitly appear in our set of parameter estimates.

currently lacking. Finally, NL allows us to examine whether larger utilities tend to be more efficient than smaller utilities. The monetary variables finally used in our application are measured in 1000 NOK and have been deflated using the consumer price index to express them in 2004 real terms.

For robustness analyses, we will extend the above set of cost drivers to include several geographic and weather (W&G) variables. In particular, in our extended models we include six environmental variables: WIND=average reference wind from measuring stations; WINDEX=expected extreme wind exposure; and DIS=average distance to coast; FOREST=a measure of forest density in the service areas of networks;[9] AVESLOPE=average slope of terrain; and MAXSLOPE=maximum slope of terrain.

The above geographic and weather variables were obtained from the Norwegian regulator. The NVE regulator has access to more than 60 different weather and geographic condition variables that can potentially affect the performance of the networks. However, for practical reasons only a few of these variables can be included in parametric efficiency analysis models. Most of our selected environmental variables are considered as relevant by the Norwegian regulator. For instance, the regulator uses the ratio of squared wind speed over distance to coast in order to reflect the effect of coastal climate and corrosion caused by a combination of wind and salt water on the networks. Similar reasons apply to our variables measuring the slope of terrain. Moreover, the regulator considers a range of variables in pre-benchmarking analysis to account for the effect of different degrees of forestation in the service area, as fast-growing forest may represent a cost disadvantage due to the added cost of forest

[9] The variable Forest is a composite variable computed by principal component analysis of a large set of variables measuring different forest types and features. The procedure is carried out after the variables are centered with respect to sample mean. Thus it could take both negative and positive values.

clearing. We use here an aggregate measure of forestation (FOREST) that has been computed using principal component analysis due to we encountered convergence problems in Orea and Jamasb (2017) when we included the whole set of variables that are available in our data set to account for forest conditions.

In our study we follow the common approach in the literature for capturing and measuring the spatial interdependence using a physical contiguity matrix, *W*, whose elements are one for two bordering areas, and zero otherwise. As a result, the diagonal elements of *W* are null, while its off diagonal entries take a value of 1 for the areas that are adjacent and 0 otherwise. Therefore, WX should be interpreted as the sum of the X variables for the adjacent areas. The same applies for the WY product. In order to include the spatial interactions, we consider the map showing the distribution of service areas provided by NVE in October, 2015 (see Figure 1). This map is georeferenced using ArcGIS data system. We have used this georeferenced information to identify the adjacent distribution areas.

[Insert Figure 1 here]

Finally, it is noteworthy that our observations are the service areas of distribution utilities. Both the data on firms' costs and the map provided by the Norwegian regulator include the name of the distribution utilities. This information allowed us to match the distribution areas with the data of the firms operating in those service areas. The data for each distribution area normally coincides with the data of a single firm. However, the data for a small number of distribution areas involves more than one firm because they were involved in mergers from 2004 onwards and their individual distribution areas are not available as the map provided by the regulator only shows the distribution of service areas many years later. We only have the overall distribution area of the merged firms in

2015. Therefore, we aggregated the data of merged firms from 2004 onwards until the merger happened.[10]

Table 1 provides a descriptive summary of the variables used in this study. As the number of distribution areas in 2015 with available data is 129, the total number of observations used in our analysis is 1032.

[Insert Table 1 here]

5. Results

5.1. First-stage GMM Regression and Predicted Values of Omitted Cost Drivers

We first estimate equation (5) using GMM in order to control for the endogeneity of the spatial lagged dependent variable. The following strategy is then adopted for instrumental variables. Proper instruments should be strong (i.e. highly correlated with the endogenous variable) and exogenously determined. The spatial lagged dependent variable is a measure of the costs of neighbouring firms, and the main cost drivers in the sector are the output variables. Demand for electricity network services is exogenous and beyond the control of the firm. Therefore, the output variables of the neighbours are both strong and exogenous instruments for the spatial lagged dependent variable. We use the spatial lagged number of customers and the spatial lag of its square value (i.e. $W_i lnCUS_t$ and $W_i lnCUS_t{}^2$) as instruments for $W_i lnC_t$. We performed the conventional Hansen's (1982) test, and the F-test for weak instruments (Staiger and Stock, 1997) to test for overidentifying restrictions and

[10] In previous specifications of our models, we have included a merger dummy variable to control for possible aggregation biases. As expected, the coefficient of this variable was not statistically significant likely due to the small number of mergers for the period analysed in this paper.

strength of the instruments. The results of both tests indicate that the chosen instruments are generally valid.

Table 2 shows the estimated coefficient of this variable. We do not provide the other coefficients of the model in this table as they are similar to those obtained in the next section, mainly focused on technological characteristics of the cost frontier of the firms.

[Insert Table 2 here]

We observe that the coefficient of spatial correlation λ is positive and significant. Hence, we conclude that the *unobserved* cost drivers are, at least to some extent, spatially correlated. This result also indicates that weather and geographic conditions, and other spatially unobserved cost drivers (such as the population structure, electricity demand patterns, input prices) matter and that they should be included as cost determinants.[11]

The fact that the coefficient of spatial correlation λ is statistically different from zero implies that we can use equation (9) and the data of surrounding firms to compute a proxy variable for the omitted cost drivers. The predicted values of the omitted cost drivers are summarized in Figure 2, where we plot kernel density functions of the percentage of cost attributable to (unfavourable) environmental conditions, measured in relation to the "average" firm. Figure 2 thus suggests the existence of remarkable cost differences between utilities attributable to different environmental conditions. This is most probably what regulators wish to control for.

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[11] Growitsch et al. (2012) have found a similar conclusion using a different approach to control for unobserved and observed environmental conditions.

[Insert Figure 2 here]

The firm with the most unfavourable omitted conditions has 33.5% higher costs than the representative firm. On the other hand, the firm with the most favourable omitted costs has 22.5% less costs than the representative firm. Orea et al. (2015) have found similar results using supervised environmental composite variables. For instance, their preferred model predicts up to 35% higher costs for utilities operating in areas with unfavourable environmental conditions. For utilities operating in good environmental conditions, their preferred model predicts up to 44% lower costs.

Table 3 shows the between and within standard deviations of the predicted values of the omitted variables and the main observed drivers of firms' costs. It is worth mentioning that the within-variation of $\hat{Z}_{it}$ is only slightly lower than the between-variation. Thus, our approach based on a spatial econometric model to capture unobserved heterogeneity uses both the between and within-variation contained in the data of neighbouring firms.

In contrast, a FE-type estimator only uses the within-variation contained in the data to estimate the coefficients of the other cost drivers. If we use one of these estimators we will obtain negative and statistically non-significant coefficients for delivered energy, number of customers, network length and other crucial determinants of utility costs. The low precision of a FE-type estimator in the present application is caused by the fact that the within-variations of most of these variables tend to be much lower than the between-variation (see Table 3).

[Insert Table 3 here]

5.2. Second-Stage MLE Parameter Estimates

Once we have generated a proxy variable for the omitted cost drivers, we proceed to estimate the stochastic cost frontier in equation (15) without the W&G variables. The results adding environmental variables are discussed later on.

In Table 4 we show four alternative specifications of the stochastic cost frontier. The simple-SFA model does not include the estimated values for Z_{it}, and it is only included for comparison purposes. The next three models include the generated variable $\hat{Z}_{it}$ as a proxy for the omitted variable Z_{it}. In this sense, they are labelled as "spatial" models. The spatial-SFA1 model only includes the generated variable $\hat{Z}_{it}$. The subsequent model (spatial-SFA2) adds the number of adjacent firms (N_i) to the specification of γ_{it}. Finally, as the inefficiency term is heteroskedastic, the spatial-SFA3 model extends the previous one by adding the spatial lags of all determinants of firms' inefficiency.

[Insert Table 4 here]

It should be noted that, compared to the simple-SFA model, the simplest spatial model that only adds the estimated values for Z_{it} improves the joint significance considerably, based on the likelihood function value. The estimated value of γ_0 is smaller than unity, an expected result as $\hat{Z}_{it}$ tends to overestimate the true values of Z_{it}. The next two spatial SFA models allow for firm-specific values of γ_{it}. In this case, as all variables are mean-centred, γ_0 can be interpreted as the sample mean value of γ_{it}. It is worth mentioning that the new spatial models again improve the likelihood function values. Interestingly, the estimated value for γ_0 in both models is now not statistically different from unity. This seems to indicate that only controlling for the number of adjacent firms is enough to obtain the unbiased value of γ_{it}, at least evaluated at the sample mean. This supports our empirical strategy based on a linear specification of γ_{it} that takes into account that h_{it} is the sum of several inefficiency terms, so its expected value depends on the number of adjacent firms (and their average inefficiency levels, which in turn depends on their efficiency determinants).

As comparing likelihood values is not a satisfactory approach to choose a model, Table 4 also provides a set of model selection statistics (the well-known AIC and BIC criteria, and some of their variants such as the AICc and HQC criteria), which penalize the model as new explanatory variables are added. Thus, these criteria involve minimizing an index that balances the lack of fit (too few variables) and overfitting (too many variables). Models with lower values are generally preferred. Most model selection statistics indicate that more comprehensive models are preferred. Thus, the overfitting issue of the most complex models seems less important than the improvements in the goodness-of-fit.

Regarding the parameters of the cost frontiers, generally all the first-order coefficients have the expected sign and their magnitudes are also reasonable from a theoretical standpoint. The first-order coefficients of all three outputs are positive and statistically different from zero.[12] A similar observation can be made with respect to the coefficients of input prices, which are also positive and statistically significant. The

[12] The traditional collinearity between the number of customers and energy delivered in our application is not severe (the correlation is 86%). This explains why we found positive and significant coefficients for both output variables. Interestingly, while we found a strong correlation (over 97%) for larger firms in the sample as in Jamasb et al (2012) using UK data, the collinearity between these two output variables is much less for smaller firms. This explains why dropping the energy delivered variable in our model is rejected using any model selection test.

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 cost. Dimitropoulos and Yatchew (2017) found that underground cables tend to reduce the operating costs of firms. These two results together reflect the considerably higher capital costs of underground cables.

The sum of the first-order coefficients of customer numbers and energy delivered allows us to measure density economies, associated with *vertical* output, i.e. output expansions that do not require additional network in the existing service areas. We find that the elasticity of density evaluated at the sample mean is quite similar in all models, i.e. 0.48. The estimated coefficients for these two outputs in Table 4 indicate that electricity distribution networks have strong natural monopoly characteristics. In contrast, scale economies are associated with *horizontal* output expansions that require enlarging the existing network. These economies can be measured by the sum of cost elasticities with respect to customer numbers, energy delivered and network length. The elasticity of scale evaluated at the sample mean in both models is about 0.94. This value suggests that Norwegian electricity distribution networks still exhibit natural monopoly characteristics when the network is expanded to meet new demand.[13]

In addition to the frontier parameters, Table 4 displays the coefficients of the variables that are related to the inefficiency term. The lack of significance of the coefficient of OH seems to indicate that managing firms with a relatively large proportion of overhead lines (more likely to be serving rural areas), have been managed

[13] These results are in line with the actual features of the Norwegian electricity distribution networks. While Norway has one of the highest levels of per capita energy consumption in the world, with the exception of a few cities, the number of network utilities is large relative to the population and, on the whole, the customer density across the networks is generally low.

similarly to those firms with more underground lines (more likely to be serving urban areas).

Following Orea and Jamasb (2017), in addition to the percentage of overhead lines, we have included the logs of the network length (NL) in order to capture the size effects on firms' inefficiency, and the number of substations (ST) as a proxy for network complexity. As mentioned in our previous paper, we obtain a negative and statistically significant coefficient for NL, indicating that larger utilities tend to be more efficient than smaller utilities. In contrast, the positive coefficients of ST indicate that it is costlier to manage firms with more stations.

5.3. Efficiency Scores

Table 5 presents the summary statistics of the efficiency scores. The estimated efficiency estimates are high, on average about 92% using our preferred model (Spatial SFA 3). The high level of efficiency of this industry is attributable to the maturity of the regulator's economic regulation that has consistently been supervising and incentivizing the utilities to perform efficiently.[14] Similar figures are obtained in Orea et al. (2015) using a SFA approach for the period 2004 to 2011, Miguéis et al. (2012) using a DEA method for the period 2004 to 2007, and in Growitsch et al. (2012) using a SFA approach for the 2001-2004 period.

[14] As the efficiency level of the Norwegian networks is high, we have only found a slight improvement in the efficiency of the firms over time and some reduction in the dispersion of their efficiency. On the other hand, and suggested by an anonymous referee, we have examined whether there is a relationship between the firms' efficiency scores and affluence of the county (or counties) they serve. Using county level data from the StatBank of Norway, we have not found a clear relationship between both variables. We found that the most inefficient firms are located in medium wealth counties.

[Insert Table 5 here]

On the other hand, it should be pointed out that the estimated efficiency levels in the models with spatial interactions (about 92.5%), are slightly higher than those obtained using the single SFA model (on average 91.6%), indicating that ignoring the omitted variables of a spatially correlated nature tends to *underestimate* the firms' efficiency scores. However, the small difference found between the single and the spatial SFA models might be suggesting that this bias is not severe. We observe in the next subsection that this is not the case.

5.4. Complementarities of Spatial and Panel Data Models

We examine in this subsection the complementarities between our spatial model and the panel data models that take advantage of different (spatial vs. temporal) dimensions of our data. In particular, we examine whether there are spatial spillovers once we control for firm-specific but time-invariant effects in a panel data SFA setting, using the TFE and TRE panel stochastic frontiers introduced by Greene (2005) and a Mundlak (1978)-type specification of our more comprehensive pooled model in Table 4 (that we label hereafter as the Pooled model).

The parameter estimates of these models are shown in Table 6. As expected, the TRE model yields similar results as our Pooled model because both models use the same variation of the data and are inconsistent if the firm-effects are correlated with the regressors. As anticipated in the introduction section, the fixed-effect based estimators are problematic in our application due to the presence of slowly changing variables. Indeed, both the TFE and the Mundlak specification of our pooled model yield negative coefficients for the most important output (i.e. the number of customers) of the cost function of the electricity distribution utilities. The coefficient of the energy delivered is still positive, but now it is not statistically significant. For this reason, the results (especially the frontier parameters) of these models should be interpreted with caution.

[Insert Table 6 here]

Although the frontier results of the panel data models should be interpreted with extreme caution, the estimated coefficients of the spatial variables have similar signs to those estimated in the pooled models, and many of them are still statistically significant. This implies that, conditional on the existence of (fixed or random) firm-specific effects, we find that still there are spatially omitted variables, not controlled by the individual effects added to the model. This result thus suggests that still there is room for unobserved spatial effects in panel SFA models.

5.5. Robustness analysis using weather and geographic data

One advantage of the present application is that the Norwegian energy regulator (NVE) has systematically examined the effects of several environmental factors such as geographic and weather conditions on cost and service quality performance of the utilities and it has reflected these in the cost efficiency benchmarking models used in incentive regulation of these utilities (see, Growitsch et al. 2012; Orea et al. 2015). This information is often not available in most countries because collecting the relevant environmental data requires a substantial effort and financial resources as well as time. Therefore, our results in previous subsections – that, on purpose, ignore weather and geographic information - are the likely outcomes that one could expect in other applications to electricity distribution, or indeed in other utilities sectors such as gas and water, where the regulator does not have access to W&G data.

However, in our application, we have the benefit of having data on some key environmental factors to test the robustness of our empirical strategy based on spatial econometric techniques to capture the effect of omitted variables on the costs of neighbouring utilities. Our robustness exercise only attempts to compare the estimated spatial SFA models in subsection 5.2 with a simple SFA model that includes a set of weather and geographic variables. The complete model (hereafter W&G SFA model) is used to produce a type of a counterfactual scenario, which is not readily available in many other applications. As many of the W&G variables are spatially correlated (see Appendix A), we expect similar efficiency scores using a (non-spatial) model that includes W&G cost drivers and a spatial model that "replace" the W&G data (often not available) with data from surrounding firms using spatial econometric techniques.

The parameter estimates of the W&G SFA model are shown in Appendix B. In our W&G SFA model, we extend the previous set of cost drivers with several W&G variables. In particular, we include three weather variables (WIND, WINDEX, and DIS),[15] and three geographical variables (FOREST, AVESLOPE, and MAXSLOPE). This appendix also includes the results of an extended version of our previous spatial SFA3 model where we have now added W&G variables. This model (hereafter W&G spatial-SFA3 model), will allow us to examine whether omitted variables that are spatially correlated are still present.

Overall, our new results indicate that weather is an important in determining cost efficiency in this sector as the estimated coefficients for the weather variables are always significant. For instance, we find that a higher exposure to wind conditions

[15] We use the geographic variable (DIS) in order to capture the effect of coastal climate on the networks. In Norway, this effect is related to problems with corrosion on network components normally caused by a combination of wind and salt water.

implies larger costs for the distribution networks. On the other hand, the coefficient of the distance to the coast is negative as expected because inland weather conditions are likely to be less severe than coastal weather conditions. Our results also indicate that some geographic features of the terrain on which the networks are supported (i.e. forestry and maximum terrain slope), are also important determinants of cost efficiency. Finally, it is worth mentioning that all coefficients associated to $\hat{Z}_{it}$, are not statistically significant, except for $\hat{Z}_{it}$ alone whose coefficient is slightly larger than unity.

Figure 3 compares the individual efficiency scores that are obtained using the four models in Table 4 that do not include any environmental variable (see "dot" observations), with the scores that are obtained using the W&G SFA model in Appendix B (see "cross" observations), which serves as a benchmark model because it includes relevant environmental variables. This figure relates several interesting stories.

[Insert Figure 3 here]

First, most observations in Figure 3 are above the bisecting line, indicating that the efficiency scores of a simple SFA Model tend to be downward biased if either spatial effects or W&G variables are ignored. This result has been partially highlighted in the previous subsection. However, Figure 3 now shows that the bias is much larger when the efficiency scores are small. This implies that the most inefficient firms in a simple SFA specification of firms' cost would be wrongly penalized in an incentive regulated framework.

The second story has to do with the evolution of firms' efficiency scores when we move from simpler to more comprehensive models. Indeed, it is apparent in Figure 3 that we move closer to the benchmark efficiency scores when we add spatially generated variables as cost determinants. Moreover, the efficiency scores of the Spatial

SFA3 model (the yellow dots) are quite close to the efficiency scores of the W&G SFA model (see the cross observations). This implies that we have been able to (almost) reproduce the same results as a SFA model that includes a set of relevant environmental variables that are not available in many cases. This result thus suggests that when W&G data are not available, this lack of information can likely be compensated by using data from surrounding firms using spatial econometric techniques.

Finally, in Figure 4 we compare the individual efficiency scores obtained using the non-spatial W&G SFA model and the W&G spatial-SFA3 model that extends our previous spatial SFA3 model by including W&G variables. We find that both efficiency scores are quite similar. This result indicates that, once we have controlled for W&G variables, the remainder of the spatially correlated omitted variables are of little importance. In other words, most of the omitted information that is spatially correlated has to do with environmental conditions. In summary, we have shown that the spatial econometric techniques can offer an effective and efficient possibility to control for this issue without recurring to the collection of costly weather and environmental data.

[Insert Figure 4 here]

6. Conclusions

This paper provides an innovative approach for measuring efficiency when spatially correlated omitted variables play an important role in firms' efficiency. The paper also provides an example of its application to the electricity distribution sector. However, the proposed method can be applied to measure efficiency in other sectors where unobservable cost drivers (e.g., environmental variables) are also very relevant, e.g. gas, water, agriculture, fishing.

This study combines stochastic frontier and spatial econometric techniques to evaluate a firm's efficiency in the Norwegian electricity distribution sector, taking into account spatially correlated omitted variables. In doing so, first we propose estimating a spatial econometric model to obtain a proxy for this type of variable by means of the available data for neighbouring utilities. Next we plug the variable generated into a standard SFA model. We illustrate our approach using panel data for the Norwegian distribution utilities for the years 2004 to 2011. In order to implement our empirical strategy, we have matched the information on concession areas of distribution utilities with the data provided by the Norwegian regulator on firms' costs. We are not aware of other studies that have carried out a similar spatial matching exercise.

We find that the coefficient of the spatial correlation is significant in our auxiliary regression, indicating that the unobserved cost drivers are correlated. This result justifies the use of neighbouring firm data in order to control for unobserved cost drivers in our application. Next, the estimated stochastic cost frontier that includes our generated variable outperforms the model that excludes the omitted cost drivers. In this sense, as expected, the firm efficiency scores are larger when we include our proxy for the omitted variables, especially for firms that are more inefficient. In an incentive regulation framework, the upshot is that the latter types of firms are likely to be more severely penalized when the effect of this variable is not taken into account.

One advantage of the present study is that the Norwegian energy regulator has collected data on a set of W&G variables. In many countries, this information is often not readily available. As some environmental data is available in our application, we have been able to produce a type of a counterfactual scenario to examine the robustness of our empirical strategy. We have found that our spatial SFA model is able to roughly reproduce the efficiency scores of a more comprehensive model that includes the W&G

variables that are not available in many applications. That is, we find that this lack of information can likely be compensated with data from surrounding firms using spatial econometric techniques. Finally, we have detected that most of the omitted information that is spatially correlated has to do with environmental conditions.

We have also examined the complementarities between our approach that takes advantage of the spatial structure of the data to deal with omitted but spatially correlated variables, and several panel-data SFA models aiming also to control for unobserved but time-invariant variables. We have found that the frontier results should be interpreted with caution when fixed-effect estimators are used due to the lack of temporal variation of our data. However, the main conclusion that we get from these panel data SFA models is that still there are spatially omitted variables not controlled by the firm-specific effects.

Our approach is useful in utilities sectors where collecting environmental data requires substantial human or financial resources as well as time. However, this approach presents some limitations. For instance, our methodology should perform better with a large number of distribution service areas or firms as the environmental conditions in surrounding areas are likely to be similar, i.e. their spatial correlation is likely to be larger than in applications with a small number of firms with large service areas (e.g., in the UK and Spain) where environmental conditions within given service areas are not homogeneous. On the other hand, the spatial lags can be interpreted as averages for the surrounding areas. We use these average values to obtain predictions of the underlying environmental conditions that are not observable by the researcher or the regulato. Therefore, our predictions should improve as the number of observations used to compute the average values (i.e. the number of surrounding firms) increases. The methodology is also useful in applications with few firms if data on the distribution units of each firm is available. This is, for instance, the case in Coelli et al (2013) that use data on the 92 electricity distribution units operated by ERDF in France.

The proposed methodology does not likely perform well in cross-country studies where utilities may be exposed to different environmental conditions as the spatial correlations of environmental conditions across countries tend to be weaker. In this regard, we are assuming that the *definition* of the Z variable in our model is the same for all observations and, hence, that the set of environmental conditions captured by Z variable in surrounding areas are similar. The main difficulties in cross country analysis include currency conversions, different technical as well as economic definition of variables, differing regulatory constraints and objectives (Jamasb et al, 2008; Jamasb and Pollitt, 2003).

Finally, this paper opens a new research field in the context of regulated utilities if we refocus the model to study different spillovers among utilities. Indeed, as pointed out by a former referee, the lack of causal spatial spillovers seems to contradict a body of economic and business-strategy literature suggesting that firms benefit from best practices implemented in their adjacent firms. This literature is more focused on the knowledge and R&D spillovers between firms than in mature and regulated industries. These benefits might also have a non-spatial nature. For instance, in an incentive-based regulation framework, the benefits from best practices are likely to come from firms that are “peers” in a benchmarking exercise. On the other hand, if the peers are not observed, the spillovers might stem from firms of similar size, because peers should have similar characteristics than the evaluated firm in order to control for differences in scale economies. Future research can adapt the spatial nature of our proposed approach to study such spillover effects in the utilities sectors.

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Table 1.

Descriptive statistics of the data

		Mean	*St.Dev.*	*Min*	*Max*
SCOST	1000 NOK	92899.7	192397.6	793.4	1797173.2
CUS	Number	21118.5	56320.3	14	552342
DE	1000 MWh	570990.7	1570418.9	3979	17000000
NL	Km	752.5	1290.7	9	8648
OH	%	0.66	0.20	0.00	0.97
PK	%	0.06	0.01	0.05	0.1
PL	Index	163.86	16.89	139	189.5
PE	NOK/MWh	331.01	73.93	234.6	436.3
ST	Number	948.1	1828.7	8	13525
WIND	m/s	25.5	2.48	22	31
WINDEX	m/s	5.28	1.02	2.71	8.13
DIS	km	53455.3	54567	191	19637
FOREST	Index	0	2.45	-3.21	22.51
AveSLOPE	%	10.13	3.74	2.86	22.22
MaxSLOPE	%	51.09	11.91	19	75

Table 2.

First-stage GMM parameter estimates

	Coefficient	Robust-t
Intercept	10.5699	378.74
Spatial lag of the dependent variable (W·lnC)	0.1660	5.69
Cost drivers:		
Output variables		Yes
Input prices		Yes
Overhead variable		Yes
Hansen Chi-squared test (df)		0.1332 (1)
Weak instruments F-test (df in parenthesis)		47.21 (24,1007)
R-squared	0.9870	

Notes:
(a) For more details about the cost drivers and the functional form of the cost function, see Table 4.
(b) Instruments= all exogenous explanatory variables plus the spatial lag of lnCUS and $lnCUS^2$.

Table 3.

Between and within standard deviations of the main cost drivers

Variable	***Between***	***Within***	***B/W ratio***
$\hat{Z}_i$	0.065	0.045	1.45
lnCUS	1.454	0.160	9.09
lnNL	1.162	0.035	32.76
lnDE	1.404	0.100	13.99
OH	0.201	0.026	7.83

Table 4. Second stage parameter estimates. Cost frontier function

Parameters	**Single SFA** Estimates	t-ratio	**Spatial SFA 1** Estimates	t-ratio	**Spatial SFA 2** Estimates	t-ratio	**Spatial SFA 3 (Pooled)** Estimates	t-ratio
Frontier coefficients								
Intercept	10.511	677.7	10.518	665.1	10.518	636.1	10.521	745.21
lnCUS	0.291	10.81	0.273	10.72	0.276	10.74	0.271	10.30
lnNL	0.549	25.53	0.564	28.06	0.560	27.53	0.561	27.53
lnDE	0.142	6.01	0.146	6.45	0.147	6.51	0.148	6.55
OH	-0.312	-4.83	-0.298	-4.91	-0.294	-4.80	-0.285	-4.68
$0.5 \cdot \ln CUS^2$	0.130	6.46	0.124	5.85	0.120	5.75	0.121	5.67
$0.5 \cdot \ln NL^2$	-0.007	-0.08	-0.041	-0.50	-0.036	-0.45	-0.048	-0.60
$0.5 \cdot \ln DE^2$	0.196	4.99	0.202	5.24	0.199	5.26	0.204	5.36
$0.5 \cdot OH^2$	0.227	0.40	0.349	0.64	0.445	0.81	0.466	0.86
lnCUS·lnNL	-0.007	-0.18	0.003	0.07	0.000	0.00	0.005	0.14
lnCUS·lnDE	-0.109	-4.42	-0.114	-4.48	-0.110	-4.36	-0.113	-4.51
LnCUS·OH	-0.127	-1.07	-0.145	-1.20	-0.113	-0.94	-0.136	-1.10
lnNL·lnDE	-0.056	-1.22	-0.045	-1.00	-0.046	-1.03	-0.046	-1.02
LnNL·OH	-0.390	-1.87	-0.370	-1.82	-0.395	-1.96	-0.391	-1.94
LnDE·OH	0.483	3.34	0.492	3.37	0.483	3.34	0.506	3.47
lnPK	0.277	14.19	0.263	13.99	0.264	13.93	0.263	13.81
lnPL	0.662	16.89	0.664	17.98	0.663	17.88	0.661	17.79
Spillover variables								
Z			0.894	11.19	1.034	11.40	0.999	11.18
Z·N					-0.100	-2.74	-0.150	-3.84
Z·WlnNL							-0.299	-2.22
Z·WOH							0.109	0.59
Z·WlnST							0.229	1.83
Log of standard deviation of disturbance								
$\ln\sigma_v$	-2.136	-51.02	-2.182	-51.69	-2.184	-49.28	-2.181	-48.51
Log of standard deviation of half-normal								
$\ln\sigma_u$	-2.376	-11.15	-2.447	-10.79	-2.436	-10.34	-2.463	-10.08
lnNL	-1.623	-3.55	-1.621	-3.56	-1.485	-3.28	-1.497	-3.18
OH	0.659	1.85	0.064	0.17	-0.004	-0.01	-0.168	-0.45
lnST	1.012	2.64	1.085	2.84	0.971	2.56	1.008	2.54
Mean log-likelihood	0.553		0.612		0.616		0.621	
Observations	1032		1032		1032		1032	
LF	570.51		631.72		635.37		640.43	
AIC	-1097.0		-1217.4		-1222.7		**-1226.8**	
BIC	-988.3		-1103.8		**-1104.1**		-1093.5	
CAIC	-1096.0		-1216.3		-1221.5		**-1225.3**	
HQIC	-1137.1		-1259.5		-1266.8		**-1276.9**	

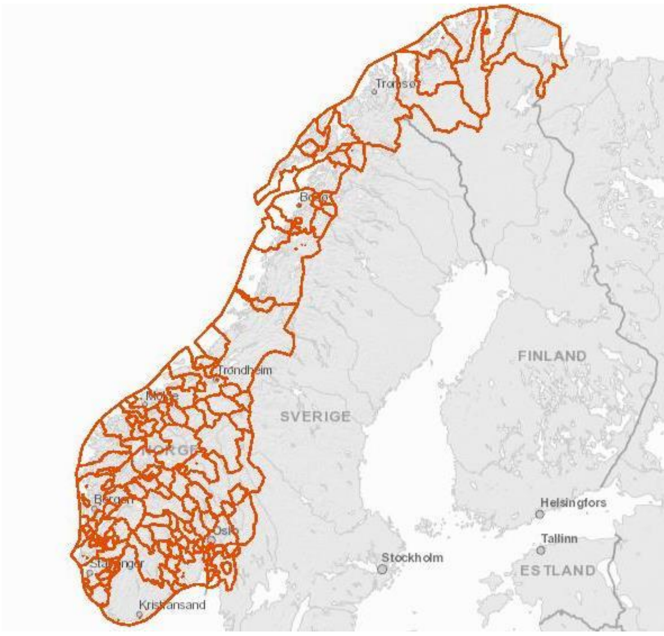
Table 5. Efficiency scores

	Mean	Std. Dev.	Min	Max
Single SFA	0.916	0.064	0.535	0.990
Spatial SFA 1	0.923	0.058	0.498	0.987
Spatial SFA 2	0.923	0.057	0.498	0.985
Spatial SFA 3	0.925	0.055	0.485	0.985

Table 6. Second stage parameter estimates. Panel data specifications.

	Pooled		**TRE**		**TFE**		**Pooled+Mundlak**	
Parameters	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Frontier coefficients								
Intercept	10.521	745.21					10.320	77.81
lnCUS	0.271	10.30	0.378	30.01	-0.117	-1.21	-0.104	-0.66
lnNL	0.561	27.53	0.478	42.58	0.242	2.79	0.385	2.31
lnDE	0.148	6.55	0.105	10.33	0.027	0.68	0.020	0.24
OH	-0.285	-4.68	-0.226	-7.63	-0.503	-3.61	-0.539	-1.92
$0.5\cdot \ln CUS^2$	0.121	5.67	0.086	5.78	-0.009	-0.18	0.002	0.02
$0.5\cdot \ln NL^2$	-0.048	-0.60	0.119	2.87	0.243	1.11	0.186	0.46
$0.5\cdot \ln DE^2$	0.204	5.36	0.184	11.39	-0.009	-0.16	-0.016	-0.11
$0.5\cdot OH^2$	0.466	0.86	1.629	6.12	1.249	1.60	0.703	0.46
lnCUS·lnNL	0.005	0.14	-0.028	-1.43	-0.155	-1.38	-0.142	-0.63
lnCUS·lnDE	-0.113	-4.51	-0.061	-5.59	0.000	0.00	-0.011	-0.11
LnCUS·OH	-0.136	-1.10	0.141	2.37	0.407	1.48	0.337	0.62
lnNL·lnDE	-0.046	-1.02	-0.116	-5.11	-0.035	-0.40	-0.016	-0.09
LnNL·OH	-0.391	-1.94	-0.663	-7.12	-0.904	-2.65	-0.723	-1.03
LnDE·OH	0.506	3.47	0.453	6.56	0.376	1.92	0.389	0.83
lnPK	0.263	13.81	0.262	27.77	0.218	16.30	0.229	10.65
lnPL	0.661	17.79	0.661	27.33	0.711	30.51	0.690	18.15
Spillover variables								
Z	0.999	11.18	0.939	21.34	0.634	7.78	0.784	8.42
Z·N	-0.150	-3.84	-0.065	-3.01	-0.037	-1.07	-0.147	-3.78
Z·WlnNL	-0.299	-2.22	-0.124	-1.82	-0.085	-0.90	-0.351	-2.75
Z·WOH	0.109	0.59	-0.122	-1.63	-0.115	-0.96	0.228	1.29
Z·WlnST	0.229	1.83	0.078	1.27	0.046	0.55	0.263	2.23
Log of standard deviation of disturbance								
$\ln\sigma_v$	-2.181	-48.51	-2.771	-21.07	-2.785	-69.97	-2.197	-49.30
Log of standard deviation of half-normal								
$\ln\sigma_u$	-2.463	-10.08	-0.063	-0.30	-3.994	-4.33	-2.602	-8.97
lnNL	-1.497	-3.18	0.502	1.83	0.889	0.77	-1.803	-3.18
OH	-0.168	-0.45	-0.624	-2.33	2.198	1.18	1.612	1.91
lnST	1.008	2.54	-0.636	-2.48	-1.403	-1.04	1.284	2.70
Random effect								
Mean(α_i)			10.553	1349.7				
sd(α_i)			0.114	46.84				
Mean LF	0.621		1.013		1.322		0.659	
Observations	1032		1032		1032		1032	
LF	640.43		1045.44		1364.17		679.77	

Figure 1: Norwegian electricity distribution service areas



Source: Norwegian Water Resources and Power Directorate (NVE)

Figure 2. Histograms and Kernel density plots of estimated environmental cost differences

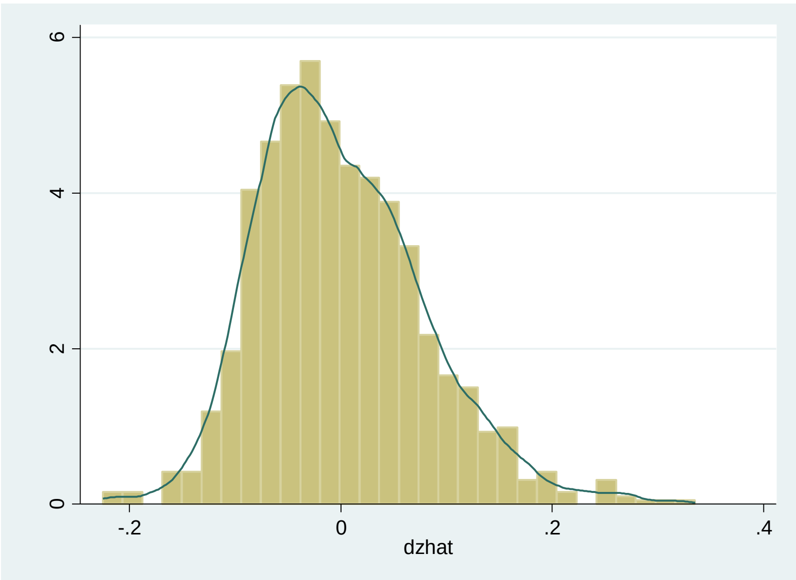
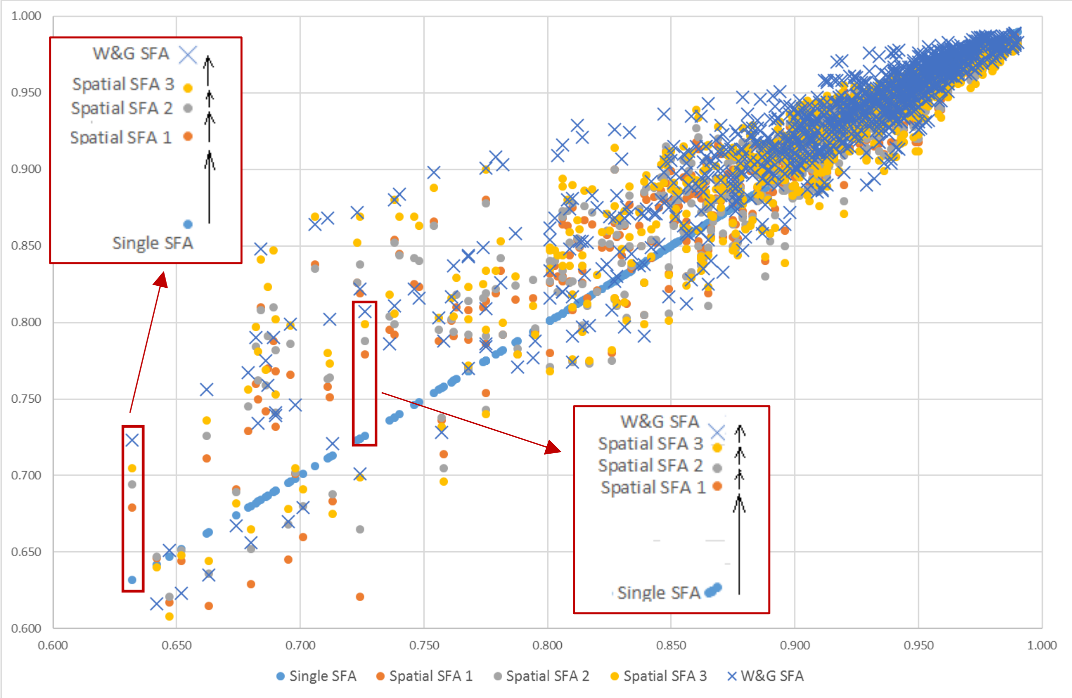
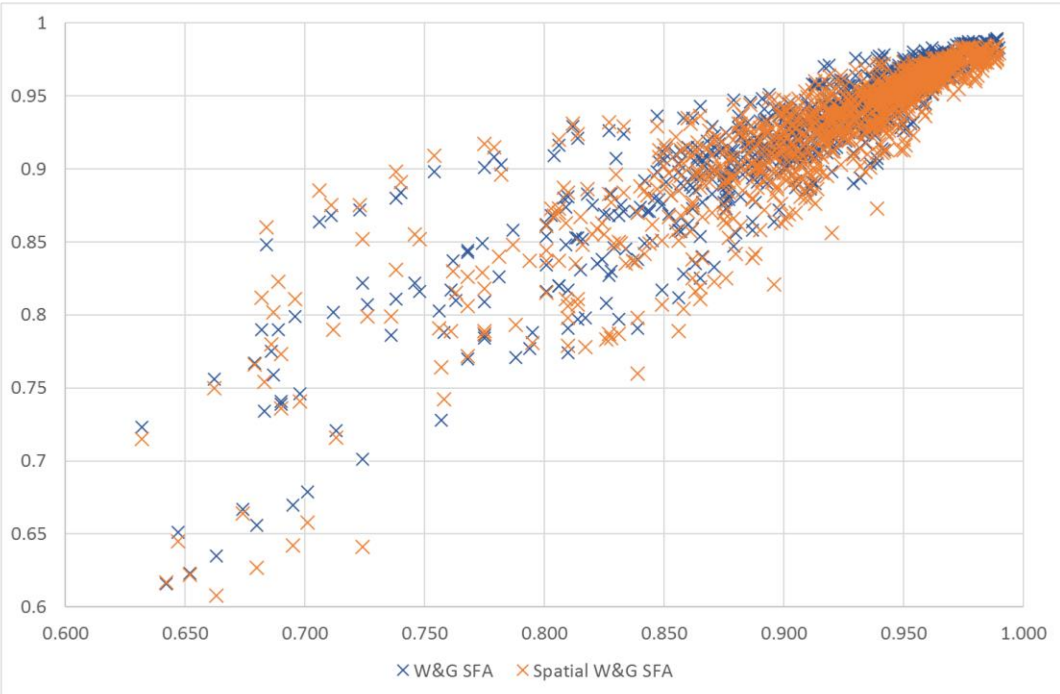


Figure 3. Efficiency scores



Note: Efficiency scores of the Simple SFA model in the horizontal axis.

Figure 4. Efficiency scores using W&G data



Note: Efficiency scores of the Simple SFA model in the horizontal axis.

Appendix A

Spatial correlations of the main cost drivers. OLS auxiliary regressions

Regression	Coef.	t-ratio
Customer numbers		
Intercept	-0.1356***	-2.75
Spatial lag	0.0816***	6.48
R^2	0.0392	
Network Length		
Intercept	-0.0571	-1.44
Spatial lag	0.0443***	3.41
R^2	0.0111	
Delivered Energy		
Intercept	-0.0861*	-1.89
Spatial lag	0.0677***	5.92
R^2	0.0329	
Overhead lines (%)		
Intercept	-0.0048	-0.83
Spatial lag	0.1482***	14.43
R^2	0.1683	
Wind		
Intercept	26.2482***	140.30
Spatial lag	-0.0061***	-4.37
R^2	0.0183	
Wind Exposure		
Intercept	5.4931***	70.78
Spatial lag	-0.0086***	-3.04
R^2	0.0089	
Distance to coast (in logs)		
Intercept	8.3434***	79.73
Spatial lag	0.0328***	17.60
R^2	0.2314	
Forest		
Intercept	-0.0367	-0.47
Spatial lag	0.0448***	3.26
R^2	0.0103	
AveSlope		
Intercept	6.7957***	33.00
Spatial lag	0.0657***	18.58
R^2	0.2512	
MaxSlope		
Intercept	37.9739***	50.63
Spatial lag	0.0505***	19.31
R^2	0.2659	

Appendix B

SFA models with W&G variables

	W&G SFA		Spatial W&G SFA	
Parameters	Estimates	t-ratio	Estimates	t-ratio
Intercept	10.668	101.334	10.595	107.749
lnCUS	0.295	10.979	0.285	10.954
lnNL	0.523	22.291	0.539	24.433
lnDE	0.148	6.143	0.142	6.169
OH	-0.181	-2.923	-0.259	-4.483
$0.5 \cdot \ln CUS^2$	0.108	5.117	0.101	4.999
$0.5 \cdot \ln NL^2$	-0.108	-1.150	-0.154	-1.730
$0.5 \cdot \ln DE^2$	0.193	4.861	0.168	4.659
$0.5 \cdot OH^2$	0.822	1.388	0.548	0.979
lnCUS·lnNL	0.040	0.980	0.058	1.523
lnCUS·lnDE	-0.123	-4.591	-0.128	-4.902
LnCUS·OH	-0.142	-1.124	-0.194	-1.538
lnNL·lnDE	-0.028	-0.583	-0.002	-0.048
LnNL·OH	-0.365	-1.625	-0.244	-1.163
LnDE·OH	0.500	3.324	0.449	3.141
lnPK	0.273	14.427	0.268	14.470
lnPL	0.667	17.661	0.663	18.500
Z			1.195	10.512
Z·N			-0.080	-1.615
Z·WlnNL			0.050	0.298
Z·WOH			-0.153	-0.694
Z·WlnST			-0.051	-0.343
WIND	-0.015	-4.667	-0.014	-4.766
WINDEX	0.041	4.536	0.045	5.250
lnDIS	-0.017	-4.191	-0.016	-3.965
Forrest	0.008	2.745	0.008	2.866
AveSlope	0.002	0.854	0.001	0.224
MaxSlope	0.003	3.706	0.004	4.493
$\ln\sigma_v$	-2.147	-52.673	-2.235	-52.423
$\ln\sigma_u$	-2.600	-10.736	-2.497	-12.658
lnNL	-2.138	-3.770	-1.847	-3.967
OH	0.017	0.039	-0.114	-0.300
lnST	1.602	3.278	1.371	3.383
Mean log-likelihood	0.608		0.668	
Observations	1032		1032	
LF	627.159		689.086	