Pushing the Frontier:
Three Essays on Bayesian Stochastic Frontier Modelling

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Abstract

This thesis presents three essays in Bayesian Stochastic Frontier models for cost and production functions and links the fields of productivity and efficiency measurement and spatial econometrics, with applications to energy economics and aggregate productivity. The thesis presents a chapter of literature review highlighting the advances and gaps in the stochastic frontier literature. Chapter 3 discusses measurement of aggregate efficiency in electricity consumption in transition economies in a cost frontier framework. The underlying model is extended to a Spatial Autoregressive model with efficiency spillovers in Chapter 4, showing good performance in simulations. The model is applied to aggregate productivity in European countries, leading to evidence of convergence between eastern and western economies over time, as in the previous chapter regarding efficiency in electricity consumption. Finally, Chapter 5 proposes a spatial model which allows for dependence in the structure of the inefficiency component while accounting for unobserved heterogeneity. This approach is applied to New Zealand electricity distribution networks, finding some evidence of efficiency spillovers between the firms. All essays explore the performance of the model using simulations and discuss the utility of the approaches in small samples. The thesis concludes with a summary of findings and future paths of research.

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To the two desktops I have killed running R code, I am very sorry but I cannot turn back the time and unmelt you. The third desktop complained it was warm but made it to the end.

I thank my parents for their unconditional support from far away. It was always important to me to have them next to my heart and this would not have been possible without them.

Finally, I thank Inês for her love and support and for always being by my side. But also for repeatedly enduring a long list of useless facts about energy consumption and transition economies.

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List of Abbreviations

2SLS	- Two Stage Least Squares
AR(p)	- Autoregressive of order p
ARMS	- Adaptive Rejection Metropolis Sampling
ARS	- Adaptive Rejection Sampling
CIS	- Commonwealth of Independent States
DEA	- Data Envelopment Analysis
DGP	- Data Generating Process
EBRD	- European Bank for Reconstruction and Development
EU	- European Union
FSU	- Former Soviet Union
GDP	- Gross Domestic Product
GLS	- Generalized Least Squares
GMM	- Generalized Method of Moments
GTRE	- Generalized True Random Effects
GWM	- Guided Walk Metropolis
JLMS	- Jondrow et al. (1982) efficiency estimate
LIML	- Limited Information Maximum Likelihood
LMRC	- Long Run Marginal Cost
LSDV	- Least Squares Dummy Variable
MCMC	- Markov Chain Monte Carlo
MH	- Metropolis Hastings
ML	- Maximum Likelihood
MLE	- Maximum Likelihood Estimator
MSL	- Maximum Simulated Likelihood
OECD	- Organisation for Economic Co-operation and Development
OLS	- Ordinary Least Squares
OPEX	- Operational Expenditure
PPP	- Purchasing Power Parity
RWMH	- Random Walk Metropolis Hastings
SAIDI	- System Average Interruption Duration Index
SAR	- Spatial Autoregressive
SEM	- Spatial Error Model
SFA	- Stochastic Frontier Analysis
TFE	- True Fixed Effects
TFP	- Total Factor Productivity
TRE	- True Random Effects
USA	- United States of America
USSR	- Union of Soviet Socialist Republics
WWII	- World War II

Chapter 1. General Introduction

This thesis explores two research paths in the field of Stochastic Frontier analysis: persistent inefficiency and spatial dependence. The determination of cost and technical efficiency levels of firms is an increasingly popular exercise with policy making consequences. The approach is now a wide reaching technique, with frequent applications that range from classical measurement of efficiency of industries to health economics, school efficiency, energy, agricultural, transport economics and even cost efficiency of football clubs.

There are some new rising trends in the literature. In the past decade, the influential work of Greene (2005) has led to a focus on unobserved heterogeneity and the implications to efficiency measurement. Many researchers have worked on various types and methods of estimation of models that measure persistent and time-varying inefficiency. Although there is a consensus on the underlying idea, the methods to estimate these models diverge greatly, with multiple competing frequentist and Bayesian methods. However, many methods have thus far not resulted in applications by other authors or particularly recognizable applied contributions to the field. Other trends have pushed the literature towards non-parametric estimation, the consideration of dynamic firm behaviour and endogeneity in frontier estimation. This thesis will also focus on the spatial frontier literature, which is in its infancy compared to other fields. Only in the past few years there have been some limited advances in the consideration of spatial interactions of firms and their efficiency and how to capture and measure those effects. Like other fields of the literature, there are both frequentist and Bayesian options available to the applied researchers, but little use of them beyond the construction of the estimation approach. The first efforts of the literature often struggled to develop the models beyond the point of limited interpretation and limited understanding of the implications of integrating a spatial structure in frontier models.

The thesis explores the theory and practice of Bayesian Stochastic Frontier models, contributing to the literature with two modelling extensions to the current spatial literature, an empirical exploration in the context of energy economics and the use of mostly unexplored Bayesian rejection techniques to improve estimation performance.

Small sample performance of this type of models is often not investigated and of great importance to applied economists.

The objectives of the thesis are as follows. First, the thesis aims to summarize the current state of the literature and identify gaps and issues in the literature requiring further attention. Secondly, the thesis aims to make an empirical exploration of well-known models, and also to extend them to the context of Bayesian spatial econometrics. Thirdly, it also aims to explore small sample performance and the role of priors across all three essays. Finally, the thesis explores alternative estimation techniques to assess performance versus traditional Bayesian techniques.

Further detail follows. The thesis develops an application of the most recent techniques in estimation of persistent inefficiency to the context of energy economics, and then investigate the spatial domain of the modelling approaches, developing models that associate the spatial dependence to the output of the cost or production function and to the inefficiency component of the function. The thesis is based on Bayesian techniques which facilitate estimation of complicated models and allow for the role of prior information. In chapter 2, I present a literature review which covers the basic concepts of Stochastic Frontier modelling, the key aspects of the literature and the current state of the research in the field. One of the key findings of the review of the literature is the lack of applications of a vast amount of theoretical models and estimation techniques available to address multiple challenges. This field appears to show a persistent gap between theory and practice, which is partially justified by the multitude of alternatives and the lack of easily usable statistical packages to estimate these models. This thesis shows applications not only of the cutting edge models in the literature but also of the proposed extensions to the literature. For that effect, I present a review and three essays that cover the efforts to extend this literature:

Chapter 2: Concepts and Literature Review. This chapter introduces and discusses the basic concepts behind Stochastic Frontier modelling. It also examines the latest extensions in Stochastic Frontier (SF) models, particularly the ones that have risen since the construction of fixed and random effects approaches in SF modelling to account for unobserved heterogeneity. The SF literature allowed for considerable amount of work on technical efficiency and contributed to build further knowledge and orientate policy measures since the seminal work of Aigner et al. (1977). However, in the past decade, particular attention was given to issues previously overlooked, such as accounting for unobserved heterogeneity, the problem of endogeneity, how to account for partial adjustments in efficiency of firms through the construction of dynamic models, and also spatial dependence. Various modelling approaches have stemmed from these concerns, growing in diversity and complexity. This chapter conducts a survey of techniques and their uses and discusses those new approaches for efficiency measurement, mostly unused in applied econometrics so far, but of great potential to applied researchers.

Chapter 3: Aggregate Energy Efficiency Measurement. The chapter outlines and estimates a measure of underlying efficiency in electricity consumption for an unbalanced panel of 28 transition economies and 5 Western European OECD countries in the period 1994-2007. Extensive data collection efforts from multiple sources lead to a rich dataset that allows to explore weaknesses in past literature. A Bayesian Generalized True Random Effects (GTRE) Stochastic Frontier model that estimates both persistent and transient inefficiency is estimated. This approach is now well established in the literature (although mostly through ML methods) but empirical applications are scarce and require further investigation. The properties of alternative GTRE estimation methods in small samples are explored to guide the estimation strategy. The chapter analyses the behaviour of underlying efficiency in electricity consumption in these economies after accounting for time-invariant technological differences. After outlining the specific characteristics of the transition economies and their structural economic changes, an aggregate energy demand function is estimated to obtain efficiency scores that give more insights for transition economies than a simple analysis of energy intensity. There is some evidence of convergence between the CIS countries and a block of Eastern European and selected OECD countries, although other country groups do not follow this tendency, such as the Balkans.

Chapter 4: Spatial Dependence and Unobserved Heterogeneity. This chapter contributes to the literature of SF modelling and efficiency measurement in production and cost functions in panel data by discussing estimation of technical or cost inefficiency in a context of spatial dependence and unobserved heterogeneity. The common pitfalls of previous literature are discussed to pave the way for a new modelling approach. A Bayesian Random Effects Spatial Lag Stochastic Frontier Model is proposed, allowing for the decomposition of inefficiency into a time-varying component and a persistent component, both with important policy implications in many empirical contexts. An extension to a Spatial Durbin Model is technically straightforward in this context but of important value to the applied researcher. A Bayesian approach with a standard assumption of a half-normal distribution for both inefficiencies is outlined. The chapter also contributes to the literature by exploring the performance of the proposed approach with competing methods. Small sample performance of the model is deeply related to the underlying signal-to-noise ratios with good performance for larger samples and encouraging results for applied research. The model is applied to aggregate productivity in 43 European countries between 1992 and 2005, highlighting the role of spatial dependence and unobserved heterogeneity in the production frontier. The results show a large amount of persistent inefficiency which would be ignored under less complex estimation methods, and also non-negligible spatial dependence.

Chapter 5: Efficiency Spillovers. This chapter develops a Bayesian Random Effects Stochastic Frontier model with spatial dependence associated to the inefficiency component, allowing for spillovers between firms. The proposed model is designed for contexts of unobserved heterogeneity, the existence of technical or cost inefficiency (assumed to be exponentially distributed) and spatial spillovers of inefficiency, using an exogenous spatial weights matrix determined by the researcher. The chapter also reviews the sparse efforts to include spatial dependence in the stochastic frontier literature, highlighting its contribution, with a particular focus on small sample performance. It also explores the Guided Walk Metropolis method as an alternative to classic rejection techniques to draw from non-standard distributions. The chapter applies the proposed model to a sample of 27 New Zealand electricity distribution firms in a stable post-unbundling period between the 2001 and 2009 fiscal years, discussing some pitfalls in the multiple perspectives on this topic in the literature. Some evidence of spillovers exists when a second order neighbour matrix is used.

Chapter 6: Conclusion. This chapter summarizes the findings of this thesis, the implications of the conducted research and a discussion on future research paths, along with concluding remarks.

Chapter 2. Stochastic Frontier Modelling: General framework and literature review

2.1. Introduction

The stochastic frontier literature has evolved greatly over the past few decades. Deriving from theoretical productivity and efficiency analysis, it is now a key area of economics with a large literature. A large set of applications have used approaches that are well established in the literature. However, since the work of Greene (2005) to account for heterogeneity and disentangle it from inefficiency in panel data, many researchers have tried to tackle different issues in the literature, as well as estimation challenges, diverging considerably in goals and achieved results. An extensive survey of cross-sectional and panel data stochastic frontier models was conducted by Greene (2008). This chapter intends to broaden the discussion towards more recent research and further issues in recent literature and rounds up all the latest work developed and how it has been applied, showing the need to have a broad view of the literature in order to merge some of the concerns of researchers and achieve modelling approaches that tackle all the key issues, such as heterogeneity, persistent inefficiency, endogeneity and spatial dependence. It also stresses how the failure to account for those issues in the past compromises results of empirical work and why it is important to focus on new approaches and make sure the links between them are established to improve the existing literature and provide more accurate inference on efficiency. Many of the approaches presented in this chapter had very few empirical applications as of yet. This chapter also aims to justify the approaches used in subsequent chapters regarding spatial modelling and the estimation of persistent inefficiency in a Bayesian context.

The chapter is organized as follows: Section 2 presents the origins and the basics of the field and an overview of the established literature in stochastic frontier modelling up to the seminal work of Greene (2005). Section 3 presents concerns about that work and ways to tackle the issues of heterogeneity, persistent inefficiency and consistent estimation in the fields of random and fixed effects modelling, which are very popular approaches in applications of stochastic frontier modelling. This section highlights multiple points that are the basis of contributions of this thesis regarding new estimators that consider persistent inefficiency. Section 4 digresses into other important issues of the efficiency literature and focuses on the increasing dynamic stochastic frontier literature and partial adjustments of inefficiency, with a comment on the use and application of Bayesian approaches. Section 5 focuses on common shocks and endogeneity, as well as presenting some other significant developments in the literature to tackle alternative issues. Section 6 digresses into the issue of spatial dependence and spatial econometrics and efficiency measurement. However, much of the space for that is open for the next chapters to discuss further, as it constitutes a key part of the contributions in this thesis. Section 7 discusses the issue of skewness and the interpretation of counter-intuitive skewness from a theoretical perspective. Section 8 contrasts Bayesian and frequentist approaches to justify the use of Bayesian approaches to problems raised in Sections 3 and 6. Section 9 concludes the chapter.

2.2. From the origins of stochastic frontier analysis to the use of fixed and random effects in panel data models

In the first half of the 20th century, average productivity of labour was deemed as an acceptable measure of productive efficiency, although that ignores that other inputs save labour. In the 1950s the foundations of modern economic thinking laid the first stones of modern efficiency and productivity analysis. Koopmans (1951) defines technical efficiency as the impossibility to produce more of one output without producing less of other output or using more of some input. Hicks (1935) observed that "the best of all monopoly profits is a quiet life", as the absence of a competitive environment gives monopolists the freedom to not pursue conventional optimization objectives. This relates to the idea that not all firms operate on full efficiency. One of the building blocks of the literature was, rather indirectly, the work of Leibenstein (1975) which argues production is bound to be inefficient as a result of multiple problems such as information, monitoring and agency problems within the firm. This general and rather vague definition of inefficiency can perhaps be attributed to poor model specification in some cases. A more direct contribution to the foundations of the Stochastic Frontier literature comes from the theoretical literature on productive efficiency.

Measuring productive efficiency in firms and industries in a more elaborate form and with further use of economic theory was a decisive step in policy making and gave valuable insight from both empirical and theoretical perspectives. The research of Farrell (1957) was a crucial turning point, by paying attention to the issue of productive efficiency and how firms and industries can increase their outputs without absorbing further resources. The author discussed the concept of an efficient production function, where overall efficiency corresponded to the product of technical efficiency (the success in producing a maximum level output from a given set of inputs) and price efficiency (the success in choosing an optimal set of inputs). The author stressed that technical efficiency is a relative concept, as it depends on the set of firms included in the estimation of the function. Statistical methods to solve the problem are discussed, and in fact, work in the following decade tried to close the gap between theory and empirical work. Incidentally, in practical terms, the work of Farrell influenced the (mostly non-stochastic) alternative literature of Data Envelopment Analysis (DEA). Aigner and Chu (1968) state that an "industry production function is conceptually a frontier of potential attainment for given input combinations" (pp. 826). One can consider technical efficiency to be the ratio of observed output to maximum feasible output in the production function:

$$TE_i = \frac{y_i}{f(x_i;\ \beta)} \tag{1}$$

The starting point of the analysis is a function denoting the maximum output possible (y_i) given inputs:

$$y_i = f(x_i;\ \beta).TE_i \tag{2}$$

In this equation, $TE_i = \exp(-u_i)$. Assuming a log-linear Cobb-Douglas form, this deterministic production frontier model becomes:

$$lny_i = \beta_0 + \sum_n \beta_n lnx_{ni} - u_i \tag{3}$$

The restriction $u_i \geq 0$ implies that $TE \leq 1$ and $y_i \leq f(x_i;\ \beta)$ in this deterministic case. This model can be solved through linear programming, which calculates the parameter vector which minimizes the sum of proportionate deviations of the observed output below maximum output (Aigner and Chu, 1968). The model can also be solved by minimizing the sum of quadratic proportionate deviations. In these approaches, the parameters are calculated rather than estimated. Other suggested approaches that predate stochastic modelling are Corrected Ordinary Least Squares (Winsten, 1957) and Modified Ordinary Least Squares (Afriat, 1972). In both cases, the first step is OLS estimation, followed by a "correction" of the constant, shifting it up according to the level of inefficiency.

The production function considered above is a mathematical representation of the technology that transforms inputs into outputs. A well-defined production function $f(x)$ satisfies the following regularity conditions (Chambers, 2001):

i) $f(x)$ is finite, non-negative, real-valued and single-valued for all non-negative and finite x. For example, a single input cannot lead to multiple values of an output, and the production cannot be negative;

ii) $f(0) = 0$, simply meaning that if the input is zero, the output will be zero;

iii) Monotonicity – it preserves ordering, as more input will lead to no lesser output;

iv) $f(x)$ is a continuous function and twice-differentiable at any point, as this is important for maximization and mathematical treatment of the production function;

v) The input requirement set is a convex set, as $f(x)$ is quasi-concave, meaning that there is a diminishing marginal rate of technical substitution;

vi) The input requirement set is closed and non-empty for any positive output.

Consider a simple example with two inputs and one output as in Herrero and Pascoe (2002).

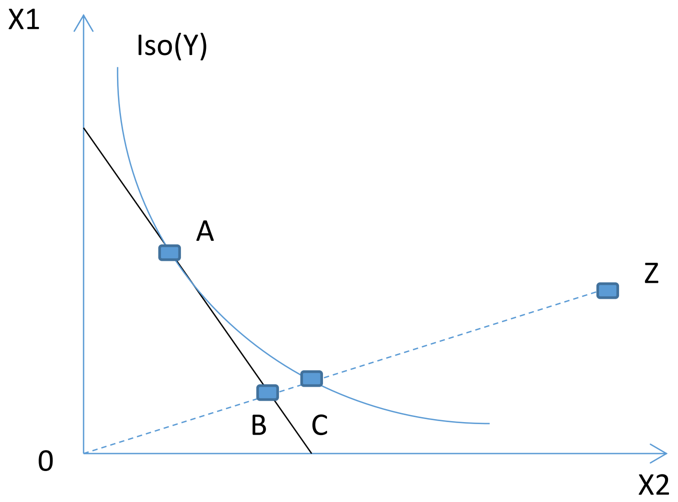

Figure 2.1. Cost Frontier with two inputs

If the agent fails to optimize, the producer ends up beneath the estimated production, revenue or profit frontier. On the other hand, in the case of a cost frontier, it will be above the frontier. Consider a firm in position Z, with a demonstrative combination of inputs X1 and X2. The firm is producing an output using the input combination defined in Z. One could use less inputs into point C, where the isoquant is. This isoquant reflects the minimum level of energy consumption required to produce Y. Technical efficiency is 0C/0Z, as Z is far from the isoquant. However, the minimum cost to produce Y would be at point A (least-cost combination). To achieve the same level of expenditure on inputs, the inputs would have to go to point B. Therefore, 0B/0Z is "cost efficiency", the combination of allocative and technical inefficiency, and 0B/0C is input allocative efficiency.

In order to have estimates with known statistical properties, the following (general notation) stochastic frontier model can be considered:

$$y_i = f(x_i;\ \beta) + \varepsilon_i \tag{4}$$

It is possible to estimate this model by Maximum Likelihood (ML) by making assumptions on the distribution of ε_i. The first work to develop this was conducted by Schmidt (1976), that assumed ε_i to be a one-sided (positive) error term, but this model still does not allow to invoke asymptotic properties because the regularity conditions are violated. A definitive step in building the modern stochastic frontier literature was achieved with the assumption $\varepsilon_i = v_i + u_i$, with the first being a symmetric disturbance and the latter being a one-sided error term with a truncated normal distribution, making the frontier clearly stochastic (Aigner et al., 1977). The random disturbance results of unfavourable external events, measurement and observation errors on y_i. The one-sided disturbance reflects the fact that the output of firms must lie on or below the frontier $y_i = f(x_i;\ \beta) + v_i$ and deviations are related to factors under the control of the firm. Meeusen and van Den Broeck (1977) suggest a similar model arguing that the exponential distribution for the one-sided error is the most appropriate[1]. Therefore, from a very early stage in the literature, different distributional assumptions about the error components were considered and used in empirical work – half-normal, truncated-normal, exponential

[1] Stevenson (1980) also suggested that the mean of the underlying normal distribution of the efficiency could be nonzero, so that this mean can vary with inputs.

and gamma are common examples in literature. However, Greene (2008) suggests that the results of truncated-normal and exponential models are extremely similar. A survey of early work in production functions was conducted by Førsund et al. (1980).

A key issue is the measurement of (relative) efficiency that can be retrieved from estimations: while estimating $(v_i + u_i)$ for each observation is easy, u_i is the key component in efficiency analysis and it is important to disentangle it from v_i. Jondrow et al. (1982) (JLMS) do this by knowing that u_i is conditional on $(v_i + u_i)$ and giving formulas for the half-normal and exponential cases. This enables the researcher to evaluate the levels of efficiency of firms after carrying on estimations, making it possible to have insight into distances to the frontier and relative rankings of firms in industries. The Battese and Coelli (1992) model allows efficiency to evolve over time although it also requires calculations of conditional expectations like the JLMS approach. Expected value calculations and mode calculations (which relate to ML estimation) are often seen as competing methods for efficiency estimation.

The mentioned work assumes error terms that are independently distributed across observations, an assumption that is sometimes not reasonable beyond a single cross-section. This meant that conducting panel data studies was problematic and new solutions were needed to extend efficiency analysis to panel data frameworks, using fixed effects and random effects. An overview of the established literature of both fixed and random effects models is presented next, culminating in the models of Greene (2005).

2.2.1. Fixed Effects

The seminal work of Schmidt and Sickles (1984) can be classified as a starting point for a rich literature in Fixed Effects SF modelling. The authors interpret the firm-specific (time-invariant) effect as inefficiency, leading to consistent estimation through ordinary least squares by using dummy variables. As such, considering a (linear) panel data example:

$$y_{it} = \alpha_i + x_{it}\beta + v_{it} \tag{5}$$

$$\hat{u}_i = max(\hat{\alpha}_i) - \hat{\alpha}_i \tag{6}$$

This approach strongly depends on the interpretational assumptions done on the fixed effects, although estimation becomes straightforward. However, there are three problems in this approach. First, the time-invariance assumption of the efficiency estimate is unrealistic for panels with larger T. Second, since the fixed effect is being interpreted as inefficiency, modelling firm heterogeneity becomes an issue. This model forces any time-invariant heterogeneity into the same term being used to capture inefficiency, meaning that the model may pick up heterogeneity instead of technical inefficiency. Finally, the large number of parameters growing with N can become a computational issue (Greene, 2005). Some approaches have been conducted to make efficiency estimates vary with time, but they are restrictive as they still imply a time-invariant fixed effect. Cornwell et al. (1990) introduce a quadratic function of time in the production function with coefficients varying across firms, with this representing different productivity growth at a rate that varies over firms.

Other attempts have taken place, with more modern approaches and the use of the Generalized Method of Moments (GMM). Ahn et al. (2001) present a model where individual effects vary over time with an arbitrary pattern that is the same for all firms, allowing to control for time-varying unobservable events that are faced by all firms. Han et al. (2005) propose to extend the previous model, allowing for a parametric function for time–varying coefficients of individual effects, using a number of GMM estimators. Other applications of the fixed effects estimator have appeared, for example a dynamic approach by Ahn and Sickles (2000) that focuses on long-run inefficiency levels and models inefficiency following an AR(1) process and a partial adjustment process. Further discussion of dynamic models is given in Section 4 of this chapter.

To address the issues of time-invariance and heterogeneity, Greene (2005) suggested the "True Fixed Effects" model (TFE):

$$y_{it} = \alpha_i + x_{it}\beta + v_{it} + u_{it} \tag{7}$$

Where α_i captures firm heterogeneity and u_{it} is a one-sided (positive) error with a particular distributional assumption to capture inefficiency – for example, half-normal or exponentially distributed. This model can be solved by "brute force" using ML, even with a very large amount of parameters. However, the fixed effects approach suffers from the problems of incidental parameters and a small T bias. One is a consequence of the other, as larger N leads to more nuisance parameters, not allowing the estimator to approach the true parameter value. Greene (2005) conducts Monte Carlo analysis and verifies that the bias of the coefficients of the explanatory variables of the TFE model are lower than expected and lower against those verified in binary response models. However, the bias in efficiency estimates is more serious, and considering its importance in analysis of results, this becomes rather worrisome. Insight into the bias the problem causes and ways to overcome it are discussed further in Section 3.

An example of an application of the “true fixed effects” model is the work of Kawaguchi et al. (2012) that assesses unique components of 127 Japanese hospital production structures over a period of three years. Studies with such a small T are prone to suffer more from the incidental parameters problem. Another example is a study of efficiency of 436 Finnish Upper Secondary schools between the years 2000 and 2004 (Kirjavainen. 2012).

In Random Effects models, the effects can be viewed as unobserved random variables instead of incidental parameters if N is large. This leads to a more parsimonious problem. These models are discussed next.

2.2.2. Random Effects

The first considerable effort to make a Random Effects SF model was conducted by Pitt and Lee (1981) to investigate the technical inefficiency of the Indonesian weaving industry. This is almost the same model as in equation (5) but with a normally distributed random component that is time-invariant and is assumed to be uncorrelated with the included variables (instead of including dummy variables for each firm). However, the issue of time invariance has been tackled in following years, for example, by using a monotonic decay model (Battese and Coelli, 1988), but the time-invariant random component still is a costly restriction in some circumstances. As in the case of fixed effects estimation, there were some attempts to achieve time-varying estimates although the random effect is time-invariant. To address the issues of time-invariance and heterogeneity, Greene (2005) suggested the “true random effects” (TRE):

$$y_{it} = x_{it}\beta + w_i + v_{it} + u_{it} \tag{8}$$

The difference against the Pitt and Lee (1981) approach is the inclusion of w_i, a random firm specific effect. Also, this model now includes a constant and can be solved through Maximum Simulated Likelihood (MSL). This model can also be extended easily to a single or doubly heteroscedastic model, therefore related to both v_{it} and u_{it}, as some variables can impact the distribution of the idiosyncratic error term or the distribution of inefficiency. Applications of the TRE model are slightly more common than the TFE model in the literature, probably due to the signalled problems in consistent estimation of the latter. Examples of applications of this include a productivity and efficiency of large and community US bank mixing this technique with a Bayesian approach (Feng and Zhang, 2012), benchmarking of regulated firms in the railway sector (Smith, 2012), economic-wide energy efficiency through an energy demand approach (Filippini and Hunt, 2011), efficiency of Ethiopian manufacturing firms (Hailu and Tanaka, 2015) and efficiency of Norwegian electricity distribution networks (Growitsch et al., 2012), among others. This model is increasingly popular because of its ability to separate heterogeneity from inefficiency and its easy application in software applications, for example through the program "sfpanel" for Stata (Belotti et al., 2012). However, a key limitation of both TRE and TFE models is at times ignored in empirical work, with serious consequences to the estimation of technical efficiency. Persistent inefficiencies that are time-invariant are absorbed by the heterogeneity component, meaning that they are not captured as inefficiency. This can result in abnormally high efficiency scores, as noted for example by Filippini and Hunt (2011). This can distort relative efficiency rankings of firms if some of them have high levels of persistent inefficiency and that is captured by the heterogeneity term, even if the model appropriately captures the actual heterogeneity in the data. However, in some contexts this approach is valid if persistent inefficiency is not of interest for analysis or there is a strong reason to believe it is undesirable to estimate it (an example of this is explored in Chapter 5).

The next section will discuss the latest work on both fixed and random effects modelling to deal with the issues discussed above, so that the following section can then discuss other issues present in the literature that are of interest beyond heterogeneity. For further discussion on the established models of the literature, efficiency estimators and confidence intervals for efficiency measurement, see Greene (2008).

2.3. Heterogeneity and persistency in inefficiency: latest developments in Fixed and Random effects modelling

While the focus of the literature has shifted from fixed effect models that do not truly account for unobserved heterogeneity to the TFE approach (Tsionas and Kumbhakar, 2014), the issues of persistent inefficiency being captured as heterogeneity and the issue of the incidental parameters problem are not yet fully clarified. The latter problem implies that the number of parameters changes with the sample size, leaving doubt on whether the fixed effects MLE estimator is consistent. While it is clear that the fixed-effects logit estimator is not consistent and the fixed effects linear model with normal errors has a consistent β if $N \to \infty$ and an inconsistent error variance unless $T \to \infty$ (which is quite unusual in empirical work), the behaviour of the true fixed effects MLE is less clear, although Greene points that the behaviour resembles the latter case (Chen et al., 2014). The error variance is particularly important as efficiency estimates clearly depend on accurate estimation of the error components. One of the first efforts to achieve consistent estimation (Wang and Ho, 2010) shows that first-difference and within transformation can be analytically performed on the TFE model to remove the fixed effects, rendering the estimator immune to the incidental parameters problem, with the interesting property of achieving consistency by either $N \to \infty$ or $T \to \infty$. While the authors consider the random portion of u_{it} to be time invariant, Chen et al. (2014) build a similar strategy but letting u_{it} vary randomly over t. In fact, different transformations of the fixed effects model are possible because it does not have the property of information orthogonality (Lancaster, 2000). This is an example of the use of the closed skew normal distribution to build feasible ML estimators and overcome the incidental parameters problem, although they are quite complicated from a technical point of view. The properties of the closed skew normal distribution are very useful for Stochastic Frontier analysis (Dominguez-Molina et al., 2004) and were developed later for fixed effects estimation and, as will be seen later in this section, for random effects models that try to disentangle heterogeneity from persistent inefficiency.

A parallel effort to avoid the incidental parameters problem had two different approaches: marginalizing the inefficiency term via simulation (which imposes some restrictions on the heteroscedastic specification as they can only be expressed as a function of time invariant explanatory variables) or an alternative procedure that uses the analytical closeness property of the maximum likelihood function (Belotti and Ilardi, 2012).

However, all these approaches to solve the incidental parameters problem still do not help solving the issue of disentangling persistent inefficiency from time-invariant heterogeneity. Still, extensions of the TRE model have managed to solve that problem and are discussed next.

Efforts in the development of extensions of the TRE model were mostly focused in making estimation efforts easier and overcoming the problem of disentangling persistent inefficiency from firm heterogeneity. As a first effort to facilitate estimation, Tsay and Ke (2010) derive an analytic approximation formula of the likelihood function for T=2 and combine it with a pairwise likelihood estimator for estimation with T>2. This is implemented without resorting to numerical integrals or simulation-based techniques. Regarding persistent inefficiency, the way that was found to disentangle it from firm heterogeneity was to add another specific random effect to account for long-run sources of inefficiency. This is justified by the fact that firm management changes over time but a considerable part of it is also time-invariant, giving economic rationale for the appearance of this new error component. The model can be written as follows, with the notation that will be followed for the rest of the thesis:

$$y_{it} = x_{it}\beta + \alpha_i + v_{it} + u_{it} + \eta_i \tag{9}$$

This resembles equation (8) except for the addition of a one-sided time-invariant random effect η_i. This will capture persistent (long-run) sources of inefficiency, which are now separated from heterogeneity α_i. Total inefficiency is therefore captured by $u_{it} + \eta_i$. Colombi et al. (2011) were the first authors to suggest this approach, using results from the closed skew normal distribution under a series of assumptions (for example that all random variables are independent in probability and all random vectors are independent in probability). The authors state that this approach is particularly appropriate when firms are heterogeneous and the panel is long. Since the resulting log-likelihood function is complex, a two-step procedure to estimate all parameters is required. In the first step, $\tilde{\beta}$ is retrieved (a consistent estimate of β) by estimating a random intercept model. In the second step, a pseudo-likelihood function using $\tilde{\beta}$ is maximized to retrieve all other parameters, following the general theory of two-step M-estimators. One of the key contributions of this paper is also the comparison of this suggested approach with the established techniques in the literature by using log-likelihood ratio tests on different applications and datasets, stressing the point that the addition of this specific long-run inefficiency effect is not necessary in all cases, depending on the nature and behaviour of the inefficiency. The authors apply their approach to three different datasets: hospitals (larger T and N), rice producers and airports (small samples). It is clear that it is in the case of the larger sample that it is undesirable to drop any of the components. However, tests for the suitability of models show that such a complete model is not necessary in all occasions, and depending on the data, one or more components can be dropped from equation (9). Colombi et al. (2011) also point that future work can include generalizing the model to introduce some dependency among random components capturing the short-run sources of inefficiency in a firm. This has several technical and theory implications. Dynamic models will be discussed in the next section of this chapter.

Another approach to solve the same problem of persistent inefficiency is a Bayesian approach (Tsionas and Kumbhakar, 2014). This approach has the advantage of proposing a more flexible Bayesian approach. The authors also contribute to the Bayesian literature by proposing parameterizations for the Gibbs sampler that provide accurate inferences and less autocorrelation in the Markov Chain Monte Carlo (MCMC) scheme, to address the correlation between persistent inefficiency and firm effects. The authors apply their method to a balanced panel of banks from 1998 to 2005, finding evidence in support of the use of their model. This paper will be examined (and criticized) in detail throughout this thesis. However, the merits of a Bayesian approach in terms of the use of priors and assessment of the strength of the results in small samples are of great interest. This will be discussed further in Section 2.8.

2.4. Dynamic models and partial adjustment of inefficiency

One good example to portray the development of the Stochastic Frontier literature and how it is growing in branches (that are not necessarily well connected to each other) is the field of firm dynamics. It is fundamentally linked to the consideration of lags in the inefficiency term, which leads to changes in interpretation of results. A reason for the visible lack of work in this specific field is the complexity of the likelihood function and the difficulty in providing inference on unobserved firm-specific inefficiencies (Tsionas, 2006). Another reason for the importance of considering dynamics in stochastic frontier models is the fact that technical efficiency scores can be argued to be only interpretable in the short-run, and firms could be found to be inefficient because they are operating at their long-run equilibrium with respect to efficiency under an interpretation of dynamic/long-run efficiency analysis (Emvalomatis, 2012). Note that this notion of "long-run" is different from the one of Colombi et al. (2011), as the latter uses that term to describe persistent inefficiency in a non-dynamic model.

One of the first efforts to include dynamics in the stochastic frontier literature was conducted by Ahn and Sickles (2000), within the time-varying efficiency fixed effects literature, taking the fixed effects model of Schmidt and Sickles (1984) as a starting point. The authors consider the existing methods in fixed effects modelling at the time inappropriate for estimation of long-run efficiency (in a dynamic sense) and propose a model where the firm-specific technical inefficiency levels are autoregressive. It is worth noting that in this specific part of the literature the fixed effect is interpreted as the inefficiency term, and therefore there is no space to account for firm heterogeneity. Another weakness of the fixed effects approach is that to retrieve time-varying efficiency measures, the score will either increase or decrease with time as in Cornwell et al. (1990), as efficiency is assumed to be also a function of time, or technical inefficiency barely varies for large T as it converges to a finite level with bigger T (Kumbhakar, 1991). The model of Ahn and Sickles (2000) can be reduced to a traditional fixed effects model with autocorrelated errors in which the fixed effects are interpreted as the firm's long run technical efficiency. Each firm's inefficiency follows an AR(1) process, meaning that a new parameter of interest appears: ρ, the ability to adjust past-period inefficiency levels, with a value between zero and one. While this allows to find long-run average inefficiency levels, adjustment speeds and output loss by sluggish adoption of technical innovations, it still suffers from the fact that it develops from the classic fixed effect literature, its interpretation of the fixed effect as an inefficiency term, and the lack of a framework to handle firm heterogeneity and therefore results only hold if no such heterogeneity is present or is controlled adequately with the use of additional regressors. The model can be estimated using Non-Linear Generalised Least Squares (NLGLS), but the error term follows a MA process and weak exogeneity of the lagged dependent variable no longer holds. Because of this source of bias, GMM is likely to be more appropriate for estimation in this context. Ahn and Sickles apply it to a panel of US airlines, finding that results for the airline industry do not strongly support the hypothesis of long-run convergence of technical inefficiency levels of firms in an industry. The results also point that ignoring dynamics in fixed effects estimation can exaggerate heteroskedasticity in long-run inefficiency.

A similar effort was conducted by Desli et al. (2003), but with a focus driven away from long-run inefficiency and focusing instead on the fact that most of the existing literature does not allow stochastic frontier models to consider the correction of past inefficiencies. The authors build a model with a time and firm specific intercept, with the latter following an AR(1) process. As technical efficiency is introduced in the model in the intercept and is not a function of time, time can be an explanatory variable and allow to distinguish technical change from efficiency change. The model is estimated using ML. This approach has been applied to the context of efficiency of financial services in China (Zhang et al., 2015). However, this modelling approach suffers from some problems (Wang, 2007), as it does not allow the efficiency of a firm in one period to be influenced by past levels, although the output may be influenced by them. Wang (2007) suggests an extension of the basic model of Aigner et al. (1977) with an AR(p) inefficiency term, meaning that technical inefficiency of firms at time t is influenced by past inefficiencies in p periods from t-p to period t-1. The author derives the log-likelihood function that can be easily maximized to obtain ML estimates.

Tsionas (2006) presents a Bayesian approach to dynamic models and applies it to a panel of large US commercial banks. The author states that the method is more appropriate for longer panels, which are an exception in efficiency analysis. While this stems from the original approach of Aigner et al. (1977), it specifies technical inefficiency in the following way:

$$log u_{it} = z_{it}'\gamma + \rho log u_{i,t-1} + \vartheta_{it} \quad for\ t = 2, \dots, T \tag{10}$$

$$log u_{i1} = z_{i1}'\gamma/(1-\rho) + \vartheta_{i1} \quad for\ t = 1 \tag{11}$$

The term $z_{it}'\gamma + \rho log u_{i,t-1}$ captures systematic, expected log-inefficiency sources while the last part ϑ_{it} captures unexpected sources, captured by a random variable. z_{i1} is a set of covariates that influence inefficiency ρ, a parameter that accounts for persistency in the inefficiency process. As the resulting likelihood function is very complex (including integrals that cannot be computed analytically), the author proposes a Bayesian approach with MCMC methods (although maximum simulated likelihood can also be used). Results from the US banking sector show that the persistence is fairly close to unity and efficiency levels are very high, being higher than the ones given by the static model. An example of empirical work using this approach studies the dynamic efficiency of Spanish outdoor and greenhouse horticulture sector (Lambarraa, 2011). The author stresses the large difference in results between static and dynamic cases in estimates of technical efficiency levels. This is consistent with a high persistency coefficient.

Emvalomatis (2012) focuses on the problem of long-run equilibrium in dynamic models and extends the work of Tsionas (2006) besides highlighting some of the problems in estimation caused by theoretical considerations. Estimates of the persistency of inefficiency can be overestimated when an interior long-run equilibrium exists due to an underlying dynamic optimization problem (depending on expectations of the managers of firms). In a turbulent industry, long-run equilibrium might change with time and the inefficiency process appears to have a trend captured by the persistency component. Other reason to inflate ρ is the presence of unobserved heterogeneity – as in this model it is interpreted partially as inefficiency – although the slope parameters will be largely unaffected. In fact, considering that persistency estimates of both the studies of Tsionas (2006) and Lambarraa (2011) are very high, this is possibly caused by the presence of unobserved heterogeneity not being modelled appropriately (more likely than the presence of large shifts in long-run equilibrium). Another consequence seen in Monte Carlo experiments when ignoring heterogeneity is that σ_u is underestimated, with consequences to the efficiency estimates (and possibly, to the comparison of models that Tsionas (2006) makes between static and dynamic models). The modelling approach of Emvalomatis (2012) implies that the long-run level of inefficiency is common to all firms, although it is possible to let it vary as a function of covariates. The author discusses the issue of unobserved heterogeneity and considers the inclusion of firm-specific effects in this model, so this model can be considered as a dynamic extension of the models of Greene (2005). However, this still suffers from the issue of time-invariant inefficiency being captured by the firm-specific terms, so estimations of efficiency can be inflated in the presence of large persistent inefficiencies. Bayesian methods are also applied.

Extensions of these models are sometimes easy to outline but hard to achieve or to interpret. A possible extension to the work of Emvalomatis (2012) is the addition of a one-sided time invariant random component to capture persistent inefficiency and therefore disentangle it from unobserved heterogeneity, while keeping an AR(1) structure on the transient component of inefficiency. However, the issue of the determination of the long-run level of efficiency would become problematic and in the presence of large and heterogeneous persistency, inference could be obfuscated, as the data could capture the process that describes evolution of inefficiency out of equilibrium – in the long-run, every firm should have the same efficiency. This can be relaxed to assume that each firm has a different long-run equilibrium level by making this vary according to a set of covariates as in Tsionas (2006), but in general interpretation of such models can be complicated.

2.5. Endogeneity, common shocks and benchmarking

As the literature keeps growing in depth and diversity, focus is placed on issues that were once overlooked. An occasional issue is the presence of unobserved common shocks that cause heterogeneous impacts across firms, causing bias in efficiency estimates. In fact, examples of this problem are not difficult to imagine, for example with the consequences of the global financial crisis and how it represented a common shock to many businesses and industries around the world. While traditional stochastic frontier methods do not distinguish these shocks from technical inefficiency, Hsu et al. (2015) try to control for those shocks and obtain consistent estimates of technical inefficiency by modifying the ML estimator, applying the methodology to OECD banking data. However, there is no current effort in the literature to reconcile the treatment of this issue with other issues discussed in this chapter.

Another important topic that only received attention recently is the issue of endogeneity in SFA. While it is now established in other parts of the econometrics literature how to deal with this issue, the technical difficulties of solving this issue in stochastic frontier modelling implied that the first effort is extremely recent (Kutlu, 2010). The author modifies the Battese and Coelli (1992) estimator of inefficiency to account for endogenous variables. This is done by decomposing the irregular term (v_{it} in previous equations), assumed to be correlated with the regressors and independent of the inefficiency term, in two parts: one correlated with the regressors and the other not. This two-step procedure leads to inconsistent standard errors and a bootstrapping approach is required. However, Monte Carlo experiments show the improved performance and the severe bias of the Battese-Coelli estimator in presence of correlation, which is not surprising. The work of Kutlu (2010) is not generalized and focused specifically on the Battese-Coelli efficiency estimator, leaving space for further work to be done in addressing the issue of endogeneity in stochastic frontier models. A more general framework is proposed by using a one-step GMM approach that provides the correct standard errors of the estimated parameters (Tran and Tsionas, 2013). This is achieved by looking at the first order conditions of the resulting likelihood function when endogeneity is accounted for. Monte Carlo simulations show that performance is similar to MLE when there is no endogeneity in regressors, but the MLE deteriorates quickly with increasing correlation. The suggested approach presents good finite-sample performance and is applied to Norwegian farm data, showing more plausible estimates of returns to scale when using GMM, while efficiency estimates are generally lower and less dispersed. Farm dummies are implemented in this example, meaning that this can be seen as a variation of the TFE model that accounts for endogeneity in regressors. Accounting for that, estimates of efficiency appear to be very low, considering that the fixed effects should absorb persistent inefficiency and then the visible inefficiency is considered as transient or “short-run” inefficiency. However, the estimates of output factor elasticity are much more reasonable, leading to the belief that estimations are probably more trustworthy than the ones conducted using a simpler approach. Amsler et al. (2016) conducted the most recent survey on endogeneity in stochastic frontier models, elaborating on 2SLS and LIML techniques to address the issue, but also copula approaches (a joint distribution whose marginal distributions are uniform) to model the distributions in case of correlation between the error components and the variables. Griffiths and Hajargasht (2016) have also outlined alternatives for Bayesian estimation of endogenous stochastic frontier models.

It is important to point that all of the literature mentioned so far generally discusses parametric stochastic frontier models. This means that the distributions of the error terms are known up to the specific values of the parameters, estimated using maximum likelihood, simulated maximum likelihood or Bayesian methods. Fully nonparametric approaches avoid all forms of misspecification and allow for heteroskedasticity of unknown form. This constitutes a small (yet growing) part of the stochastic frontier literature and will not be discussed further in this thesis. For further details on semi parametric and nonparametric approaches, including latent class models, see Greene (2008). An example (not included in the aforementioned survey) is the approach of Tran and Tsionas (2009), a nonparametric specification for covariates that affect the mean of technical efficiency, applied to the British manufacturing sector. However, only average technical efficiency can be estimated, as a key limitation of this modelling approach is that distributional assumptions need to be made in order to retrieve individual efficiency scores, removing much of the added value on the application of a nonparametric method. This was however solved by using Local Maximum Likelihood (LML) in Kumbhakar and Tsionas (2011).

Another important aspect overlooked in the literature is that while neoclassical production theory considers all firms are fully efficient and the current stochastic frontier literature assumes that no firms are fully efficient, a reasonable compromise is to assume that something "in between" happens: while some firms are fully efficient, others are not. This issue was dealt with by constructing latent class models, where a cluster of firms sometimes has very high efficiency estimates, indicating some clusters at full efficiency but not others. Kumbhakar et al. (2013) built a "zero inefficiency" model that accounts for this economic problem that is particularly important for benchmarking, as the benchmark is preferred to have more than one firm. This also gives a better landscape of inefficiency in an industry and provides some clustering insights to policy making. Tran and Tsionas (2016) propose a semi-parametric zero inefficiency model, with encouraging results in simulations. However, as many papers in the field, the focus on very small samples that matter to the applied researcher is at times ignored. The smallest sample of the simulations of the authors has 2500 observations, a number that is hard to reach when considering firm data for specific industries, a set of limited regions in a country, or a set of countries in the world.

2.6. Spatial Frontier Models

Another increasingly important aspect of efficiency analysis is the issue of spatial dependence. A Spatial Autoregressive (SAR) dependence in the cross-sections, for example, can lead to omitted variable bias if a spatial lag of the dependent variable is not included in the model. On the other hand, a Spatial Error Model (SEM) specification can also capture spillovers, but they are related to the error components and therefore with less of a structural economic interpretation. Both approaches will be investigated further in this thesis. A brief survey of the literature follows. A more descriptive literature review on Spatial Stochastic Frontier models is explored in detail in Chapters 4 and 5 in the context of the contributions to the literature contained in those chapters.

The literature can be divided in three broad categories: SAR based approaches (developed further in Chapter 4), SEM based approaches (developed further in Chapter 5) and other mixed approaches related to spatial econometrics.

Noticeable early efforts in the literature include Druska and Horrace (2004), that develop a GMM frontier model and apply it to rice farms in Indonesia, and also Schmidt et al. (2009) that focus on the unobserved local determinants of inefficiency in farm productivity in the Centre-West of Brazil. In this (Bayesian) study, spatial dependency is allowed through lagged latent regional effects, instead of farm effects, unlike Druska and Horrace (2004).

Spatial Autoregressive approaches are becoming more established in recent literature. In Areal et al. (2012), the spatial spillovers are modelled directly in the efficiency components, so there is a spatial relationship between firms' efficiencies. Pavlyuk (2013) develops a cross-sectional maximum likelihood estimator for SARSF (Spatial Autoregressive Stochastic Frontier model) and SARARSF (Spatial Autoregressive Stochastic Frontier model with spatial autoregressive disturbances) models. Affuso (2010) used a SARSF model to evaluate the impact of agricultural extension programmes that have positive effects not only on chosen farmers but also to other farmers due to spatial spillover effects. Another contribution to the literature is a spatial extension of the CSS estimator (Cornwell et al., 1990) to the case of a spatial autoregressive dependence which involves direct, indirect and total efficiency (Glass et al., 2014). Glass et al. (2016) make further analysis of spatial spillovers and the modelling approach, with important aspects which will be considered and developed further throughout this thesis, such as efficiency measurement after estimation.

The development of SEM based models is scarcer and received less attention in the literature, particularly in high impact journals. Areal et al. (2012) apply a spatial stochastic frontier model with an autoregressive specification of the inefficiency component of the compound error term. The key contribution of this paper is the direct specification of inefficiency to be spatially autoregressive and including a parameter that measures the level of spatial dependence. Fusco and Vidoli (2013) present a similar approach to Areal et al. (2012) with the key difference of the use of a half normal inefficiency assumption and estimation using ML methods. Tsionas and Michaelides (2016) propose a latent random effects vector that is specified to follow a spatial autoregressive process for panel data. The idiosyncratic part of inefficiency is assumed to be half-normal and the model is estimated using complex Bayesian methods.

There are also other recent efforts in the literature linked to spatial stochastic frontier models. Adetutu et al. (2015) study the effects of efficiency and TFP growth on pollution in Europe in a two stage approach. In a first stage, non-spatial and local spatial stochastic production models are estimated. In a second stage, measures of productive performance are used as regressors in models of per capita emissions of nitrogen and sulphur oxides. Some advances in spatial stochastic frontier modelling have also taken place in the macroeconomic literature. Mastromarco et al. (2013) use a two-step approach to investigate the channels under which globalisation factors lead to technical efficiency by combining a dynamic stochastic frontier model with a time series approach. Mastromarco et al. (2016) propose a framework to accommodate both time and cross-sectional dependence by combining the exogenously driven factor-based approach with an endogenous threshold efficiency regime selection mechanism.

Up to this point, no spatial frontier model that takes into account persistent inefficiency while accounting for unobserved heterogeneity seems to exist in the literature. There are also no current significant signs of research done about dynamic frontier models with spatial dependence. To add to this, the development of models where spatial dependence is placed on the inefficiency components is also in its infancy. Another fact that does not help dissemination of this work is the lack of spatial econometrics aspects in broad SFA literature reviews, such as the review of Parmeter and Kumbhakar (2014). These issues lead to the detection of a gap in the efficiency measurement literature that could be filled for better benchmarking procedures in efficiency measurement.

2.7. A note on economic interpretation of skewness and "wrong" skewness

Most of the literature focuses on the estimation of inefficiency without delving considerably into a complete interpretation of the principles on which stochastic frontier analysis is based on. A key factor is the skewness of the error term, how it is interpreted and how inefficiency measurement arises from that. It is generally considered that in production frontiers the skewness of the error term should be negative and that in cost frontiers it should be positive. An example of a discussion about the theoretical foundations of the direction of the existing skewness is present in Bhattacharjee et al. (2009). The usual skewness interpretation is associated with the Neo-Schumpeterian theory of growth – where a frontier results from the forging ahead of firms, overcoming the best practices. However, the behaviour of residuals in empirical work does not always follow that theory, as there are production function settings where positive skewness is found or cost function settings where negative skewness is found. This cannot be compatible with the assumptions made about the one-sided error in classic Stochastic Frontier models. Various reasons can be considered, from measurement errors to misspecification, or an economic interpretation of "super efficiency" where all firms are efficient, as this skewness shows little evidence of inefficiency in the sample (Greene, 2008).

However, two other theories exist in the literature: one that considers that wrong skewness is a finite sample problem and another that considers wrong skewness not to be a problem, but just a consequence of the strong assumptions made about the one-sided error or other theoretical considerations. The first starts from consequences of small-sample estimation: if the signal-to-noise ratio is very small, then in a very small sample there is a high probability of finding wrong skewness in that sample. Simar and Wilson (2009) apply a bootstrapping procedure to retrieve inefficiency measures independently of the direction of the skewness. Other approaches are, for example, to impose negative skewness constraints on the residuals in ML estimation for production frontiers or apply corrected least squares estimation.

In the latter perspective of the literature mentioned above, Carree (2002) considers a binomial distribution for inefficiency so that skewness can take both positive and negative values. In this case, a positive skewness in a production frontier setting is interpreted as a low probability of small inefficiencies and high probability of large inefficiencies. The theory behind it is related to cycles of innovation and imitation and transient dominance of firms within an industry, where innovation leads to positive skew and imitation leads to negative skew. Almanidis and Sickles (2011) consider a doubly-truncated normal model, allowing skewness in both directions. The authors consider that misspecification should only happen if the wrong distribution for the inefficiency process is assumed and show that the wrong skewness is also a large sample problem. However, this econometric advance that consists of a bounded inefficiency approach clashes with the pre-established theory that justifies the direction of the skewness. This leaves space for some discussion between theory and practice. Considering the base foundations of the field, it is probably not recommended to conduct efficiency analysis if the skewness of the residuals seems to be incorrect. Econometric procedures to get around that problem will still struggle with the underlying (lack of) meaning of what is being estimated.

2.8. Bayesian Approaches

A common trend in the literature has appeared in recent years. While the literature has tried to address problems that are increasingly harder to solve, Bayesian approaches have gained popularity as practical tools to solve those problems and increasingly appear in different applications of stochastic frontier models in efficiency analysis, instead of classic ML estimation approaches. This popularity has certainly benefitted from exciting computational advances in recent decades which put large computational power at the hands of any researcher in small and low cost machines. These approaches usually imply better small-sample properties and more flexible approaches towards efficiency measurement when used correctly. Early work in Bayesian stochastic frontier modelling includes Koop et al. (1995) and van den Broeck et al. (1994). Further Bayesian analysis of such models is in Koop and Steel (2003). However, Greene (2008) stresses that assuming an informative prior distribution is important to get estimates of inefficiency that are specific to individual observations. With diffuse priors, the Bayesian applications are nothing else than alternative methods of maximizing the likelihood function, while appearing more modern and complex. Procedures such as Local Maximum Likelihood (Kumbhakar et al., 2007) or Simulated Maximum Likelihood (Greene, 2003) show advantages over simpler classical methods when estimating different Stochastic Frontier models. When facing more complicated problems, it is also possible to decouple the estimation into a simple first step where the cost or profit function is estimated and a second step where the error term is decomposed as required. However, two-step approaches suffer from loss of information that can be particularly damaging in small samples and is hard to quantify.

However, the literature contains examples of Bayesian approaches which go beyond what is seen in the classical literature, for example with the spatial stochastic frontier model of Areal et al. (2012) and the work on dynamic firm behaviour of Emvalomatis (2012). It is also possible to assess the sensitivity of results to different priors and evaluate the strength of the underlying signal in the data in small samples. For example, it is very difficult to assess the stability of the results in the classical GTRE approach of Filippini et al. (2016) as the model estimates persistent inefficiency with very small N and there is no information on the performance of the estimator. The sensitivity of the results to different choices is a key objective of chapters 3, 4 and 5. Bayesian techniques can also facilitate estimation to overcome obstacles that would often lead to two-step approaches in frequentist estimation, overcoming the issue of loss of information between the steps. These issues justify the use of such techniques throughout the thesis and will be explored further in subsequent chapters.

2.9. Conclusion

The Stochastic Frontier literature has clearly evolved in recent years, both in depth and range. It is now possible for researchers to ask deeper questions and get more accurate answers, tuning their methodology according to the increasingly available range of modelling and estimation approaches. The issue of heterogeneity has seen significant developments in the literature, linked to the expansion of estimation techniques, both through Bayesian approaches and extensions of the established Maximum Likelihood estimation methods. Techniques like Local Maximum Likelihood and Maximum Simulated Likelihood greatly increased the possibilities of researchers in efficiency measurement, just like advances in computational power and statistical software made complex Bayesian MCMC approaches possible. More attention was given to the incidental parameter problem, which might have affected the conclusions of some studies conducted in the past. However, other technical and theoretical details were investigated leading to significant developments in recent years. Recent tools allow researchers to account for endogeneity in the production or cost function, include dynamics in the specification of the stochastic frontier model and account for spatial links between the efficiency of a firm and its neighbours. These tools are growing in depth and generality, allowing for a promising future in the field. The next step is the catching up process of the applications of stochastic frontier models with the large amount of modelling innovations in recent years, considering that the overwhelming majority of the applications over the last few decades ignores key issues due to the lack (at the time) of proper tools to tackle the particular issues at hand. There is, however, still room for improvement in theory and econometric approaches to efficiency measurement, as zero inefficiency models and spatial models can grow in complexity and dynamic models can increasingly account for heterogeneity. Allowing for endogeneity in the production function while also accounting for the problems mentioned above is a possible extension to this large body of literature.

Spatial dependence is an issue capturing increasing attention and is witnessing interesting developments of great importance to efficiency measurement. However, empirical work needs to close the gap and take advantage of the new developments in the literature to fully capitalize on such advances. It is also necessary to keep building strong bridges between the undeniable advances in econometrics and the existing theory on efficiency measurement. The lack of ready to run statistical packages and code provided by the authors that conduct estimation of many of the models referenced above might justify most of the gap between theory and application seen up to this day.

The issues of persistent inefficiency and spatial spillovers discussed in Sections 3 and 6 respectively are of particular interest and will be combined in the contributions of this thesis to the existing literature. The choice of a Bayesian approach is of particular interest when related to small sample issues, which will be recurrent throughout the thesis.

Chapter 3. Energy Efficiency in Transition Economies: A Stochastic Frontier Approach

3.1. Introduction

Energy efficiency and energy-saving measures are a heavily debated topic in recent years, both in high profile environmental discussions and in the media, as issues like energy security, energy supply, carbon emissions and climate change take increasing shares of the attention of policy makers, the media and society in general. The issue has been approached from multiple perspectives, from renewable energies to changes in consumer behaviour, spanning a large spectrum of research on technical aspects, policy making and economic analysis.

The world energy demand profile has changed in past decades, with some noticeable geographic differences. The oil shocks of 1973 and 1979 fundamentally changed energy demand in the OECD, slowing down the growing patterns of energy demand that were ongoing since WWII (Cooper and Schipper, 1992). Eastern Europe and the USSR were mainly isolated from price shocks, which allowed the bloc to carry on with its industrial expansion which in turn came to an end with the collapse of the political and economic system. After this turning event, the reform packages of the Washington Consensus were applied to try to recover and transform the economies, with heterogeneous paces of implementation and different results across the region. After 25 years of the process, some countries of the Former Soviet Union (FSU) still maintain an economy with very fragile market mechanisms and do not seem to be approaching a free market economy status anytime soon.

Economies that transitioned from a centrally planned economy to a market economy after the fall of the USSR often experienced rapid improvements in energy intensity as market reforms alleviated problems such as resource misallocations and price distortions. Research has often focused on energy intensity as a measure of what impacts energy efficiency, with transition economies not being an exception. However, deep changes were also ongoing as market reforms took place, changing the role of the government in the economy and the structure and key sectors that contribute to the economy. By using energy intensity as a proxy for energy efficiency, the considerable changes in the structure of these economies are mostly ignored in the assessment of efficiency. By modelling energy demand for the purpose of the analysis, a measure of underlying energy efficiency is estimated, as it is separated from some changes in intensity caused by economic collapse or other deep structural changes of the economy. This is achieved through recent developments in the estimation of SF models, the Generalized True Random Effects model (Colombi et al., 2011), exploring the Bayesian reparametrized estimation approach of Tsionas and Kumbhakar (2014) and also the simpler Gibbs sampling approach of Makiela (2016) as competing estimation solutions. Simulations show that results in small samples are very sensitive to prior choices, but this sensitivity is mostly dependent on the underlying signal-to-noise ratio of the data, allowing for meaningful estimation and interpretation under strong enough ratios. This chapter contributes to the literature by estimating both time-varying and persistent inefficiency measures in an electricity demand equation approach (a cost frontier), while accounting for unobserved heterogeneity in a random effects framework. It also uses a rich dataset from multiple sources to consider issues previously overlooked in the literature, such as climate effects and economic structure. The countries in the sample provide particularly interesting insights, as they were the target of one of the most ambitious reform programmes in recent history (even if executed at different paces and intensities) and were subject to an extreme situation of political and economic turmoil at the start of the transition period and sometimes beyond that. In this approach, "true" efficiency can be measured by focusing on other aspects, such as norms, traditions, use of appliances, habits and conscience on energy consumption in both households and the industrial sector. Selected OECD countries are added to the sample as a comparison term, due to their large role in the EU and also to expand data available for estimation. While there is an undeniable decrease in energy intensity in transition economies in the 1990s (Cornillie and Fankhauser, 2004), that can be due to de-industrialization and the collapse of economic activity, and not because of actual improvements in the use of energy in existing activities at a given time. Therefore, the purpose of this chapter is to measure underlying energy efficiency levels in electricity consumption and its changes by accounting for structural changes in the economy and other key socio-economic variables, in a challenging context of limited data.

While research in the past has heavily focused on using energy intensity as a proxy for energy efficiency, few attempts to discuss and identify mismatches between the two concepts have been done. Transition economies in and around the FSU, which represent one of the most interesting episodes of quick and radical transformation in the past decades, are the location of a unique type of “natural experiment”. Results give evidence that a part of the gap between East and West has been closed mostly by the time Eastern European countries joined the EU, with the Balkans being a clear exception and lagging behind, as well as most of the countries further to the East. There is evidence of convergence across most groups but with a few clear exceptions which are worthy of a discussion around possible reasons for such results.

3.2. Energy in Transition: key facts and literature review

Key differences separated the western economies from the centrally planned economies in the FSU and Former Yugoslavia spheres of influence. Planning and policy in the energy sector were also fundamentally different from western countries, as the communist regimes focused on supply-side solutions to meet increasing demand instead of tackling demand issues and waste (Cooper and Schipper, 1992). This implied large investments were made in fuel extraction and power generation in order to meet demand, instead of tackling energy efficiency problems or consumer behaviour with demand driven policies. Serbia and Uzbekistan are still examples of countries where the main electricity generation firm is deeply involved in coal extraction and the energy industry is highly integrated. Another important issue was the pricing system of transition economies. Over 24 million goods had fixed prices in the Soviet Union, with prices being inflexible and unable to provide any correct information about scarcity. Microeconomic efficiency was not achievable (Ericson, 1991), cascading into macroeconomic outcomes.

Some serious problems still persisted in the power sector long after the start of the transition process. Energy companies mostly continued to function as "quasi-fiscal institutions" after a decade of transition, providing large implicit subsidies to households and (state-owned) enterprises through low energy prices, preferential tariffs or free provision of services to privileged groups, the toleration of payment arrears, and noncash arrangements (Petri et al., 2002). This generated considerable inefficiencies and distortions. Such arrangements were necessary, for example in Russia, as insolvent companies kept doing business and generated a non-payment crisis (Martinot, 1998). Another consequence is that underinvestment and capital stock depletion occur under a scenario of tariffs set below cost recovery levels. Although some tariff rebalancing has taken place, cross-subsidizing was still present in the transition process as residential tariffs were more expensive than industrial tariffs, especially in the CIS (Kennedy, 2003). Removing this distortion maximizes economic benefits. Another major issue is general under-pricing in the power sector, as prices are well below Long Run Marginal Cost (LMRC) and they should be above LMRC in order to recover past accumulated energy debt, which is a major component of total sovereign or quasi-sovereign debts in some CIS economies. While different countries have heterogeneous marginal costs, it is clear from Table 3.1. that there is a gap in prices between countries where regulators are established and others where that is not the case, and energy intensities are clearly higher in countries with lower electricity prices, as there is no clear incentive to reduce consumption through appropriate pricing.

	Independence of electricity regulator	Household expenditure on power and water (%)	Energy use (kg of oil equivalent) per $1,000 GDP (constant 2005 PPP) (2008)	Residential electricity tariffs (USc kWh) (2008)
Albania	Partial	5	90.1	9.6
Armenia	Partial	6.8	173.3	7.9
Azerbaijan	No	3.5	189.7	7.4
Bulgaria	Full	11.2	216.3	10.9
Croatia	Full	13.1	118.4	12.4
Georgia	Partial	11	151.9	10.3
Hungary	Full	10.9	147.2	22.5
Kazakhstan	Partial	3.7	422.0	5.3
Kyrgyzstan	Partial	4.4	253.8	1.6
Latvia	Full	3.8	126.5	11.8
Lithuania	Full	3.8	155.3	10.5
Macedonia	Partial	6.6	160.4	6.1
Moldova	Partial	9.6	318.7	10.1
Poland	Full	6.8	156.0	20.0
Romania	Full	3.7	155.5	14.5
Russia	Partial	6.6	328.4	6.7
Slovakia	Full	9.5	165.9	22.8
Slovenia	Full	9.1	140.6	18.4
Ukraine	Partial	9.1	436.8	4.6

Table 3.1. – Power Sector and Energy Intensity information on selected transition economies. Sources: EBRD/World Bank

Cornillie and Fankhauser (2004) argue that the industry has no incentive to use energy efficiently, as electricity prices are below cost-recovery level, particularly in the CIS, and tariff collection rates were not appropriate. This effect is augmented by the lack of restructuring and reform, as there is "a substantial overlap between the policies needed to improve energy intensity and some of the region's key transition challenges" (p.294). Their study decomposes energy data to identify the factors driving energy intensity using data collected between 1992 and 1998. Main conclusions point towards the importance of energy prices and enterprise restructuring as the causes of more efficient energy use. Markandya et al. (2006) consider economic growth as the driving force in changes in energy intensity to study the convergence of energy efficiency and income between 15 EU countries and 12 countries of Eastern Europe. Conclusions point that there is convergence between the two blocks of countries, but the rate of convergence differs between countries. Nepal et al. (2014) take an institutional approach to explain changes in energy efficiency using dynamic panel data (Bias Corrected LSDV method), using energy intensity as a dependent variable. The authors find that market liberalization, financial sector and infrastructure industries (excluding the power sector) improved energy efficiency in these countries, while privatization programmes were only effective in that sense in South Eastern Europe. However, in this case, energy intensity is directly interpreted as energy efficiency, an assumption that is not consensual across the literature.

To estimate stochastic frontier models, research is mostly based on the seminal work of Aigner et al. (1977) that introduces the specification of the error term into two separate components, one that is normal and the other that has a one-sided half-normal distribution, as discussed in Chapter 2. Greene (2005) presents several extensions to the stochastic frontier model accounting for unmeasured heterogeneity and firm inefficiency. These extensions include two noticeable additions: the true fixed effects model (TRE) and the true random effects model (TFE). The used methodology in this case will rely on an extension of the true random effects model with an additional one-sided component (Colombi et al., 2011). However, this is done using Bayesian estimation techniques, as in Tsionas and Kumbhakar (2014) and Makiela (2016). This extension allows to consider both time-varying and time invariant inefficiency, unlike the TRE and TFE models which translate to a loss of information about time-invariant inefficiency. This methodology is sparsely used in the applied econometrics literature, for example in efficiency measurement of Swiss railways (Filippini and Greene, 2016) or electricity distribution in New Zealand (Filippini et al., 2016). Both of those applications are frequentist.

A major methodological and conceptual influence for estimation of energy efficiency scores of this chapter is the energy demand cost frontier approach of Filippini and Hunt (2011). Their study conceptualizes a measure of energy efficiency by estimating a stochastic cost frontier model which tackles the fragilities of energy intensity as a proxy for energy efficiency. Demand is larger in countries where energy is used inefficiently (holding all else constant), as demand is bounded from below. This level of minimum attainable consumption given all factors leads to a cost frontier. The authors estimate an aggregate energy demand function to estimate "underlying energy efficiency" after controlling for income and price effects, climate, technical progress and other exogenous factors, using a pooled model (Aigner et al., 1977) and the TRE model (Greene, 2005). The authors also argue that without conducting such analysis it is not possible to know if the changes in energy intensity over time are a reasonable reflection of actual efficiency improvements. The study concludes that although for a number of countries the proxy is good, that is not always the case, with Italy being an extreme example. While the study of Filippini and Hunt (2011) focuses on a long sample period (1978-2006) for 29 OECD economies, the analysis of transition economies leads to different backgrounds and frameworks, due to the underlying changes in the political system and the economy. However, the aforementioned study had three countries in common with the analysis that will be conducted in this chapter (Hungary, Poland and Slovakia). The aforementioned study overlooks the issue of heterogeneity among countries by choosing an estimation method that might suffer from heterogeneity bias. It also has an unrefined approach on accounting for climate and the structure of the economy, which will be discussed in further detail in this chapter. The size of the time dimension of the panel also raises some concerns about the stationarity of the data and therefore the validity of the obtained results, some of them of difficult interpretation or justification. Another article with similar methodology by Filippini and Hunt (2012) is an application of stochastic frontier models to estimate efficiency within the context of residential demand in the USA. Since the TRE model is unable to capture persistent and time-invariant inefficiency, and the model was rendering very high and implausible efficiency scores possibly due to the omission of the aforementioned inefficiency, the chosen method was a Mundlak (1978) version of the model as discussed in Farsi et al., (2005).

Stern (2012) is an influential example in the energy efficiency measurement literature. The author analyses efficiency trends in 85 countries over a 37 year period. However, due to the lack of data for FSU countries, those countries are not included. Differences in energy efficiency are modelled as a stochastic function of explanatory variables (instead of being considered as random) and the model is estimated using the cross-section of time-averaged data. One of the key advantages of this method is that no assumptions are made about technological change over time. The aforementioned paper has two important differences from Filippini and Hunt (2011). Efficiency is measured using a distance function and estimation is conducted using random effects, fixed effects and finally a distance function with an auxiliary regression, using variables that co-vary with the unobserved state of technology (such as state of democracy, openness, corruption and total factor productivity), in order to reduce omitted variable bias. Secondly, it contains key conceptual differences - the dependent variable is energy intensity and the study is also based on the productivity literature instead of the energy demand modelling literature. Stern (2012) chases the drivers behind changes in both energy prices and efficiency, while Filippini and Hunt (2011) take policy as given and observe how households and firms react to the economic environment. The complex data building process includes a series of assumptions in order to include capital and human capital as variables in the model such as linear growth of years of schooling and assumptions about the rate of depreciation. Results differ with fixed and random effects estimations.

Other approaches are implemented across the literature. The DEA (Data Envelopment Analysis) technique is non-parametric which means that it is robust to misspecification of the functional form (Cornwell and Schmidt, 2008). However, it is more difficult to assess uncertainty in DEA efficiency measures, making it unclear up to which extent uncertainty impacts results and conclusions in empirical work. It is also more difficult to assess the impact of noise in DEA results. Zhou and Ang (2008) used this technique to measure energy efficiency in 21 OECD countries between 1997 and 2001.

In contrast to most previous work in the literature, this chapter will tackle the issue of economy-wide energy efficiency in the specific context of transition while using up to date Stochastic Frontier techniques, specifically for efficiency in electricity consumption. The context of these economies implies that data collection is difficult and the price variable has to be constructed carefully. Due to the small sample size, investigations on the performance of the estimators are also conducted. In the next section, the research framework is clarified further.

3.3. Conceptual Framework

The concepts of energy intensity and energy efficiency are fundamentally different, although the first is sometimes used as a proxy for the latter. Energy intensity is simply the ratio of total energy consumption per unit of GDP. This indicator suffered severe changes in transition economies since 1990, but not homogeneously across transition economies. The same happened with electricity intensity, the ratio of electricity consumption per unit of GDP. The Caucasus region countries managed to achieve great reductions in electricity intensity from high levels since the early 1990s. The current members of the EU have lower electricity intensities but their levels were already considerably low in the early 1990s. Kazakhstan, Kyrgyzstan, Russia, Moldova and Ukraine had high energy intensities in 1992 and didn't manage to considerably bring those levels down by 2007. It is also clear that there is some heterogeneity in efforts bringing down energy intensity even within the subset of current EU members, which is easy to spot by comparing Latvia and Czech Republic, as it can be seen in Figure 3.1 below.

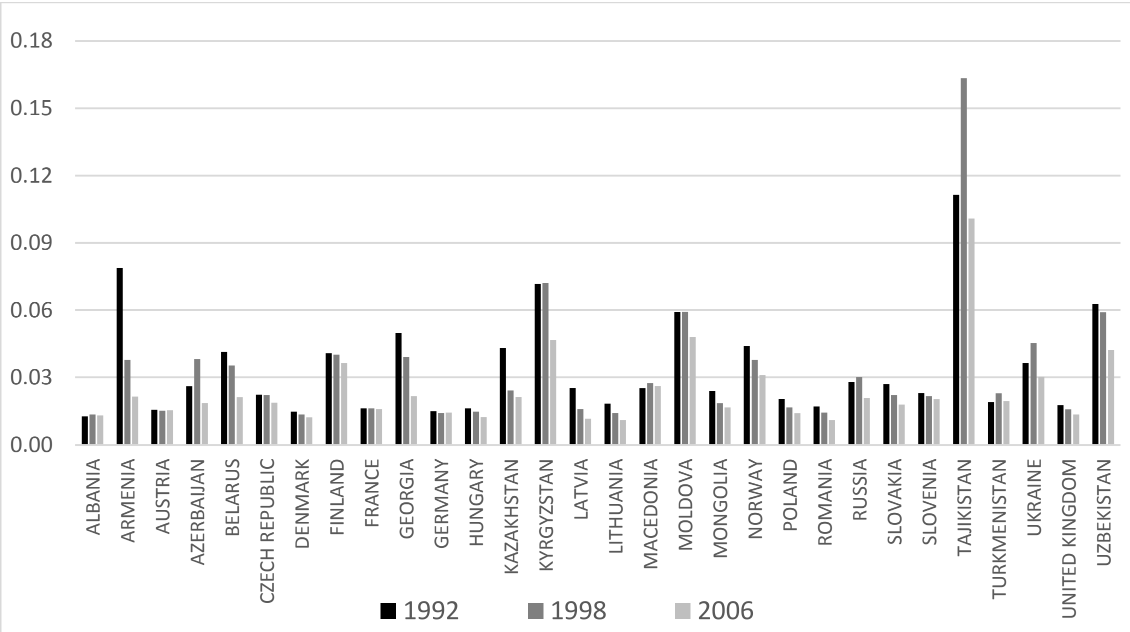

Figure 3.1. – Electricity use (tonnes of oil equivalent) per $1,000 GDP (constant 2005 PPP). Data source: World Bank

Energy efficiency is a more complex concept, as it is the activity that can be made with a certain amount of energy, involving not only structural but also behavioural changes. It depends on a number of factors that are not considered for energy intensity such as climate, output and composition of the economy (OECD, 2011). Energy efficiency can fundamentally vary through behavioural change in both households and industry, as the reform packages applied to transition economies shifted the public and businesses away from a Soviet supply-side mentality and also gave an incentive for more efficient use of energy through government policies, price signals and improved management practices.

The framework outlined in the previous section points for several theoretical and estimation challenges. It is possible that a decrease in energy intensity is not accompanied by a decrease in underlying efficiency, as the decrease in energy intensity could have been mostly explained by deep structural changes in the economy, resulting from large changes in the industrial sector or a shift of capital and labour to other sectors in the economy with different electricity consumption profiles and/or value added. As such, the key differences between electricity intensity and the proposed measure of efficiency should be clearly noticeable when the structural changes in the economy are not followed by other sort of real efficiency gains that are channelled through change in traditions and norms, different consumption profiles and improved government regulations and other incentives for a more rational use of energy, in the sense that a troubled economy is not necessarily efficient (conditional on its few surviving activities, for example).

It becomes clear that there is a large overlap between energy intensity and energy efficiency but the concepts are not interchangeable. The key drivers of changes in energy efficiency that are highlighted here also impact energy intensity, but are just a component of those changes. By building an energy demand approach with controls for economic structural changes and many other factors, the efficiency effect can be separated from other effects and effectively measured.

The model uses aggregate (final) electricity consumption for each economy. Demand in general translates to demand for several energy services: heating, manufacturing, lighting, etc. This requires capital equipment for machinery, home appliances, etc. The model takes an input demand function perspective, so the difference between the observed input and the cost-minimizing input demand represents both technical as well as allocative inefficiency (Filippini and Hunt, 2011). This is in line with the fact that technical efficiency is necessary, but not sufficient, for the achievement of cost efficiency (Kumbhakar and Lovell, 2004).

Due to the changes the economies went through in the transition period, it is important to consider that there can be large differences in trends between the estimated level of efficiency and the energy intensity measure. That could lead to dangerous policy advice, for example, if technological advances, structural change towards services and the purchasing of energy efficient equipment in the economy leads to a decrease in energy intensity but in fact the use of such technology is not optimal (in the sense of "underlying" efficient use). Another very important aspect is the consideration of persistent sources of inefficiency, which can be particularly large in transition economies due to the economic history and previous economic systems of these countries. These sources of inefficiency can be larger in countries where no significant reform efforts were made following the collapse of the Soviet Union. This will be taken into account in the modelling approach. The productivity approach of Stern (2012) will not be followed for two reasons. First, such an approach would require a set of data that is not available for those economies and had to be approximated or estimated. Second, the productivity approach intends to find deep drivers of differences in efficiency and energy prices between countries, but transition economies have the peculiar framework of strong (even if heterogeneous) reform efforts from the conclusions of the Washington Consensus. As such, policy parameters are taken as given, and an attempt to assess how households and firms react to the economic environment is made, at the light of the available data and taking into account unobserved heterogeneity between countries.

3.4. A stochastic frontier model for transition economies: data and methodology

3.4.1. Estimation approach

A firm is technically efficient if it uses the minimal level of inputs given output and input mix or if it produces the maximal level of output given inputs (Cornwell and Schmidt, 2008). In this context, SFA has been used often in empirical research to estimate firm level technical efficiency. It can be argued that an SFA approach using electricity consumption as a dependent variable given a set of inputs can retrieve economy-wide efficiency scores which represent national aggregate efficiency. Therefore, the seminal SFA research that was originally used within the neoclassical theory of production is now used at an aggregate level in an electricity demand cost frontier.

A neoclassical framework for frontier approach is considered, although such a framework is partially discarded as the concept of stochastic frontier will be used here within the empirical approach traditionally used in the estimation of an aggregate energy demand function. However, as pointed by Filippini and Hunt (2011), this still implies a kind of production process. Further discussion about the conceptual framework first developed by these authors will follow. The usual regularity conditions need to be assumed (Orea et al., 2014) – and the functional form is chosen to achieve estimation simplicity.

The role of the random effects is related to heterogeneity in cost functions. They can be considered as country specific intercepts in the cost function to account for unobserved heterogeneity in electricity consumption across countries. The random effects correct the bias in the parameters of the cost function so that the frontier is estimated correctly. The DEA literature already considers a parametric approach to be too restrictive in the description of the cost function. Naturally, the cost function needs to be identified correctly for accurate results. In a scenario of constant differences in technology across countries, the GTRE model presumably works well in finding true measures of cost efficiency. Time-invariant technological differences between countries are accounted for in this way. One could consider that this relates to the use of random effects models with large enough T to raise concerns about what is time-invariant and what is not, so changes in relative technological gaps between regions could be captured by the inefficiency measure – but a modelling compromise is necessary given the limitations of the data – and even the existing limitations of Stochastic Frontier models.

The estimation approach is deeply linked to the issues of country heterogeneity and the possible persistence of inefficiencies in energy consumption in transition economies. Since the TRE approach of Greene (2005) cannot disentangle time-persistent inefficiencies from country heterogeneity and the approach of Aigner et al. (1977) fails to account for country heterogeneity leading to biased results, the GTRE approach of Colombi et al. (2011) is followed to solve both issues. The authors point that this approach is particularly appropriate for cases where firms are heterogeneous (in this case, countries) and the panel is long. The distributional assumption for inefficiency is a half-normal distribution for tractability purposes, although alternatives are available, such as an exponential distribution (Meeusen and van Den Broeck, 1977). A Bayesian Generalized True Random Effects model with exponential distribution assumptions is outlined in Griffiths and Hajargasht (2016). Also, note that in the case of assumed exponential inefficiencies the draws for time-varying inefficiency require some rejection method as the distribution is not easily simulated in statistical software. This is not an obstacle found in the case of the half-normal assumption. Here, the frontier gives the minimum level of energy consumption attainable by a country. The frontier concept is applied to estimate the baseline energy demand - the frontier reflecting demand of countries that use high efficiency equipment and have good use practices (Filippini and Hunt, 2011). As such, the following cost frontier model accounts for persistent sources of long-run inefficiency and variable sources of inefficiency:

$$y_{it} = x_{it}\beta + \alpha_i + \eta_i + u_{it} + v_{it} \tag{12}$$

$$\alpha_i \sim i.i.d.N(0;\sigma_\alpha^2) \qquad v_{it} \sim i.i.d.N(0;\sigma_v^2) \tag{13}$$

$$u_{it} \sim i.i.d.N^{+}(0;\sigma_u^2) \qquad \eta_i \sim i.i.d.N^{+}\left(0;\sigma_\eta^2\right) \tag{14}$$

x'_{it} is a row vector of regressors and β is a column vector of unknown parameters to be estimated (note the model also has a constant). α_i captures latent heterogeneity (random effect) and v_{it} is an idiosyncratic error component. Attention is focused on η_i and u_{it}, as they represent time-invariant inefficiency (long-run) sources of inefficiency and time-varying (short-run) inefficiency respectively. In fact, this model is an extension of the TRE model (Greene, 2005)[2], as it adds another time-invariant random effect to capture persistent inefficiency (η_i). The identification of the model is assured through the distributional assumptions on the four error components (without those assumptions, the model is not identified). In a random effects model, the effects cannot be correlated with the explanatory variables, as it leads to bias in estimates. Since there is a possibility of such a problem in applied econometrics, a Mundlak (1978) transformation can be conducted to account for correlation between the time-varying explanatory variables and country-specific effects:

$$\alpha_i = \gamma\bar{X}_i + \varphi_i \quad \text{where} \quad \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it} \quad \text{and} \quad \varphi_i \sim N(0, \sigma_\varphi) \tag{15}$$

[2] The heterogeneity could possibly be dealt with through alternative approaches such as a model with random slopes, but the estimation would be difficult given the relatively small sample panel size and the large number of regressors.

Cross-section means for variables with very low variation are not added, such as population and urbanization rate, as recommended by statistical software.

Two econometric approaches to Bayesian estimation of the GTRE model will be considered and compared in a context of small samples to investigate the robustness of the results. The first econometric approach follows Tsionas and Kumbhakar (2014) with a Bayesian approach which involves reparameterizing the model to reduce autocorrelations in the draws of the model parameters. The model can be rewritten by stacking the time series observations:

$$y_i = (\alpha_i + \eta_i) \otimes l_T + x_{it}\beta + (u_{it} + v_{it}) = \delta_i \otimes l_T + x_{it}\beta + \varepsilon_{it} \tag{16}$$

ε_{it} has a skew-normal distribution and all random components are mutually independent as well as independent of x_{it}. Therefore, all the building process of the likelihood function follows Tsionas and Kumbhakar (2014). Gibbs sampling will be used, keeping latent variables to increase computational efficiency of MCMC schemes instead of integrating them out. The prior distributions are:

$$p(\beta, \sigma_e, \sigma_u, \sigma_\varphi, \sigma_\alpha) = p(\beta)p(\sigma_v)p(\sigma_u)p(\sigma_\eta)p(\sigma_\alpha) \tag{17}$$

With regression parameters assumed to follow the k-variate normal distribution $\beta \sim N_K(\overline{\beta}, A^{-1})$ with mean vector $\overline{\beta} = 0_{(kx1)}$ and precision matrix[3] $A = 10^{-4}.I_K$. Therefore, there is very little information in the prior about the coefficients of the regressors. For scale parameters, it is assumed that:

$$\frac{1}{\sigma_Z^2} \sim f_G\left(\frac{\overline{N}_Z}{2}, \frac{\overline{Q}_Z}{2}\right), \text{for } Z = v, u, \eta, \alpha \tag{18}$$

For the rest of the chapter, f_G follows the shape-rate gamma parameterization. It is also set that $\overline{N}_Z = 1$, representing the length of a prior sample from which a sum of squares $\overline{Q}_k$ is obtained. For posterior consistency, $\overline{Q}_Z$ has to be larger than zero, and Tsionas and Kumbhakar (2014) set this to be 10^{-4} in the context of an application to the banking

[3] The authors originally define $A = 10^{-4}.I_K$. This has no impact in any key results and is done for consistency with the choices in Makiela (2016).

sector with relatively low estimated inefficiency. However in this application there is a belief that all variances should be important although there is uncertainty their relative magnitudes. As such, information in the prior[4] is set as $\overline{\mathrm{Q}}_v = 10^{-4}, \overline{\mathrm{Q}}_u = 10^{-3}, \overline{\mathrm{Q}}_\alpha = 10^{-3}$ and $\overline{\mathrm{Q}}_\eta = 0.25$. Further discussion on the consequences of these choices is in subsequent sections of this chapter. A Gibbs sampler is implemented, with draws being taken from the various posterior conditional distributions. According to Tsionas and Kumbhakar (2014), the "naïve" Gibbs sampling scheme will not have good mixing properties and easily collapses. This claim will be debated later in the chapter. To reduce the natural correlations among parameters in the Markov Chain Monte Carlo (MCMC) scheme, reparametrizations are implemented. First, a δ-Parametrization[5] is conducted, with $\delta_i = \alpha_i + \eta_i$, grouping firm-specific effects and persistent inefficiency, which would be grouped implicitly in Greene (2005) TRE model (the reason why persistent inefficiency would be treated as heterogeneity), although it would be forced to have a mean of zero in the latter. As in Tsionas and Kumbhakar (2014), this allows to obtain the posterior conditional distributions of $\delta_i, {\sigma_u}^2, {\sigma_v}^2$ and β. However, note that obtaining δ_i does not allow to quantify persistent inefficiencies and only short-run inefficiencies can be obtained from this first step of analysis. However, it should point for the magnitude of the mean persistent inefficiency (i.e. mean δ_i). In a second step, a ξ-Parametrization is conducted (taking the estimates of β from the δ-Parametrization as given), as in panel data GLS, with $\xi_{it} = \alpha_i + v_{it}$. This allows to draw η_i independently of the draw for α_i, and in turn the conditional distributions of not only η_i but also u_{it}.

Tsionas and Kumbhakar (2014) set a simulation experience to show the good properties of their reparameterization. However, these results do not hold in simulations attempted in this chapter, even for a similar DGP, with estimation of inefficiencies easily collapsing when signal to noise ratios are not large. There are also some inaccuracies in the distributions of the published paper which are corrected here for the purpose of the simulations (see Appendix 3.2. for the correct expressions used and further details).

[4] Lower values of Q can lead to issues in convergence and density plots of variances that were clearly not reasonable, due to an unreasonably tight prior, as pointed by Makiela (2016). There is also previous research that shows that vague priors with small amounts of data can be problematic Lambert et al. (2005).

[5] Tsionas and Kumbhakar (2014) use a special rejection technique to draw δ. They also argue that a general-purpose rejection sampler for log-concave densities (Gilks and Wild, 1992) is well behaved and this is the chosen option as its timing properties were found to be appropriate. In this chapter, adaptive-rejection sampling is used to draw δ.

Makiela (2016) revisited the GTRE "naïve" approach and the approach of Tsionas and Kumbhakar (2014), exploring other priors that allow for correct estimation without any reparameterization, leading to much better numerical efficiency and results. The model is therefore estimated without any reparameterization and with the following prior:

$$p(\beta, \sigma_v, \sigma_u, \sigma_\eta, \sigma_\alpha) = p(\beta)p(\sigma_v)p(\sigma_u)p(\sigma_\eta)p(\sigma_\alpha) \tag{19}$$

where the prior for β as in the aforementioned paper is uninformative, and the prior on variances of symmetric error components is:

$$\frac{1}{\sigma_Z^2} \sim f_G\left(\frac{\overline{N}_Z}{2}, \frac{\overline{Q}_Z}{2}\right), \text{for } Z = v, \alpha \tag{20}$$

For the priors of the inefficiency components, a key change in the approach is the use of a more flexible prior that is easier to tune to fit the needs of the researcher:

$$\frac{1}{\sigma_Z^2} \sim f_G(5{,}10 \ln^2(r_Z^*)), for\ Z = \eta, u \tag{21}$$

In the equation above, r_η^* represents prior median persistent efficiency and r_u^*represents prior median transient efficiency. The shape parameter influences the weight of the prior in the estimation as it changes the sample of prior observations, as it can be observed from equation (20). If $r_\eta^* = 0.7$, mean prior persistent efficiency is 0.683 and the 95% highest prior density interval is (0.323 ; 0.999). If $r_u^* = 0.85$, mean prior transient efficiency is 0.83 and the 95% highest prior density interval is (0.597 ; 0.999). These values of r_Z^* will be used in simulations in Section 3.5.The rate parameterization of the gamma distribution is used throughout this chapter. In any of the aforementioned cases, the following measure of total efficiency (bounded between 0 and 1) is used to measure efficiency:

$$Eff_{it} = \exp(-u_{it} - \eta_i) \tag{22}$$

To incorporate uncertainty, a simple Monte Carlo approximation is proposed. Suppose $\tilde{u}_{it}{}^{(s)}$ is a draw from the conditional posterior of ũ for the s^{th} pass of the MCMC scheme and that the same argument is applicable for $\tilde{\eta}_i{}^{(s)}$:

$$Eff_{it} = S^{-1} \sum_{s=1}^{S} \exp[-\tilde{u}_{it}^{(s)} - \tilde{\eta}_i{}^{(s)}] \tag{23}$$

All estimations are conducted using own code in R 3.1.1, a language and environment for statistical computing and graphics, available as free software.

3.4.2. Variable choice and data

Data availability is an additional challenge in the context of transition economies, and the particular characteristics of the countries in this analysis demand some specific modelling features to address concerns. As such, the following electricity demand model is estimated:

$$Electricity\ Demand = f(VA, P, CW, STRUCTURE, POP, URBRATE, T, EFF)$$

Variable	**Description**
VA	Value Added
P	Electricity Prices
CW	Climate Variable
STRUCTURE	Structure of the economy (manufacturing, construction and primary sector)
POP	Population
URBRATE	Urbanization rate (%)
T	Time dummies
EFF	Efficiency (to be estimated, not a regressor)

Table 3.2. Explanatory variables of energy demand model

The chosen dependent variable is electricity demand instead of total energy demand as was the case in Filippini and Hunt (2011). This choice relates to data availability issues, as there is no available energy price data for most of the transition economies and possible proxies are very likely to be of low quality. However, the availability of substitute fuels might become a problem in the analysis, particularly with natural gas, as direct use of oil and coal have less use as substitutes for electricity. Substitution effects from primary fuels to electricity can show in results as artificial efficiency decreases, while substitution of electricity for gas can show the opposite effect. The possibility of issues related to fuel substitution are explored in robustness checks in Section 3.6.

All variables except for T and EFF are logarithmically transformed. Electricity demand is represented by final electricity consumption in thousand tonnes of oil equivalent (International Energy Agency, 2014). Economic activity is measured through national Value Added (VA) sourced from the United Nations National Accounts database, excluding sectors C and E (mining and extraction activities), and with PPP and constant prices. This allows to consider the economic activity that is deeply linked to the electricity consumption considered. This is preferred to GDP as many of the considered economies have considerable shares of GDP from oil, gas and mining activities which don't consume any electricity. Further control variables are necessary to account for factors that influence electricity consumption. CW is a variable that takes into account extreme temperatures and the need to use additional energy in such events. A function that applies penalties to deviations from a base temperature every month is defined. The suggested function is:

$$CW_{it} = \sum_{m}^{12}(|16 - AMT_{it}|) \tag{24}$$

This will capture not only annual patterns in weather but also extreme monthly deviations, for both warm and cold weather, reducing distortions in time-varying efficiency estimates which would be affected by extreme variations in weather conditions. AMT is the average monthly temperature in country i, in month m of year t. Thus, higher values of CW reflect higher deviations from the base temperature in a given year for each country and should translate to higher energy consumption. This is a superior control for weather when compared to a climate dummy because that dummy is time invariant and fails to control for annual climate variability that can be particularly extreme and affect time-varying inefficiency estimates. This index uses data from the University of Delaware Air Temperature and Precipitation Database V3.01 (Willmott and Matsuura, 2001),which contains global high resolution monthly data for the timeframe of the considered dataset.

It is also necessary to incorporate variables that account for the structure of the economy and the importance of energy intensive activities. As such, to insert measures of the structure of the economy in the model, the share of value added in percentage of GDP manufacturing (hereafter "MAS" – ISIC D), construction ("CON" – ISIC F) and primary sector (ISIC A and B) as separate variables[6]. These variables are chosen instead of a disaggregation between industries and services as in Filippini and Hunt (2011) because of the importance of such activities in ex-Soviet economies and the need to separate energy intensive from non-intensive activities and also to consider the transition towards a service based economy. POP is the population of the country at a given year, and URBRATE is the urbanization rate in percentage of population. T is a set of time dummies which can be interpreted as technological change but can also capture other common effects. The price of electricity (P) constitutes one of the key estimation issues. Prices are reported in US dollars (mostly sourced from EBRD Transition Report data, multiple reports[7]). However, the complicated issue of deflation and the overall issue of data quality needs to be considered. The data is extended using a variety of sources[8] and is deflated using CPI in non-OECD economies. Otherwise, OECD real energy price index are used. Observations where yearly inflation is more than 35% are removed to avoid distortions caused by outliers at periods of extreme turmoil. This model also implies a simplification in the sense that possible asymmetric effects in prices and income are not considered[9]. Finally, EFF is the "real energy efficiency" term. The information is retrieved from the residuals, as the exponential of the negative one sided estimated residuals for inefficiency provide a measure of efficiency from 0 to 1 (fully efficient). This can be translated into a score from 0 to 100% (or 0 to 1).

This study is based on an unbalanced panel of 33 economies over the period 1994-2007. The dataset contains 389 observations, with a minimum T of 5, a maximum T of 14 and an average T of 11.8 across the sample (higher than the conservative T=10 set in simulations in the next section to assess model performance). The choice of timeframe is mostly associated to the availability of electricity price data as a proxy for energy prices and also the necessary information to deflate it (there is lack of economic data for transition economies in many aspects). The countries in the sample are Albania, Armenia,

[6] According to the ISIC Revision 3.1. Data sourced from National Accounts Main Aggregates Database 1970-2011, December 2012 Update, United Nations Statistics. These shares are calculated according to the value added variable chosen (i.e. sectors C and E are removed from calculations).
[7] Average tariffs are used, but when data is missing, residential tariffs or an average of the year before and after are used for completeness. The latter issue affects a very small part of the sample.
[8] Besides the use of EBRD data, the price dataset for the construction of a price index is extended using data for Albania, Lithuania and Ukraine (Krishnaswamy, 1999),Belarus (International Energy Agency, 1994), Bosnia (Ding and Sherif, 1997), Mongolia (Energy Regulatory Authority of Mongolia, 2010) and Uzbekistan (Karabaev, 2005).
[9] For details on such asymmetries, see Gately and Huntington (2002).

Azerbaijan, Belarus, Bosnia, Bulgaria, Czech Republic, Croatia, Estonia, Georgia, Hungary, Latvia, Lithuania, Kazakhstan, Kyrgyzstan, Macedonia, Moldova, Mongolia, Poland, Russia, Romania, Slovakia, Slovenia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan (transition) and Austria, UK, France, Germany, Finland and Denmark (OECD). This extensive data collection exercise from multiple sources allows this thesis to conduct empirical research with a larger dataset, while taking into account some of the weaknesses from previous studies in the literature.

3.5. Artificial examples and performance of GTRE model in small samples

Consider the following data generating process: $y_{it} = 1 + x_{it} + \alpha_i + \eta_i + u_{it} + v_{it}$, where x_{it} is a standard normal distribution. Different parameters can be set for $\sigma_{v,}\sigma_u, \sigma_\eta, \sigma_\alpha$, using different scenarios. The panel size is set to be quite small with N=35 and T=10, to resemble the small-sample issues that the transition data used here might face in estimation. As an alternative sample size and to assess convergence to true values as the sample size increases, simulations are repeated with a larger panel of N=100 and T=10. The following scenarios are created:

Scenario 1: $\sigma_v = 0.1, \sigma_u = 0.2, \sigma_\eta = 0.5, \sigma_\alpha = 0.2$. This scenario is the same as the case N=50 in Tsionas and Kumbhakar (2014) and implies moderate signal-to-noise ratios. With not very strong ratios there is an expectation of bigger performance degradation as the sample size decreases.

Scenario 2: $\sigma_v = 0.05,\ \sigma_u = 0.2, \sigma_\eta = 0.5, \sigma_\alpha = 0.1$. This scenario has stronger signal-to-noise ratios and is expected to perform better in small samples.

The Makiela approach is computationally much more efficient than the Tsionas and Kumbhakar (2014) approach (hereafter “TK”), allowing for faster simulations. Gibbs samplers for the Makiela approach simulations uses 70,000 draws with the first 40,000 discarded and keeping only one in 5 of the remaining 30,000. TK approach simulations use 10,000 draws with the first 5,000 being discarded, and one in two of the remaining 5,000 being kept as the method is considerably slower. The columns not signed as “TK” correspond to Makiela (2016) approach (“new GTRE” in the mentioned paper).

Scenario 1 **N=35 , T=10**	$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 r_η = 0.7 r_u = 0.85		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 r_η = 0.85 r_u = 0.85		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 r_η = 0.6 r_u = 0.85		TK: $\bar{Q}_v$=$\bar{Q}_\alpha$ = $\bar{Q}_u$=0.001 $\bar{Q}_\eta$=0.25	
	True	Est.	True	Est.	True	Est.	True	Est.
α_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
η_i	0.400	0.451	0.406	0.254	0.400	0.501	0.396	0.369
u_{it}	0.168	0.161	0.160	0.166	0.160	0.168	0.160	0.135
σ_v	0.1	0.094	0.1	0.095	0.1	0.094	0.1	0.110
σ_u	0.2	0.212	0.2	0.209	0.2	0.211	0.2	0.176
σ_η	0.5	0.559	0.5	0.322	0.5	0.650	0.5	0.483
σ_α	0.2	0.164	0.2	0.280	0.2	0.119	0.2	0.227
S.D. (u_{it})	0.121	0.127	0.120	0.125	0.121	0.126	0.120	0.112
S.D. (η_i)	0.292	0.326	0.300	0.218	0.300	0.341	0.298	0.289
Correlation between true and est. u_{it}	0.753		0.749		0.752		0.755	
Correlation between true and est. η_i	0.828		0.836		0.833		0.845	
Bias of mean u_{it} less than 20% (% of repet.)	96%		93%		93%		62%	
Bias of mean η_i less than 20% (% of repet.)	61%		11%		40%		53%	

Table 3.3. Simulation results for Scenario 1 with N=35 and T=10

Scenario 1 **N=100 , T=10**	$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 r_η = 0.7 r_u = 0.85		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 r_η = 0.85 r_u = 0.85		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 r_η = 0.6 r_u = 0.85		TK: $\bar{Q}_v$=$\bar{Q}_\alpha$ = $\bar{Q}_u$=0.001 $\bar{Q}_\eta$=0.25	
	True	Est.	True	Est.	True	Est.	True	Est.
α_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
η_i	0.402	0.420	0.396	0.277	0.401	0.464	0.395	0.359
u_{it}	0.160	0.162	0.159	0.163	0.161	0.160	0.159	0.156
σ_v	0.1	0.098	0.1	0.097	0.1	0.099	0.1	0.103
σ_u	0.2	0.204	0.2	0.205	0.2	0.203	0.2	0.196
σ_η	0.5	0.527	0.5	0.353	0.5	0.592	0.5	0.461
σ_α	0.2	0.184	0.2	0.273	0.2	0.157	0.2	0.233
S.D. (u_{it})	0.121	0.123	0.120	0.124	0.120	0.122	0.121	0.119
S.D. (η_i)	0.302	0.313	0.299	0.230	0.302	0.332	0.299	0.280
Correlation between true and est. u_{it}	0.754		0.754		0.755		0.753	
Correlation between true and est. η_i	0.834		0.835		0.840		0.845	
Bias of mean u_{it} less than 20% (% of repet.)	100%		100%		100%		98%	
Bias of mean η_i less than 20% (% of repet.)	84%		30%		69%		76%	

Table 3.4. Simulation results for Scenario 1 with N=100 and T=10

Scenario 2 **N=35 , T=10**	$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 $r_\eta = 0.7$ $r_u = 0.85$		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 $r_\eta = 0.85$ $r_u = 0.85$		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 $r_\eta = 0.6$ $r_u = 0.85$		TK: $\bar{Q}_v$=$\bar{Q}_\alpha$ = $\bar{Q}_u$=0.001 $\bar{Q}_\eta$=0.25	
	True	Est.	True	Est.	True	Est.	True	Est.
α_i	0.000	0.000	0.000	0.000	0.000	0.000	0.00	0.001
η_i	0.394	0.422	0.403	0.317	0.391	0.444	0.402	0.381
u_{it}	0.159	0.162	0.161	0.163	0.159	0.162	0.159	0.160
σ_v	0.05	0.047	0.05	0.047	0.05	0.048	0.05	0.050
σ_u	0.2	0.204	0.2	0.205	0.2	0.204	0.2	0.200
σ_η	0.5	0.531	0.5	0.387	0.5	0.601	0.5	0.493
σ_α	0.1	0.079	0.1	0.159	0.1	0.072	0.1	0.137
S.D. (u_{it})	0.120	0.122	0.120	0.122	0.120	0.121	0.121	0.120
S.D. (η_i)	0.302	0.308	0.303	0.259	0.298	0.308	0.299	0.289
Correlation between true and est. u_{it}	0.901		0.898		0.900		0.903	
Correlation between true and est. η_i	0.947		0.943		0.944		0.944	
Bias of mean u_{it} less than 20% (% of repet.)	100%		100%		100%		99%	
Bias of mean η_i less than 20% (% of repet.)	84%		51%		71%		81%	

Table 3.5. Simulation results for Scenario 2 with N=35 and T=10

Scenario 2 **N=100 , T=10**	$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 $r_\eta = 0.7$ $r_u = 0.85$		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 $r_\eta = 0.85$ $r_u = 0.85$		$\bar{Q}_v$=$\bar{Q}_\alpha$=0.001 $r_\eta = 0.6$ $r_u = 0.85$		TK: $\bar{Q}_v$=$\bar{Q}_\alpha$ = $\bar{Q}_u$=0.001 $\bar{Q}_\eta$=0.25	
	True	Est.	True	Est.	True	Est.	True	Est.
α_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
η_i	0.401	0.411	0.393	0.360	0.400	0.427	0.396	0.371
u_{it}	0.159	0.160	0.161	0.159	0.159	0.160	0.159	0.159
σ_v	0.05	0.049	0.05	0.048	0.05	0.049	0.05	0.050
σ_u	0.2	0.201	0.2	0.202	0.2	0.201	0.2	0.200
σ_η	0.5	0.516	0.5	0.445	0.5	0.552	0.5	0.472
σ_α	0.1	0.089	0.1	0.122	0.1	0.076	0.1	0.137
S.D. (u_{it})	0.120	0.121	0.120	0.121	0.120	0.121	0.120	0.120
S.D. (η_i)	0.303	0.305	0.297	0.280	0.302	0.307	0.297	0.283
Correlation between true and est. u_{it}	0.899		0.900		0.900		0.900	
Correlation between true and est. η_i	0.946		0.944		0.946		0.946	
Bias of mean u_{it} less than 20% (% of repet.)	100%		100%		100%		100%	
Bias of mean η_i less than 20% (% of repet.)	97%		77%		96%		89%	

Table 3.6. Simulation results for Scenario 2 with N=100 and T=10

	Scenario 1 N=35	Scenario 1 N=100	Scenario 2 N=35	Scenario 2 N=100
Change in mean η_i from change in $\mathrm{r}_\eta = 0.7$ to $\mathrm{r}_\eta = 0.85$ (0.15 change in prior median efficiency)	0.197	0.143	0.105	0.051
Change in mean η_i from change in $\mathrm{r}_\eta = 0.7$ to $\mathrm{r}_\eta = 0.6$ (0.1 change in prior median efficiency)	0.095	0.044	0.022	0.016

Table 3.7. Key results from prior changes in simulations

The summary table shows how the prior drives the results in a small sample when there is little data to draw from with low signal-to-noise ratios. With $\mathrm{r}_\eta = 0.85$ the prior is tightened into intervals of low inefficiency that are incompatible with the underlying DGP and results suffer severely as a result. With $\mathrm{r}_\eta = 0.6$ the witnessed change is smaller as the prior is still quite vague about the interval in which efficiency lies. This is in line with the recommendations of Makiela (2016) to keep these hyperparameters within reasonable values (0.7 or 0.75, for example), with evidence of irregular behaviour as these approach 0.9 if the true inefficiency is rather large. As the signal-to-noise ratio strengthens in Scenario 2, the impact of changing priors in the posteriors is greatly reduced.

There are three key conclusions to take from these results. The first is that in relevant sample sizes for the analysis of energy efficiency in transition economies, the prior will drive the results if there is not enough information in the data. However, if the underlying signal is strong enough, the results should not vary much independently of using a Makiela or TK approach with different reasonable priors. Although the TK approach can render reasonable results if priors are tuned enough, the underlying priors are problematic. The "naïve" approach seems to be more intuitive and much more computationally efficient but both methods can be used for robustness of the analysis. Either way, it is clear and not unexpected that with an extremely small sample of N=35 it is difficult to obtain robust results unless the underlying signal in the data is strong.

The second conclusion relates to the behaviour of efficiency levels and correlations between true and estimated values. Across both scenarios and all sample sizes and priors, the correlation of estimated transient inefficiency with true values is at least 0.74 and the correlation of estimated persistent inefficiency is at least 0.83. This means that the relative rankings within each type of inefficiency are well preserved even in small samples. However, as the total efficiency scores are a combination of both types of inefficiency, this also implies that if the prior drives the mean of persistent inefficiency significantly then a distortion of the true efficiency rankings is likely, if the size of both inefficiencies is significant. From the behaviour seen in the tables 3.2 to 3.6, it is recommended that analysis on efficiency scores is only conducted if the mean persistent inefficiency is not significantly affected by changes in hyperparameters, as that implies there is sufficient underlying data (strong signal) for estimation. However, it is also true that if the signal-to-noise ratio grows significantly, it is likely that the random effects become increasingly irrelevant and barely distort the efficiency rankings – making the case for estimation of a simpler model in which the random effects are dropped. This is an interesting outcome to have in mind when estimating the GTRE model in small samples.

The third and final conclusion is that the TK approach is overall not competitive or attractive for multiple reasons. First, results are not improved with the reparameterization versus the alternative "naïve" approach in terms of mean bias, the spread of that bias over repetitions and the overall performance of key parameters. Second, the prior leads to problems in applied research, as will be explored further in the next section. Finally, the TK approach is considerably slower computationally due to the additional steps. Also, given that the authors originally consider all Q to be 0.0001 in their simulations, it is very puzzling how their results were so close to the true values, as that prior would lead to very irregular results in the simulations above. There can only be some limited speculation for the reasons of this, but one of them can be that one of the incorrect conditional posteriors in the paper confuses one signal-to-noise ratio with the other (time-varying where there should be a persistent one), combined with the fact that both of the simulations had both ratios being equal in the DGP. This could have artificially stabilized results close to the true values, but lead to huge bias under a different DGP.

These results are broadly in line with the findings of the detailed simulation previously conducted on the (frequentist) GTRE model (Badunenko and Kumbhakar, 2016). The key to good estimation is the relationship between the sizes of the four components. The authors refer that unless the noise and the random effects are nearly non-existent, only one of the inefficiency components can be estimated correctly. In some scenarios, efficiency analysis is not recommended due to the unreliability of the estimates. The authors also find that the largest and smallest efficiencies measured are estimated more imprecisely. These findings align well with the simulations conducted above, although the use of priors in Bayesian econometrics gives less pessimistic insights about some scenarios, particularly in smaller samples. The message from the simulations above is that once can proceed with estimation, but with a careful approach towards the interpretation and the stability of the results.

3.6. Results and Discussion

The economic theory in which this cost frontier approach is based requires positive skewness for inefficiency to exist and have valid interpretation. Preliminary frequentist random effects estimation shows positive skewness in both the idiosyncratic error and the random effects, indicating the need to indeed pursue this modelling approach.

Both Makiela (2016) approach (hereafter "Makiela") and Tsionas and Kumbhakar (2014) approach (hereafter "TK") are used to estimate the model. 1,300,000 draws are taken, with a burn-in of 400,000 and taking one in each twenty of the remaining draws for both approaches, including TK. The latter method is much slower computationally, taking many hours to run, while the "new GTRE" approach of Makiela takes about an hour[10]. Although credible intervals for efficiency estimates can be considered (Horrace and Schmidt, 1996), it is not common to analyse the results from Stochastic Frontier analysis by restricting statements to events of strong statistical significance due to the naturally high uncertainty of estimates. The analysis will mostly rely on point estimates and group average analysis over time. Some coefficients of the cross-sectional means of regressors are significant, justifying the use of the Mundlak extension in this context. Therefore, estimates without these additional regressors are not reported as they are expected to be biased.

Two datasets were considered: one excluding the data points where inflation is over 35% including Norway, and another where Norway is excluded[11]. For each case, parameter

[10] Note that this is valid for an unbalanced panel framework such as the one in this application – simulations with balanced panels require simpler programming which runs slightly faster.

[11] Norway is an advanced economy with large oil exports and a very cold climate, combined with low access to natural gas. This can distort results and presents Norway as an extremely inefficient consumer. For results summary with Norway included, see Appendix 3.3.

estimates and efficiency estimates will be presented under multiple priors to assess the robustness of the results. In all cases, 95% credible intervals are presented in square brackets. The full dataset is in Appendix 3.4. The analysis of results is focused on the column where prior and posterior persistent inefficiency are rather close, with $r_{\eta} = 0.6$, as explained below.

Dataset 2 (excluding Norway)	$\overline{Q}_v$=0.001 $\overline{Q}_\alpha$=0.01 $r_\eta = 0.7$ $r_u = 0.85$	$\overline{Q}_v$=0.001 $\overline{Q}_\alpha$=0.01 $r_\eta = 0.6$ $r_u = 0.85$	$\overline{Q}_v$=0.001 $\overline{Q}_\alpha$=0.01 $r_\eta = 0.5$ $r_u = 0.85$	TK: $\overline{Q}_v = 0.001$ $\overline{Q}_\alpha = 0.01$ $\overline{Q}_u = 0.01$ $\overline{Q}_\eta = 0.25$
$\beta_{Intercept}$	-15.083 [-21.50;-8.72]	-16.023 [-22.86;-8.81]	-15.794 [-22.55;-8.96]	-15.776 [-22.21;-8.48]
β_{VA}	0.2080 [0.15;0.27]	0.2054 [0.15;0.26]	0.2042 [0.15;0.26]	0.2075 [0.15;0.26]
$\beta_{Elec.\ Price}$	-0.0505 [-0.08;-0.02]	-0.0497 [-0.08;-0.02]	-0.0493 [-0.08;-0.02]	-0.0488 [-0.08;-0.02]
$\beta_{Weather}$	0.0492 [-0.11;0.21]	0.0483 [-0.11;0.21]	0.0479 [-0.11;0.21]	0.0554 [-0.10;0.22]
$\beta_{Urb.Rate}$	1.0470 [0.64;1.45]	1.0970 [0.70;1.47]	1.1357 [0.73;1.55]	1.0834 [0.69;1.46]
$\beta_{Population}$	0.7581 [0.53;0.96]	0.7340 [0.51;0.98]	0.7215 [0.45;0.98]	0.7256 [0.47;0.96]
$\beta_{Manuf.\ Share}$	0.0951 [0.02;0.17]	0.0888 [0.02;0.16]	0.0838 [0.01;0.16]	0.0867 [0.01;0.16]
$\beta_{Constr.\ Share}$	0.0413 [-0.00;0.09]	0.0391 [-0.01;0.08]	0.0373 [-0.01;0.08]	0.0383 [-0.01;0.08]
$\beta_{Primary\ Share}$	-0.0006 [-0.08;0.08]	-0.0021 [-0.09;0.08]	-0.0034 [-0.09;0.08]	-0.0031 [-0.09;0.08]
Mean(η_i)	0.484	0.552	0.608	0.481
Mean(u_{it})	0.099	0.098	0.098	0.096
σ_v	0.0177 [0.010;0.028]	0.0176 [0.010;0.028]	0.0176 [0.010;0.028]	0.0200 [0.011;0.032]
σ_u	0.1348 [0.123;0.147]	0.1346 [0.123;0.147]	0.1344 [0.123;0.147]	0.1280 [0.115;0.141]
σ_η	0.5912 [0.401;0.828]	0.7018 [0.510;0.942]	0.8217 [0.634;1.073]	0.6049 [0.256;0.981]
σ_α	0.1896 [0.046;0.424]	0.1573 [0.046;0.383]	0.1237 [0.041;0.307]	0.2042 [0.050;0.459]
Mean Efficiency (0-100%)	59.6%	56.7%	54.1%	60.2%

Table 3.8. Key regression results

The first three columns comfortably show signs of convergence according to the Geweke convergence diagnostic (Geweke, 1992). This is based on a test for equality of the means of the first and last part of a Markov chain (typically the first 10% and the last 50%). The Z-score from the test is asymptotic normal if the two means from the parts of the chain are stationary. Z-scores for each parameter are in Appendix 3.1. However, the convergence results for the TK approach are very poor, with multiple parameters with higher Z-scores. This highlights the poor mixing of the model, although the results are not very different.

Parameter estimates are intuitive and show the expected signs, although elasticities of income and prices are rather small (yet perfectly plausible). Deviations from an average temperature level also show an effect on higher electricity consumption, although the impact is not statistically significant. The urbanization rate has a strong impact on electricity consumption as people move from rural to urban areas, which often leads to switches in fuel use and fuel availability. In the case of transition economies, this is not a move to areas with electricity supply, as one of the consequences of the soviet legacy is full or almost full electrification. As expected, population also has a strong positive effect, although the coefficient is smaller than 1. The manufacturing share of value added seems to be the only activity share variable that is significant, leading to more consumption than other activities, as expected.

Unsurprisingly, there is larger persistent inefficiency than transient inefficiency in the context of transition economies. Mean efficiency in the sample is just above 56%, and given the small sample context, is prone to some changes with different priors. As seen in Section 5, in comparable sample sizes the results will be severely affected if the underlying signal-to-noise ratio is not strong enough (as in Scenario 1). Therefore, different priors are tested to assess the impact of priors on results. When the prior median persistent efficiency is changed from 60% to 50% (second to third column of Table 3.8), with both cases showing prior efficiency relatively close to posterior efficiency, posterior mean efficiency changes from 56.7% to 54.1%, a relatively small change of 2.6 p.p. caused by a 10 p.p. in median prior inefficiency and comparable to the one seen in Scenario 2 simulations in Section 5. The median changes by 3.3 p.p., making it very likely that a sufficient amount of information is present in the data for meaningful estimation, given that it is difficult to get much more robust results than this from such a small sample. Estimation using the TK paper method gives reassurance about the robustness of results as they are reasonably similar, even if the methodology can be problematic. However, a comparison of density plots of the draws for the variance of persistent inefficiency shows how the priors in the method of Makiela (2016) might be more appropriate to deal with the problem of identification. The figure below shows density plots for ${\sigma_\eta}^2$ for two priors under the Makiela approach and two priors under the TK approach.

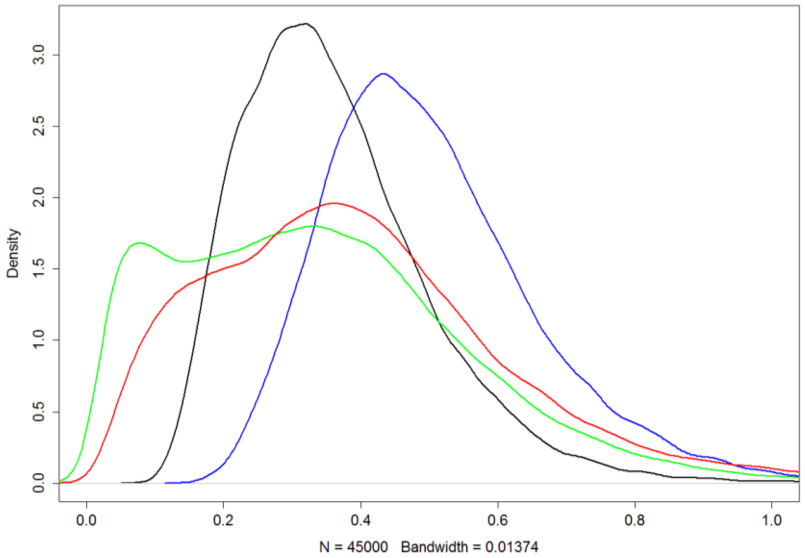

Figure 3.2. Posterior densities of ${\sigma_\eta}^2$ under different priors and approaches. $\mathrm{r}_\eta = 0.7$ (black), $\mathrm{r}_\eta = 0.6$ (blue) , $\overline{\mathrm{Q}}_\eta$=0.1 (green), $\overline{\mathrm{Q}}_\eta$=0.25 (red).

Given the behaviour seen in simulations, the $\mathrm{r}_\eta = 0.6$ case might be the most appropriate choice, as the prior efficiency is centred close to the posterior and results in a smooth posterior. Therefore, analysis of results will be based on the case $\mathrm{r}_\eta = 0.6$. For analysis of results, most countries are divided into key groups: core EU nations (UK, France, Germany and Austria), CIS core nations (Russia, Ukraine, Belarus and Moldova), Balkans (Slovenia, Croatia, Bosnia, Albania and Macedonia), Caucasus (Armenia, Azerbaijan and Georgia) and Eastern EU members (Estonia, Lithuania, Latvia, Poland, Czech Republic, Slovakia, Romania and Bulgaria). When considering group averages, there are some signs of convergence. This is a sign that after controlling for technological differences and other heterogeneity in the data, the groups effectively have similar efficiencies in energy consumption. Their fundamental differences in the use of energy can then probably be attributed to differences in technology and equipment instead of their use, when taking such technology and equipment as given. It appears that most country groups are converging towards an average level of approximately 60% with the Balkans being a clear exception.

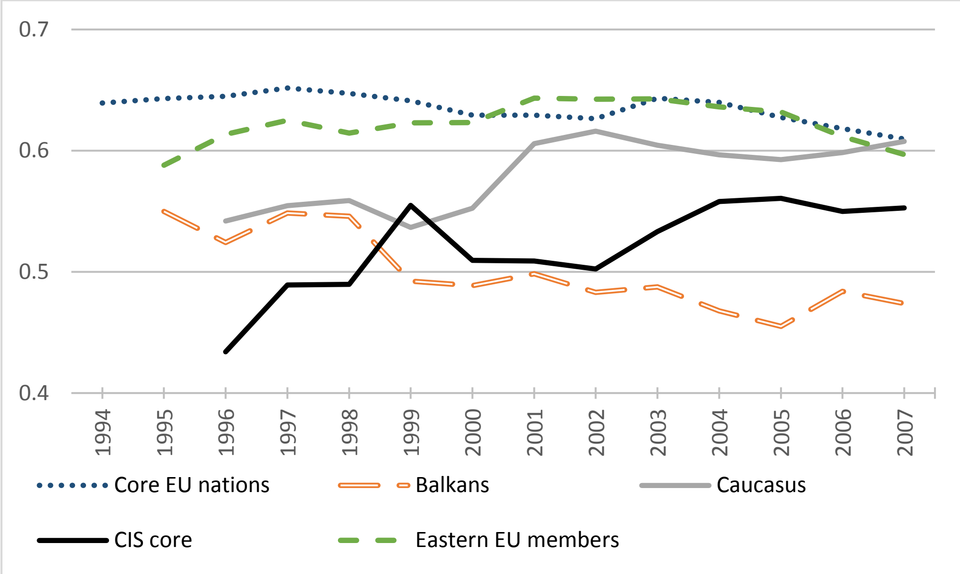

Figure 3.3. Efficiencies across country groups

The convergence behaviour (seen in the figure above) is compatible with the removal of Soviet and Eastern European barriers to efficient use of energy. It is also possible that technological catching-up with energy efficient equipment is partially driving the results, as the Eastern EU members and the CIS core countries quickly adopt technologies that were already a standard in core EU nations. This resembles the argument of Gomułka (2000), where not only there is visible macroeconomic convergence during the 1990s, but there is also an assumption that international technology transfer is proportional to investment and also the technology gap, highlighting the importance of capital accumulation. The CIS members had more of a gap to close from the start in this case. The author also points that in the late 1990s the reform strategies were less divergent between transition economies, compared to the early 1990s. This argument can be transposed to energy efficiency and investment in equipment in this context. The modelling approach attempts to abstract from the technological differences of the countries, but deep changes in technological catching-up might be visible in the time-varying efficiency results.

The group that stands out as diverging from the others is the Balkans, with this result being robust to some changes in the composition of the group. In this group, only Albania escapes a tendency of clear decrease in efficiency levels in the second half of the sample period. Albania is a clear exception with major political and social instability in the late 1990s that seem to take a toll on efficiency scores. Conflicts could lead to interruptions of productive processes and overall economic activity that translate to efficiency decreases even if that is most likely to be an artefact due to large decreases in GDP – which can be naturally associated to energy consumption not translating to output in general. The Balkans countries have not experienced significant changes in gas supply availability or relative use of natural gas as a fuel over the sample period. However, this region of Europe is partially dependent on local coal fired generation for electricity, which is a highly pollutant fuel, but also cheap to obtain locally. In some countries of the region the national electricity company also has a significant role in coal mining, and the mining/generation/distribution industries are deeply integrated. When considering other fuel availability as well, this region is mostly self-sufficient in terms of energy consumption. The political and social paradigm of the Balkans differs in multiple ways from the one in Eastern Europe and the CIS, as there was already a significant private sector role in the 1990s. It is likely that this region has failed to capitalize as much in terms of efficiency gains as others in the sample, although the starting point was relatively comparable to other economies in the mid-1990s.

There are three further groups of countries not displayed in Figure 3.3. Kazakhstan and Kyrgyzstan display very volatile and low efficiency scores (average of 0.369), the Far East CIS group, and Scandinavia. Regarding Far East CIS (Uzbekistan, Tajikistan and Turkmenistan), this group highlights some of the issues that can arise when fitting stochastic frontier models in this context. Although Uzbekistan and Tajikistan are some of the most inefficient countries in the sample as expected, Turkmenistan is the fourth most efficient country in the sample. This is probably driven by factors other than true underlying efficiency, such as the abundant and virtually free gas supply which feeds industry and households and extremely low electricity consumption, although the population access to electricity is close to 100%. Given that electricity consumption per capita is comparable to other countries in the region and other countries in the sample, this points that there is likely to be much more inefficiency in gas consumption than in electricity consumption, although an investigation on such claims falls out of the scope of this chapter.

One of the most noticeable decreases in efficiency throughout the sample is the case of Armenia, with a drop around 11% mostly concentrated in the last few years of the sample. This happens at a time of a large construction boom in the country that finds no parallel in the sample – however, the inclusion of construction shares in the model does not give rise to any strong statistical significance.

Some complications appear when discussing this partial convergence behaviour. There is possibly some measurement error in some variables, for example in electricity prices and 1990s macroeconomic variables for poorer countries, although the results that are obtained are mostly intuitive. Another issue is that the size of the shadow economy in many of these countries is rather large (Schneider et al., 2010). The underestimation of value added that varies across time and across countries could possibly lead to a situation where efficiency results are distorted by levels and changes in the shadow economy, as that shadow economic activity can also consume some electricity. However, this theory is somewhat in conflict with the obtained results. One of the most inefficient countries in the sample (Uzbekistan) was one of the countries in the Former Soviet Union with the smallest shadow economy throughout the 1990's (Schneider, 2002). On the other hand, for the example of Hungary, both aforementioned studies show rather low levels of shadow economy but the economy appears to be quite efficient in electricity consumption. There is no clear correlation between shadow economy sizes and levels of efficiency and there is no empirical argument supporting the claim that this is distorting results. Regarding changes throughout the sample period, there are also some further examples to support this perspective. Poland, for example, sees some rather consistent efficiency gains in periods where the shadow economy appears to be stabilized or even increasing. Croatia's level of shadow economy probably peaked around 2000 but the decrease in efficiency levels is very consistent throughout time and does not follow the pattern of the size of the shadow economy.

Countries where reform efforts were shy still present efficiency scores that are lower than other countries in general. One example of that is Uzbekistan, an economy that didn't make as much progress as others and remains with very low scores for economic reforms according to the EBRD. The economy is still focused in agriculture and commodities and large obstacles to foreign investment and currency convertibility exist, with corruption looming and a clearly slow paced and gradualist approach towards any economic reform. The efficiency scores for this country are quite volatile but consistently low.

Another possible issue to consider is a correlation between efficiency scores and fuel availabilities, as briefly mentioned in Section 3.4.2. If an economy has abundant or cheap gas supply, that might influence electricity consumption. In the 33 countries considered in the sample, the correlation between individual efficiency scores and the percentage of electricity consumption in total energy consumption (in ktoe) varies greatly. 11 of the correlations are positive, with only 10 of the remaining 22 correlations located between -0.5 and -1. Although a strong negative correlation might imply that results are being driven by substitution of fuels and fuel availability, these results give little supporting evidence, even if the overall correlation of the two vectors for the entire sample is -0.497. A possibly more accurate diagnostic is the correlation between efficiency scores and the share of natural gas in total energy consumption, with a large positive correlation showing potential problems (fuel substitution arising as efficiency in consumption of another fuel). This substitution is more likely than others using fuels such as oil or biomass. However, this overall correlation is only 0.105, giving no evidence of any serious problems of distorted results. The correlation between efficiency scores and the relative ratio between electricity consumption and gas consumption is -0.02.

Possible endogeneity issues related to the regressors might require further work in the future in the stochastic frontier literature. Mutter et al. (2013) point that it is also important to consider if the endogeneity is present in the idiosyncratic error or in the inefficiency, and finds that the latter case is much more dangerous, while endogeneity in the idiosyncratic error does not affect efficiency results as much. Tran and Tsionas (2013) present an alternative for estimation of a simple stochastic frontier model with GMM and endogenous regressors. In this case, it would be hard to solve a possible endogeneity issue (i.e. finding and using appropriate instruments) but regressions do not show any strong significance of lags of prices or value added in this case. In this chapter, exogeneity is assumed as is the case in the energy demand frontier literature, including Filippini and Hunt (2011).

A clear restriction from the parametric stochastic frontier estimation is that a functional form has to be imposed to the cost equation, and it often has to be a simple form to allow for estimation. More accurate results could in theory be achieved with a more complex functional form for the cost function, but the number of parameters in the model is high for such a small sample.

Another important issue worth mentioning is that this frontier concept is closely related to the concept of the rebound effect. The expenditure reduction in energy services due to increased efficiency can lead to increased consumption, which can partially offset the savings. Therefore, as Orea et al. (2014) point out, the elasticity of demand for energy with respect to changes in this energy efficiency measure in this context provides a direct measure of the rebound effect. The model estimated in this chapter implicitly imposes the restriction of a zero rebound effect like the rest of the literature, which according to the evidence from past research from other regions is possibly too restrictive. The issue of rebound effects in transition economies is not well studied at the moment, so prospective size estimates are unclear. While theory would point that in least developed countries the unmet demand for energy services could increase the rebound effect, the tight budget constraint that was experienced in transition economies could lead to this budget relaxation being directed towards increased spending in other goods and services, which would counter the increase of the effect. It is possible that the first effect overrides the latter, and the rebound effect is slightly larger on transition economies than in developed economies, according to evidence from developing countries. While it is true that the rebound effect might have an important effect which is implicitly ignored in the chosen estimation procedure, there is also a very large trade-off in choosing another approach to account for this issue. Since the problem of assuming an elasticity of energy savings with respect to changes in energy efficiency of -1 affects changes in efficiency, persistent inefficiency should not be affected by this discussion. One can speculate that in the presence of a strong rebound effect the convergence effect will be attenuated, leading to some difference between CIS and OECD countries, for example. That effect should be loosely proportional to the size of the rebound effect. This can be a topic of future research.

3.7. Conclusion

This chapter presents a methodology to estimate underlying efficiency in electricity consumption in the context of transition economies after the fall of the Soviet Union, between 1994 and 2007. This methodology focuses on measuring efficiency after accounting for multiple factors such as economic activity by sector, climate, electricity prices and population. Estimation is conducted using the Stochastic Frontier GTRE model, which is mostly unexplored in energy economics applications, even if it displays a diverse literature on technical and estimation aspects. The Bayesian approach of Makiela (2016) is preferred for analysis of results after a comparison with an alternative reparameterization method, with additional investigations on the small sample performance of this model, given the nature of the sample in this context. Some large differences in efficient use of electricity are found mostly in groups of economies where market economy reforms were not thoroughly conducted. Convergence behaviour is witnessed between Western economies and most transition country groups, with the exception of the Balkans and countries in the Far East. The importance of the measurement of persistent inefficiency is particularly strong in the results. The results and their analysis are an important contribution to the energy efficiency and applied econometrics literature as there is no other significant work in the application of the Bayesian GTRE approach, the region of study and the discussion of the issues around the estimation of the efficiency measures.

The chapter also highlights some of the difficulties and challenges surrounding cost frontier estimation in an energy demand framework and the trade-off between complex modelling and tractability. Large uncertainty around estimates leads to a discussion of group averages rather than a detailed discussion on individual efficiency scores and country rankings. On average, this average inefficiency level stayed mostly stable through the time frame of this study. The model clearly distinguishes some countries with a low level of market reforms, such as Tajikistan and Uzbekistan, as lagging behind in terms of efficiency and containing large persistent inefficiency which is compatible with the Soviet legacy and its implications, even after controlling for unobserved heterogeneity.

Chapter 4. Spatial Dependence and Unobserved Heterogeneity in Stochastic Frontier Models: A Bayesian Approach

4.1. Introduction

The stochastic frontier literature has advanced considerably in the last four decades. Panel models have been outlined and extended to be able to account for multiple factors, such as heterogeneous technologies and spatial dependence. As mentioned in previous chapters, recent advances in the literature allow for the separation of firm effects from technical or cost inefficiency in a production or cost function framework (Greene, 2005). Further work has been conducted to allow a more complete separation of those effects from inefficiency, specifically a more complete separation by allowing for two inefficiency components, a time varying and a time invariant one, besides accounting for unobserved heterogeneity. On the other hand, spatial models have been slowly populating a small literature in the past decade, but those often do not consider approaches to separate these effects from inefficiency and simply allow, for example, a spatial lag to capture spatial spillovers in the model. This chapter combines the two literatures and proposes a spatial model that allows for full separation of unobserved heterogeneity and the inefficiency components. Bayesian estimation is conducted, focusing on the issues of identification as the model complexity increases.

The economic rationale for an extension of the literature is straightforward. Consider an example of an industry with heterogeneous management. It is natural to assume that management skills and quality change over time, but also natural to assume that there is some persistent inefficiency associated to the management activities or the firm in general, some core inefficiency associated to management that does not change with time, but is not attributed to heterogeneous technologies or unobservable characteristics when compared to other firms. However, the policy maker might want to ignore the time-invariant inefficiency from the analysis as it can be attributed for example to regulation, even if some authors argue for its estimation in either case (Tsionas and Kumbhakar, 2014). Also, it is possible that there is unobserved heterogeneity (technological availability, for example) as well as endogenous spatial interactions between the outputs or costs of the firms and also exogenous spatial interactions among the independent variables that constitute the production or cost function. In the context of the application of this chapter, which relates to aggregate productivity across European economies, there is unobserved heterogeneity between countries but also productivity spillovers. Large amounts of inefficiency are clearly present, with most of it being persistent, justifying the inclusion of both time-varying and time-invariant inefficiency components. The size of unobserved heterogeneity is also not negligible.

The contribution of this chapter is twofold. First, it presents a Bayesian modelling approach which allows for the measurement of efficiency in the presence of simultaneous challenges of spatial dependence and unobserved heterogeneity. Given the increased complexity of this model, identification is an issue which is explored in detail. This allows for a flexible framework. Secondly, the model allows for easy estimation in most standard statistical software packages in an age of increasing computational power. Section 2 outlines a literature review of the fields of spatial dependence and heterogeneous technologies in stochastic frontier modelling. Section 3 presents the model and discusses its characteristics. Section 4 presents the MCMC scheme with two competing alternatives for estimation. Section 5 explores the identification issues and small sample performance of the model. Section 6 outlines an application of the model to aggregate production in 43 European continent economies between 1992 and 2005, in a context of some spatial dependence and large inefficiencies that are mostly persistent but also vary across time. Section 7 concludes.

4.2. Literature Review

The field of Stochastic Frontier Analysis (SFA) grew immensely since the 1970s, with the seminal work from Aigner et al. (1977) opening the path for a stream of literature that measured efficiency of productive units while still allowing for noise in the estimation process, which is separated from the inefficiency by making distributional assumptions. This was a key contrast to other usually non-stochastic techniques such as Data Envelopment Analysis (DEA). In the last few decades, the SFA literature has focused intensely on the issue of heterogeneous technologies, to account for differences in technology across productive units when measuring their technical efficiency. More recently, the literature has also focused, although sparsely, on the issue of spatial dependence in cost and production frontiers. Different streams of the literature appeared regarding the issue of heterogeneity in applied research.

In more recent developments of the literature, there has been considerable advance in both fields of unobserved heterogeneity and spatial dependence. In the field of heterogeneity, Tsionas and Kumbhakar (2014) propose a Generalized True Random Effects model (GTRE) in a Bayesian setting which separates persistent inefficiency from unobserved heterogeneity by assuming the presence of a zero-mean random effect and one sided inefficiency components with a half-normal distributional assumption. As highlighted in Chapter 2, the model was originally proposed by Colombi et al. (2011) and is an extension of the TRE model of Greene (2005) to allow for the measurement of persistent inefficiency, which is otherwise omitted from the analysis as it is implicitly embedded in the random effect. Makiela (2016) discusses the shortcomings of the Tsionas and Kumbhakar (2014) approach and proposes tweaks to the "naïve" approach to improve estimation. Other ways of estimating the same underlying model are ML estimation using closed-skew normal properties (Colombi et al., 2014) and a three step frequentist approach where the first step is a simple random effects regression and the other two steps are simple frontier estimates (Kumbhakar et al., 2014). The underlying model for is outlined as below, in a cost frontier framework.

$$y_{it} = X_{it}\beta + \eta_i + \alpha_i + v_{it} + u_{it} \tag{25}$$

$$v_{it} \sim N(0, \sigma_v^2) \qquad u_{it} \sim N^+(0, \sigma_u^2) \tag{26}$$

$$\eta_i \sim N^+(0, \sigma_\eta^2) \qquad \alpha_i \sim N(0, \sigma_\alpha^2) \tag{27}$$

The four components are the idiosyncratic error, time-varying (short-run) inefficiency, persistent (long-run) inefficiency and a zero mean random effect respectively, allowing for the correct measurement of total inefficiency in the presence of unobserved heterogeneity as long as the distributional assumptions are adequate. However, precise efficiency measurement is in jeopardy if any existing spatial dependence in the process is ignored by the researcher.

The field of spatial analysis is a late bloomer within the SFA literature. Ignoring this issue can lead to biased efficiency estimates. There is also the theoretical aspect of considering production or cost processes with some sort of spatial dependence. Even Farrell (1957), two decades before Aigner et al. (1977), recognized that his method of measuring agricultural efficiency in the United States would show that differences in efficiency are also related to geographical factors such as climate and location, besides other sources.

The SFA literature developed throughout the following decades but only very recently significant efforts to create spatial SF models were conducted. While the efficiency literature often considers spatial heterogeneity as the differences in efficiency due to location, controlled for by using dummy variables or similar approaches, spatial dependence relates to the dependence of outcomes in different locations – the concepts do not necessarily overlap, creating the reasoning for the use of spatial approaches in SF modelling. In the case of Areal et al. (2012), the spatial spillovers are modelled directly in the efficiency components, so there is a relationship between firms' efficiencies. Pavlyuk (2013) stresses that with an increase in mobility and transportation capabilities, the efficiency of airports, sea ports and coach terminals suffers from the influence of spatial interaction as terminals become closer to their neighbouring competition and intensify spatial effects. The author develops a cross-sectional maximum likelihood estimator for SARSF (Spatial Autoregressive Stochastic Frontier model) and SARARSF (Spatial Autoregressive Stochastic Frontier model with spatial autoregressive disturbances) models. The author outlines the SARSF model as, again in a cost setting and in matrix form:

$$y = \rho W y + X\beta + v + u \tag{28}$$

v and u are an error term and an inefficiency term respectively, following from Aigner et al. (1977). This SARSF model has a (N x N) spatial weights matrix W, which is often an inverse distance matrix, and parameter ρ as a measure of spatial dependence. w_i is the i^{th} row of the matrix W. If the spatial relationship of the symmetric error terms is considered as well, the SARARSF model is considered, following equation (28) but with the particular detail that v_{it} also depends on a matrix of dependencies between errors and a parameter that measures that level of spatial dependence. A comparison of the standard model of Aigner et al. (1977) with the SARSF model shows that the bias of the classic stochastic frontier model becomes serious as ρ increases, which is an expected result. For low levels of ρ such as 0.1, the parameter estimates are not severely biased. However, there is noticeable bias in σ_u, which is crucial for inefficiency estimates and is a fundamental part of the analysis of stochastic frontier models. This study then applies the spatial methodology to a set of European airports, finding significant spatial effects. Applying the SARARSF model shows that in this case there is significant spatial heterogeneity – previously considered as inefficiency in other models, although the author does not follow into a discussion of result interpretation and calculation of efficiency scores after this, leaving a gap in the literature. Affuso (2010) used a SARSF model to evaluate the impact of agricultural extension programmes that have positive effects not only on chosen farmers but also on other farmers due to spatial spillover effects. This was, as far as the knowledge of the literature allows, the first effort of its kind in the literature. It is also possible to conceive spatial frontier applications that use alternative interpretations of the efficiency term and alternative estimation methods. Naturally, besides the interpretation of the one-sided error term, spatial frontier models have also used random effects and fixed effects and interpret them as efficiency measures to retrieve efficiency estimates while accounting for spatial dependence.

Adetutu et al. (2015) study the effects of efficiency and TFP growth on pollution in Europe in a two stage approach. In a first stage, non-spatial and local spatial stochastic production models are estimated. In a second stage, measures of productive performance are used as regressors in models of per capita emissions of nitrogen and sulphur oxides. Another contribution to the literature is a spatial extension of the CSS estimator (Cornwell et al., 1990) to the spatial autoregressive case which involves direct, indirect and total efficiency (Glass et al., 2014). A key paper in this particular aspect of the literature makes further analysis of spatial spillovers and the modelling approach (Glass et al., 2016). This is based on a SARSF model for panel data and the authors also analyse the measurement of efficiency across units and time, the role of direct and indirect efficiencies, and the extension to a Spatial Durbin model within a SF framework. Although technically straightforward, the latter extension allows for a more flexible and rich modelling approach. The authors apply this approach to aggregate productivity in European economies, showing that the worst performing countries in the sample show higher efficiency levels than in a non-spatial model because the spatial model controls for the disadvantageous location of those economies. The model proposed throughout this chapter can be seen as a cross-over between the GTRE model (Colombi et al., 2011) and the SAR stochastic frontier model for panel data (Glass et al., 2016).

In similar efforts, but not directly using Spatial Autoregressive models, Druska and Horrace (2004) develop a GMM frontier model and apply it to rice farms in Indonesia. The spatial autocorrelation term is introduced in the production frontier model as an exogenous variable, and as such, shifts the frontier technology. Estimation follows the random effects methodology (Schmidt and Sickles, 1984) meaning that the retrieved efficiency measure is time-invariant and follows the implied interpretation of the effects as inefficiency. As discussed above, this also implies that all existing unobserved heterogeneity is captured as inefficiency.

Schmidt et al. (2009) focus on the unobserved local determinants of inefficiency in farm productivity in the Centre-West of Brazil. The TRE model (Greene, 2005) is considered, besides the conditionality of inefficiencies related to unobserved heterogeneity and the possibility of a spatial structure in the unobserved heterogeneity. The particular aspect of this study is the existence of several farms within each municipality – making the inefficiency component a realization from a distribution that depends on a unobserved effect w_i. This effect follows a process that spreads through spatial contagion (such as a new technology). The model is specified assuming that w_i follows a conditional autoregressive distribution that depends on its neighbours, imposing a spatial structure but not affecting output directly. This setting with two levels of hierarchy allows to identify municipal effects even when municipal level covariates are included. In this study, spatial dependency is allowed through lagged latent regional effects, instead of farm effects, unlike Druska and Horrace (2004). Analysis was conducted using Bayesian inference.

It becomes rather clear that there is a gap in the literature in terms of combining the aspects of spatial dependence and correct measurement of inefficiency under the presence of unobserved heterogeneity captured in a random effects framework. While literature reviews in the Stochastic Frontier modelling field have managed to cover the issue of unobserved heterogeneity rather heavily in recent years, they have often ignored the issues of spatial dependence. Examples of this arise in recent reviews (Parmeter and Kumbhakar, 2014). This chapter proposes a methodology that gathers strengths from the spatial branch of the literature and the heterogeneity branch of the literature to achieve a more flexible framework.

4.3. The Generalized Spatial Stochastic Frontier Model

The modelling approach follows in this section. It implies a larger amount of error components than the standard stochastic frontier models and also some endogeneity problems which will be addressed. The model has the same distributional assumptions as in equations (26) and (27). If the model is to be written as a production frontier, the distributions of the inefficiency components would be truncated from above at zero. The identification of the model depends on distributional assumptions about the shape of each of the four components, as otherwise it is impossible to separate them. Note that in the GTRE model and in the majority of the stochastic frontier literature it is assumed a priori that there is no spatial dependence, which translates to the assumption $\rho = 0$. X_{it} represents a set of exogenous variables that relate to the production or cost function and β corresponds to their associated parameters. Assume the following model:

$$y_{it} = \rho \sum_{j \neq i} w_{ij} y_{jt} + X_{it}\beta + \eta_i + \alpha_i + v_{it} + u_{it} \tag{29}$$

$$i = 1, \dots, N \qquad t = 1, \dots, T$$

The equation contains four error components – two of them normal and two of them half normal. v_{it} is an idiosyncratic error in the classic sense of linear regression. u_{it} is a one-sided error term that varies across time and across unit, defined as time-varying inefficiency or short-run inefficiency. This inefficiency component is the typical component in models that do not account for unobserved heterogeneity, and is seen as the only inefficiency term in the TRE model, for example. η_i captures inefficiency that varies across units but not across time, and has been called long-run inefficiency or persistent inefficiency in the literature. Finally, α_i is a random effect to absorb any time-invariant unobserved heterogeneity. The assumptions of the Random Effects model must hold in this context – there must be no correlation between the unobserved heterogeneity and the explanatory variables – although this assumption can be relaxed by adding cross-sectional means of explanatory variables.

This model captures spatial dependence through a spatial lag, which leads to issues of endogeneity. W is a (N x N) spatial weights matrix assumed to be exogenously determined by the researcher. Often, this matrix is defined according to the existence of neighbours of a given unit, or the distance between given units. w_i is the i^{th} row of the spatial weights matrix. It is important to define a correctly specified spatial weights matrix to avoid biased estimates, but the true matrix is not known. ρ is a parameter measuring the strength of the spatial dependence in the context of a given production or cost process, and it is bounded theoretically between -1 and 1. The researcher can bound it further inside that interval for some specific reason, for example by only allowing it to be only non-negative.

The endogeneity is taken into account by adding the Jacobian term of the transformation of ε_{it} to y_{it} to the log-likelihood function (Anselin, 1988). In a more practical sense, the coefficient of ρ is restricted to the interval between $\frac{1}{W_{MIN}}$ and $\frac{1}{W_{MAX}}$, where W_{MIN} and W_{MAX} are the characteristic roots of the spatial weights matrix W. The restriction of ρ to its parameter space is done by the addition of the Jacobian term in the log-likelihood function, while it could be unrestricted (and possibly leading to odd results) in alternative IV/GMM methods.

There are two notes to make in this context. First, the extension of this model to include spatial lags of the exogenous variables is technically straightforward in the context, given that it is simply the addition of more regressors to the model, although it can lead to highly correlated regressors. However, this addition can be of great value to some applications and specific contexts of efficiency measurement where the production or the cost function involves not only spatial dependence related to the dependent variable, but also to the explanatory variables. Secondly, note that this particular model is very recent in the literature, but also that to the best of my knowledge, there is no Spatial Autoregressive True Random Effects model outlined in the literature as well – either in frequentist or Bayesian forms. The Spatial TRE model is easier to estimate, although it assumes a priori the non-existence of persistent inefficiency or it implicitly treats it as a part of unobserved heterogeneity. However, the validity of the model for less complex situations is clear. Although details on this specific model are not presented here, the MCMC scheme for that model is presented in Appendix 4.1.

The choice of a half-normal distribution is justified by a combination of practicality and information about the performance of different distributions in parametric stochastic frontier models. It is known that often relative rankings and decile compositions are not very sensitive to the choice of distributional assumption between half-normal, truncated normal and exponential (Kumbhakar and Lovell, 2004). Other flexible distributional assumptions such as Gamma (Greene, 1990) and Weibull (Tsionas, 2007) distributions might be more appealing from a theoretical perspective, but they often lead to increasing difficulty or additional parameters to estimate, which would make estimation more unreliable in complex models.

The interpretation of the parameters of the model is not as straightforward as in a non-spatial model. LeSage and Pace (2009) highlight that the coefficients of the explanatory variables cannot be directly interpreted as elasticities, because the marginal effects are linked to the spatial autoregressive variable. Therefore, and following the authors, it is possible to separate the total effect of the independent variables into direct and indirect effects using the estimated parameters. An issue of interest is that the same argument holds when considering the efficiencies. Total efficiency can also be decomposed into direct efficiency and indirect efficiency, which is related to the effect of the neighbouring units. Note that in the modelling approach where spatial dependence is not taken into account (Kumbhakar et al., 2014), the measure of efficiency is:

$$\widehat{EFF_{it}} = \widehat{TVE} * \widehat{TIE} = \exp(-\omega\widehat{u_{it}} - \omega\widehat{\eta_i}) \tag{30}$$

The notation is, as before, $\omega = 1$ for a cost frontier, and $\omega = -1$ for a production frontier. However, the case of the suggested model is slightly more complicated due to the introduction of the spatial aspects in the model. Starting from the core idea of technical efficiency in equation (1) of Chapter 2, technical efficiency is now the ratio of the output of a unit divided by the maximum attainable output given inputs but also the outputs of other units.

After stacking observations in equation (29) and re-organizing the model as $y = (I_{NT} - I_T \otimes \hat{\rho}W)^{-1}(X\beta + I_T \otimes \eta + I_T \otimes \alpha + v + u)$, the typical mathematical calculation of efficiency would lead, in a notation more consistent with equation (30), to the vector $\widehat{EFF} = \exp[(I_{NT} - I_T \otimes \hat{\rho}W)^{-1}(-\omega\hat{u} - I_T \otimes \omega\hat{\eta})]$. This stems from the reduced form of the model. Placing the inverse matrix inside of the exponential for efficiency measurement renders the nice property of efficiency bounded between 0 and 1, in line with the suggestion of Fusco and Vidoli (2013). However, this would lead to counterintuitive effects as the median and the minimum efficiency observations would be increasingly more distant from the most efficient observation. Another unintended consequence of difficult interpretation of that alternative is that mean efficiency in the sample goes to 0 as the spatial parameter goes to 1, independently of the level of direct efficiency in the sample. This method follows the traditional mathematical implications of stochastic frontier analysis, but does not pass the test of practical interpretation. Therefore, an alternative method is explained below.

The alternative in the literature, as in Glass et al. (2016), is to start by taking the exponential of u and η from the structural form of the model. Then, by considering the part of the reduced form that relates to efficiency, $\exp[(I_{NT} - I_T \otimes \hat{\rho}\mathrm{W})^{-1}(-\omega\hat{u} - I_T \otimes \omega\hat{\eta})]$ is calculated based on the corresponding exponential from the structural form of the model.

Reverting to a more explicit definition of the efficiency vectors, the total time-varying efficiency (TVE) will be $(I_{NT} - I_T \otimes \hat{\rho}\mathrm{W})^{-1}exp(-\omega\hat{u})$, a (NT x 1) vector as suggested previously in the literature (Glass et al., 2016) and correspondingly the total time invariant efficiency (TIE) will be $(I_N - \hat{\rho}\mathrm{W})^{-1}exp(-\omega\hat{\eta})$, a (N x 1) vector. This leads to the following vector of efficiencies:

$$\widehat{EFF} = (I_{NT} - I_T \otimes \hat{\rho}\mathrm{W})^{-1}\exp(-\omega\hat{u} - I_T \otimes \omega\hat{\eta}) \tag{31}$$

However, the efficiency measure in equation (31) is not bounded between 0 and 1 in some cases, leading to cases where the mathematical calculation does not lead to an intuitive interpretation supported by theory and the specificities of a spatial model. To gain an advantage over the alternative method and successfully interpret this measure, a relative scale must place the most efficient firm at the benchmark, while ranking all other observations with respect to that calculated maximum. This argument follows Glass et al. (2016) but leaves little room, for example, to consider the distance of the most efficient firm from the actual frontier, particularly in contexts of larger inefficiency (be it persistent or time-varying). However, it is desirable to measure efficiency in some form of absolute scale to assert how distant firms are from the frontier in general.

In this case, the frontier model efficiencies are influenced by the spatial interactions, and there is no straightforward interpretation of an efficiency score below 0 or above 1. The following absolute measure is proposed in this thesis as a contribution to the literature, under the condition of non-negative ρW:

$$Total\ Efficiency = S^{-1}\sum_{s=1}^{S}\frac{\left(I_{NT} - I_T \otimes \rho^{(s)}\mathrm{W}\right)^{-1}\exp[-\hat{u}\ -\ I_T \otimes \hat{\eta}]}{max[(I_{NT} - I_T \otimes \rho^{(s)}\mathrm{W})^{-1}l_u]} \tag{32}$$

In equation (32) l_u represents an (NTx1) vector which is equal to 1, representing full efficiency. This denominator represents a value of maximum efficiency given the observed level of spatial dependence for one (abstract) fully efficient sample. The denominator is not bounded between 0 and 1, but it represents an attainable maximum by the firm that is the benchmark to compare all observations. With this proposed measure, the relative distance between the most and the least efficient unit decreases with increasing ρ, as in the relative efficiency measure proposed by Glass et al. (2016). The ratio between the median score and the lowest score in the proposed relative and absolute measures is exactly the same, retaining the original structure. Note that the condition of non-negative ρW is relatively general, as long as there is a positive spatial parameter coefficient and the spatial matrix is, for example, an inverse distance matrix or a neighbourhood matrix.

The debate on what is the most appropriate approach is far from finished, as the approach of Fusco and Vidoli (2013) is well bounded but difficult to interpret, the approach of Glass et al. (2016) is easy to interpret but imposes relative measurement, and the approach of equation (32) expands efficiency measurement to an absolute scale in the spatial context, but is not applicable under some conditions such as a negative spatial parameter (context of competition between units).

Direct and indirect efficiencies arise from the chosen procedures with spatial stochastic frontier models, as noted in the literature by Glass et al. (2016). Denoting the j'th (NT rows) row of $\exp(-\omega\hat{u}\ -\ I_T \otimes \omega\hat{\eta})$ as A_{it}, the resulting matrix will have a diagonal of direct effects, with all other values being indirect effects.

$$(I_{NT} - I_T \otimes \hat{\rho}\mathrm{W})^{-1}\begin{pmatrix} A_1 \\ \cdots \\ A_j \end{pmatrix} = \begin{pmatrix} A_{11}^{Direct} & + & \cdots & + A_{1j}^{Indirect} \\ \vdots & + & \ddots & + \quad \vdots \\ A_{j1}^{Indirect} & + & \cdots & + A_{jj}^{Direct} \end{pmatrix} \tag{33}$$

This allows for asymmetric efficiency spillovers which affect indirect and total efficiency results. Indirect efficiency estimates can be obtained relating to the efficiency spillover to (from) one unit from (to) another unit (a particular indirect effect in equation (33)) or the efficiency spillover to (from) all units from (to) another unit (the sum of indirect effects across a row or a column in equation (33)). In other words, units can “import” efficiency from their neighbours and “export” efficiency to their neighbours, with possibly asymmetric effects.

When computing efficiency measures, it is also important to account for parameter uncertainty. This is dealt with in classic Rao-Blackwell fashion as in Tsionas and Kumbhakar (2014), but also with the spatial lag parameter influencing the computation of the efficiency measures. A model for balanced panel data is being considered in this context, as in SAR models it is a problem to consider unbalanced panels if the reason for missing data is not known (Elhorst, 2010). However, some assumptions can be made to proceed with estimation for unbalanced panels, such as assuming the data are missing at random (Pfaffermayr, 2013). All the measures above are computationally easy to calculate with little effort unless the sample is very large. In the next section, the MCMC scheme is presented to guide us through the estimation of the model.

Given the use of a Bayesian approach, one can make inference on the uncertainty of efficiency measures by calculating at each draw the total efficiency measure. However, any credible intervals obtained should be rather large, given the nature of the stochastic frontier techniques. This is particularly true for persistent inefficiency with small N. To test hypothesis of dropping one error component from the model, for example persistent inefficiency, leading to a spatial autoregressive version of Greene (2005) True Random Effects model, an approximation of Bayes Factors can be used (Verdinelli and Wasserman, 1995).

4.4. MCMC Scheme

The MCMC approach will follow two paths of investigation. The first is an extension based on an augmentation of the GTRE model following propositions in van den Broeck et al. (1994). This follows the approach of Makiela (2016) for the GTRE model. The second path is an extension of the Tsionas and Kumbhakar (2014) model using their reparameterization approach. Both are outlined in detail and their properties explored in the next section.

For the rest of the thesis, standard notation for conditional posterior distributions is used, with $p(\tau|y, X, \theta_{-\tau})$, denoting the posterior conditional distribution for τ, given y, data X and all parameters other than τ.

4.4.1. A simple Gibbs sampling approach

Unless explicitly stated otherwise, the panel data is stacked by order of time first and then by unit. The scheme is presented in a cost frontier notation when $\omega = 1$ and in a production frontier notation when $\omega = -1$. The u and η components will be positive in a cost frontier and negative in a production frontier.

The following priors are defined for the model:

$$\beta \sim N(c, A^{-1}) \tag{34}$$

$$\frac{1}{\sigma_Z^2} \sim f_G\left(\frac{\overline{N}_Z}{2}, \frac{\overline{Q}_Z}{2}\right), \text{for } Z = v, \alpha \tag{35}$$

$$\frac{1}{\sigma_Z^2} \sim f_G[5{,}10 \ln^2(r_Z^*)], for\ Z = \eta, u \tag{36}$$

The shape-rate parameterization of the gamma distribution is used throughout the rest of the chapter. All Q's can be set, for example, to be 10^(-4) (the prior sum of squares of each of the error components). c can be set to be a vector of zeros (a vector of prior means of the regressors of the explanatory variables). Although in general terms the prior in (34) can be used, a standard uninformative reference prior is defined in this chapter, following Makiela (2016). Setting Nv=N$\alpha = 1$ implies that a prior sample of size 1 has a sum of squares $\overline{Q}_Z$. r_Z^* refers to the prior medians of inefficiency and this flexible prior allows for good tuning to meet the needs of the applied researcher. Note that this is linked to direct efficiency, and not total efficiency after accounting for the spatial aspect for the model. More on that follows in the next section. Also, note that if the researcher desires to input stronger prior information, this can be achieved, for example, by changing c and A to reflect prior beliefs about the effect of particular exogenous variables, or some beliefs about the size of the inefficiencies.

The draws for the parameters are obtained in the following way:

$$p\left(\beta \middle| y, X, \theta_{-\beta}\right) \propto N(b, B) \tag{37}$$

$$b = (X'X + \sigma_v^2 A)^{-1}(X'Sy + \sigma_v^2 Ac) \tag{38}$$

$$B = \sigma_v^2 (X'X + \sigma_v^2 A)^{-1} \tag{39}$$

$$Sy = (I_{NT} - I_T \otimes \rho W)y - [\mathrm{lt} \otimes \alpha] - [\mathrm{lt} \otimes \eta] - u \tag{40}$$

In equations (38) and (39) all multiplicative parts containing A will drop out of the equations using the reference uninformative prior. The conditional posteriors of the variances of the error components are drawn from well-known distributions:

$$p\left(\sigma_v^2 \middle| y, X, \theta_{-\sigma_v}\right) \propto \mathrm{Inv} - \chi 2(NT + Nv\,;\ ((Qv + v'v)/(NT + Nv))) \tag{41}$$

$$v = (I_{NT} - I_T \otimes \rho W)y - X\beta - u - [\mathrm{lt} \otimes \alpha] - [\mathrm{lt} \otimes \eta] \tag{42}$$

$$p\left(\sigma_\alpha^2 \middle| y, X, \theta_{-\sigma_\alpha}\right) \propto \mathrm{Inv} - \chi 2(NT + N\alpha\,;\ ((Q\alpha + \alpha'\alpha)/NT + N\alpha)) \tag{43}$$

$$p\left(\sigma_u^2 \middle| y, X, \theta_{-\sigma_u}\right) \propto \mathrm{Inv} - \mathrm{Gamma}(NT/2 + 5\,; ((Qu + u'u)/(2 + \ln^2(r_u^*)))) \tag{44}$$

$$p\left(\sigma_\eta^2 \middle| y, X, \theta_{-\sigma_\eta}\right) \propto \mathrm{Inv} - \mathrm{Gamma}(N/2 + 5\,; ((Q\eta + \eta'\eta)/(2 + \ln^2(r_\eta^*)))) \tag{45}$$

$$p(u|y, X, \theta_{-u}) \propto N^+(\tilde{u}\frac{\sigma_u^2}{\sigma_v^2 + \sigma_u^2}, \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + \sigma_u^2} I_{NT}) \tag{46}$$

If a production frontier is desired instead of a cost frontier, u is drawn from a N^- distribution (truncated from above at zero).

$$\tilde{u} = [(I_{NT} - I_T \otimes \rho W)y - X\beta - [\mathrm{lt} \otimes \alpha] - [\mathrm{lt} \otimes \eta]] \tag{47}$$

$$p(\eta|y, X, \theta_{-\eta}) \propto N^+(\tilde{\eta}\frac{\sigma_\eta^2}{\sigma_v^2/T + \sigma_\eta^2}, \frac{\sigma_v^2\sigma_\eta^2/T}{\sigma_v^2/T + \sigma_\eta^2} I_N) \tag{48}$$

$$\tilde{\eta} = (I_N - \rho W)\bar{y} - \bar{X}\beta - \alpha - \bar{u} \tag{49}$$

$$p(\alpha|y, X, \theta_{-\alpha}) \propto N^+(\tilde{\alpha}\frac{\sigma_\alpha^2}{\sigma_v^2/T + \sigma_\alpha^2}, \frac{\sigma_v^2\sigma_\alpha^2/T}{\sigma_v^2/T + \sigma_\alpha^2} I_N) \tag{50}$$

$$\tilde{\alpha} = (I_N - \rho W)\bar{y} - \bar{X}\beta - \eta - \bar{u} \tag{51}$$

The only parameter which is not drawn from a well-known distribution with easy simulation in modern statistical software packages is the spatial parameter:

$$p(\rho|y, X, \theta_{-\rho}) \propto |S| \exp(-\frac{v'v}{2\sigma_v^2}) \tag{52}$$

$$|S| = |(I_N - \rho W)| \tag{53}$$

This parameter is drawn using the Random Walk Metropolis-Hastings approach, a well-established technique in the literature, which poses no problem for estimation in this case and is often used in estimating Bayesian spatial econometrics models. In Chapter 5 some other techniques will be explored, in a context of more intensive use of rejection techniques. However, for simplicity these are not explored in Chapter 4.

4.4.2. Reparametrization approach

Tsionas and Kumbhakar (2014) highlight in the GTRE model that a naïve data augmentation technique will not easily explore the true parameter spaces due to the very high autocorrelation between the latent variables. Therefore, the same reparameterization is proposed as an alternative and investigated further in this chapter. Unless explicitly stated otherwise, the panel data is stacked by order of time first and then unit.

The following priors are defined for the model:

$$\frac{1}{\sigma_Z^2} \sim f_G\left(\frac{\overline{N}_Z}{2}, \frac{\overline{Q}_Z}{2}\right), \text{for } Z = v, u, \eta, \alpha \tag{54}$$

In practice, this model implies that there are two skew-normal variables associated to this model. First, the convolution of the idiosyncratic error and time-varying inefficiency is $\varepsilon_{it} = v_{it} + u_{it}$. Separating the two is a typical problem in the literature and considered rather straightforward as long as assumptions on the shape of the time-varying inefficiency are set:

$$f(\varepsilon) = \frac{2}{\sigma} \varphi\left(\frac{\varepsilon}{\sigma}\right) \Phi\left(\frac{\omega\varepsilon \frac{\sigma_u}{\sigma_v}}{\sigma}\right) \tag{55}$$

And secondly, the convolution between the random effects and the persistent inefficiency $\delta_i = \eta_i + \alpha_i$, which is also a skew normal variable:

$$f(\delta) = \frac{2}{\sigma_\delta} \varphi\left(\frac{\delta}{\sigma_\delta}\right) \Phi\left(\frac{\omega\delta \frac{\sigma_\eta}{\sigma_\alpha}}{\sigma_\delta}\right) \tag{56}$$

In this notation, $\omega = 1$ for a cost frontier, and $\omega = -1$ for a production frontier. This model can be presented in two different parameterizations, with the first of them being:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it}\beta + \delta_i + v_{it} + u_{it} \tag{57}$$

This implies that the random effects and the persistent inefficiency components are estimated jointly. In a first stage, δ, ρ, β, σ_u and σ_v are estimated without the unnecessary added correlation of draws from trying to estimate the individual components of the convolution $\delta_i = \eta_i + \alpha_i$. Focus on estimating the remaining parameters from the model will be put on the other parameterization of the model.

The draws for the parameters are obtained in the following way, with some differences compared to the other approach:

$$\mathrm{p}\left(\beta \middle| \mathrm{y}, \mathrm{X}, \theta_{-\beta}\right) \propto \mathrm{N}(\mathrm{b}, \mathrm{B}) \tag{58}$$

where b and B are drawn the same way as in the previous approach, except for the difference in Sy:

$$\mathrm{Sy} \ = (I_{NT} - I_T \otimes \rho\mathrm{W})y - [\mathrm{lt} \otimes \delta] - \mathrm{u} \tag{59}$$

The conditional posterior of the skew normal δ_i is:

$$\mathrm{p}(\delta_i|\mathrm{y}, \mathrm{X}, \theta_{-\delta}) \propto \exp(\frac{(\mathrm{R}_i - [\mathrm{lt} \otimes \delta_i])'(\mathrm{R}_i - [\mathrm{lt} \otimes \delta_i])}{2\sigma_v^2} - \frac{{\delta_i}^2}{2\sigma_\delta^2})\Phi(\frac{\frac{\sigma_\eta}{\sigma_\alpha}\omega\delta_i}{\sigma_\delta^2}) \tag{60}$$

where $\mathrm{R2} = \ (I_{NT} - I_T \otimes \rho\mathrm{W})y - \mathrm{X}\beta - \mathrm{u}$, with $\mathrm{y}, \mathrm{X}, \mathrm{u}$ being matrices of data first stacked by unit and then time, with R2 being then calculated and then re-stacked by time first and then unit – resulting in R. R_i then relates to a specific unit i under consideration.

It is known that this distribution is skew-normal and log-concave. Simple methods can be applied, such as an Adaptive Rejection Sampler (ARS) (Gilks and Wild, 1992), where the logarithm of the target density is enveloped using tangents to the log-density. However, for computational reasons, draws from this distribution are taken in R using Adaptive Metropolis Rejection Sampling, ARMS (Gilks et al., 1995), using the package "dlm" in R. This method has an additional Metropolis step (Metropolis et al., 1953) to assure stability in the computations in extreme cases, although in all cases this should reduce to ARS due to log-concavity. This method does not require analytical derivatives.

An alternative to the use of rejection sampling is a tailored rejection algorithm using derivatives. A candidate draw δ_i^* is obtained using a normal distribution with mean equal to the mode of the distribution, and standard deviation s equal to the negative inverse second derivative of the distribution evaluated at the mode. This standard deviation is guaranteed to be positive, as the second derivative at the maximum is always negative. This draw is then accepted with probability:

$$\frac{\mathrm{p}(\delta_i|\mathrm{y},\mathrm{X},\theta_{-\delta})/f_N(\delta_i|\delta_i^*,s^2)}{\mathrm{p}(\delta_i^*|\mathrm{y},\mathrm{X},\theta_{-\delta})/f_N(\delta_i^*|\delta_\mathrm{i}^*,s^2)} \tag{61}$$

The conditional posteriors of the variances of the idiosyncratic error and the time-varying inefficiency are as follows:

$$\mathrm{p}\left(\sigma_\mathrm{v}^2\middle|\mathrm{y},\mathrm{X},\theta_{-\sigma_v}\right) \propto \ \mathrm{Inv}-\chi2(\mathrm{NT}+\mathrm{Nv}\,;\ ((\mathrm{Qv}+\mathrm{v'v})/(\mathrm{NT}+\mathrm{Nv}))) \tag{62}$$

$$\mathrm{p}\left(\sigma_\mathrm{u}^2\middle|\mathrm{y},\mathrm{X},\theta_{-\sigma_u}\right) \propto \ \mathrm{Inv}-\chi2(\mathrm{NT}+\mathrm{Nu}\,;\ ((\mathrm{Qu}+\mathrm{u'u})/(\mathrm{NT}+\mathrm{Nu}))) \tag{63}$$

$$\mathrm{p}(\mathrm{u}|\mathrm{y},\mathrm{X},\theta_{-\mathrm{u}}) \propto \mathrm{N}^+(\mathrm{U},\frac{\sigma_\mathrm{v}^2\sigma_\mathrm{u}^2}{\sigma_\mathrm{v}^2+\sigma_\mathrm{u}^2}I_{NT}) \tag{64}$$

If a production frontier is desired instead of a cost frontier, u is drawn from a N^- distribution (truncated from above at zero).

$$\mathrm{U} = \frac{[(I_{NT}-I_T\otimes\rho\mathrm{W})y-\mathrm{X}\beta-[\mathrm{lt}\otimes\delta]]\,\sigma_\mathrm{u}^2}{\sigma_\mathrm{v}^2+\sigma_\mathrm{u}^2} \tag{65}$$

$$\mathrm{p}\left(\rho\middle|\mathrm{y},\mathrm{X},\theta_{-\rho}\right) \propto |\mathrm{S}|\,\exp(-\frac{v'v}{2\sigma_\mathrm{v}^2}) \tag{66}$$

$$|\mathrm{S}| \ = \ |(I_N-\rho\mathrm{W})| \tag{67}$$

$$\mathrm{v} \ = \ (I_{NT}-I_T\otimes\rho W)y-X\beta-u-[\mathrm{lt}\otimes\delta] \tag{68}$$

Draws of the spatial lag are taken using a Metropolis-Hastings step where the candidate distribution is a normal distribution keeping the rejection rate at a reasonable level. Note that a uniform prior on this parameter is implicit. Any other restrictions on this parameter can be easily imposed, for example to force this parameter to be positive between 0 and 1.

The jointly estimated (and skew-normal) δ_i needs to be separated if there is an interest in estimating time-invariant inefficiency. If it has a positive (negative) mean that is rather distant from zero in a cost (production) frontier that means there is considerable persistent inefficiency. This roughly means that if the estimated mean of δ is zero or very close to zero, the random effects dominate and the time-varying inefficiency might be all one cares about. If the opposite belief exists for some particular reason and the researcher thinks the random effects are negligible, one can proceed with the assumption that $\delta_i = \eta_i^+$.

The second parameterization is as follows:

$$\mathrm{y_{it}} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \mathrm{X_{it}}\beta + \eta_i^+ + \zeta_{\mathrm{it}} + \mathrm{u_{it}}^+ \tag{69}$$

This implies that the random effects and the idiosyncratic error are concentrated in a ζ parameterization. At this stage, we can estimate η independently of α, reducing the correlation of the draws:

$$\zeta_{it} = \alpha_i + v_{it} \tag{70}$$

Draws for persistent inefficiency come from the following conditional posterior:

$$\mathrm{p}\left(\eta_i \middle| \mathrm{y}, \mathrm{X}, \theta_{-\eta}\right) \propto \mathrm{N}^+(\mathrm{m_i}; \varphi^2) \tag{71}$$

$$\varphi^2 = \sigma_\delta^2 (1 + \sigma_\delta^2 l_t' \Sigma^{-1} l_t)^{-1} \tag{72}$$

$$m_i = \varphi^2 l_t' \Sigma^{-1} D_i \tag{73}$$

$$\sum = \sigma_\alpha^2 J_T + \sigma_v^2 I_T \tag{74}$$

$$J_T = l_t' l_t \tag{75}$$

Also, $D2 = (I_{NT} - I_T \otimes \rho W)y - X\beta - u$ where y, X, u are first stacked by unit and then time, with $D2$ being then calculated and re-stacked by time first and then unit – resulting in D. For each unit, D_i has t observations. If a production frontier is desired instead of a cost frontier, η is drawn from a N^- distribution (truncated from above at zero).

Now, it is straightforward that the draws for the random effects are:

$$\alpha_i = \delta_i - \eta_i^+ \tag{76}$$

With the variance of random effects:

$$p(\sigma_\alpha^2 | y, X, \theta_{-\alpha}) \propto \mathrm{Inv} - \chi 2(NT + 1\,;\ ((Q\alpha\ + \alpha'\alpha)/NT + 1)) \tag{77}$$

The draws for the variance of the convolution in the previous parameterization are simply:

$$\sigma_\delta^2 = \sigma_\eta^2 + \sigma_\alpha^2 \tag{78}$$

Note that in terms of estimation, the extension to a Durbin model only implies the estimation of an additional set of β's , so the MCMC scheme presented above holds without any change.

4.5. Performance of the model

The performance of the model will be assessed with both aforementioned estimation strategies. It is known that in stochastic frontier modelling the information of interest is usually not in the parameters associated with the explanatory variables of the production or cost function (which still need to be estimated correctly), but instead it is located in the inefficiency estimates that are extracted from the error terms. It is also important to assess the performance in small samples, to ensure that the model accurately measures inefficiency in situations often seen in applied research in productivity and efficiency measurement.

The performance of the model will be assessed with two different scenarios and two sample sizes, both with T=10. It is important to consider the performance of the model under a reasonably small T, not only given the nature of many stochastic frontier modelling applications, but also because of the fact that some applications with larger T often ignore the problem of non-stationarity and spurious regression, which should lead to consider other modelling approaches that diverge from the methods of this thesis.
The chosen data generating process for all scenarios is:

$$y_{it} = 1 + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it} + \eta_i + \alpha_i + v_{it} + u_{it} \tag{79}$$

ρ is chosen to be 0.3 or 0.6 and x is generated from a standard normal variable. The simple Gibbs sampler approach is computationally efficient and allows faster estimation. 100,000 draws are taken, with a burn-in of 50,000 and thinning of 5. In the (much slower) reparameterization approach, 10,000 draws are taken, with a burn-in of 5,000 and thinning of 2. This approach is more inefficient computationally and requires longer running times, making a much higher number of draws hardly feasible. Inference is conducted on 100 datasets in both cases. Performance is focused on two measures: the posterior means and the average correlation between the true values and the estimated values (a mean across repetitions). The second measure is particularly appealing as it is not enough to accurately find the mean of inefficiency – the relative efficiency ranking of units is a common exercise in applied research and highly relies on high correlations between true values and estimated values to be a correct one. The panel dimension N will be varied between 36 and 100 units that are composed of squared grids (6 x 6 and 10 x 10 respectively), while T is set to be 10 in both cases. Performance is expected to increase with increasing T. In all scenarios, charts with mean bias for each sample size will be presented, for both inefficiency components.

The following scenarios are created:

Scenario 1: $\sigma_v = 0.1, \sigma_u = 0.2, \sigma_\eta = 0.5, \sigma_\alpha = 0.2$. This scenario is the same as the case N=50 of the TK paper and implies moderate signal-to-noise ratios. With not very strong ratios there is an expectation of bigger performance degradation as the sample size decreases.

Scenario 2: $\sigma_v = 0.05,\ \sigma_u = 0.2, \sigma_\eta = 0.5, \sigma_\alpha = 0.1$. This scenario has stronger signal-to-noise ratios and is expected to perform better, particularly in small samples.

The first key result is the poor performance of the TK approach (Tables 1 and 2). The figures below show percentage deviations from the true mean for each repetition in each case for the Makiela approach.

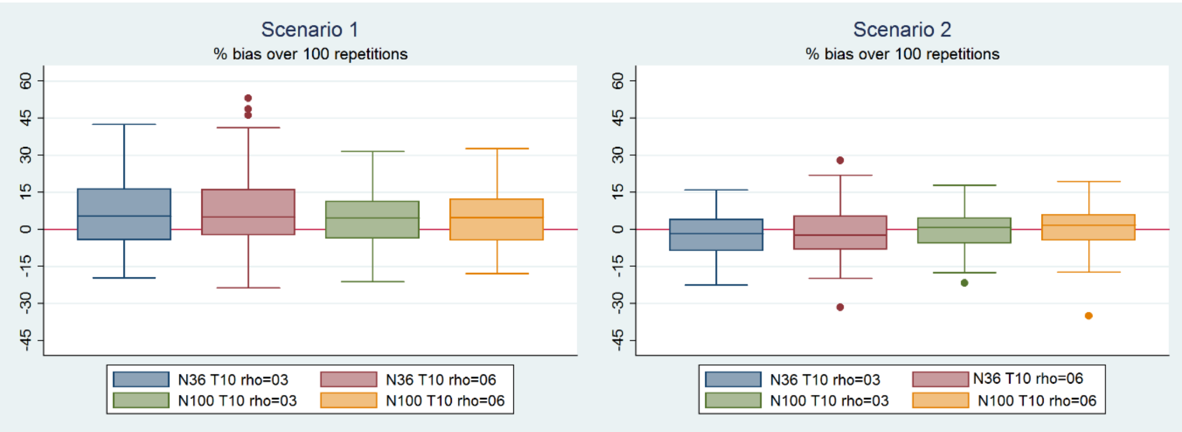

Figure 4.1. Persistent Inefficiency, % mean bias over 100 repetitions

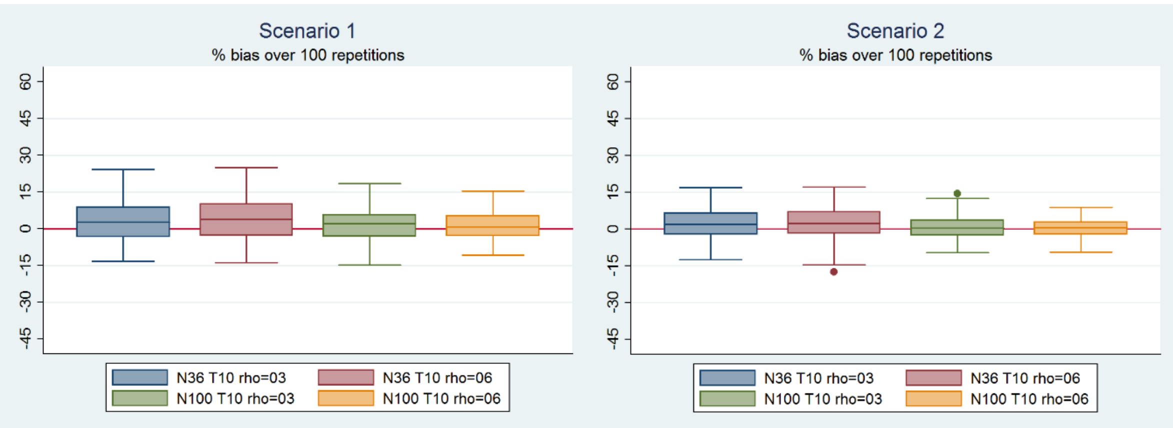

Figure 4.2. Transient Inefficiency, % mean bias over 100 repetitions

Scenario 1 N=100 , T=10	$\overline{Q}_v$=$\overline{Q}_\alpha$=0.001 $r_\eta = 0.7$ $r_u = 0.85$		TK: $\overline{Q}_v = \overline{Q}_\alpha =$ $\overline{Q}_u$=0.001 $\overline{Q}_\eta$=0.25		$\overline{Q}_v$=$\overline{Q}_\alpha$=0.001 $r_\eta = 0.7$ $r_u = 0.85$		TK: $\overline{Q}_v = \overline{Q}_\alpha =$ $\overline{Q}_u$=0.001 $\overline{Q}_\eta$=0.25	
	True	Est.	True	Est.	True	Est.	True	Est.
α_i	0.001	0.000	0.000	0.000	0.001	0.000	-0.001	0.002
η_i	0.397	0.412	0.402	0.262	0.393	0.410	0.393	0.258
u_{it}	0.160	0.162	0.160	0.155	0.159	0.161	0.160	0.157
σ_v	0.1	0.098	0.1	0.102	0.1	0.099	0.1	0.101
σ_u	0.2	0.204	0.2	0.195	0.2	0.202	0.2	0.197
σ_η	0.5	0.520	0.5	0.341	0.5	0.518	0.5	0.336
σ_α	0.2	0.185	0.2	0.326	0.2	0.186	0.2	0.320
ρ	0.3	0.307	0.3	0.308	0.6	0.610	0.6	0.610
S.D. (u_{it})	0.120	0.123	0.120	0.118	0.121	0.122	0.121	0.119
S.D. (η_i)	0.300	0.310	0.302	0.210	0.298	0.309	0.298	0.207
Correlation between true and est. u_{it}	0.7540		0.7532		0.7533		0.7538	
Correlation between true and est. η_i	0.8393		0.8405		0.8301		0.8341	

Table 4.1. Simulation results for Scenario 1 with N=100

Scenario 2 N=100 , T=10	$\overline{Q}_v$=$\overline{Q}_\alpha$=0.001 $r_\eta = 0.7$ $r_u = 0.85$		TK: $\overline{Q}_v$=$\overline{Q}_\alpha =$ $\overline{Q}_u$=0.001 $\overline{Q}_\eta$=0.25		$\overline{Q}_v$=$\overline{Q}_\alpha$=0.001 $r_\eta = 0.7$ $r_u = 0.85$		TK: $\overline{Q}_v$=$\overline{Q}_\alpha =$ $\overline{Q}_u$=0.001 $\overline{Q}_\eta$=0.25	
	True	Est.	True	Est.	True	Est.	True	Est.
α_i	0.000	0.000	-0.000	0.002	0.001	0.000	-0.000	-0.000
η_i	0.403	0.399	0.398	0.255	0.400	0.400	0.404	0.254
u_{it}	0.160	0.161	0.160	0.159	0.160	0.160	0.160	0.160
σ_v	0.05	0.050	0.05	0.049	0.05	0.049	0.05	0.049
σ_u	0.2	0.202	0.2	0.201	0.2	0.201	0.2	0.201
σ_η	0.5	0.504	0.5	0.330	0.5	0.506	0.5	0.329
σ_α	0.1	0.111	0.1	0.272	0.1	0.105	0.1	0.280
ρ	0.3	0.303	0.3	0.304	0.6	0.605	0.6	0.605
S.D. (u_{it})	0.120	0.121	0.121	0.121	0.120	0.121	0.121	0.121
S.D. (η_i)	0.303	0.300	0.297	0.201	0.302	0.301	0.306	0.201
Correlation between true and est. u_{it}	0.9006		0.9011		0.8998		0.8999	
Correlation between true and est. η_i	0.9483		0.9361		0.9483		0.9409	

Table 4.2. Simulation results for Scenario 2 with N=100

Two key results become apparent. The first one is the exceptional performance of the “naïve” approach in this case, even in small samples. The performance is very similar to the non-spatial case, which is encouraging for this modelling extension. The figures show that bias is very low and reasonably centred around zero in simulations, even when N is as low as 36 (a 6 x 6 grid of units). Correlations between true and estimated inefficiencies are also extremely high, so the model seems to capture not only the mean correctly, but also the relative ranking structure likely to exist in the data. The second key result is that the TK approach suffers from more issues than those found in the non-spatial case in Chapter 3, which was to be expected at least to some extent. Although correlations are well preserved, mean persistent inefficiency is very poorly estimated even with tuned priors. This result is consistent across both scenarios and is present under the use of both ARMS and a rejection algorithm when drawing the time-invariant skew-normal variable. Identification of mean persistent inefficiency is sensitive to prior choices, but another problem is the poor mixing of this approach. As seen in the empirical results of Chapter 3 for transition economies, the identification of the variance of persistent inefficiency under the TK approach is not satisfactory in some conditions. All of this is in line with multiple performance problems found with this approach in Makiela (2016) for the non-spatial case. Therefore, the TK approach is even less competitive for the spatial case and will not be considered in the application of this chapter.

Although the performance of the simple approach seems appropriate, the influence of priors is also investigated. For each case, the prior median persistent efficiency is changed from 0.7 to 0.6, implying a roughly similar change in terms of mean. As expected, Scenario 2 implies less influence of the prior on posterior results, due to a higher signal-to-noise ratio. However, results are satisfactory for both scenarios, as results are only residually influenced by a significant shift in prior efficiency, even with N as small as 36.

Change in mean direct persistent inefficiency	**N = 36 ρ =0.3**	**N = 36, ρ =0.6**	**N = 100 ρ =0.3**	**N = 100 ρ =0.6**
Scenario 1	0.0355	0.0356	0.0241	0.0291
Scenario 2	0.0230	0.0249	0.0090	0.0081

Table 4.3. Influence of prior in the results for both scenarios and sample sizes

Some investigations on the performance of the Spatial Durbin model were conducted, leading to similar results, although with residually lower correlations with true values, and less precise identification of mean efficiency. These results, omitted here due to the similarity to the results presented above, are encouraging for use in applied research. However, it is likely that in some contexts with multiple regressors the Durbin estimation procedure is complicated further due to the large number of regressors.

Regarding the time dimension of the panel, reducing the small sample case further to T=5 leads to performance degradation as expected. In the case of Scenario 1, with ρ=0.6 and N=36, the correlation between true and estimated transient inefficiency falls from 0.75 to 0.71 by reducing T from 10 to 5. Correlations of persistent inefficiency fall less, from 0.858 to 0.852. No significant impact is seen in mean efficiencies. In the case of Scenario 2, under similar circumstances, similar changes in both correlations are seen, with a bigger impact in transient inefficiency. However, the spread of mean bias across repetitions increases as T decreases, pointing that there is less certainty about identifying the true parameters with decreasing T. In any case, these results are satisfactory given such a small sample size and should be encouraging for estimation by applied researchers even in cases of small samples, such as countries or a small set of firms within an industry. Obviously, additional challenges can appear in applications with a large number of regressors.

4.6. An application to European aggregate productivity

The model is now applied to the context of efficiency in aggregate productivity in Europe for 43 countries between 1992 and 2005, focusing in particular on the transition economies and the transition process as this is a critical period after the fall of the Soviet Union. This choice is justified for a variety of reasons. First, this allows to assess the progress of the transition economies against the developed Western European economies in the critical transition process. Secondly, this also allows to assess if that progress has led to convergence between the two country groups before the global financial crisis. Given the results from simulations, the Makiela (2016) approach will be used as it is more likely to successfully retrieve accurate information about efficiency in the sample.

A Cobb-Douglas specification is used, in the spirit of the neoclassical growth model. Consider the following specifications:

(1): $y_{it} = X_{it}\beta - \eta_i^+ + \alpha_i + v_{it} - u_{it}{}^+$

(2): $y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it}\beta + t + t^2 - \eta_i^+ + \alpha_i + v_{it} - u_{it}{}^+$

(3): $y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it}\beta - \eta_i^+ + \alpha_i + v_{it} - u_{it}{}^+$

(1) corresponds to the base GTRE model. (2) and (3) are the Spatial GTRE model with a (quadratic) time trend and with no time trend respectively. The Durbin specification could be an alternative method, but it renders unstable results and convergence problems, meaning that the Durbin specification will not be discussed in the context of this application.

The matrix W is a row-normalized inverse distance matrix as other choices of spatial weights matrices, for example linked to trade flows, would lead to endogeneity issues. A row-normalized matrix loses information on absolute distance. However, the choice to row-normalize is made on the basis of distance as a relative concept, as normal journeys for people in more outpost locations can be seen as long journeys by people located in more central locations. The same analogy applies to economic agents and economic relationships between countries. All data is sourced from the Penn Tables version 8.1, PWT8.1 (Feenstra et al., 2015). y_{it} is log output side real GDP in 2005 million dollars and PPP (rgdpo). X_{it} includes log of employment in millions of people (emp), log real capital stock in 2005 million dollars (ck) and the level of net exports in percentage of GDP 100*(csh_x+csh_m). This net trade openness measure shifts the frontier and is expected to have a positive impact on output, like labour and capital which are more traditional independent variables in a production function. This is a similar approach and variable choice to the efficiency measurement in aggregate productivity of Glass et al. (2016) for a sample of 41 European countries between 1990 and 2011. However, the authors do not include time-invariant heterogeneity in their modelling, implying the estimation of only one (and hence possibly biased) inefficiency component. Also, government spending is not included due to the different paradigms and approaches to public spending between developed economies and eastern economies during the critical transition period.

The use of stochastic frontier models to assess efficiency in aggregate productivity is relatively well established in the literature, for example in a "world stochastic frontier" approach for 75 countries over 50 years (Pires and Garcia, 2012) or to assess efficiency of aggregate production in 49 Asian countries between 1965 and 1990 (Kim and Lee, 2006). Both examples use data from Penn Tables. It is important to notice that the use of such stochastic frontier estimation techniques relies on the stationarity of data to avoid spurious efficiency results, which is unlikely with large T in these contexts. Only the latter example focuses on spatial dependence and its effects on efficiency measurement, but the effects and importance of spatial dependence have been well established in the growth literature (that does not focus on efficiency measurement). Kim and Lee (2006) use a trans-log production function, while the other example uses a Cobb-Douglas production function deeply related to the neoclassical growth model. Some examples of this are the use of an empirical reduced form spatial Durbin model specification of the Mankiw-Romer-Weil model (Fischer, 2011), a spatially augmented Solow model that explicitly models technological interdependence between economies (Ertur and Koch, 2007) and a modelling approach for technological interdependence and R&D spillovers between economies from a Schumpeterian perspective, using a neoclassical growth model (Ertur and Koch, 2011).

Summary estimation results follow. The spatial models was estimated with the proposed MCMC scheme, with 4,000,000 draws, a burn-in of the first 1,000,000 draws and thinning of 30 (from each 30 draws, only one was taken to reduce autocorrelation). The large amount of draws in this application is mainly justified by the slow exploration of the parameter space of the spatial lag. To speed up computations with such a large amount of draws, a grid of log-determinants was calculated prior to the MCMC, with calculations done in intervals of 0.000015 to keep a level of precision without severely slowing down estimation.

	(1) GTRE	(2) Spatial SF	(3) Spatial SF No Time Trend
$\boldsymbol{\rho}$	-	0.5022 [0.4080 ; 0.5844]	0.5603 [0.4845 ; 0.6319]
$\boldsymbol{\sigma_u^2}$	0.0261 [0.0190 ; 0.0341]	0.0266 [0.0195 ; 0.0345]	0.0246 [0.0181 ; 0.0319]
$\boldsymbol{\sigma_v^2}$	0.0053 [0.0034 ; 0.0076]	0.0045 [0.0026 ; 0.0066]	0.0051 [0.0034 ; 0.0071]
$\boldsymbol{\sigma_\eta^2}$	0.1875 [0.1042 ; 0.3073]	0.1600 [0.0828 ; 0.2759]	0.1579 [0.0813 ; 0.2769]
$\boldsymbol{\sigma_\alpha^2}$	0.0134 [0.0023 ; 0.0384]	0.0247 [0.0049 ; 0.0601]	0.0283 [0.0066 ; 0.0650]
$\boldsymbol{\beta_{EMP}}$	0.3063 [0.2231 ; 0.3859]	0.3349 [0.2405 ; 0.4284]	0.3253 [0.2329 ; 0.4180]
$\boldsymbol{\beta_{CAP}}$	0.6896 [0.6231 ; 0.7566]	0.6447 [0.5733 ; 0.7165]	0.6515 [0.5800 ; 0.7230]
$\boldsymbol{\beta_{TRADE}}$	0.5454 [0.3538 ; 0.7356]	0.4479 [0.2505 ; 0.6455]	0.4115 [0.2173 ; 0.6061]
Cons.	2.7941 [2.0013 ; 3.5785]	-2.2767 [-3.5094 ; -0.9263]	-3.0312 [-3.9071 ; -2.1290]
$\boldsymbol{t}$	0.0073 [-0.0032 ; 0.0177]	-0.0088 [-0.0199 ; 0.0021]	-
$\boldsymbol{t^2}$	0.0009 [0.0002 ; 0.0016]	0.0008 [0.0001 ; 0.0015]	-

Table 4.4. Estimation results for sample of 43 European Countries. Note: Bayesian credible intervals using 0.025 and 0.975 percentiles.

Specifications (1) and (2) comfortably show signs of convergence according to the Geweke convergence diagnostic (Geweke, 1992) with z-scores for all parameters between -2 and 2, but some problems are seen in specification (3) with almost half of the parameters falling out of that interval. Z-scores for each parameter are in Appendix 4.2. A first key result is that in all models the overwhelming majority of inefficiency is persistent and that the variance of the random effects is similar to the variance of the time-varying inefficiency. This implies that using a less complex model that does not account for unobserved heterogeneity would bias results, but also implies that solving that unobserved heterogeneity problem without accounting for persistent inefficiency would hide the majority of it. As in Glass et al. (2016) the finding is that the coefficient for capital is higher than the one for employment. It seems that a part of the unobserved heterogeneity captured by the Random Effects in (1) increases once the spatial dependence is taken into account, which is possibly due to small corrosion in the identification process (the signal-to-noise ratio).

Changing the priors on persistent inefficiency does not significantly impact the results, indicating robustness of the obtained results. By changing prior direct median efficiency from 0.75 to 0.7, the mean efficiency changes only by 0.0171 and the median efficiency changes only by 0.0194, implying that relative rankings and mean efficiencies are not severely affected by prior choices, rendering reasonable results considering the extremely small sample size. This change in mean efficiency due to the change in the prior corresponds to less than a sixth of time-varying inefficiency, and both of the persistent inefficiency priors are centred close to the obtained posterior mean persistent inefficiency.

Identification of persistent inefficiency is relatively stable and is in line with that would be expected from the simulations. For easier interpretation of results, analysis is conducted with country groups. The following groups are considered: CIS (Russia, Ukraine, Moldova, Belarus, Georgia and Armenia), Central Europe (UK, France, Germany, Italy, Holland, Belgium, Luxembourg, Switzerland, Austria and Denmark), Eastern EU members (Poland, Romania, Bulgaria, Croatia, Slovenia, Slovakia, Latvia, Lithuania, Estonia), Scandinavia (Finland, Sweden and Norway), Balkans (Bosnia, Montenegro, Serbia, Macedonia and Albania) and Southern Europe (Portugal, Spain, Malta, Greece and Cyprus). Other countries are included in the sample but not grouped with others for analysis due to their peripheral geographic location and lack of similar core characteristics linked to the nearest region considered (Turkey and Iceland).

A clear pattern across groups is a clear convergence towards the end of the sample period between all groups except Scandinavia and CIS. Another pattern is a decrease of efficiency between 2003 and 2005, except for the CIS, during a period of weak economic growth and increasing oil prices. The non-eastern EU (most of the EU-15) members clearly have the highest efficiency in the sample in the early 1990s. While the Balkans quickly converge to the rest of core EU countries by 1997, after the end of the Balkans war, the Eastern EU members had a much slower convergence. However, this result is quite different from the one obtained regarding efficiency in electricity consumption in

Chapter 3, where some divergence was witnessed for this group when compared to others. The CIS group bottomed out in 1999, as the crisis dragged on for a decade of recession or very slow recovery, only to have a shy recover towards the end of the sample, maintaining a large gap to all the other groups. All these patterns are visible on both total and direct efficiency, and are not significantly affected by the inclusion or exclusion of a quadratic time trend. However, this differs slightly from the (non-spatial) GTRE results where the pattern of convergence of most groups towards the end of the sample is not clearly visible. Figures 4.3 and 4.4 show direct and total efficiencies for each country group, with the same scaling. Figure 4.5 shows less convergence towards the end of the sample period in the non-spatial model.

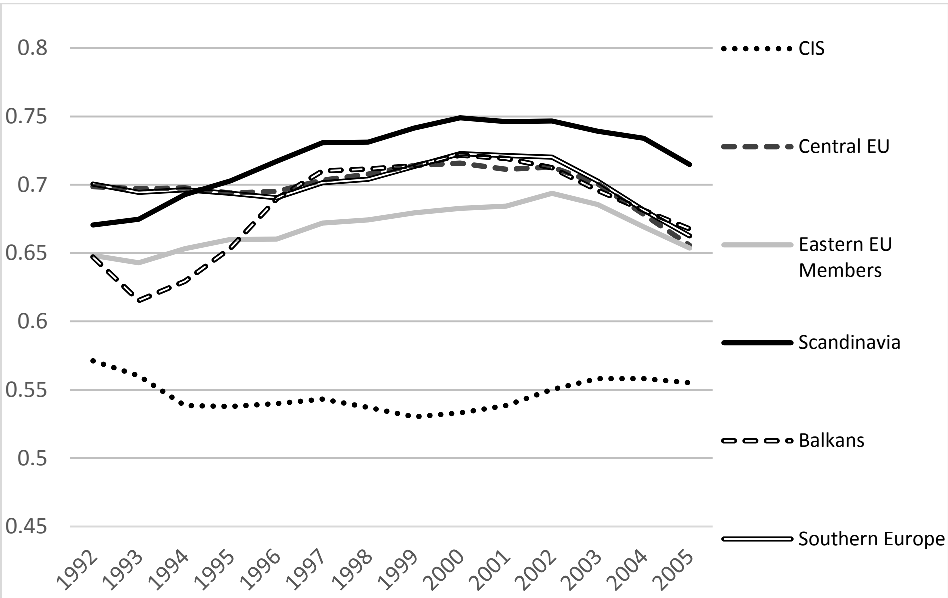

Figure 4.3. Efficiency scores across groups (Spatial GTRE with quadratic time trend)

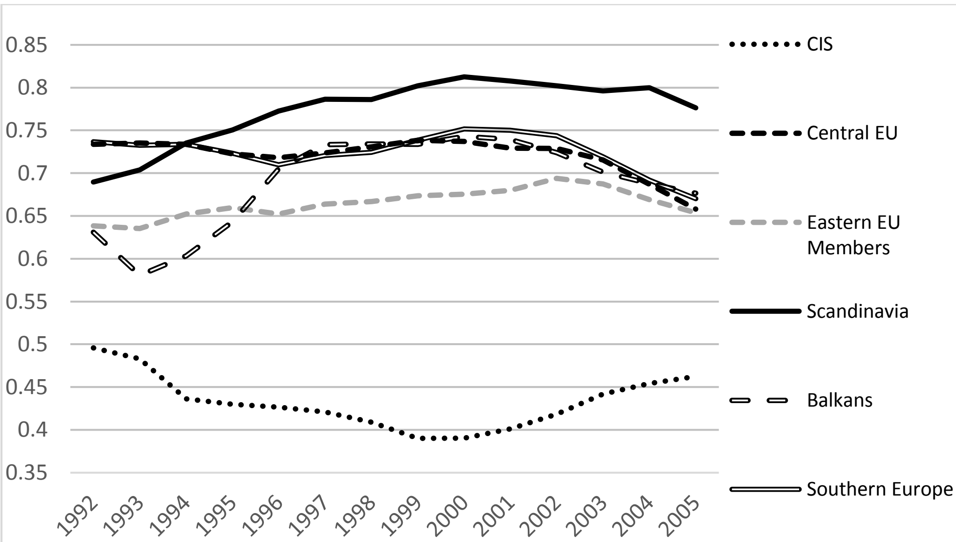

Figure 4.4. Direct Efficiency scores across groups (Spatial GTRE with quadratic time trend)

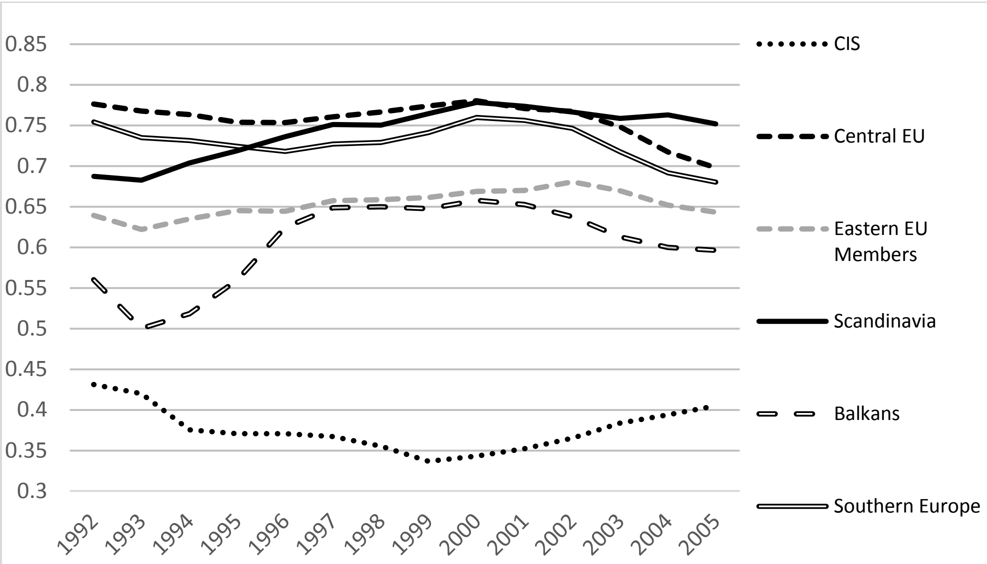

Figure 4.5. Direct Efficiency scores across groups (Non-Spatial GTRE with quadratic time trend)

There is clear regional clustering in the results, with indications that the countries further to the East obtain worse efficiency scores. Differences are clear between new EU members and those eastern economies that did not join the EU, with a few exceptions, such as Bulgaria. These results highlight the gaps between spatial and non-spatial GTRE estimation. The inclusion of cross-sectional averages creates very small and negligible differences in the patterns seen across the figures, as the variables are not significant in both the spatial and the non-spatial case.

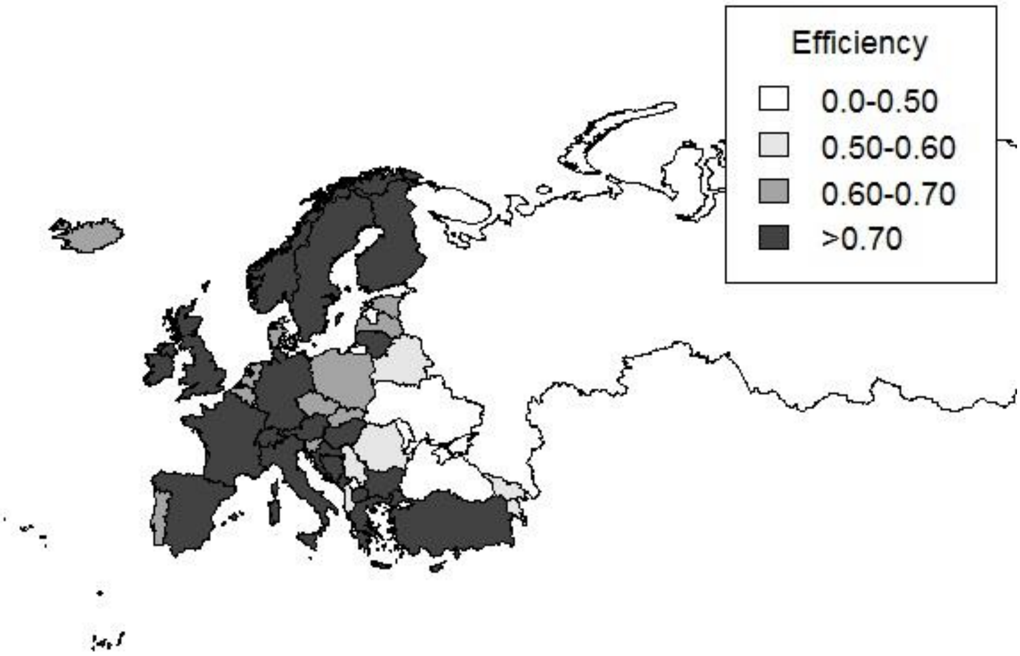

Figure 4.6. Direct efficiency scores map (Spatial GTRE with quadratic time trend)

The most efficient countries in the sample are Turkey, Sweden, Greece and Italy, followed closely by the UK. However, Scandinavia is the out-performing group as all three countries have direct efficiencies above 0.74, while the sample average is only around 0.67. Ukraine and Moldova severely lag behind with direct efficiencies below 0.4. In a staggering difference between East and West, the bottom six in the average efficiency rankings are the six CIS economies in the sample. Furthermore, this group does not show strong evidence of convergence over time, deepening the differences between the new EU members and those countries left behind in the European integration process. Figure 4.7 shows the spillovers (differences between total and direct efficiency), highlighting the benefits to the Eastern economies.

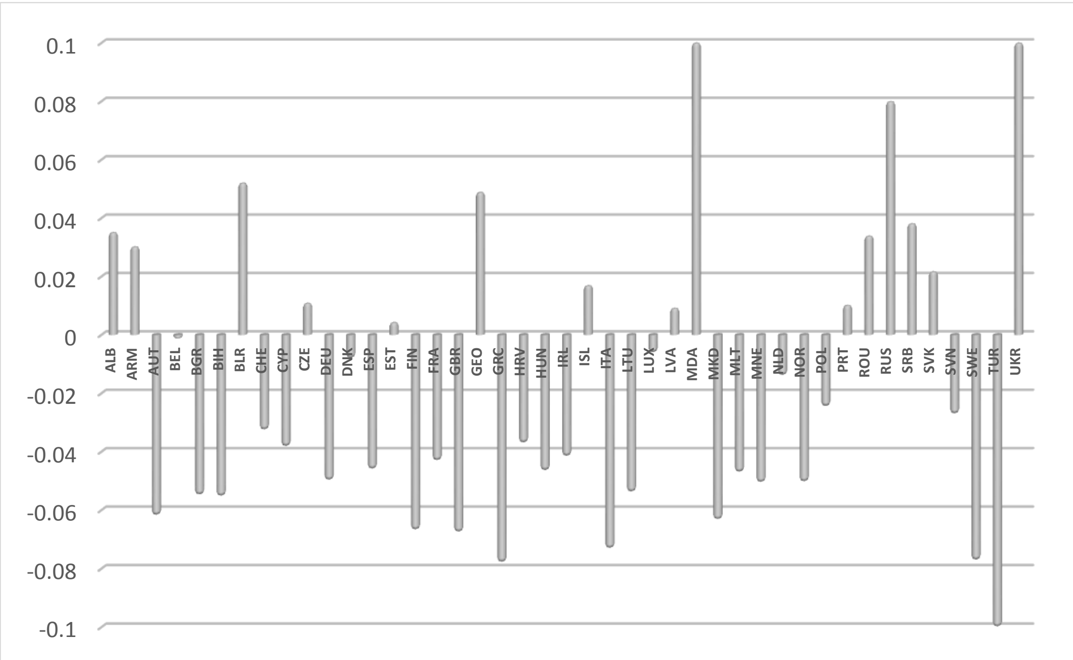

Figure 4.7. Efficiency spillovers per Country (average 1992-2005)

4.7. Conclusion

This chapter presents a novel stochastic frontier modelling technique to account for unobserved heterogeneity and spatial dependence in cost and production functions which is estimated using Bayesian methods. The proposed methodology allows estimation of time-varying and persistent inefficiency components, while also estimating random effects to account for unobserved heterogeneity, and allowing for spatial dependence to be account for as in a Spatial Autoregressive model. Evaluation of the model performance shows that performance depends clearly on signal-to-noise ratios present in the data, sample size and priors, but it is very encouraging in general for applied researchers, even in the context of small samples. The paper presents two alternatives for estimation, with a "naïve" approach out-performing a reparameterization approach. It is easy to implement in most statistical software packages, which is of great relevance to any applied research that can replicate this methodology easily, especially in an age of increasingly powerful computing power.

The application of the proposed model to aggregate productivity in the European continent between 1992 and 2005 highlights the need to have a more complex (yet tractable) model in cases where both unobserved heterogeneity and spatial dependence are present, allowing for estimation of both time varying and time invariant inefficiencies in a panel setting. This allows a discussion of convergence of efficiency in aggregate productivity in Europe, with the CIS region being an exception to this behaviour. The non-spatial version of the model does not show such strong signs of convergence across regions.

Chapter 5. Efficiency Spillovers in New Zealand electricity distribution networks: A Bayesian Stochastic Frontier Approach

5.1. Introduction

Firms in an industry are often subject to benchmarking and other research efforts regarding their levels of efficiency, for the construction of relative firm rankings, but also the measurement of average levels of efficiency and other information relevant to regulators and the industry. Extensive efforts have been conducted in the SF literature to build panel data models capable of estimating efficiency levels under different econometric challenges, such as unobserved heterogeneity. Most of those efforts span from the seminal work of Aigner et al. (1977), with the True Random Effects (TRE) and True Fixed Effects (TFE) models (Greene, 2005) being some of the most influential models for modern empirical research, as well as being easily available on statistical software for straightforward estimation. The literature has expanded to consider multiple concerns, such as heteroskedasticity, nonparametric estimation, different distributional assumptions and determinants of efficiency. However, most of these issues have been studied in more detail than spatial dependence.

This chapter focuses on the often unexplored issue of spatial dependence and efficiency spillovers between economic agents from a different perspective than that of Chapter 4. Spatial dependence in the cross-sections can lead to omitted variable bias. In the case of this chapter, a Spatial Error Model (SEM) specification is used to capture spillovers, but they are related to the error components and therefore with less of a structural economic interpretation than in the case of Chapter 4 with a SAR model. A time-varying version of the Spatial Error Model of Areal et al. (2012) is extended to the case of Random Effects to account for unobserved heterogeneity, with a computationally efficient MCMC scheme. The approach uses a spatial error structure instead of a spatial autoregressive structure in order to model spillovers associated to inefficiency more intuitively and also measure the strength of the spatial dependence between units. This chapter also investigates alternative methods in Bayesian econometrics, suggesting the use of Guided Walk Metropolis (Gustafson, 1998) to take draws from distributions not readily available in statistical software packages, due to the need to draw more latent variables from non-standard distributions than in other cases in the literature. The performance of the model is assessed under different scenarios with relatively small samples. As in other stochastic frontier models, performance is encouraging when signal is large relative to noise, in this case even under significant levels of spatial dependence. As performance degrades, the estimate of the spatial parameter estimate suffers more than the estimate of the parameter of the exponential distribution of inefficiency. However, this can have consequences on the overall quality of efficiency measurement. Simulation results are encouraging for use in empirical analysis of efficiency under a set of reasonable conditions.

Finally, the chapter applies the proposed model to a sample of 27 New Zealand electricity distribution firms in a stable post-unbundling period between the 2001 and 2009 fiscal years, covering some pitfalls in the multiple perspectives on this topic in the literature and adding some insight on the debate of efficiency spillovers in the industry and the purpose of efficiency measurement for the regulators. The case of New Zealand is of particular interest as it was the first case of a full reform of vertical separation in the power sector associated to transparent data reporting of multiple aspects of the operation of distribution networks. Some evidence of spillovers exists when a second order neighbour matrix is used.

5.2. Literature Review

As mentioned in Chapter 4, while the efficiency literature usually considers spatial heterogeneity as the differences in efficiency due to location, controlled for by using dummy variables or similar approaches, spatial dependence is the relationship between efficiency in a firm and efficiency in other firms (Areal et al., 2012). The concepts do not overlap, creating the reasoning for the use of spatial approaches in stochastic frontier modelling.

Early efforts in the literature are scarce. Druska and Horrace (2004) developed a GMM frontier model and apply it to rice farms in Indonesia. The spatial autocorrelation term is introduced in the production frontier model as an exogenous variable, shifting the frontier technology. Estimation follows the random effects methodology of Schmidt and Sickles (1984), meaning that the retrieved efficiency measure is time-invariant and follows the implied interpretation of the effects as inefficiency. Schmidt et al. (2009) is another example of work in the field which focuses on the unobserved local determinants of inefficiency in farm productivity in the Centre-West of Brazil.

The efforts in the literature can be divided into three key areas: one that relies on Spatial Autoregressive models (SAR), another based on Spatial Error models (SEM), and finally a category of other mixed models. The first category summarizes works already explored in Chapter 4. Affuso (2010) uses a SAR type model to evaluate the impact of agricultural extension programmes that have positive effects not only on chosen farmers but also to other farmers due to spatial spill-over effects. As a more general and encompassing example of the literature, Pavlyuk (2013) derived ML estimators of stochastic frontier models with spatial dependence associated to the dependent variable, the idiosyncratic error and both. The author does not elaborate on details on firm specific efficiency measurement or other aspects of the model besides the magnitude of the spatial parameters and the variance of the inefficiency error component. Other contributions to the literature include a spatial autoregressive stochastic frontier model for panel data with a specification that allows for time-varying efficiency measurement and asymmetric efficiency spillovers (Glass et al., 2016). The latter contribution has been explored in further detail in Chapter 4.

Some advances in spatial stochastic frontier modelling have also taken place in the macroeconomic literature. Mastromarco et al. (2013) use a two-step approach to investigate the channels under which globalisation factors lead to technical efficiency by combining a dynamic stochastic frontier model with a time series approach. Mastromarco et al. (2016) propose a framework to accommodate both time and cross-sectional dependence by combining the exogenously driven factor-based approach with an endogenous threshold efficiency regime selection mechanism. This is applied to a dataset of 26 OECD countries over the period 1970-2010.

However, the use of Spatial Error Models in the efficiency literature is rather sparse and of particular interest to this chapter. Areal et al. (2012) apply a spatial stochastic frontier model with an autoregressive specification of the inefficiency component of the compound error term. The model is applied to a sample of 215 dairy farms in England and Wales with data between 2000 and 2005, with the estimation of time-invariant inefficiency which implies the estimation of a pooled model with a reasonably high number of observations. The key contribution of this paper is the direct specification of inefficiency to be spatially autoregressive and including a parameter that measures the level of spatial dependence. However, the authors do not show the performance of the model in simulations and the conditions in which it performs well and also do not discuss how to retrieve unit specific measures of efficiency. Both the lack of performance studies and discussion of measurement leave further space for research in the literature.

Fusco and Vidoli (2013) present a similar approach to Areal et al. (2012) with the key difference of the use of a half normal inefficiency assumption and estimation using ML methods. However, this paper gives additional insights into performance of the model, showing a simulation with 107 observations which leads to downward bias of the spatial parameter when it is set to 0.8. The variance of the inefficiency is also slightly underestimated. Tsionas and Michaelides (2016) propose a latent random effects vector that is specified to follow a Spatial Autoregressive process for panel data. The idiosyncratic part of inefficiency is assumed to be half-normal and the model is estimated using complex Bayesian methods. Tsionas and Michaelides (2016) also consider methods for posterior predictive efficiency measurement, including a simple Monte Carlo approximation. However, the authors do not consider the performance of the model in simulations to assess the fragility of the model in different sample sizes and situations. Also, in this case, if the true underlying data contains time-invariant unobserved heterogeneity besides time-invariant inefficiency, total efficiency measures are likely to be biased. The literature leaves some unexplored space for the evaluation of the influence of sample sizes and varying signal-to-noise ratios and the intensity of the spatial dependence.

5.3. Modelling Approach

The following cost frontier model with random effects and spatial dependence associated to the efficiency term is considered, in matrix form:

$$y = X\beta + v + u + \alpha \otimes l_T \tag{80}$$

$$u = \rho W u + \tilde{u} \tag{81}$$

$$v \sim N(0, \sigma_v^2 I_{NT}) \tag{82}$$

$$\tilde{u} \sim Exp(\lambda) \tag{83}$$

$$\alpha \sim N(0, \sigma_\alpha^2 I_N) \tag{84}$$

y is a (NT x 1) vector of the dependent variable, while X is the (NT x K) matrix of exogenous variables, with K regressors, including a constant. v is a (NT x 1) vector of traditional idiosyncratic errors of standard linear regression and u is a (NT x 1) vector of one-sided errors that capture inefficiency. The inefficiency is then decomposed into two components: one that is spatial and reflects spillover effects for a given exogenous and known exogenous (N x N) spatial weight matrix W, and another that is idiosyncratic and given by a variable $\tilde{u}$ that follows an exponential distribution. α is a (N x 1) vector of time-invariant, zero mean random effects which aim to account for unobserved heterogeneity. Cross-sectional means of regressors can be added if there are concerns about violation of the assumptions of the Random Effects model (Mundlak, 1978).

A Bayesian approach is preferred for a variety of reasons. It allows the use of prior information in the model, such as past information about a parameter (for example, past inefficiency levels). It also provides inference that is conditional on the data without asymptotic approximations, it obeys the likelihood principle and uses MCMC methods which make computations tractable for nearly all parametric models (Tsionas and Michaelides, 2016). A production frontier is considered by simply switching the sign of the inefficiency component in equation (80). A standard Bayesian Stochastic Frontier model has been discussed in Koop (2010). The following Gibbs sampler follows the Bayesian formulation of the True Random Effects model as in Feng and Zhang (2012), with an extension linked to the spatial model of Areal et al. (2012).

The priors are as follows, starting with the variance components:

$$\mathrm{p}(h_v) \propto 1/\sigma_v^2 \tag{85}$$

$$\mathrm{p}(h_\alpha) \propto 1/\sigma_\alpha^2 \tag{86}$$

In both cases, symmetric error precisions h_v and h_α are fully determined by the likelihood function and are bigger than zero, so they simply correspond to the inverse of the variance of each symmetric error component. The prior for u_{it} follows a special case of the gamma distribution, the exponential distribution with parameter λ^{-1}. To obtain a proper posterior for u_{it}, a prior distribution for λ^{-1} is also necessary (Fernández et al., 1997):

$$\mathrm{p}(u_{it}|\lambda^{-1}) \propto \mathrm{f}_G\ (1\,;\lambda^{-1}) \tag{87}$$

$$\mathrm{p}(\lambda^{-1}) \propto\ \mathrm{f}_G\ (1\,;-ln\tau^*) \tag{88}$$

The rate parameterization of the gamma distribution is used throughout this chapter. τ^* is the prior median of the efficiency distribution, which is defined according to the researcher's prior information or beliefs. However, this does not immediately correspond to the efficiency estimated by the model, as that will also depend on the spatial weights matrix and the strength of the spatial relationship between the units. Therefore this hyperparameter defines the prior beliefs about direct inefficiencies, excluding those caused by spatial spillovers between neighbours.

Finally, the prior for the spatial parameter is:

$$\mathrm{p}(\rho) \propto\ \mathrm{I}(\rho \in [0,1]) \tag{89}$$

This prior implies an indicator function with a uniform distribution for this parameter that is assumed to be non-negative, between 0 and 1. This assumption follows Areal et al. (2012) and can be relaxed further to allow for a less restrictive interval between -1 and 1. However, the assumption stems from the fact that in most applied contexts of the model a positive spillover is expected and there is a desire by the researcher to limit the possible parameter values to that interval.

The conditional likelihood function is defined as:

$$p(y|\beta, h_v, h_\alpha, \rho, \tilde{u}, \lambda^{-1}) \propto h_v^{\frac{NT}{2}}|\mathrm{I}_N - \rho\mathrm{W}|\exp[-\frac{h_v}{2}(\tilde{y} - X\beta)'(\tilde{y} - X\beta)] \tag{90}$$

$$\tilde{y} = y + (I_{NT} - I_T \otimes \rho\mathrm{W})^{-1}\tilde{u} + \alpha \otimes l_T \tag{91}$$

Equation (90) follows from the standard form used for efficiency analysis (Koop et al., 1995). The determinant is added to the likelihood function as in other Spatial Error models and Spatial Autoregressive models following Anselin (1988), to account for the fact that the joint log-likelihood for a spatial regression does not equal the sum of the log-likelihoods associated with the individual observations. Conditional posteriors for each of the parameters follow, leading to a Gibbs sampler where draws are taken sequentially from the conditional posteriors. This is a simple methodology and easily implemented in most statistical software packages. For the following Gibbs sampler, the data is stacked first by time *t* and then by unit *i*.

The conditional posterior for β is:

$$\mathrm{p}(\beta|\mathrm{y}, \mathrm{X}, \theta_{-\beta}) \propto \mathrm{N}[(\mathrm{X'X})^{-1}[\mathrm{X'}(\mathrm{y} - X\beta - S^{-1}\tilde{\mathrm{u}} - l_T \otimes \alpha)]\,;\ \mathrm{h}_{\mathrm{v}}^{-1}(\mathrm{X'X})^{-1}] \tag{92}$$

The conditional posterior for h_v follows a Gamma distribution:

$$\mathrm{p}(h_v|\mathrm{y}, \mathrm{X}, \theta_{-h_v}) \propto \mathrm{f}_G\left(\frac{\mathrm{NT}}{2}; v'v\right) \tag{93}$$

$$\mathrm{S} = (I_{NT} - I_T \otimes \rho\mathrm{W}) \tag{94}$$

$$v = y - \mathrm{X}\beta - S^{-1}\tilde{\mathrm{u}} - l_T \otimes \alpha \tag{95}$$

The conditional posterior for the parameter of the exponential distribution of inefficiencies is also a Gamma distribution:

$$\mathrm{p}(\lambda^{-1}|\mathrm{y}, \mathrm{X}, \theta_{-\lambda^{-1}}) \propto \mathrm{f}_G\,(\mathrm{NT}+1\,;\ \tilde{\mathrm{u}}' l_{NT} - \ln\tau^*) \tag{96}$$

The conditional posterior for the inefficiencies is:

$$\mathrm{p}(\tilde{\mathrm{u}}_{\mathrm{it}}|\mathrm{y}, \mathrm{X}, \theta_{-\mathrm{u}}) \propto \exp[-\frac{h_v}{2}\,[\mathrm{u}_{\mathrm{it}} - (\mathrm{y}_{\mathrm{it}} - \mathrm{X}_{it}\beta - \alpha_i)]^2 - (\tilde{\mathrm{u}}_{\mathrm{it}} - \mathrm{u}_{\mathrm{it}})\,\lambda^{-1}] \tag{97}$$

Equation (81) is then updated to reflect the new draw for ũ. The conditional posterior for the inefficiencies is a non-standard distribution, for which the usual method to obtain draws is often Metropolis-Hastings (Metropolis et al., 1953). To improve performance, a Guided Walk Metropolis method is used (Gustafson, 1998), allowing for better performance at a wider range of rejection probabilities. The algorithm is explained below. First, a candidate draw for the current state of the variable Y is taken as:

$$Y = \mathrm{X} + P.\,|Z| \tag{98}$$

where X is the existing state of the variable, P takes values -1 or 1, and $Z = c.N(0,1)$, with c being a positive tuning parameter to adjust the algorithm and avoid over-rejection or under-rejection of the candidate draws. Secondly, the draw Y has an acceptance probability $\pi(Y)/\pi(X)$. If the draw is accepted, then the new value of the variable becomes Y and the sign of P remains the same. If the draw is rejected, the previous value X is kept and the sign of P is inverted. This can allow for better exploration of the parameter space and faster convergence than standard Metropolis-Hastings methods under a wide interval of proposed rejection rates. This is particularly applicable when no good starting values can be determined and there is no knowledge of how far they are from the true values. This method has been sparsely used in applied research, with only a few examples such as the marketing literature (Ansari et al., 2008) and has not been used in the field of econometrics. Note that for parameters using this method, any acceptance rate between 15% and 85% should lead to satisfactory results. This implies that, unlike the classic Metropolis-Hastings method which is more sensitive to acceptance rates, the draws can be taken using a unique tuning parameter as in most cases this will allow for acceptance rates that are spread across an acceptable interval. The exception to this will be cases with large inefficiencies (extreme values above 40% or 50%) where the spread in true values will mean an increasingly unacceptable spread of the acceptance rate vector under a single tuning parameter for the entire inefficiency vector.

The conditional posterior of the spatial parameter also follows a non-standard distribution:

$$\mathrm{p}\left(\rho\middle|\mathrm{y}, \mathrm{X}, \theta_{-\rho}\right) \propto |\mathrm{I}_N - \rho\mathrm{W}|\exp(-\frac{v'v}{2\sigma_{\mathrm{v}}^2}) \tag{99}$$

Draws for this parameter are taken using Guided Walk Metropolis as above. For numerical stability, the distribution can be log-transformed and in that case the algorithm acceptance probability is $\exp(\pi(Y) - \pi(X))$. To take draws of the vector random effects, the data is re-stacked first by time and then by unit (unlike the other parameters), with draws taken from a normal distribution as follows:

$$p(\alpha_i|y, X, \theta_{-\alpha}) \propto N(\bar{\alpha}\frac{\sigma_v^2\sigma_\alpha^2}{\sigma_v^2(\sigma_v^2 + T\sigma_\alpha^2)}; \frac{\sigma_v^2\sigma_\alpha^2}{(\sigma_v^2 + T\sigma_\alpha^2)} I_N) \tag{100}$$

$$\bar{\alpha} = (\overline{\alpha_1}, \dots, \overline{\alpha_N}) \quad , \qquad \overline{\alpha_i} = \sum_{t=1}^{T}(y_{it} - X_{it}\beta - S^{-1}\tilde{u}_{it}) \ \ for\ each\ i \tag{101}$$

The conditional posterior related to the variance of the random effects is as follows:

$$p(h_\alpha|y, X, \theta_{-h_\alpha}) \propto f_G\ (N/2\ ;\ \alpha'\alpha/2) \tag{102}$$

If the random effects are dropped from the model, the model is reduced to a time-varying efficiency version similar to the model in Areal et al. (2012). This approach might be more appropriate when dealing with panels with small T and with little expectation of time-invariant unobserved heterogeneity in the sample. If the spatial component is dropped from the model, the model is then reduced to the Bayesian Random Effects Stochastic Frontier model in Feng and Zhang (2012).

Although Areal et al. (2012) focused mostly on the issue of the measurement of the degree of the spatial relationship between the units, it might be of interest to the researcher to determine efficiency scores and efficiency rankings. A simple Monte Carlo approximation is proposed. The measure is based on the exponential of equation (81). Suppose $\tilde{u}_{it}{}^{(s)}$ is a draw from the conditional posterior of ũ for the s^{th} pass of the MCMC scheme. That leads to the following vectors of posterior means of total relative and direct efficiency:

$$Relative\ Efficiency \ = S^{-1}\sum_{s=1}^{S}\frac{\left(I_{NT} - I_T \otimes \rho^{(s)}W\right)^{-1}\exp[\tilde{u}^{(s)}]}{max[(I_{NT} - I_T \otimes \rho^{(s)}W)^{-1}\exp[\tilde{u}^{(s)}]]} \tag{103}$$

$$Direct\ Efficiency = S^{-1}\sum_{s=1}^{S}\exp[\tilde{u}^{(s)}] \tag{104}$$

This relative efficiency measure has been proposed for the frequentist case by Glass et al. (2016) and can be decomposed into direct and indirect efficiency, as discussed in Chapter

4. The indirect effects matrix summarizes the effects that efficiency levels of the neighbours have on a firm's own efficiency. This is of great importance to the applied researcher, as it makes it possible to measure the magnitude and the sign of efficiency exchanges between the units. For example, a firm can "import" or "export" efficiency depending on its location.

For the purpose of efficiency analysis, efficiency is calculated in the same spirit as Chapter 4, similar to equation (32):

$$Total\ Efficiency = S^{-1} \sum_{s=1}^{S} \frac{\left(I_{NT} - I_T \otimes \rho^{(s)} \mathrm{W}\right)^{-1} \exp[\tilde{u}^{(s)}]}{max[(I_{NT} - I_T \otimes \rho^{(s)} \mathrm{W})^{-1} l_u]} \tag{105}$$

Note that it is also possible that some persistent inefficiency exists. In fact, the use of a random effects model opens the way for this research path, unlike fixed effects which make the separation of noise and inefficiency more difficult. However, this adds a new layer of complexity to the model and will not be pursued as it falls out of the scope of the chapter.

5.4. Model Performance

5.4.1. Performance under different scenarios

The assessment of model performance in Stochastic Frontier models should aim to be mostly directed towards small sample performance, as most of the empirical work in the literature relies on relatively small panels. Therefore, two scenarios are created, for two sample sizes: N=100 / T=10 (a square grid of 10 x 10 units) and N=36 / T=10 (a square grid of 6 x 6 units). For both scenarios, two exogenous regressors are considered in the DGP, a constant and a standard normal variable, with both coefficients equal to 1. The spatial parameter ρ is considered to be 0.3 or 0.6 to represent lower and higher levels of dependence in efficiency between the units. The scenarios are as follows:

Scenario 1: $\sigma_v^2 = 0.01$, $\lambda^{-1} = 4$ and $\sigma_\alpha^2 = 0.05$;
Scenario 2: $\sigma_v^2 = 0.01$, $\lambda^{-1} = 10$ and $\sigma_\alpha^2 = 0.05$;

Scenario 1 has a high signal-to-noise ratio with some unobserved heterogeneity. However, Scenario 2 has a much lower signal-to-noise ratio and keeps the moderate amount of unobserved heterogeneity of Scenario 1. The expectations of worse performance are therefore centred on Scenario 2. Besides showing the means of efficiency to highlight that the model renders relatively small average bias, the correlations between estimated and true individual scores are also crucial for relative firm rankings. Therefore, both the mean correlation across repetitions and the smallest correlation seen across all repetitions are shown. All examples have a prior assuming 80% direct efficiency. Changing this prior does not significantly change results except in extremely small samples.

	N=36 / T=10		**N=36 / T=10**		**N=100 / T=10**		**N=100 / T=10**	
Means	Est.	True	Est.	True	Est.	True	Est.	True
u_{it}	0.246	0.251	0.234	0.251	0.246	0.251	0.237	0.251
λ^{-1}	4.109	4	4.319	4	4.078	4	4.231	4
σ_{α}^2	0.050	0.05	0.050	0.05	0.050	0.05	0.050	0.05
σ_v^2	0.011	0.01	0.017	0.01	0.012	0.01	0.016	0.01
ρ	0.286	0.3	0.597	0.6	0.278	0.3	0.602	0.6
β_0	1.005	1	1.031	1	1.019	1	1.031	1
β_1	1.000	1	1.001	1	1.001	1	1.001	1
s.d.(u_{it})	0.247	0.250	0.240	0.251	0.248	0.251	0.243	0.251
Mean Correlation between est. and true u_{it}	0.925		0.923		0.926		0.925	
Worst Correlation between est. and true u_{it} across repetitions	0.885		0.878		0.901		0.901	

Table 5.1. Simulation results for Scenario 1

In this scenario, there is a very high correlation between estimated and true inefficiency error components, meaning that relative efficiency rankings should be well preserved. There is a small downward bias in the average of the estimated component, but always within 10% or less of the true value. The spatial parameter is also estimated correctly, although with some instability as the true value decreases. This performance issue will contaminate indirect efficiency measurement if the spillovers are not fully detected. A possible reason for this is the increased difficulty of identifying the spillovers of efficiency as they become increasingly irrelevant. When N is increased from 36 to 100, the correlations between true and estimated values increase, while the λ^{-1} parameter approaches the true value further. However, the improvements are small or not noticeable for other parameters of the model, as the performance in this scenario is already very encouraging in small samples. Increasing T to 20 also shows further improvements in estimation results. In all four columns, the average correlation between true and estimated values rises above 0.93 with larger T.

	N=36 / T=10		**N=36 / T=10**		**N=100 / T=10**		**N=100 / T=10**	
Means	Est.	True	Est.	True	Est.	True	Est.	True
u_{it}	0.101	0.100	0.102	0.100	0.100	0.101	0.100	0.101
λ^{-1}	10.296	10	10.155	10	10.091	10	10.099	10
σ_α^2	0.050	0.05	0.050	0.05	0.050	0.05	0.050	0.05
σ_v^2	0.010	0.01	0.011	0.01	0.010	0.01	0.012	0.01
ρ	0.211	0.3	0.478	0.6	0.196	0.3	0.483	0.6
β_0	1.009	1	1.044	1	1.020	1	1.057	1
β_1	1.000	1	1.000	1	1.000	1	1.000	1
s.d.(u_{it})	0.101	0.100	0.102	0.100	0.101	0.100	0.101	0.100
Mean Correlation between est. and true u_{it}	0.741		0.751		0.743		0.753	
Worst Correlation between est. and true u_{it} across repetitions	0.615		0.623		0.679		0.689	

Table 5.2. Simulation results for Scenario 2

In this scenario the signal-to-noise relationship fundamentally changes as the level of inefficiency decreases considerably, making it harder to separate the error components. The correlations between true and estimated values are lower and more volatile than in the first scenario, which is an expected result. The spatial relationship is underestimated, leading to identification problems of indirect efficiency results although the idiosyncratic component of inefficiency is estimated correctly (on average). However, the correlations between true and estimated values are improved when the time dimension increases to T=20.

Due to the disappointing results related to the spatial parameter in Scenario 2, the relationship between the spatial parameter and the underlying signal in the data is investigated further. For the case N=100, T=10 and ρ=0.3, a wide grid of 200 inefficiency exponential distribution parameters are used to assess the changes in performance as inefficiency decreases in size versus the variances of the components $\sigma_\alpha^2 = 0.05$ and $\sigma_v^2 = 0.01$ as before.

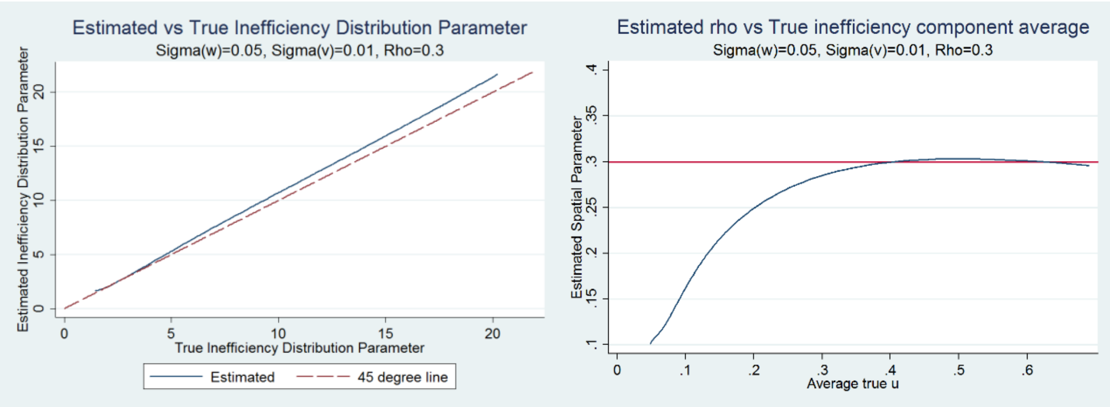

Figure 5.1. Model performance with varying size of inefficiency components.

Note: 5th order polynomials used for fitting the curves.

In general, there are negligible distortions in the estimate of λ^{-1}, with increasing distortion as the parameter increases and inefficiency becomes smaller. There is upwards bias, resulting in a downward bias of average estimated inefficiency, which is a typical result in Stochastic Frontier models when signal is small compared to noise. The comparison of estimated spatial parameters with the average of true inefficiency components renders more insightful results. The spatial parameter is identified correctly for a large set of high average true values, and decreases rapidly when the average true values of inefficiency decrease. As standard deviation is equal to the mean in the case of the exponential distribution, interpretation becomes straightforward. An average true u of 0.1 is equivalent in this case to a very low signal-to-noise ratio of 1, leading to a visible downward bias in ρ which however is not accompanied by a severe bias in λ. An average true u of 0.4 is equivalent to a signal-to-noise ratio of 4, leading to reasonable results which improve as the ratio increases further. Although λ^{-1} seems to be estimated correctly under a wide range of underlying true values, a correct identification of average u with a bias in ρ suggests there might be some contamination in the correlation between true and estimated u. Changing the signal-to-noise ratio from 1 to 2 in this case increases that correlation from approximately 0.7 to 0.9, with correlations as high as 0.98 as the ratio keeps increasing further.

With ρ=0.6, it is clear that the performance of the model varies greatly according to signal-to-noise ratios. Performance degradation is faster in smaller samples as the signal is reduced. As the spatial parameter increases, some positive bias in the estimated parameter is observed in general, but of relatively small proportions.

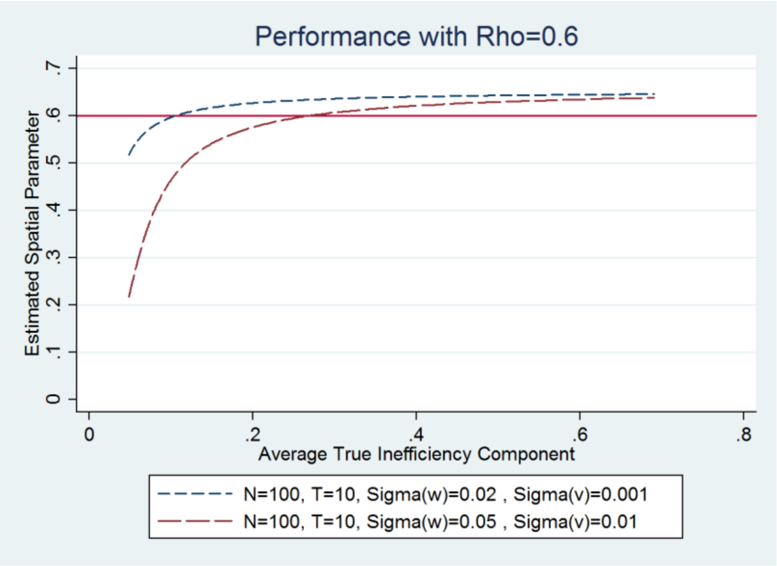

Figure 5.2. Model performance with varying size of inefficiency components and different variances of error components

In general, these findings point for good overall model performance, but with some issues to have in mind for the empirical researcher. The model is expected to perform worse with lower levels of signal-to-noise ratios. However, in this case, performance degradation is more visible on the spatial parameter than on the average of the idiosyncratic component and it might be difficult to identify small amounts of dependence in efficiency between the units, even with relatively large sample sizes.

5.4.2. The added value of Guided Walk Metropolis

The Guided Walk Metropolis (GWM) algorithm (Gustafson, 1998) presents an alternative to the classic RWMH algorithm. The author shows that the algorithm outperforms RWMH in a variety of examples, including a standard normal, a multivariate normal, a more complicated bivariate distribution and an exchangeable multivariate normal distribution. In all cases, relative error is reduced by using GWM, and it is shown that the method performs well in a wide range of acceptance rates. The reasoning for discussion and use of this method in this context is twofold: first, it allows for some performance gains against RWMH under various acceptance rates, and secondly, those gains might be more important in this case, as there is both a spatial parameter and also an NT vector of latent variables to estimate using rejection techniques in this case. This implies a much larger set of values to be drawn using these techniques than in other stochastic frontier models and therefore a bigger role of improvements in the use of such techniques in the results of interest.

To assess the performance of the competing methods in this specific case, a simulation is set to compare the absolute cumulative deviations (hereafter ACD) from the true value for the spatial parameter with the example N=100, T=10 and in the case of Scenario 1 for $\rho = 0.6$. Starting value is defined as $\rho = 0.4$. A grid is set with 200 different tuning parameters for the draws of ρ, representing a large spectre of rejection probabilities between approximately 5% and 95%. The ACD from the two approaches is compared graphically for 500 draws and the next 1500 draws after the first 500 are taken. GWM is used to draw the inefficiency components in both cases, with the same tuning parameter in all cases. The curves in Figure 5.3 are constructed using a fifth order polynomial to fit the 200 ACD points after 500 draws have been taken.

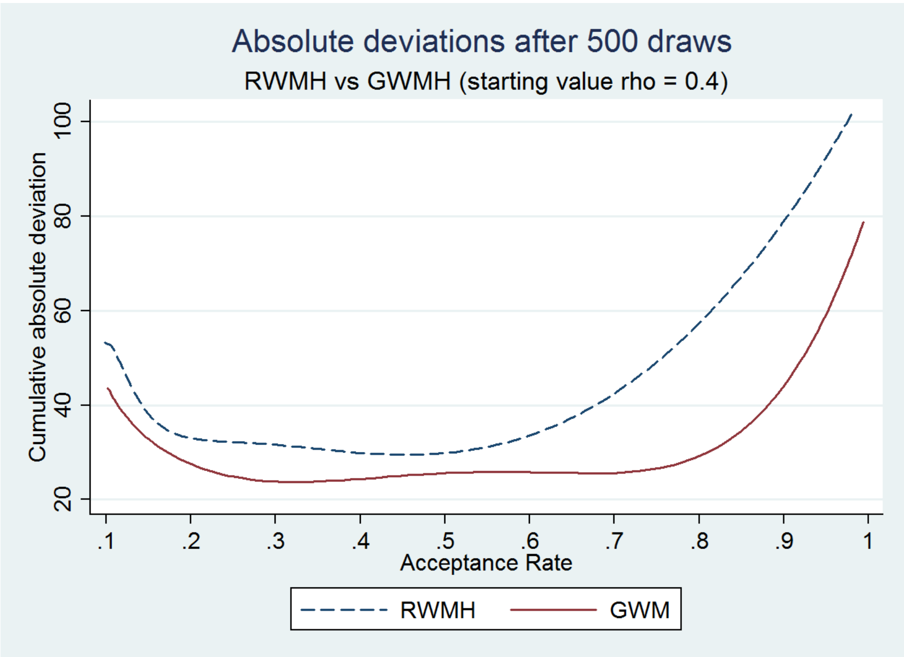

Figure 5.3. Performance of competing rejection methods

As pointed by Gustafson (1998) for different examples, the GWM method seems to perform well for a very wide range of acceptance rates as it runs towards the true value faster if the starting value is distant. The GWM approaches the target distribution faster, resulting in lower cumulative deviations across most of the spectre of acceptance rates. This implies that the method requires a smaller burn-in to ensure convergence. In the same exercise, evaluated in the range between 2000 and 10000 draws, the two fitted curves are flat and similar, pointing that once the algorithms have approached the true value sufficiently, there is no significant difference between the two. However, due to the size of the inefficiency component vector to draw using one of the two methods, significant changes might occur once the NT vector is drawn using different methods. Therefore, the methods are also fully separated to assess the performance of the draws of the inefficiency component, and also the correlations between estimated and true values (with 200 repetitions). The RWMH method struggles in three dimensions: lower estimated average inefficiency, lower correlation between estimated and true values (0.917 vs 0.925) and also more inaccurate quantiles of estimated inefficiency error components. Both approaches struggle to detect that some of the true values are extremely close to zero, as the uncertainty of the estimates and the lower bound of the draws at zero create some distortions often seen in this type of models. However, RWMH pushes the quantiles closer together than GWM, with the latter already having quantiles that are less spread out than in the true values. The 10th percentile for the true values of u_{it} is 0.0265, while the corresponding GWM percentile is 0.074, and the RWMH percentile is 0.089. These results are not very sensitive to small changes in tuning parameters of the underlying algorithms.

5.5. Model Application to cost efficiency of Electricity Distribution Networks

The proposed modelling approach is now applied to the context of energy economics. The New Zealand case of liberalization and restructuring of the electricity sector in 1998 forced a vertical separation of the electricity supply industry (ESI) with respect to ownership (also known as ownership unbundling). The primary motive of ownership unbundling is to prevent any discriminatory behaviour of network owners and facilitate market entry and competition (Nepal et al., 2016). The process was concluded in 2000. This case study has been the subject of research in the efficiency literature from a series of different perspectives.

Nillesen and Pollitt (2011) examine the impact of this policy on electricity prices, quality of service and costs. The authors estimate a Cobb-Douglas cost function and find a significant effect of the unbundling dummy variable on costs, implying that the unbundling of the industry managed to drive down costs of the industry. Nepal et al.

(2016) also find that the unbundling of the industry has contributed to a fall in the frequency and duration of outages, but has no effect in reducing distribution losses in the industry.

Ozbugday and Nillesen (2012) estimate a cost frontier function for distribution networks between 1998 and 2010, estimating a compound annual growth rate of over 2% using a time-varying decay frontier model. Filippini and Wetzel (2014) estimate a cost frontier with data between 1996 and 2010, with both variable cost and total cost as dependent variables, with the results suggesting a positive one-off shift in efficiency levels when ownership unbundling is introduced. The authors estimate the model using the Battese and Coelli (1995) approach with and without fixed effects, allowing for the introduction of explanatory variables in the inefficiency component equation (a feature which is not possible in many SF models). As expected, when the fixed effects are included, the variance of the inefficiency component is reduced, as some persistent inefficiency might be diluted into the fixed effect. The average efficiency level is measured at approximately 82%. Filippini et al. (2016) introduce the measurement of persistent inefficiency to this dataset using the GTRE model, and involving regulation and imperfect information concepts to explain the necessity for the regulator to consider the level of persistent inefficiency in the sample. The model is estimated using the Filippini and Greene (2016) estimation approach with MSL. Despite the lengthy theoretical background given by the authors, some concerns about the practicality of the estimation and interpretation of persistent inefficiency appear in this context and will be explored later in this section.

However, it is also possible to analyse the problem from a spatial perspective, where the industry is defined by a cost function which takes into account time-invariant differences between the distribution networks, but also tries to quantify spatial spillovers of inefficiency across distribution networks. These effects could appear due to interactions between managerial practices or other factors in the cost structure in a competitive industry, where distribution units can learn from each other and be affected by the efficiency of their neighbours. This is a particularly important effect in an industry which has been recently unbundled and is dealing with an unusually competitive environment in the sector, as New Zealand was one of the first countries in the world to apply this kind of reform. The application of the model focuses on time-varying inefficiency estimation, to assess how efficiency levels have evolved since the introduction of the reform.

The dataset is a balanced panel from 2001 to 2009 fiscal years (yearly data), across 27 electricity distribution networks, with a total of 216 observations. The data starts in 1st April 2000 and ends in 31st March 2009. The only company missing from this dataset is Otago Power (a relatively small network) due to gaps in the data. All variables are logarithmically transformed as usual for stochastic frontier analysis, implying that the coefficients can be interpreted as elasticities. The dataset has been compiled by the author of this thesis and is a subset of the data published in the article of Nepal et al. (2016) to exclude the years before vertical separation of the industry. The research question at hand is the spatial relationship between units in terms of efficiency, exclusively post-unbundling, instead of the effects of the unbundling process in a particular variable of interest. The data was compiled using information in the "NZ EDB Database" from Economic Insights, as in other papers of the literature. The data is augmented for the year 2009 by using Electricity Information Disclosures but not extended further due to the existence of natural disasters and climate effects possibly affecting results in later years, such as the Christchurch earthquake which devastated local areas in the fiscal year of 2011. Operating Expenditure data for 2008 is also taken from Electricity Information Disclosures instead of the Economic Insights database as it is more likely to be up to date. However, this implies some revisions to the data which will be discussed further in this section. Data is available in Appendix 5.2.

A Cobb-Douglas function is estimated. In the model, Variable Cost (VC) of the firm i at time t is a function of a constant, the energy delivered by the firm (ENERGY), the number of costumers (CUSTOMERS), the load factor (LOADFACTOR), the System Average Interruption Duration Index (SAIDI), customer density (CUSTDENSITY) and a measure of capital of the network (CAPITAL). Cross-sectional averages of the variables are also added to relax the assumptions of the random effects model. A quadratic time trend is also included in the model.

Variable	Description	Mean	Std. Dev.
VC	Total Operational Expenditure, deflated by the OECD energy consumer price index for New Zealand (base year=2005)[12], in New Zealand dollars	1.10e+07	1.83e+07
ENERGY	Energy delivered in KWh, calculated as the energy entering the network minus losses	984.67	1794.37
CUSTOMERS	Number of customers	63980.68	116783.6
LOADFACTOR	Amount of electricity entering the system divided by the maximum demand multiplied by the total number of hours in the year	62.75	6.85
SAIDI	Average total duration of interruptions experienced by the customer	220.40	207.43
CUSTDENSITY	Length of business unit lines in km per each customer of the business unit	11.35	7.43
CAPITAL	Maximum system demand in KW (proxy for capital stock)	193.16	355.78

Table 5.3. Description of dependent variable and explanatory variables

Operational Expenditure includes general management, administration and overhead expenses, system management and operations, routine and preventive maintenance, refurbishment and renewal expenses and fault and emergency maintenance expenses, besides pass-through costs. Due to data availability issues, input prices are not included in the cost function. As the specification does not include these prices and contains outputs such as energy delivered and other controls, a short run Leontief cost function is being estimated. As a result, it is assumed that input quantities are fixed in the short run or change in fixed proportions. More energy delivered should lead to higher expenditure, as well as having more customers, particularly if they are more scattered across the operational area, as that implies longer lines to supply a customer. The maximum system demand acts as a proxy for the capital stock of the distribution firm. A larger SAIDI indicates more interruptions and malfunctions which are associated with more expenditure.

Two spatial weights matrices are built for estimation of the model. The first reflects first order contiguous neighbours where the spatial weight is 1 if a unit is a direct neighbour of the unit under consideration and 0 otherwise. The second is a second order matrix where the spatial weight is 1 if a unit is a direct neighbour of the unit under consideration

[12] Different deflation procedures exist in the literature. Nillesen and Pollitt (2011) deflate cost by a PPP index, while Filippini and Wetzel (2014) deflate cost by the OECD consumer price index for New Zealand. Note that in this case the price index was rebuilt using the average of quarterly data corresponding to the New Zealand fiscal year, finishing 31st of March each year, instead of the OECD calendar year data. Choice of deflators has little impact on time-varying behaviour of estimated average efficiency.

or the neighbour of a neighbour of the unit under consideration and 0 otherwise. Networks from different islands are never considered as being neighbours. The number of neighbours in this second spatial weights matrix varies between 2 and 11 depending on the firm under consideration, with a sample average of 6.9 neighbours. The first order matrix has a lower sample average of 3.1 neighbours per unit.

	First order neighbours W matrix	Second order neighbours W matrix
ρ	0.100 [0.004 ; 0.272]	0.229 [0.019 ; 0.468]
β_{CONSTANT}	2.107 [-3.388 ; 7.216]	2.094 [-3.353 ; 7.226]
β_{ENERGY}	0.219 [-0.096 ; 0.531]	0.233 [-0.081 ; 0.543]
$\beta_{\text{CUSTOMERS}}$	0.548 [0.218; 0.887]	0.535 [0.205 ; 0.873]
$\beta_{\text{LOADFACTOR}}$	-0.161 [-0.418 ; 0.120]	-0.148 [-0.405 ; 0.125]
β_{SAIDI}	0.066 [0.032 ; 0.100]	0.066 [0.032 ; 0.100]
$\beta_{\text{CUSTDENSITY}}$	-0.310 [-0.618 ; -0.004]	-0.316 [-0.623 ; -0.010]
β_{CAPITAL}	-0.068 [-0.174; 0.032]	-0.065 [-0.171 ; 0.035]
$\beta_{\text{TIME TREND}}$	-0.001 [-0.031 ; 0.030]	0.002 [-0.031 ; 0.036]
$\beta_{\text{TIME TREND}^2}$	-0.000 [-0.003 ; 0.003]	-0.001 [-0.004 ; 0.003]
σ_α^2	0.037	0.037
σ_v^2	0.008	0.007
λ^{-1}	11.075	10.963
Signal-to-noise ratio	1.085	1.110

Table 5.4. Cost Frontier regression results. Note: Credible interval between 2.5% and 97.5% percentiles in [brackets]

Both specifications comfortably show signs of convergence according to the Geweke convergence diagnostic (Geweke, 1992) with z-scores for all parameters between -2 and 2. Although some coefficients contain zero in the credible interval due to uncertainty in parameter estimates of this small sample, all coefficients follow the sign expected from economic theory. Operating expenditure is expected to increase with the amount of energy delivered and the number of customers served. Units with a higher load factor are expected to use their line investment better, which could lead to a decrease in operating costs. Units with longer average interruptions of service imply higher costs, due to maintenance and emergency fixes. Higher customer density implies more customers concentrated in a given area, and less service to isolated customers, which can lead to lower operating costs. Higher capital stock can also lead to lower operating expenditure, holding all else constant. The time trend components appear to not significantly influence results. Four of the six cross-sectional mean regressors inserted to relax assumptions of the random effects model are significant. No variable that is not significant at the 5% level becomes significant at the 10% level. Alternative estimation using time dummies or a linear trend instead of a quadratic time trend indicates no changes in the general pattern of average efficiency detected over time. The estimated signal-to-noise ratio is close to 1, as in Scenario 2 of the simulations, which points to possible difficulties in the identification of the spatial parameter. However, there are strong signs of the presence of a positive spatial parameter when a second order neighbour matrix is used. Simulations conducted in the previous section point that it is likely that there is some downward bias in the estimated spatial parameter, supporting the theory of positive spatial spillovers further.

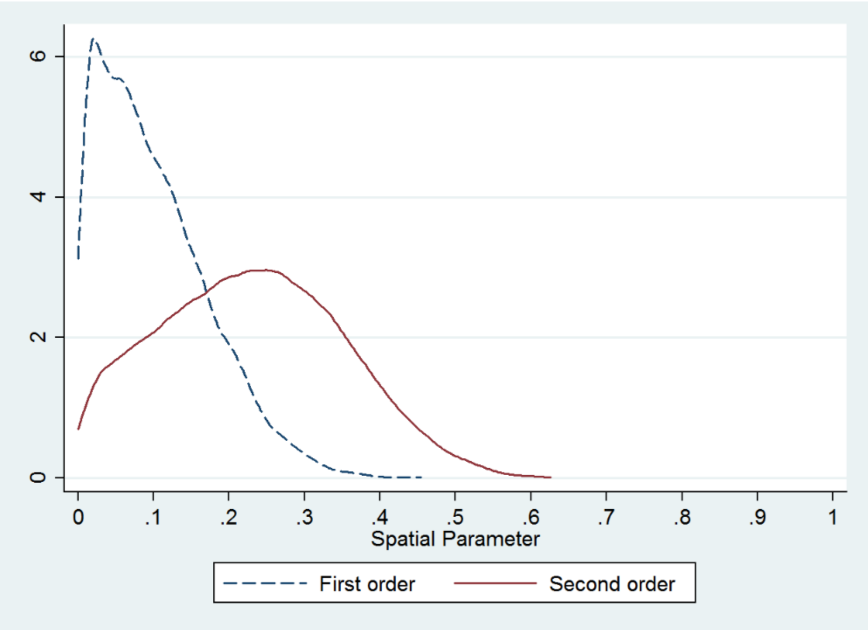

Figure 5.4. Density plots for spatial parameter with different W

One of the key assumptions in the estimation is a non-negative spatial parameter, to represent positive spillovers of efficiency between the distribution networks. Although there is no intuition for negative spillovers in this case, the assumption is relaxed to assess the changes in results. For the first order neighbour matrix, there is clear indication that there is no spatial relationship between the units, with a mean of -0.012 and a credible interval at the 95% level between -0.28 and 0.23. In the case of the second order neighbourhood matrix, the mean becomes approximately 0.18 with only 15% of the draws having negative values. However, the negative tail of the distribution is rather irregular and unintuitive, with the first 0.5% of the draws spread between -1 and -0.4, suggesting that the identification of the model becomes problematic without the appropriate restriction. Nevertheless, the correlation between the vectors of relative efficiency measures of the restricted and unrestricted models is 0.9997. This reinforces the consideration of a non-negative restriction, besides helping with the interpretation of results.

There were clear gains in efficiency between 2003 and 2007, as the first years of the industry as a competitive business unfolded and improvements became visible. The gains dwindled away in the last two years of the sample period. However, there are data revisions in OPEX between sources towards the end of the sample period, leading to a possible break in the data in 2008 or 2009, depending on the choice of data source for 2008. The nine firms with significant upward revisions in OPEX data between the Economic Insights database and the Economic Disclosures for the year 2008 appear to have an impact on the time-varying average efficiency scores for that year exclusively. The figure below shows the results with and without those nine firms. However, the downward trend is still clear and confirmed in 2009. Therefore, the inversion of the efficiency gains of previous years seems to be confirmed by the data in both cases. Regarding outages, 2007 was the most problematic year, but also the most efficient year for the industry. 2008 and 2009 are years with above average levels of SAIDI.

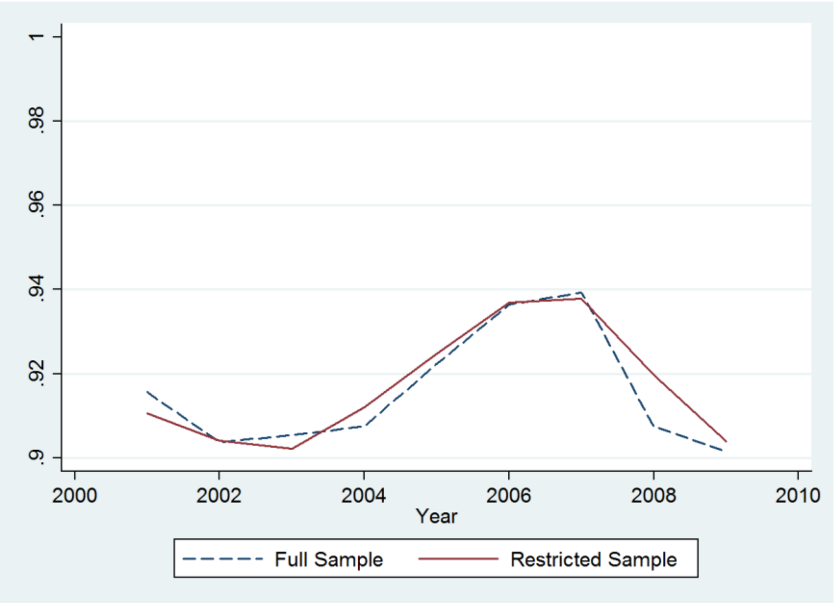

Figure 5.5. Time-varying average efficiency for full and restricted sample (second order neighbourhood matrix)

There is strong evidence of positive skewness of the random effects, pointing that there could be a reasonable amount of persistent inefficiency, as investigated by Filippini et al. (2016). However, there are two reasons why estimation of separated time-invariant error components is not attempted in this context. Firstly, the identification of all the components of the model would be complicated, given the small size of the panel in both of its dimensions. These could lead to unstable results which can become meaningless due to identification issues. Secondly, there are some theoretical considerations to have in mind when estimating the model. Even if extreme positive skewness of the random effects in the distribution network cost function exists, its meaning might not intuitively point for the separation of a time-invariant convolution. These distribution networks operate in extremely different geographical locations, with different contexts of supply in flat or mountainous terrain, and regions that persistently experience different issues in winter months or with vegetation and wild life. It is extremely difficult to account for these factors, and it is possible that an attempt to estimate a complete model would simply capture extreme geographical and climatic difficulties of supply instead of meaningful managerial practices and cost efficiency issues which are of interest to a regulator. The firms with the most positive random effects in the results above are Buller Electricity and Marlborough Lines. In a scenario of a large signal-to-noise ratio of persistent inefficiency and low or negligible influence of a zero-mean random effect, these should be the firms diagnosed as being more inefficient. These firms are located in the northern half of the South Island. Both firms contain National Parks inside their operational areas and also operate in colder than average and considerably more mountainous areas than other distributors in New Zealand. These are underlying conditions of the terrain in which the distributors operate and can hardly be attributed to cost inefficiency for regulation purposes just because they are not accounted for in the regression. A regulator could then take these findings and penalize the firms for factors that are out of their control. Filippini et al. (2016) find a positive correlation between persistent efficiency and the inverse of SAIDI, which again can be a circular argument if difficult climate and terrain conditions not entirely confined to the zero mean random effect cause outages, and those regions are also diagnosed as being more inefficient by a one sided error assumption. The authors quantify the inefficiency from a GTRE model in this context, but do not show individual firm rankings, making it impossible to assess if their results also point in this direction. Their analysis spans from 1996 to 2011, including pre and post-unbundling sample periods, as well as years with significant natural disasters such as the Christchurch Earthquake. The large standard deviation of persistent inefficiency in relation to the standard deviation of the random effects points that the signal-to-noise ratio is large. Therefore, if the random effects resemble the ones presented above, the aforementioned pitfalls of the analysis might apply.

5.6. Conclusion

This chapter proposes a strengthening of the links between the spatial econometrics and stochastic frontier modelling literatures with a Bayesian Spatial Error model placing spatial dependence in the efficiency component while also accounting for unobserved heterogeneity. A simple and easily implementable MCMC is presented, allowing for flexible priors on mean efficiency and estimation of inefficiency assuming an exponential distribution. The measurement of efficiency in absolute and relative terms is discussed under different conditions. There is also a contribution to the applied Bayesian econometrics literature by proposing a Guided Walk Metropolis method to take draws from the non-standard distributions of the spatial parameter and the vector of the one sided error components, a method which allows for quick and easy computation but also faster convergence. This is an attractive alternative to the classic rejection methods that are well established. The model appears to perform well under a variety of contexts and sample sizes, while suffering from identification problems when signal-to-noise is increasingly low, a usual drawback in SF models.

The modelling approach is applied to the context of cost efficiency in New Zealand electricity distribution networks, a well-known and previously studied case in the energy regulation literature. In this case, focus is on the post-unbundling period between 2001 and 2009, estimating time-varying inefficiency while accounting for unobserved heterogeneity. A spatial relationship in cost efficiency between firms is detected, particularly when using a more encompassing spatial weights matrix with second order neighbours. This suggests some level of interaction with other firms in the industry. An argument is made for not considering persistent inefficiency in this empirical case, but it is definitely a path for future research in terms of modelling technical and cost efficiency.

Chapter 6. Conclusion

6.1. Summary

This thesis conducted a literature review and a description of the key concepts in Stochastic Frontier Analysis, followed by three essays in Bayesian Stochastic Frontier modelling, applied to contexts of measurement of persistent inefficiency and/or spatial dependence in production and cost functions, with a particular focus on model performance in small samples. The literature review concluded that while the field is expanding quickly in multiple directions, there are still a few gaps and some distance between the state of the art modelling and the state of empirical work in multiple contexts. Besides that, there is no up to date survey on spatial stochastic frontier models, and some of the existing surveys also ignore important parts of the literature. As a whole, it appears that measurement of persistent inefficiency, the issues associated to spatial econometrics and some issues associated with dynamics are relatively unexplored. The thesis then continues with Chapter 3, where an electricity demand function is modelled as a cost frontier to measure aggregate efficiency in electricity consumption in transition economies between 1994 and 2007, along with five other OECD developed economies in the sample. The chapter discusses and addresses some of the issues overlooked in the previous literature on aggregate energy efficiency measurement. Two alternative GTRE MCMC approaches are considered for this purpose, finding that a more complicated and computationally slower reparameterization approach that exists in the literature has no competitive advantages over a “naïve” approach with a different prior suggested recently. There is evidence of convergence between most country groups independently of the approach considered. Chapter 4 then extends the Bayesian GTRE approach to a Spatial Autoregressive model which incorporates a spatial structure into the model. Performance of the model in simulations is encouraging, but only for the “naïve” approach as the reparameterization performance degrades further than in the non-spatial case. The formula for efficiency measurement is discussed in the spatial context and the approach is then applied to aggregate productivity in European countries, where evidence of convergence over time is also found. Finally, the spatial structure is seen from a different perspective in Chapter 5, as it is now placed on the inefficiency error component, resembling a Spatial Error model. In this case, only time-varying inefficiency is considered in a model with Random Effects. Performance of the model is again encouraging and the conditions for good performance regarding signal-to-noise ratios and sample sizes are investigated. The approach is then applied to the context of cost efficiency measurement of electricity distribution networks in New Zealand after a vertical separation (unbundling) policy. Some spatial dependence in efficiency between the firms is seen as the ranges of the neighbour relationships widen. All three essays focus on inspecting performance of the proposed approaches in small samples, to give the applied researcher an idea of the problems he might be facing when conducting estimation with other data. Signal-to-noise ratios are crucial, as learned many times in the past in (often simpler) Stochastic Frontier models.

In a brief summary, this thesis has explored the theory and practice of Bayesian Stochastic Frontier models. It explored the gaps in the literature and identified research paths and topics requiring further attention, making an empirical exploration of the well-known GTRE model, and extended this model to the context of spatial econometrics. All chapters had a clear focus on small sample performance and evaluating the influence of decreasing sample size and priors in results, with encouraging results for use in small samples with some caution regarding signal-to-noise ratios. The thesis has also successfully explored alternative rejection techniques versus traditional rejection techniques by using Guided Walk Metropolis successfully to improve performance in Chapter 5.

6.2. Lessons and implications of the research

There are general lessons to take from this thesis, both in terms of Econometrics and also Energy and Transition Economics. This thesis has shown that further extensions to SF models are possible from an estimation point of view without serious degradation of the performance of the models. This is shown in simple simulations with a few parameters, but also in applications of the modelling approaches which show stable and intuitive results. The role of priors is important and needs further care and understanding in the efficiency and productivity literature. The thesis has shown that Bayesian econometrics in this setting is not about playing with priors until the pre-defined objective efficiency result is obtained – it is mostly a process in which we identify efficiency levels from little data with a possibly weak signal. Understanding that process is crucial.

It is also shown that the standard literature in persistent inefficiency estimation in Bayesian Stochastic Frontier models needs refreshing. The benchmark (published) paper of Tsionas and Kumbhakar (2014) contains several errors and simulations that I have been unable to replicate, leading to very different results. The (unpublished) effort of Makiela (2016) to shed some light and solutions on these issues is also very welcome and has inspired one of the extensions in this thesis towards spatial econometrics. However, spatial models have increased implications in terms of interpretation, becoming an entirely legitimate challenge on their own. There is little study in this field and hopefully this thesis has advanced some of the knowledge in the field.

Some lessons were also learned in the field of Energy Economics and Transition Economics while this thesis was carried out. First, working with data of transition economies is very challenging. Data collection, particularly on prices, is particularly complicated and requires compiling data from multiple sources. Choices on deflation and measures of the economy are scarce and all have their own merits and problems. Measuring and including weather effects and the structure of the economy is also complicated, but necessary up to some extent. Many other problems can plague the results, and even if all of them are considered, only some of them can be efficiently addressed. However, the pattern of convergence seen across the economies is seen both in efficiency in electricity consumption and in aggregate productivity as measured by two different stochastic frontier models with different purposes, dependent variables and exogenous regressors. This is largely in line with previous literature, but also adds to it from different perspectives. Also, an examination about variations in efficiency levels since the vertical separation of electricity distribution networks in New Zealand allows to see no consistent gains in efficiency levels, but detects some level of spatial dependence in efficiency between the networks, a result which might of interest to the regulators when considering policy making.

In all of these studies, there was a particular focus in relatively small samples. Gaining understanding about how those models work with little data is important, as most researchers in the productivity and efficiency literature often have to deal with scenarios like this. A lesson for the future of the literature is that proposals for modelling and estimation approaches should be accompanied by at least some sort of simulation work to gain an understanding of the circumstances in which the measurement of efficiency is reliable and makes sense.

6.3. Further research and concluding remarks

This thesis outlined a series of contributions in the SF literature but also in the Energy Economics literature. The research paths leave some additional steps to be unfolded in the future, if time allows.

Chapter 2 outlined a literature review which highlighted some gaps in the literature. However, these are quickly being closed in the literature. A generally observed pattern is the construction of several alternatives for tackling econometric challenges in modelling which are then not followed by applied research by other authors. Chapter 3 outlines a method to estimate efficiency in electricity consumption across transition economies. Future research paths could include further investigations into a more complete dataset and alternative measures of energy prices, as well as considering modelling the rebound effect. In Chapter 4, the proposed approach opens new paths for research in Stochastic Frontier models in more challenging contexts. Possible paths for future research include the adaptation of techniques of estimation of the spatial weights matrix to avoid incorrect specification, as in Bhattacharjee and Jensen-Butler (2013) and Ahrens and Bhattacharjee (2015), to the stochastic frontier framework. Another interesting path of research is the consideration of stochastic spatial metafrontiers to estimate group specific frontiers and envelope it over groups to be able to measure the distance of a unit to the group frontier and also the global frontier (O'Donnell et al., 2008). Finally, the exploration of different and more flexible distributional assumptions of inefficiency and distributional assumption choice criteria is also a possible extension of the model. Chapter 5 presents another proposal for modelling spatial dependence of efficiency in production or cost functions in a scarce literature. The extension of the model with time-varying and persistent inefficiency with an exponential distribution assumption (Griffiths and Hajargasht, 2016) to the spatial case (where the spatial structure is associated to only one of the two inefficiency components) is straightforward in terms of intuition, but will raise further challenges. The spatial structure will have to be considered carefully, leaving the question if the spatial dependence parameter is unique for both kinds of inefficiency or is parameterized in a more flexible way. This growth in complexity and number of parameters will cause performance issues, at least in small samples.

The choice of a Bayesian path to this thesis can be discussed in the context of competing approaches. Many Bayesian applications in the Stochastic Frontier literature have marginally different results from the corresponding ML approaches (if different at all) due to the use of diffuse priors. This means that many of those applications are merely demonstrations of the existence of their ML counterparts, producing little more than an alternative method to maximize a likelihood function and then calling it something else (Greene, 2008). The GTRE model can also be estimated in two steps, where the first step estimates the frontier accurately and the second step separates the residuals from the first step. A frequentist econometrician can then argue that this produces more robust results than one step approaches which can compete against the gains of Bayesian approaches. It is also true that very informative priors can distort results if the underlying data is scarce and without strong underlying signal. If that is the case, one should consider why the model is being estimated at all. However, the Bayesian approach has merits in its favour, even in the context of these issues. Some Bayesian applications highlight problems in Stochastic Frontier modelling that receive little or no attention in the classical literature. As highlighted by this thesis, it is also possible to introduce techniques to improve the estimation further, such as Guided Walk Metropolis. Regarding the two-step approach in the classical literature, this implies an unknown amount of information loss between the steps, something that can be countered in Bayesian econometrics by looking at the sensitivity of the results with different priors.

Many other aspects of efficiency and productivity measurement are not considered in these essays. This thesis is a drop in a glass of literature. We are yet to know how full the glass is and, as we push the frontier, we hopefully never will. Most importantly, something transparent and useful must come out of all of our efforts, with important and informed policy decisions resulting from them.

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Appendices

Appendix 3.1. Geweke convergence diagnostic z-scores for each parameter

<table>
<tr><th>Dataset 2 (excluding Norway)</th><th>$\bar{Q}_v$=0.001
$\bar{Q}_\alpha$=0.01
$r_\eta = 0.7$
$r_u = 0.85$</th><th>$\mathbf{\bar{Q}_v}$=0.001
$\mathbf{\bar{Q}_\alpha}$=0.01
$\mathbf{r_\eta = 0.6}$
$\mathbf{r_u = 0.85}$</th><th>$\bar{Q}_v$=0.001
$\bar{Q}_\alpha$=0.01
$r_\eta = 0.5$
$r_u = 0.85$</th><th>TK:
$\bar{Q}_v$=0.001
$\bar{Q}_\alpha = 0.01$
$\bar{Q}_u$=0.01
$\bar{Q}_\eta$=0.25</th></tr>
<tr><td>β</td><td>-0.70828 -0.96588
0.44643 -0.77939
1.00358 0.82910
1.13901 0.05442
-0.74369 -0.72594
0.73409 0.63558
0.75245 0.34208
0.77498 0.88616
0.66359 0.48300
0.55892 0.17896
1.09100 0.95204
-0.25433 1.48583
-0.32178 0.59572
-0.64925 -0.02308</td><td>1.0635 0.1165
0.3498 -1.7786
1.4281 2.0864
3.4501 1.3038
0.1386 -1.6585
0.6801 0.4173
0.6765 0.9933
0.6912 1.4460
1.1129 1.3661
1.4796 0.5991
0.9151 0.9110
-1.2430 -1.0901
-0.2510 -0.5572
-2.1083 1.4294</td><td>-1.15369 1.33449
-0.50005 -0.08861
1.23811 -0.36246
-0.97600 2.30293
-0.29377 -1.19872
-1.72481 -1.58321
-1.26046 -0.92789
-0.95818 -0.39452
-0.99955 -1.04993
-1.24311 -1.05419
-1.56943 -0.62772
0.92513 0.87743
0.17527 0.78580
0.75223 0.25746</td><td>0.53390 0.84891
0.30252 -2.36312
3.91490 2.55414
2.16867 1.25583
-2.04565 0.45665
2.48611 1.65903
2.48999 2.48150
2.46764 2.93370
1.62807 2.04311
1.75783 1.39730
0.53303 2.26276
-0.43318 1.39241
-1.15129 -0.48796
0.02205 -0.99601</td></tr>
<tr><td>σ_v</td><td>-1.255</td><td>1.159</td><td>-0.05584</td><td>1.918</td></tr>
<tr><td>σ_u</td><td>-0.1887</td><td>0.864</td><td>-0.6302</td><td>-1.228</td></tr>
<tr><td>σ_η</td><td>-0.7133</td><td>0.07871</td><td>0.5243</td><td>-2.461</td></tr>
<tr><td>σ_α</td><td>1.233</td><td>-1.341</td><td>-0.2224</td><td>1.496</td></tr>
</table>

Note: Outliers outside of the interval between -2.3 and 2.3 in red. Considering the outlier in the second column of results, the Geweke diagnostic has been attempted also with a first split of the data at the 5^{th} percentile instead of the 10^{th}. That makes all z-scores within the interval of -2 and 2.

Appendix 3.2. Correct TK paper equations

Equation (8) of the paper is rebuilt in this thesis as:

$$p(\delta_i|y, X, \theta_{-\delta}) \propto \exp\left(\frac{(R_i - [\mathrm{lt} \otimes \delta_i])'(R_i - [\mathrm{lt} \otimes \delta_i])}{2\sigma_v^2} - \frac{\delta_i^2}{2\sigma_\delta^2}\right)\Phi\left(\frac{\frac{\sigma_\eta}{\sigma_\alpha}\omega\delta_i}{\sigma_\delta^2}\right)$$

where $R_i = y_{it} - X_{it}\beta - u_{it}$.

Equation (11) of the paper is rebuilt in this thesis as:

$$u_{it} = \frac{[y_{it} - X_{it}\beta - [\mathrm{lt} \otimes \delta_i]]\,\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$$

Appendix 3.3. Results with the inclusion of Norway in the sample

Dataset 1 (including Norway)	$\bar{\mathbf{Q}}_v$**=0.001** $\bar{\mathbf{Q}}_\alpha$**=0.01** $\mathbf{r}_\eta = \mathbf{0.6}$ $\mathbf{r}_u = \mathbf{0.85}$
$\beta_{Intercept}$	-18.840 [-26.69;-12.27]
β_{GDP}	0.2138 [0.16;0.27]
$\beta_{Elec.\ Price}$	-0.0578 [-0.09;-0.03]
$\beta_{Weather}$	0.0767 [-0.08;0.23]
$\beta_{Urb.Rate}$	0.9978 [0.61;1.36]
$\beta_{Population}$	0.6435 [0.34;0.89]
$\beta_{Manuf.\ Share}$	0.1062 [0.04;0.18]
$\beta_{Constr.\ Share}$	0.0390 [-0.00;0.08]
$\beta_{Primary\ Share}$	-0.0042 [-0.09;0.08]
Mean(η_i)	0.601
Mean(u_{it})	0.098
σ_v	0.0172 [0.010;0.027]
σ_u	0.1339 [0.122;0.146]
σ_η	0.7495 [0.537;1.037]
σ_α	0.1659 [0.043;0.407]
Mean Efficiency (0-100%)	**54.3%**

Appendix 3.4. Chapter 3 core dataset

country	country code	year	Elec_Cons_KTOE	Weather_Linear	Population	Urbanization Rate	nonenergyvappp	manuf_share	cons_share	primary_share	Real_Elec_PriceIndex_noPPP
ALBANIA		1994	158.0	73.7	3384367.2	38.4	842930332.3	3.5	8.5	33.5	128.2
ALBANIA		1995	174.0	76.6	3357856.9	38.9	1018932716.4	3.4	9.1	33.1	173.0
ALBANIA		1996	238.0	80.9	3341042.3	39.5	1289420784.2	3.3	9.5	30.1	137.5
ALBANIA		1997	181.0	78.4	3331316.0	40.0	966806026.3	2.4	8.4	26.6	72.0
ALBANIA		1998	192.0	80.9	3325456.4	40.6	1102860074.3	3.4	6.9	27.0	63.7
ALBANIA		1999	372.0	78.4	3317942.4	41.2	1365590783.0	3.8	7.6	25.9	69.4
ALBANIA		2000	366.0	76.9	3304947.1	41.7	1405356255.2	3.8	10.5	26.3	55.5
ALBANIA		2001	349.0	73.0	3286083.7	42.4	1540649457.3	3.8	12.9	24.9	55.7
ALBANIA		2002	383.0	70.0	3263597.3	43.5	1688300603.7	3.7	14.8	24.2	67.8
ALBANIA		2003	376.0	86.5	3239385.9	44.6	2077358288.8	4.5	17.5	23.8	90.5
ALBANIA		2004	458.0	74.9	3216197.4	45.7	2648526911.7	5.0	17.8	24.1	92.0
ALBANIA		2005	444.0	81.0	3196130.2	46.7	2877982745.3	5.8	18.0	23.0	100.0
ALBANIA		2006	299.0	79.4	3179573.4	47.8	2954679081.4	6.5	18.8	22.5	109.3
ALBANIA		2007	316.0	76.0	3166223.1	48.9	3596151058.3	6.8	19.2	21.0	123.9
ARMENIA	2	1994	278.0	114.0	3289943.8	66.3	482380423.0	26.1	9.4	31.0	35.3
ARMENIA	2	1995	262.0	107.9	3223173.7	66.1	529256966.0	24.9	8.2	30.1	47.9
ARMENIA	2	1996	294.0	107.8	3173423.9	65.8	556602294.8	24.1	9.9	29.4	59.2
ARMENIA	2	1997	367.0	112.0	3137652.1	65.5	552979097.3	24.0	10.1	27.6	77.9
ARMENIA	2	1998	311.0	108.1	3112958.6	65.2	619182018.5	22.3	10.6	29.6	106.5
ARMENIA	2	1999	313.0	104.3	3093818.8	64.9	602738098.8	22.2	10.9	28.7	101.5
ARMENIA	2	2000	309.0	114.7	3076098.8	64.7	608565989.1	22.5	13.3	26.9	100.1
ARMENIA	2	2001	299.0	106.4	3059959.6	64.4	656646362.2	21.3	12.8	27.6	92.8
ARMENIA	2	2002	294.0	110.7	3047001.1	64.3	725522672.0	21.9	16.0	25.3	93.9
ARMENIA	2	2003	316.0	116.0	3036031.0	64.3	856286205.1	21.9	20.1	22.7	87.7
ARMENIA	2	2004	342.0	112.8	3025651.5	64.2	1048597642.6	17.2	21.2	23.7	85.7
ARMENIA	2	2005	358.0	115.4	3014916.3	64.2	1424536308.3	16.1	23.3	22.6	100.0
ARMENIA	2	2006	389.0	120.6	3002910.3	64.1	1851768508.6	13.7	27.5	19.6	106.2
ARMENIA	2	2007	410.0	118.9	2989882.6	64.1	2585102122.7	12.3	28.8	19.1	122.4
AZERBAIJAN	3	1994	1073.0	91.6	7596997.3	52.5	551137460.2	17.9	1.5	22.1	223.4
AZERBAIJAN	3	1995	1104.0	89.5	7685001.7	52.2	488419516.8	16.2	1.9	23.7	129.0
AZERBAIJAN	3	1996	1056.0	96.9	7763001.5	51.9	495000395.7	15.1	4.0	24.3	134.9
AZERBAIJAN	3	1997	1049.0	94.3	7838249.0	51.6	603721833.9	14.4	6.3	21.3	141.6
AZERBAIJAN	3	1998	1147.0	95.2	7913003.2	51.3	654038934.2	13.6	8.9	21.2	132.1
AZERBAIJAN	3	1999	1220.0	88.0	7982751.1	51.2	663054926.4	13.2	8.4	21.2	132.9
AZERBAIJAN	3	2000	1242.0	94.0	8048599.1	51.4	734471249.6	13.1	7.9	21.7	119.2
AZERBAIJAN	3	2001	1296.0	87.8	8111199.0	51.6	758640557.9	12.8	7.8	22.5	117.4
AZERBAIJAN	3	2002	1246.0	89.4	8171947.4	51.8	830197531.3	12.3	12.6	21.3	108.8
AZERBAIJAN	3	2003	1416.0	91.9	8234101.0	52.0	969047278.8	12.3	16.4	19.8	106.4
AZERBAIJAN	3	2004	1457.0	89.0	8306496.9	52.2	1152577758.5	12.1	19.8	18.4	99.7
AZERBAIJAN	3	2005	1551.0	93.0	8391853.0	52.4	1460380770.0	13.0	18.7	18.3	100.0
AZERBAIJAN	3	2006	1689.0	100.0	8484548.9	52.6	1860183042.9	12.7	18.2	16.5	92.3
AZERBAIJAN	3	2007	1363.0	99.6	8581296.1	52.8	2541555418.4	12.5	18.9	15.4	262.6
BELARUS	4	1994	2399.0	124.8	10226992.2	67.5	5020109634.7	21.3	10.7	15.0	
BELARUS	4	1995	2177.0	123.7	10194001.6	67.9	4729576592.0	20.8	7.8	15.9	
BELARUS	4	1996	2193.0	132.2	10159993.4	68.3	4867467119.1	21.3	7.1	15.8	4799.0
BELARUS	4	1997	2302.0	128.5	10117005.9	68.7	4512580320.5	22.9	7.8	13.6	2146.7
BELARUS	4	1998	2358.0	124.6	10068994.3	69.1	4772420521.5	23.5	8.3	12.5	903.1
BELARUS	4	1999	2333.0	122.8	10035001.2	69.5	3761703160.5	24.6	7.8	11.1	114.7
BELARUS	4	2000	2303.0	104.1	10004995.9	70.0	3879047652.2	25.1	7.2	11.4	149.5
BELARUS	4	2001	2296.0	127.1	9928007.5	70.5	3692183299.1	25.6	6.4	11.0	86.1
BELARUS	4	2002	2268.0	122.6	9864999.3	70.9	4247659107.9	26.4	6.8	10.8	148.7
BELARUS	4	2003	2297.0	125.2	9797008.0	71.4	5030250293.7	27.3	7.2	10.9	117.6
BELARUS	4	2004	2342.0	122.2	9730004.8	71.9	6268958316.1	29.9	7.6	11.2	101.1
BELARUS	4	2005	2380.0	121.8	9662999.1	72.4	7947547520.2	31.2	8.2	10.5	100.0
BELARUS	4	2006	2448.0	125.2	9603998.9	72.8	9490313179.3	32.0	9.3	10.0	106.4
BELARUS	4	2007	2468.0	115.7	9560008.2	73.3	11193161853.6	32.3	10.4	9.8	119.7
BOSNIA	5	1994	296.0	90.7	3659408.4	39.4	621158611.3	15.1	7.6	22.1	
BOSNIA	5	1995	310.0	96.7	3520994.5	39.4	903523628.6	15.4	7.7	21.3	
BOSNIA	5	1996	355.0	104.3	3485573.6	39.4	1073669180.5	15.3	7.5	24.5	
BOSNIA	5	1997	419.0	96.8	3535999.2	39.4	1437306452.7	14.8	7.4	20.4	
BOSNIA	5	1998	494.0	101.1	3640819.7	39.3	1588554738.0	16.1	8.3	18.9	64.7
BOSNIA	5	1999	467.0	94.0	3752002.4	39.3	1945376697.4	13.1	6.1	14.3	91.6
BOSNIA	5	2000	504.0	88.8	3834365.1	39.3	2237065814.7	12.4	6.8	10.0	73.6
BOSNIA	5	2001	545.0	92.7	3879352.5	39.3	2237488279.8	12.5	6.3	10.5	91.7
BOSNIA	5	2002	584.0	88.1	3897578.9	39.3	2550855601.9	12.8	5.8	11.1	101.2
BOSNIA	5	2003	620.0	107.9	3895780.3	39.2	3147477955.4	12.7	5.7	10.0	109.6
BOSNIA	5	2004	636.0	95.3	3886721.8	39.2	3658813750.7	12.6	5.5	10.9	118.1
BOSNIA	5	2005	665.0	100.2	3879829.8	39.2	3820212667.0	12.9	5.8	11.1	100.0
BOSNIA	5	2006	668.0	92.9	3875155.7	39.2	4043770315.0	14.1	5.5	11.1	108.9
BOSNIA	5	2007	667.0	94.0	3868664.2	39.2	4828188198.2	14.8	5.8	10.6	124.8
BULGARIA	6	1994	2279.0	93.0	8443591.8	67.6	4878294948.7	16.9	5.2	8.1	1224.2
BULGARIA	6	1995	2467.0	98.8	8406070.5	67.8	6526684775.7	17.2	5.1	8.8	1159.7
BULGARIA	6	1996	2571.0	103.9	8362828.0	68.0	4508640032.1	14.3	4.2	8.4	840.2
BULGARIA	6	1997	2315.0	100.4	8312067.7	68.2	4737675303.3	14.6	3.9	11.9	39.4
BULGARIA	6	1998	2248.0	99.5	8256787.1	68.5	5521467757.6	15.9	5.4	12.1	41.9
BULGARIA	6	1999	2046.0	93.5	8210623.7	68.7	5062214587.4	15.4	6.6	13.9	47.7
BULGARIA	6	2000	2086.0	93.1	8170170.8	68.9	4744819413.4	16.7	6.3	11.8	54.0
BULGARIA	6	2001	2115.0	94.7	8020279.5	69.2	4940461031.5	17.0	6.4	11.4	53.2
BULGARIA	6	2002	2071.0	91.8	7868469.3	69.5	5468341510.2	17.0	6.3	11.4	50.3
BULGARIA	6	2003	2162.0	107.7	7823559.2	69.9	6793218485.7	17.8	6.2	10.8	69.2
BULGARIA	6	2004	2142.0	90.3	7781161.0	70.2	8110375947.2	17.6	6.2	10.7	75.0
BULGARIA	6	2005	2212.0	95.1	7739900.4	70.6	8857965786.5	17.4	6.5	9.3	100.0
BULGARIA	6	2006	2312.0	94.7	7699020.1	70.9	9660470693.3	17.5	7.0	8.6	97.7
BULGARIA	6	2007	2340.0	94.3	7545335.3	71.3	11760823235.7	18.5	7.4	5.9	93.2
CROATIA	7	1994	825.0	82.4	4650000.5	54.8		20.9	5.1	6.8	115.0
CROATIA	7	1995	853.0	86.3	4669001.5	54.9	14814536624.1	17.3	5.8	6.6	124.2
CROATIA	7	1996	884.0	93.9	4493999.0	55.0	15215949897.6	16.4	6.6	6.3	114.7
CROATIA	7	1997	951.0	86.9	4572001.4	55.2	14967710283.4	16.3	7.1	6.1	97.6
CROATIA	7	1998	954.0	90.5	4500998.9	55.3	15841349731.1	16.1	6.8	6.4	91.7
CROATIA	7	1999	1007.0	85.9	4553998.8	55.4	14504573783.8	16.7	6.1	6.1	85.7
CROATIA	7	2000	1018.0	77.4	4426001.5	55.6	12989397568.6	17.4	5.8	6.1	87.9
CROATIA	7	2001	1032.0	84.3	4439999.1	55.7	13443507060.5	17.0	6.0	6.0	113.7
CROATIA	7	2002	1092.0	80.3	4439999.1	55.9	15050874307.9	17.0	6.1	6.0	63.6
CROATIA	7	2003	1116.0	99.4	4439999.1	56.0	19123665376.7	16.7	7.2	5.3	82.3
CROATIA	7	2004	1178.0	87.2	4438999.9	56.2	22264506485.7	16.8	7.8	5.6	100.0
CROATIA	7	2005	1240.0	90.6	4441998.2	56.4	23870934593.3	16.6	8.2	5.3	100.0
CROATIA	7	2006	1297.0	83.9	4439999.1	56.6	25371685370.9	16.4	8.4	5.5	103.1
CROATIA	7	2007	1323.0	82.2	4435999.5	56.8	28647798615.5	16.6	8.4	5.0	109.2

ESTONIA	8	1994	412.0	143.8	1462513.8	70.5	2888337719.4	14.4	6.4	7.2	40.5
ESTONIA	8	1995	392.0	133.3	1436634.1	70.3	3081911690.1	15.3	7.0	7.1	59.0
ESTONIA	8	1996	420.0	149.6	1415594.6	70.1	3165376586.1	14.9	7.3	6.7	51.1
ESTONIA	8	1997	444.0	137.6	1399534.8	69.9	3316615559.1	15.3	7.5	6.3	49.1
ESTONIA	8	1998	443.0	141.9	1386156.0	69.7	3707489611.7	15.2	8.4	6.0	54.8
ESTONIA	8	1999	415.0	129.9	1380620.2	69.5	3696636688.2	15.0	7.0	5.3	53.0
ESTONIA	8	2000	431.0	123.5	1379342.4	69.4	3586266980.0	16.3	7.5	5.6	60.9
ESTONIA	8	2001	444.0	138.3	1373510.2	69.2	3857834644.1	17.5	7.1	4.8	65.8
ESTONIA	8	2002	459.0	132.7	1367508.4	69.1	4292469734.8	17.8	7.5	4.6	64.7
ESTONIA	8	2003	481.0	139.3	1361565.2	69.0	5537910608.0	17.9	7.7	4.6	72.8
ESTONIA	8	2004	509.0	134.5	1356153.5	68.9	6527643420.3	17.4	7.8	4.0	88.0
ESTONIA	8	2005	519.0	134.4	1351231.0	68.7	7385651881.1	17.4	9.0	3.7	100.0
ESTONIA	8	2006	558.0	129.2	1346035.0	68.6	8502552079.3	17.6	8.8	3.3	101.0
ESTONIA	8	2007	584.0	126.2	1342330.2	68.5	10602769738.3	17.2	9.1	3.5	102.0
GEORGIA	9	1994	803.0	101.7	4861600.4	54.1	967213640.3	8.1	1.8	49.9	217.8
GEORGIA	9	1995	568.0	93.3	4734000.7	53.8	977201018.9	9.9	2.4	33.7	181.3
GEORGIA	9	1996	435.0	101.9	4616098.2	53.6	1112648960.4	17.1	2.7	26.4	104.1
GEORGIA	9	1997	490.0	101.6	4531600.6	53.4	1204902093.0	16.4	3.8	25.6	107.6
GEORGIA	9	1998	542.0	96.7	4487301.0	53.1	1234085022.5	14.7	4.9	23.0	117.3
GEORGIA	9	1999	547.0	96.8	4452499.4	52.9	940250916.4	14.1	3.8	24.0	84.4
GEORGIA	9	2000	541.0	101.8	4418300.7	52.6	986916861.2	14.3	3.9	21.1	118.9
GEORGIA	9	2001	453.0	96.4	4386401.3	52.4	1025755621.9	13.4	4.1	21.6	108.5
GEORGIA	9	2002	464.0	98.6	4357000.4	52.3	1070522142.5	14.3	5.5	20.1	159.0
GEORGIA	9	2003	490.0	102.8	4328898.6	52.4	1245043392.9	13.7	7.2	19.8	105.0
GEORGIA	9	2004	506.0	96.9	4318301.7	52.4	1548240760.4	14.0	9.3	17.3	92.8
GEORGIA	9	2005	531.0	102.3	4361398.8	52.5	1930543255.9	14.1	9.4	17.2	100.0
GEORGIA	9	2006	488.0	106.9	4397999.9	52.5	2262123588.6	15.0	9.3	13.9	140.2
GEORGIA	9	2007	502.0	103.0	4388401.3	52.6	2863205161.2	15.6	9.6	12.9	167.7
HUNGARY	10	1994	2372.0	94.3	10343361.5	65.3	30975006056.8	15.5	4.7	4.5	55.7
HUNGARY	10	1995	2386.0	95.3	10328969.7	65.2	32233062228.4	16.8	4.9	4.6	65.6
HUNGARY	10	1996	2467.0	104.2	10311234.4	65.1	31610402297.5	17.6	4.6	4.8	67.0
HUNGARY	10	1997	2480.0	97.1	10290486.9	65.0	30645917712.5	19.5	4.8	4.6	78.0
HUNGARY	10	1998	2492.0	96.1	10266569.1	64.8	30723934094.5	20.5	5.0	4.6	81.9
HUNGARY	10	1999	2489.0	96.3	10237531.0	64.7	30602985300.9	21.2	5.1	4.6	85.5
HUNGARY	10	2000	2532.0	86.2	10210970.5	64.6	28699645278.5	21.0	5.4	4.0	82.5
HUNGARY	10	2001	2627.0	95.8	10187567.9	64.7	30035751327.5	21.3	5.6	4.4	81.1
HUNGARY	10	2002	2708.0	94.0	10158617.6	65.1	36319561958.8	21.7	6.0	3.5	82.6
HUNGARY	10	2003	2700.0	113.2	10129556.5	65.5	45621977496.4	22.5	5.7	3.5	90.1
HUNGARY	10	2004	2736.0	93.9	10107150.1	65.9	55128731498.2	22.8	5.5	5.0	97.7
HUNGARY	10	2005	2781.0	97.7	10087063.3	66.4	59707936607.0	23.0	5.7	4.5	100.0
HUNGARY	10	2006	2858.0	94.9	10071376.0	66.9	58846978680.1	23.6	5.3	4.0	103.2
HUNGARY	10	2007	2902.0	92.3	10055770.7	67.4	69153119077.1	25.3	5.0	3.2	111.9
KAZAKHSTAN	11	1994	4955.0	162.9	16095210.3	55.9	5706666957.8	14.6	8.0	15.3	1126.9
KAZAKHSTAN	11	1995	4438.0	148.3	15815633.6	55.9	5362257131.4	14.9	5.4	12.6	310.9
KAZAKHSTAN	11	1996	3933.0	171.6	15577890.9	55.9	5384517754.2	15.2	4.2	12.0	209.4
KAZAKHSTAN	11	1997	3344.0	148.8	15333716.4	56.0	5565038500.6	15.9	4.5	11.7	225.9
KAZAKHSTAN	11	1998	3110.0	170.1	15071304.8	56.0	5493221420.1	15.6	5.6	9.6	260.8
KAZAKHSTAN	11	1999	3143.0	148.9	14928427.7	55.9	4126374651.2	15.5	5.9	11.4	164.0
KAZAKHSTAN	11	2000	3026.0	153.1	14883620.5	55.7	4313562561.4	16.4	6.2	10.2	122.2
KAZAKHSTAN	11	2001	3347.0	152.0	14858348.0	55.5	5126538592.1	16.3	7.0	10.5	112.8
KAZAKHSTAN	11	2002	3395.0	140.7	14858943.1	55.3	5590912898.5	16.1	7.6	9.9	118.4
KAZAKHSTAN	11	2003	3607.0	154.2	14909021.2	55.1	6868734159.9	15.9	7.6	9.2	115.0
KAZAKHSTAN	11	2004	3720.0	145.7	15012976.9	54.9	9372790865.3	15.9	7.9	8.4	107.6
KAZAKHSTAN	11	2005	5226.0	153.5	15147039.5	54.7	12125360314.6	15.4	10.0	8.1	100.0
KAZAKHSTAN	11	2006	5610.0	150.5	15308088.5	54.5	16792833584.6	14.9	12.3	7.7	109.9
KAZAKHSTAN	11	2007	5976.0	147.9	15484193.4	54.3	21698282784.4	14.4	12.8	7.6	131.4
KYRGYZSTAN	12	1994	719.0	171.7	4515100.3	36.6	437369056.7	19.0	2.8	27.9	313.7
KYRGYZSTAN	12	1995	790.0	169.0	4560400.6	36.3	395158654.8	12.0	5.1	31.0	295.5
KYRGYZSTAN	12	1996	754.0	173.2	4628401.2	36.1	405735026.3	11.6	5.0	35.1	503.9
KYRGYZSTAN	12	1997	707.0	156.7	4696398.9	35.8	387087874.1	17.1	3.8	35.7	362.8
KYRGYZSTAN	12	1998	670.0	164.9	4769001.0	35.5	353643442.9	17.1	2.7	36.3	78.8
KYRGYZSTAN	12	1999	729.0	162.9	4840398.2	35.3	289099283.9	20.7	2.3	34.6	44.7
KYRGYZSTAN	12	2000	691.0	159.9	4898398.9	35.3	308698725.2	17.8	2.9	33.9	40.7
KYRGYZSTAN	12	2001	593.0	157.8	4945101.3	35.3	337099619.0	18.4	2.8	34.4	56.2
KYRGYZSTAN	12	2002	567.0	157.7	4990701.9	35.3	347285247.8	16.5	2.9	35.7	123.2
KYRGYZSTAN	12	2003	692.0	158.6	5043298.3	35.3	406111304.9	18.2	2.6	34.5	117.7
KYRGYZSTAN	12	2004	600.0	146.9	5104699.0	35.3	449453078.3	17.6	2.6	34.0	95.6
KYRGYZSTAN	12	2005	585.0	154.4	5162601.3	35.3	479746127.1	14.8	3.1	33.0	100.0
KYRGYZSTAN	12	2006	590.0	150.3	5218397.7	35.3	531308154.8	12.4	3.6	32.8	102.6
KYRGYZSTAN	12	2007	632.0	147.1	5268402.3	35.3	693658650.9	12.2	4.5	30.8	121.8
LATVIA	13	1994	379.0	132.0	2520741.5	68.9	2863297987.8	14.8	3.0	5.9	71.2
LATVIA	13	1995	384.0	120.7	2485054.8	68.8	2892345582.1	14.9	2.7	6.4	99.2
LATVIA	13	1996	356.0	140.4	2457223.0	68.6	3034825609.5	14.9	2.8	5.7	100.5
LATVIA	13	1997	360.0	128.0	2432851.5	68.6	3284183914.0	16.0	3.2	5.7	105.9
LATVIA	13	1998	387.0	126.6	2410020.0	68.5	3542944613.3	15.7	4.6	5.1	104.4
LATVIA	13	1999	384.0	120.1	2390483.0	68.2	3806458742.7	14.6	5.4	4.7	103.5
LATVIA	13	2000	385.0	109.1	2367550.1	68.1	4187552033.8	14.3	5.9	5.2	96.3
LATVIA	13	2001	394.0	127.7	2337170.6	67.9	4261389424.3	14.4	5.4	5.3	92.5
LATVIA	13	2002	420.0	124.5	2310173.0	67.8	4636461989.2	15.1	5.6	5.3	93.6
LATVIA	13	2003	447.0	129.0	2287956.0	67.8	5562152163.1	14.4	5.4	4.7	99.4
LATVIA	13	2004	465.0	123.9	2263121.4	67.9	6698712629.3	14.4	6.0	4.6	108.1
LATVIA	13	2005	493.0	125.5	2238799.7	68.0	7805952885.4	13.6	6.6	4.4	100.0
LATVIA	13	2006	528.0	121.2	2218356.2	68.0	9422819116.2	13.1	9.4	3.8	97.3
LATVIA	13	2007	568.0	115.3	2200324.7	67.9	13205708299.6	11.7	13.4	3.7	104.2
LITHUANIA	14	1994	560.0	124.0	3657144.1	67.3	3980295461.3	20.0	7.1	7.9	
LITHUANIA	14	1995	547.0	117.7	3629102.8	67.3	4130429939.2	17.3	7.4	8.7	52.0
LITHUANIA	14	1996	561.0	133.9	3601613.0	67.2	4321913323.0	17.3	7.4	9.2	47.7
LITHUANIA	14	1997	579.0	123.4	3575136.0	67.2	5182518541.6	17.4	7.4	9.2	60.2
LITHUANIA	14	1998	581.0	115.8	3549330.9	67.1	5720398055.3	18.3	8.1	8.0	57.3
LITHUANIA	14	1999	563.0	115.3	3524236.3	67.0	5584731259.2	17.8	7.3	6.8	56.8
LITHUANIA	14	2000	533.0	98.1	3499536.1	67.0	5669216717.0	19.1	6.0	6.9	62.4
LITHUANIA	14	2001	554.0	121.5	3470819.3	66.9	6053756648.9	19.6	5.9	5.9	63.6
LITHUANIA	14	2002	578.0	117.6	3443067.0	66.8	6875248463.6	19.2	6.4	5.9	79.5
LITHUANIA	14	2003	617.0	122.2	3415214.2	66.7	8674947752.5	20.0	7.2	5.8	95.7
LITHUANIA	14	2004	658.0	118.3	3377074.3	66.6	10537750160.3	20.9	7.6	5.4	97.6
LITHUANIA	14	2005	686.0	118.6	3322527.4	66.6	12068830569.5	21.2	8.2	5.0	100.0
LITHUANIA	14	2006	725.0	118.4	3269909.1	66.7	13382465603.9	21.6	9.7	4.2	86.0
LITHUANIA	14	2007	762.0	110.5	3231292.7	66.8	17204677130.6	20.3	11.2	4.2	97.4
MACEDONIA	15	1994	412.0	91.0	1968851.5	59.8	1410205591.1	14.7	7.5	14.7	87.2
MACEDONIA	15	1995	427.0	96.6	1967012.3	59.6	1860463375.0	13.1	7.3	14.9	77.2
MACEDONIA	15	1996	446.0	101.3	1975206.3	59.4	1817400444.9	13.6	7.1	14.4	83.1
MACEDONIA	15	1997	459.0	99.0	1991687.4	59.2	1543081564.6	13.6	6.9	13.8	93.7
MACEDONIA	15	1998	470.0	100.9	2013117.1	59.0	1451090311.8	13.2	7.2	13.8	98.1
MACEDONIA	15	1999	440.0	97.3	2034486.4	58.8	1485068491.0	12.9	7.5	13.3	88.0
MACEDONIA	15	2000	448.0	95.6	2052129.4	58.5	1393390788.9	13.8	7.5	13.0	132.5
MACEDONIA	15	2001	432.0	94.9	2065098.6	58.3	1297993023.0	13.7	6.7	12.1	97.4
MACEDONIA	15	2002	428.0	95.6	2074441.0	58.1	1397196463.8	13.3	6.7	12.1	109.2
MACEDONIA	15	2003	490.0	106.7	2080866.6	57.9	1678975058.6	13.7	6.7	12.1	112.6
MACEDONIA	15	2004	496.0	92.8	2085728.3	57.7	1863816212.7	14.1	6.7	12.1	116.1
MACEDONIA	15	2005	536.0	99.6	2090043.2	57.5	1879247786.2	12.0	6.6	12.1	100.0
MACEDONIA	15	2006	554.0	98.9	2093801.8	57.4	1923310217.3	15.1	6.8	12.0	112.3
MACEDONIA	15	2007	580.0	97.9	2096619.2	57.2	2334883957.9	15.2	6.8	12.1	122.7

MOLDOVA	16	1994	653.0	101.8	3693998.5	46.4	565988976.6	16.8	5.1	20.1	416.4
MOLDOVA	16	1995	619.0	109.2	3675097.5	46.3	525204369.5	17.4	4.3	21.2	238.8
MOLDOVA	16	1996	584.0	120.5	3667748.2	46.2	516977023.8	17.4	4.7	18.9	187.3
MOLDOVA	16	1997	549.0	111.0	3654208.6	46.1	567419008.0	15.2	4.0	21.3	253.8
MOLDOVA	16	1998	510.0	106.1	3652731.3	46.0	489230668.0	13.2	3.5	20.8	260.5
MOLDOVA	16	1999	467.0	104.8	3647002.0	45.9	356320583.8	12.5	3.7	20.0	158.4
MOLDOVA	16	2000	470.0	95.8	3639590.8	45.8	362378734.2	15.0	2.7	21.2	109.8
MOLDOVA	16	2001	580.0	106.1	3631460.4	45.7	402608289.1	15.0	3.1	21.7	130.2
MOLDOVA	16	2002	604.0	104.0	3623061.4	45.6	443492961.8	14.4	3.1	21.2	142.7
MOLDOVA	16	2003	621.0	119.6	3612872.5	45.5	506403717.6	16.3	3.5	18.1	119.3
MOLDOVA	16	2004	555.0	99.6	3603945.9	45.4	648049927.5	16.3	4.1	20.3	113.7
MOLDOVA	16	2005	578.0	102.8	3595185.4	45.3	704711213.1	16.0	4.0	19.6	100.0
MOLDOVA	16	2006	601.0	106.3	3585208.3	45.2	765784502.7	14.8	4.6	18.5	85.6
MOLDOVA	16	2007	548.0	104.6	3576909.4	45.1	946906307.4	14.5	5.5	11.9	92.4
MONGOLIA	17	1994	160.0	190.3	2280518.9	56.9	191421113.2	8.7	2.7	42.4	
MONGOLIA	17	1995	164.0	189.0	2298063.3	56.8	290397458.7	11.0	2.9	42.1	
MONGOLIA	17	1996	166.0	200.7	2316597.5	56.8	273727274.5	8.9	2.8	41.5	
MONGOLIA	17	1997	162.0	188.4	2335722.2	56.7	225781620.7	7.8	2.7	43.5	
MONGOLIA	17	1998	166.0	180.6	2355618.0	56.7	211572498.5	7.8	2.6	45.1	
MONGOLIA	17	1999	161.0	188.9	2376197.7	56.6	196941498.4	7.3	2.6	45.5	
MONGOLIA	17	2000	164.0	205.7	2397473.8	57.1	194532746.6	7.5	2.3	40.3	
MONGOLIA	17	2001	168.0	200.0	2419669.5	58.2	202892956.5	10.3	2.6	33.1	126.4
MONGOLIA	17	2002	175.0	196.3	2443230.7	59.3	224809172.9	12.1	3.0	27.5	128.3
MONGOLIA	17	2003	189.0	197.7	2468595.9	60.4	258136605.1	12.6	4.2	26.3	116.2
MONGOLIA	17	2004	203.0	188.9	2496247.1	61.4	298768229.9	11.6	3.8	29.0	104.7
MONGOLIA	17	2005	219.0	207.1	2526503.2	62.5	366059186.5	8.8	4.1	30.1	100.0
MONGOLIA	17	2006	232.0	188.3	2559495.0	63.5	476154371.7	9.2	3.9	29.8	99.7
MONGOLIA	17	2007	244.0	184.6	2595067.5	64.6	594335926.3	10.2	3.7	30.0	93.5
POLAND	18	1994	7338.0	103.4	38542636.2	61.4	64689713617.9	14.8	9.6	3.8	71.8
POLAND	18	1995	7713.0	108.5	38595013.8	61.5	80665813666.8	15.9	9.6	3.9	70.7
POLAND	18	1996	8162.0	118.7	38624396.9	61.5	88369606535.5	16.4	9.3	3.8	70.4
POLAND	18	1997	8305.0	109.1	38649674.1	61.6	86618905759.6	16.9	9.7	3.7	71.1
POLAND	18	1998	8355.0	101.0	38663462.1	61.6	93942189997.5	17.0	9.9	3.7	73.8
POLAND	18	1999	8263.0	99.4	38660291.0	61.7	90124401342.0	16.8	9.7	3.6	78.6
POLAND	18	2000	8484.0	85.8	38453786.6	61.7	90333155452.9	17.2	9.2	3.5	79.2
POLAND	18	2001	8494.0	109.4	38248093.0	61.8	98300836133.6	17.1	8.8	3.7	88.6
POLAND	18	2002	8388.0	103.7	38230369.9	61.8	98634014134.1	17.1	8.0	3.6	93.9
POLAND	18	2003	8702.0	110.5	38204565.4	61.7	107684094842.1	18.5	7.6	3.6	101.1
POLAND	18	2004	9001.0	102.8	38182200.9	61.6	122314502014.8	19.9	7.2	3.7	97.4
POLAND	18	2005	9066.0	104.6	38165454.4	61.5	143812236141.4	19.7	7.4	3.6	100.0
POLAND	18	2006	9553.0	106.4	38141294.2	61.3	158374001355.7	21.7	7.6	3.2	102.2
POLAND	18	2007	9850.0	96.6	38120566.6	61.2	191221066130.3	22.6	7.6	3.0	100.7
RUSSIA	19	1994	54635.0	261.7	148336069.9	73.4	187878020111.2	19.7	7.4	7.3	1322.4
RUSSIA	19	1995	53176.0	256.6	148140977.6	73.4	188299193586.4	19.5	6.2	7.0	470.8
RUSSIA	19	1996	51701.0	270.0	147738880.1	73.4	186215868306.9	19.4	5.3	6.8	410.3
RUSSIA	19	1997	50730.0	263.7	147303875.3	73.4	189312203587.2	19.5	4.9	6.8	381.4
RUSSIA	19	1998	49753.0	259.6	146899008.3	73.4	126709711385.7	19.3	4.8	5.8	252.0
RUSSIA	19	1999	50965.0	259.4	146308999.8	73.4	89127103759.8	20.2	4.9	6.5	55.3
RUSSIA	19	2000	52333.0	255.9	146302860.8	73.3	110877110240.1	20.9	5.3	6.7	37.4
RUSSIA	19	2001	53151.0	250.9	145950009.4	73.3	127041972381.8	20.9	5.6	7.2	56.5
RUSSIA	19	2002	53168.0	260.9	145300056.9	73.3	137833859479.7	20.9	5.5	7.0	71.0
RUSSIA	19	2003	54372.0	246.1	144598933.2	73.4	160269596127.8	21.3	5.8	6.5	83.3
RUSSIA	19	2004	55516.0	261.6	143849875.1	73.4	211783575522.8	21.7	6.0	6.2	91.6
RUSSIA	19	2005	55898.0	239.9	143150014.4	73.5	252246734347.2	21.4	6.2	5.8	100.0
RUSSIA	19	2006	58600.0	244.7	142500027.4	73.5	283244267969.0	20.9	6.5	5.5	108.3
RUSSIA	19	2007	60281.0	259.8	142099961.2	73.6	366344721831.2	20.5	6.7	5.0	116.7
ROMANIA	20	1994	2941.0	97.7	22730204.0	53.9	16857947933.8	22.9	7.8	14.1	712.6
ROMANIA	20	1995	3126.0	107.1	22684251.4	53.8	19232378387.6	23.1	7.9	13.9	514.4
ROMANIA	20	1996	3417.0	111.1	22619012.7	53.6	18793527019.1	23.6	8.0	13.0	335.2
ROMANIA	20	1997	3305.0	107.5	22553961.4	53.5	18453101753.1	23.2	7.0	13.8	159.3
ROMANIA	20	1998	3147.0	106.0	22507334.9	53.3	21454900118.8	23.0	7.1	13.0	148.0
ROMANIA	20	1999	2917.0	103.0	22472031.7	53.2	18375235715.2	22.3	6.9	13.1	140.3
ROMANIA	20	2000	2919.0	97.8	22442990.1	53.0	18811386719.4	23.2	6.9	10.4	100.4
ROMANIA	20	2001	3121.0	102.3	22131949.7	52.9	19061139342.3	24.6	7.3	12.8	79.3
ROMANIA	20	2002	3060.0	98.9	21730513.4	52.8	21461284974.2	24.5	7.5	11.3	87.1
ROMANIA	20	2003	3225.0	117.9	21574322.4	52.9	26668836542.9	24.6	7.5	11.4	87.4
ROMANIA	20	2004	3335.0	100.8	21451757.6	53.0	32138277430.4	25.0	7.7	12.6	82.9
ROMANIA	20	2005	3342.0	104.3	21319679.8	53.2	41107129066.0	24.8	8.2	10.0	100.0
ROMANIA	20	2006	3523.0	103.3	21193750.7	53.3	45841001186.2	25.0	9.4	9.6	107.1
ROMANIA	20	2007	3524.0	100.2	20882968.9	53.4	59296079038.7	25.2	11.6	7.7	125.9
SLOVAKIA	21	1994	1748.0	101.0	5346332.8	56.6	12600037662.7	13.1	8.8	4.6	67.1
SLOVAKIA	21	1995	1869.0	109.3	5361998.4	56.5	16321062197.6	16.0	7.3	4.1	59.9
SLOVAKIA	21	1996	2019.0	113.4	5373362.6	56.5	17024584271.9	15.7	9.7	3.8	59.5
SLOVAKIA	21	1997	1964.0	110.2	5383292.7	56.4	17079191873.7	14.9	8.7	4.0	59.8
SLOVAKIA	21	1998	1806.0	107.6	5390515.8	56.4	17615832350.6	16.4	9.1	3.9	59.0
SLOVAKIA	21	1999	1956.0	103.2	5396019.3	56.3	17731050763.5	15.1	7.7	3.3	64.0
SLOVAKIA	21	2000	1893.0	93.5	5388722.0	56.2	15951410741.4	17.3	8.1	3.5	77.4
SLOVAKIA	21	2001	2017.0	109.6	5378869.1	56.2	16182595503.2	18.9	6.9	4.1	86.5
SLOVAKIA	21	2002	1957.0	103.9	5376909.9	56.0	17845116637.3	18.5	8.3	4.4	85.6
SLOVAKIA	21	2003	1977.0	114.3	5373372.8	55.9	23068027619.3	21.1	6.9	4.4	99.6
SLOVAKIA	21	2004	2066.0	105.8	5372281.5	55.7	27190579273.1	24.0	7.1	4.2	101.7
SLOVAKIA	21	2005	1965.0	107.8	5372809.2	55.6	28856685322.3	24.9	7.2	3.8	100.0
SLOVAKIA	21	2006	2034.0	105.5	5373055.1	55.4	30882035611.8	26.0	8.0	3.8	103.5
SLOVAKIA	21	2007	2113.0	100.7	5374623.4	55.3	36695294921.0	26.3	8.2	3.9	112.0
SLOVENIA	22	1994	793.0	95.4	1989443.5	50.6	12051509394.6	22.3	6.5	3.9	113.3
SLOVENIA	22	1995	803.0	102.3	1989872.4	50.6	16710240466.1	22.0	6.8	3.8	108.9
SLOVENIA	22	1996	817.0	107.8	1988627.9	50.6	16436086158.3	22.5	7.3	3.8	99.7
SLOVENIA	22	1997	847.0	98.7	1985955.6	50.7	15515110547.1	23.1	7.3	3.9	116.5
SLOVENIA	22	1998	868.0	103.6	1981628.8	50.7	16139286954.0	22.9	7.1	3.7	112.3
SLOVENIA	22	1999	891.0	98.6	1983044.8	50.7	16295928691.0	22.5	7.7	3.3	94.8
SLOVENIA	22	2000	905.0	89.2	1988925.6	50.8	14479696445.9	23.5	7.3	3.2	75.8
SLOVENIA	22	2001	941.0	100.3	1992059.7	50.8	14652893625.4	23.6	7.0	3.1	58.8
SLOVENIA	22	2002	1005.0	93.8	1994530.9	50.8	16090661345.6	23.9	6.9	3.4	68.4
SLOVENIA	22	2003	1036.0	112.9	1995733.4	50.7	20054124294.1	24.4	7.1	2.4	84.7
SLOVENIA	22	2004	1079.0	102.0	1997012.9	50.6	22403334806.1	24.5	6.8	3.0	100.9
SLOVENIA	22	2005	1096.0	105.1	2000474.4	50.5	23314229284.0	24.6	6.8	2.7	100.0
SLOVENIA	22	2006	1132.0	100.5	2006868.1	50.4	24722998482.1	24.8	7.3	2.5	99.1
SLOVENIA	22	2007	1141.0	93.6	2018122.7	50.3	30029335775.5	25.0	8.0	2.5	100.7

TAJIKISTAN	23	1994	1232.0	159.9	5702610.6	29.4	350823778.6	27.3	5.9	21.4	
TAJIKISTAN	23	1995	1192.0	158.3	5784332.1	28.9	312503225.9	27.1	5.9	21.3	
TAJIKISTAN	23	1996	1171.0	156.4	5862347.4	28.3	258148913.4	25.0	6.6	21.1	
TAJIKISTAN	23	1997	1031.0	146.7	5937178.3	27.8	222017649.7	24.3	6.5	21.7	
TAJIKISTAN	23	1998	1067.0	150.6	6012935.6	27.3	315185584.4	24.9	6.3	21.9	58.7
TAJIKISTAN	23	1999	1137.0	144.6	6094661.9	26.8	257710577.4	25.0	6.5	21.6	184.3
TAJIKISTAN	23	2000	1141.0	149.5	6186153.6	26.5	189461462.9	29.1	3.0	23.7	138.8
TAJIKISTAN	23	2001	1150.0	146.1	6289338.7	26.5	235625853.9	29.1	4.8	23.0	125.1
TAJIKISTAN	23	2002	1169.0	144.1	6404119.2	26.4	254685811.1	30.1	3.6	24.4	111.5
TAJIKISTAN	23	2003	1189.0	118.3	6529607.2	26.4	326016010.5	28.9	5.0	23.6	134.2
TAJIKISTAN	23	2004	1212.0	107.7	6663931.5	26.4	422313910.8	25.8	4.7	24.8	107.3
TAJIKISTAN	23	2005	1248.0	122.8	6805651.8	26.4	457843316.6	25.6	5.1	23.8	100.0
TAJIKISTAN	23	2006	1262.0	127.6	6954523.3	26.4	541904053.1	25.0	5.1	23.5	90.9
TAJIKISTAN	23	2007	1266.0	130.6	7111024.1	26.5	687942942.5	21.4	5.3	23.4	120.5
TURKMENISTAN	24	1994	433.0	106.8	4095510.3	44.7	1611322649.3	40.6	6.9	33.2	
TURKMENISTAN	24	1995	430.0	109.0	4188008.9	44.8	1479101018.2	58.7	6.1	17.0	
TURKMENISTAN	24	1996	403.0	116.9	4267690.8	45.0	1403569497.8	59.5	10.8	13.2	
TURKMENISTAN	24	1997	335.0	114.5	4335992.8	45.2	1398289512.8	37.0	12.1	21.4	
TURKMENISTAN	24	1998	450.0	114.5	4395291.2	45.5	1486888100.9	31.7	13.8	26.6	400.9
TURKMENISTAN	24	1999	414.0	100.2	4449426.2	45.7	1431560936.7	30.4	12.4	25.2	202.9
TURKMENISTAN	24	2000	502.0	115.5	4501419.6	45.9	1649571823.0	33.7	6.9	23.4	187.8
TURKMENISTAN	24	2001	534.0	109.2	4551762.7	46.1	1888925356.8	35.2	5.8	25.2	168.3
TURKMENISTAN	24	2002	537.0	104.8	4600171.9	46.4	2323413436.2	33.0	8.3	22.4	123.8
TURKMENISTAN	24	2003	532.0	104.4	4648036.4	46.6	3020498346.1	33.2	6.8	20.7	117.2
TURKMENISTAN	24	2004	590.0	97.4	4696873.7	46.8	3372052546.0	32.3	6.7	19.8	110.7
TURKMENISTAN	24	2005	639.0	110.6	4747840.4	47.0	4047381557.7	29.9	6.6	19.1	100.0
TURKMENISTAN	24	2006	666.0	116.4	4801594.2	47.3	4984321585.9	29.0	6.1	17.8	92.5
TURKMENISTAN	24	2007	717.0	109.5	4858235.5	47.6	5989942382.0	30.5	6.5	19.4	87.0
UKRAINE	25	1994	12920.0	112.3	51921005.2	66.9	15569211356.0	17.4	10.7	12.8	1324.6
UKRAINE	25	1995	12341.0	114.3	51512334.9	67.0	13775179048.8	17.9	8.4	14.2	534.3
UKRAINE	25	1996	11111.0	127.4	51057190.8	67.0	12231444000.1	19.5	6.3	14.5	462.2
UKRAINE	25	1997	10677.0	120.3	50594101.2	67.0	13309992821.2	19.9	6.0	15.1	320.0
UKRAINE	25	1998	10165.0	116.3	50143914.0	67.1	11050420627.2	20.2	6.0	13.6	267.2
UKRAINE	25	1999	9896.0	112.0	49673377.8	67.1	8094303826.9	21.8	5.7	13.3	169.5
UKRAINE	25	2000	9760.0	103.0	49175825.1	67.1	7670171868.8	22.0	5.2	14.4	117.6
UKRAINE	25	2001	9264.0	114.4	48683906.4	67.2	9554298835.5	21.7	4.9	13.8	116.0
UKRAINE	25	2002	9340.0	110.4	48202516.2	67.3	10604630475.6	22.5	4.6	13.2	135.5
UKRAINE	25	2003	9819.0	121.7	47812990.1	67.4	12666784239.2	23.4	5.1	10.4	133.8
UKRAINE	25	2004	10323.0	106.3	47451585.2	67.6	16331369590.4	22.8	5.4	10.9	122.7
UKRAINE	25	2005	10587.0	108.4	47105129.5	67.8	20320376336.9	22.9	4.8	11.0	100.0
UKRAINE	25	2006	11149.0	116.9	46787789.1	68.0	24528590664.0	23.3	4.5	10.5	121.0
UKRAINE	25	2007	11613.0	110.0	46509386.9	68.1	32214869544.4	23.3	4.7	9.0	130.0
UZBEKISTAN	26	1994	3286.0	125.8	22376993.9	38.8	2957419279.6	24.3	6.6	28.5	
UZBEKISTAN	26	1995	3260.0	116.3	22784983.1	38.4	2924135300.0	23.8	6.6	30.1	
UZBEKISTAN	26	1996	3310.0	131.4	23224983.7	38.1	2945226437.8	24.3	6.6	28.4	
UZBEKISTAN	26	1997	3349.0	118.6	23666979.6	37.8	3069346102.7	23.5	6.4	28.5	262.3
UZBEKISTAN	26	1998	3336.0	126.6	24051008.3	37.7	3058849739.1	22.9	6.3	28.7	227.3
UZBEKISTAN	26	1999	3308.0	112.0	24311642.5	37.6	3435033654.2	22.5	6.1	29.0	111.2
UZBEKISTAN	26	2000	3420.0	121.4	24650401.1	37.4	2694394632.7	22.2	6.1	29.0	51.9
UZBEKISTAN	26	2001	3409.0	116.8	24964435.7	37.3	2176596075.1	22.0	6.0	29.0	56.5
UZBEKISTAN	26	2002	3497.0	110.0	25271864.5	37.1	1829849189.0	21.8	5.9	29.5	49.4
UZBEKISTAN	26	2003	3503.0	115.1	25567664.1	37.0	1885865417.7	21.4	5.9	30.0	58.2
UZBEKISTAN	26	2004	3546.0	109.1	25864360.6	36.8	2182782334.1	20.9	5.7	30.7	84.6
UZBEKISTAN	26	2005	3490.0	121.5	26166995.5	36.7	2498070348.0	20.6	5.6	30.6	100.0
UZBEKISTAN	26	2006	3612.0	120.9	26488273.4	36.5	2867495363.3	20.2	5.5	30.5	88.8
UZBEKISTAN	26	2007	3472.0	117.8	26868018.1	36.4	3624597990.8	19.9	5.4	29.8	92.7
UNITED KINGDOM	27	1994	24447.0	100.7	57865751.1	78.3	1440124134046.4	16.4	7.9	0.9	118.9
UNITED KINGDOM	27	1995	25346.0	97.9	58019037.1	78.4	1564319686035.1	16.1	7.7	0.8	115.2
UNITED KINGDOM	27	1996	26605.0	108.2	58166959.8	78.4	1586437623267.4	15.9	7.7	0.8	110.8
UNITED KINGDOM	27	1997	26763.0	95.7	58316928.0	78.5	1684578314574.1	15.8	7.5	0.8	103.0
UNITED KINGDOM	27	1998	27148.0	99.0	58487136.6	78.5	1789305479123.7	15.4	7.4	0.7	98.3
UNITED KINGDOM	27	1999	27756.0	96.2	58682460.4	78.6	1818467719413.9	15.0	7.3	0.8	96.5
UNITED KINGDOM	27	2000	28330.0	99.1	58892476.7	78.7	1715141962348.1	14.8	7.1	0.7	90.5
UNITED KINGDOM	27	2001	28614.0	102.6	59107978.9	78.8	1646770214857.7	14.3	7.0	0.6	88.3
UNITED KINGDOM	27	2002	28672.0	95.7	59362074.9	79.0	1758892402298.9	13.6	7.3	0.7	87.0
UNITED KINGDOM	27	2003	28915.0	95.5	59637734.4	79.3	2044577719564.5	12.9	7.3	0.7	85.3
UNITED KINGDOM	27	2004	29149.0	95.9	59978360.7	79.6	2320095698246.0	12.8	7.5	0.6	88.7
UNITED KINGDOM	27	2005	29986.0	96.5	60388046.0	79.9	2391051181326.1	12.4	7.1	0.7	100.0
UNITED KINGDOM	27	2006	29690.0	93.5	60828368.2	80.2	2459847076706.2	12.3	6.9	0.6	119.3
UNITED KINGDOM	27	2007	29382.0	95.1	61296915.4	80.5	2824944657303.5	12.1	6.9	0.6	119.4
FRANCE	28	1994	29024.0	73.2	59325741.0	74.7	1802118530241.4	12.8	6.4	2.1	130.4
FRANCE	28	1995	29485.0	76.9	59540670.8	74.9	2027823345253.1	13.1	6.3	2.1	126.7
FRANCE	28	1996	30602.0	82.2	59752048.9	75.1	1993896100415.4	13.0	6.0	2.2	126.3
FRANCE	28	1997	30569.0	71.1	59963833.9	75.3	1761665668537.2	13.3	5.7	2.2	117.9
FRANCE	28	1998	31600.0	75.8	60185207.7	75.4	1786819268196.8	13.5	5.5	2.2	114.4
FRANCE	28	1999	32246.0	75.2	60495490.3	75.6	1754225351068.2	13.6	5.5	2.2	111.6
FRANCE	28	2000	33102.0	69.5	60911031.0	75.9	1539858615465.2	13.7	5.7	2.1	105.1
FRANCE	28	2001	34037.0	76.5	61355751.9	76.1	1490109897682.6	13.7	5.8	2.0	103.7
FRANCE	28	2002	33840.0	68.5	61803248.1	76.4	1557944593243.7	13.5	5.7	2.1	103.1
FRANCE	28	2003	35122.0	85.2	62242491.0	76.6	1947685245873.4	13.7	5.6	1.8	103.4
FRANCE	28	2004	36134.0	77.8	62702075.7	76.9	2212318507598.8	13.7	5.6	2.1	102.9
FRANCE	28	2005	36358.0	80.1	63176258.4	77.1	2211799558552.0	13.7	5.6	1.9	100.0
FRANCE	28	2006	36716.0	78.6	63617979.2	77.4	2235559258032.4	13.7	5.6	1.9	99.5
FRANCE	28	2007	36637.0	69.0	64012587.4	77.6	2474689575394.7	13.6	5.7	1.8	113.3
GERMANY	29	1994	38147.0	93.0	81438348.4	73.3	2626316447314.4	22.9	6.9	0.9	109.7
GERMANY	29	1995	38804.0	101.4	81678065.7	73.3	3028706419396.1	22.3	6.5	0.9	107.4
GERMANY	29	1996	39419.0	111.0	81914895.8	73.2	2870274024321.7	21.5	6.1	0.9	97.8
GERMANY	29	1997	39709.0	97.8	82034819.2	73.2	2535961598901.8	21.9	5.9	0.9	96.1
GERMANY	29	1998	40087.0	89.0	82047181.2	73.1	2541132744629.9	21.7	5.6	0.9	94.5
GERMANY	29	1999	40719.0	90.2	82100249.2	73.1	2449476685708.6	21.5	5.4	1.0	89.4
GERMANY	29	2000	41577.0	81.4	82211506.3	73.1	2164671621721.9	22.4	5.2	0.9	77.5
GERMANY	29	2001	42593.0	97.1	82349925.5	73.1	2120828139128.1	22.3	4.8	0.8	81.8
GERMANY	29	2002	43732.0	91.1	82488421.0	73.2	2196936706811.5	21.8	4.6	0.8	84.8
GERMANY	29	2003	44257.0	102.6	82534218.1	73.2	2541249054937.3	22.2	4.4	0.9	92.2
GERMANY	29	2004	44829.0	93.7	82516273.8	73.3	2768725826869.6	22.8	4.2	1.1	94.2
GERMANY	29	2005	44915.0	91.0	82469385.7	73.4	2701324947849.0	23.0	4.0	0.8	100.0
GERMANY	29	2006	45405.0	95.0	82376475.3	73.5	2740501530754.4	23.9	3.8	0.7	104.4
GERMANY	29	2007	45525.0	82.1	82266406.6	73.7	3074137499882.9	24.1	3.7	0.9	109.7

CZECH REPUBLIC	30	1994	3867.0	103.2	10333580.8	74.8	33367376229.7	16.3	10.8	3.2	90.2
CZECH REPUBLIC	30	1995	4135.0	111.3	10327255.9	74.6	40247203092.0	17.2	11.2	2.7	84.0
CZECH REPUBLIC	30	1996	4324.0	122.1	10315247.3	74.5	42901064667.6	18.9	11.2	2.5	79.6
CZECH REPUBLIC	30	1997	4269.0	109.6	10304137.1	74.4	38273912297.7	20.1	9.9	2.4	80.0
CZECH REPUBLIC	30	1998	4203.0	102.5	10294373.9	74.3	40770741866.7	20.6	9.4	2.5	86.9
CZECH REPUBLIC	30	1999	4138.0	102.4	10283854.9	74.1	38887689026.0	21.8	8.1	2.6	90.2
CZECH REPUBLIC	30	2000	4247.0	93.4	10255061.4	74.0	36250561217.9	23.1	7.2	2.5	93.4
CZECH REPUBLIC	30	2001	4376.0	110.2	10216600.5	73.9	37750524628.9	23.4	6.9	2.4	92.7
CZECH REPUBLIC	30	2002	4371.0	103.0	10196918.6	73.8	44873144288.6	24.0	7.0	2.3	96.6
CZECH REPUBLIC	30	2003	4507.0	113.8	10194001.6	73.7	52362851708.6	23.7	7.0	2.3	93.8
CZECH REPUBLIC	30	2004	4630.0	106.1	10197093.6	73.7	60958194493.7	24.8	7.3	2.5	94.9
CZECH REPUBLIC	30	2005	4755.0	106.3	10211223.6	73.6	69496776003.3	27.0	7.1	2.6	100.0
CZECH REPUBLIC	30	2006	4903.0	107.5	10238898.1	73.5	77245560359.6	30.4	6.6	2.2	107.8
CZECH REPUBLIC	30	2007	4922.0	97.0	10298832.0	73.5	90186477867.5	30.8	6.5	1.6	113.5
FINLAND	31	1994	5594.0	176.3	5088333.9	80.7	131717550761.2	18.2	7.9	4.1	85.4
FINLAND	31	1995	5609.0	169.7	5107791.2	81.0	166699790507.7	18.8	6.8	3.9	86.1
FINLAND	31	1996	5719.0	177.0	5124570.6	81.2	165264085572.0	18.8	7.4	3.6	93.4
FINLAND	31	1997	6062.0	172.8	5139836.4	81.5	153782673250.1	19.5	7.6	3.6	90.5
FINLAND	31	1998	6264.0	183.4	5153496.1	81.7	157568310713.6	20.5	7.7	3.1	91.0
FINLAND	31	1999	6387.0	170.4	5165472.5	81.9	157062717963.6	21.6	7.1	3.0	87.4
FINLAND	31	2000	6508.0	154.8	5176207.9	82.2	142454047362.5	23.3	6.8	3.1	81.1
FINLAND	31	2001	6655.0	173.5	5188009.5	82.4	144073332446.8	23.6	6.1	2.9	82.2
FINLAND	31	2002	6852.0	172.6	5200596.8	82.5	152220243584.8	24.1	6.1	2.9	86.9
FINLAND	31	2003	6953.0	172.4	5213015.7	82.6	185762503152.2	24.5	6.4	2.8	104.5
FINLAND	31	2004	7147.0	166.2	5228171.0	82.8	204755823238.4	24.7	6.5	2.6	104.9
FINLAND	31	2005	6943.0	159.4	5246096.3	82.9	211049668825.9	25.0	6.6	2.7	100.0
FINLAND	31	2006	7397.0	163.4	5266267.4	83.0	215011617823.0	26.8	6.6	2.6	102.2
FINLAND	31	2007	7402.0	161.1	5288719.6	83.2	246364439997.8	27.8	6.4	2.6	99.5
DENMARK	32	1994	2645.0	108.4	5206179.4	85.0	226257036591.6	16.7	5.7	1.6	83.1
DENMARK	32	1995	2656.0	112.3	5233374.0	85.0	262225571442.9	17.0	5.8	1.6	81.7
DENMARK	32	1996	2725.0	126.9	5263074.1	85.0	257888969895.8	16.1	6.0	1.6	86.0
DENMARK	32	1997	2741.0	111.4	5284988.5	85.0	232309232546.8	17.0	5.6	1.6	86.4
DENMARK	32	1998	2756.0	113.2	5304221.4	85.1	232794039743.6	17.0	6.0	1.6	93.9
DENMARK	32	1999	2767.0	105.7	5321798.4	85.1	232494519580.7	16.7	6.3	1.5	93.0
DENMARK	32	2000	2791.0	103.6	5339617.0	85.1	207956061178.8	16.6	6.1	1.6	97.6
DENMARK	32	2001	2801.0	113.5	5358782.9	85.2	205360490090.3	16.7	5.6	1.6	97.8
DENMARK	32	2002	2796.0	103.9	5375930.6	85.2	212903027705.2	16.2	5.7	1.6	99.2
DENMARK	32	2003	2784.0	108.4	5390572.3	85.4	262877583819.2	15.7	5.8	1.5	101.7
DENMARK	32	2004	2836.0	107.6	5404522.1	85.6	289521865614.4	15.7	5.8	1.6	99.8
DENMARK	32	2005	2878.0	108.2	5419433.0	85.9	301464225193.9	15.4	5.8	1.4	100.0
DENMARK	32	2006	2906.0	101.9	5437272.5	86.1	306750567323.2	15.6	6.0	1.4	104.9
DENMARK	32	2007	2879.0	100.2	5461438.0	86.3	335929398057.0	15.6	5.7	1.5	100.0
AUSTRIA	33	1994	3922.0	104.8	7936121.4	65.8	234287607624.3	19.1	8.5	1.8	100.7
AUSTRIA	33	1995	4017.0	117.2	7948278.2	65.8	274471119207.0	19.5	8.3	1.7	100.1
AUSTRIA	33	1996	4155.0	123.5	7959018.8	65.8	264662580370.5	19.4	8.3	1.7	105.5
AUSTRIA	33	1997	4206.0	110.6	7968041.2	65.8	232655103178.6	19.7	8.1	1.7	109.8
AUSTRIA	33	1998	4275.0	109.5	7976792.4	65.8	236356753990.2	19.5	8.0	1.7	109.0
AUSTRIA	33	1999	4374.0	110.3	7992326.2	65.8	233290984068.5	19.7	7.8	1.7	87.9
AUSTRIA	33	2000	4433.0	101.0	8011564.7	65.8	205300570535.4	20.3	7.6	1.6	79.2
AUSTRIA	33	2001	4611.0	113.3	8042292.1	65.8	205169823405.2	20.7	7.3	1.6	81.0
AUSTRIA	33	2002	4631.0	103.7	8081957.7	65.8	213932078200.0	20.1	7.2	1.5	84.0
AUSTRIA	33	2003	4783.0	119.7	8121423.9	65.8	255593295840.6	20.0	7.5	1.5	56.8
AUSTRIA	33	2004	4883.0	112.7	8171963.0	65.8	285365068610.2	20.1	7.5	1.6	100.9
AUSTRIA	33	2005	5014.0	116.4	8227829.1	65.8	296965993739.5	20.4	7.3	1.5	100.0
AUSTRIA	33	2006	5239.0	114.6	8268638.5	65.8	300319285303.9	21.2	6.9	1.4	100.9
AUSTRIA	33	2007	5331.0	102.2	8300787.3	65.8	345457761698.8	22.0	6.9	1.5	110.5
NORWAY	34	1994	8755.0	180.0	4336613.1	73.5	187716475050.8	14.4	6.0	2.4	85.7
NORWAY	34	1995	8924.0	178.9	4359182.4	73.8	216598388174.2	14.0	6.2	2.5	86.0
NORWAY	34	1996	8870.0	184.6	4381334.2	74.0	218688510978.4	14.1	6.3	2.4	87.3
NORWAY	34	1997	8935.0	172.4	4405156.9	74.3	210534638505.1	14.1	6.6	2.3	87.9
NORWAY	34	1998	9412.0	180.8	4431462.5	74.4	210062528897.9	13.5	6.8	2.2	80.0
NORWAY	34	1999	9397.0	173.8	4461914.8	75.1	205972441981.9	13.3	6.7	2.2	74.3
NORWAY	34	2000	9420.0	166.6	4490965.7	76.1	182439013223.0	13.0	6.6	2.1	69.8
NORWAY	34	2001	9648.0	179.9	4513752.8	76.6	181743696408.6	12.7	6.4	2.0	89.2
NORWAY	34	2002	9384.0	171.5	4538157.0	77.0	205203872110.7	12.5	6.5	2.2	91.4
NORWAY	34	2003	8871.0	169.8	4564856.3	77.2	234459267409.8	12.7	6.6	2.1	120.1
NORWAY	34	2004	9281.0	169.0	4591909.7	77.3	252718194716.2	12.8	6.6	2.2	105.5
NORWAY	34	2005	9523.0	168.5	4623292.6	77.5	271232043355.8	12.8	6.7	2.2	100.0
NORWAY	34	2006	9236.0	165.4	4660678.0	77.9	278212806832.3	12.6	6.9	2.2	121.9
NORWAY	34	2007	9516.0	170.1	4709154.0	78.2	323235808150.1	12.4	7.2	2.2	92.7

Appendix 4.1. A Spatial Autoregressive True Random Effects Model

Consider the following model, which is an extension of the True Random Effects model of Greene (2005) in a cost frontier (Bayesian) framework:

$$y_{it} = \rho \sum_{j \neq i} w_{ij} y_{jt} + X_{it}\beta + \alpha_i + v_{it} + u_{it}$$

$$v_{it} \sim N(0, \sigma_v^2) \qquad u_{it} \sim N^+(0, \sigma_u^2) \qquad \alpha_i \sim N(0, \sigma_\alpha^2)$$

Note that this model is nested in the model presented in the paper – as it is just missing the components of persistent inefficiency. If we have unobserved heterogeneity in the data, the slope coefficients (the parameters of the cost or production function) are biased, which leads to serious bias in the inefficiency estimates of u_{it}. Ignoring this can be a serious problem in applied econometrics. One can think of this model as a spatial autoregressive model with random effects, where besides that inefficiency is disentangled from the error term.

Posteriors for each of the parameters follow:

$$\mathrm{p}(\beta | \mathrm{y}, \mathrm{X}, \theta_{-\beta}) \propto \mathrm{N}(\mathrm{b}, \mathrm{B})$$

Where:

$$\mathrm{b} = (\mathrm{X'X} + \sigma_\mathrm{v}^2 \mathrm{A})^{-1} (\mathrm{X'Sy} + \sigma_\mathrm{v}^2 \mathrm{Ac})$$

$$\mathrm{B} = \sigma_\mathrm{v}^2 (\mathrm{X'X} + \sigma_\mathrm{v}^2 \mathrm{A})^{-1}$$

$$\mathrm{Sy} = (I_{NT} - I_T \otimes \rho \mathrm{W})\mathrm{y} - \mathrm{u} - l_T \otimes \alpha$$

$$\mathrm{p}(\sigma_\mathrm{v}^2 | \mathrm{y}, \mathrm{X}, \theta_{-\sigma_v}) \propto \text{Inv-}\chi 2(\mathrm{NT+Nv}\ ;\ ((\mathrm{Qv+v'v})/(\mathrm{NT+Nv})))$$

$$\mathrm{v} = (I_{NT} - I_T \otimes \rho \mathrm{W})\mathrm{y} - \mathrm{X}\beta - \mathrm{u} - l_T \otimes \alpha$$

$$\mathrm{p}(\sigma_\mathrm{u}^2 | \mathrm{y}, \mathrm{X}, \theta_{-\sigma_u}) \propto \text{Inv-}\chi 2(\mathrm{NT+Nu}\ ;\ ((\mathrm{Qu+u'u})/(\mathrm{NT+Nu})))$$

$$\mathrm{p}(\mathrm{u} | \mathrm{y}, \mathrm{X}, \theta_{-u}) \propto \mathrm{N}^+(\mathrm{U}, \frac{\sigma_\mathrm{v}^2 \sigma_\mathrm{u}^2}{\sigma_\mathrm{v}^2 + \sigma_\mathrm{u}^2})$$

$$U=\frac{[(I_{NT}-I_T\otimes\rho W)y-X\beta-l_T\otimes\alpha]\ \sigma_u^2}{\sigma_v^2+\sigma_u^2}$$

$$p\left(\rho\middle|y,X,\theta_{-\rho}\right)\propto |S|\ \exp(-\frac{v'v}{2\sigma_v^2})$$

$$|S| = |(I_{NT}-I_T\otimes\rho W)\ |$$

$$v = (I_{NT}-I_T\otimes\rho W)y-X\beta-u-l_T\otimes\alpha$$

$$p(\alpha_i|y,X,\theta_{-\alpha})\propto N(\bar{\alpha}\frac{\sigma_v^2+\sigma_u^2}{\sigma_v^2}\ ;\ (\sigma_v^2+\sigma_u^2)I_N)$$

$$\bar{\alpha}=(\overline{\alpha_1},\dots,\overline{\alpha_N})\ ,\qquad \bar{\alpha_i}=\sum_{t=1}^{T}\left((I_{NT}-I_T\otimes\rho W)y_{it}-X_{it}\beta-u_{it}\right)\ for\ each\ i$$

$p\left(\sigma_\alpha^2\middle|y,X,\theta_{-\sigma_\alpha}\right)\propto$ Inv-χ2(NT+Nα ; ((Qv+α'α)/(NT+Nα)))

Appendix 4.2. Geweke convergence diagnostic z-scores for each parameter

	Model (1) GTRE	Model (2) Spatial Lag SF	Model (3) Spatial Lag no time trend
ρ	-	0.08326	-1.145
σ_u^2	-0.7836	-0.7457	-3.793
σ_v^2	0.8292	0.6888	4.612
σ_η^2	-0.5636	-0.1169	-1.432
σ_α^2	0.3913	0.49	0.925
Cons.	-0.7325832	-0.46750	2.731
β_{EMP}	-0.0009032	0.06288	-4.002
β_{CAP}	0.5392724	0.82358	3.866
β_{TRADE}	-0.7326538	0.29375	1.777
t	1.0314887	0.13448	-
t^2	-1.2542880	-1.828	-

Note: Outliers outside of the interval between -2.3 and 2.3 in red.

Appendix 5.1. Geweke convergence diagnostic z-scores for each parameter

	First order neighbours W matrix			Second order neighbours W matrix		
ρ	-1.907			-0.7687		
β	-0.01502	0.80671	-0.35617	-0.10101	0.80997	0.23982
	0.05712	1.61766	0.33351	-0.31531	1.00339	1.25552
	0.46697	-0.24283	-0.15267	0.94031	0.07836	-0.47561
	0.34636	-0.30156	-0.27850	0.21151	-0.56180	-0.14403
	1.56329	1.34136	-0.38266	1.86767	1.21058	-0.23661
σ_α^2	-0.3941			-0.7075		
σ_v^2	-0.3947			-1.09		
λ^{-1}	-0.354			0.761		

Note: Outliers outside of the interval between -2.3 and 2.3 in red.

Appendix 5.2. Chapter 5 dataset

edb	year	edbno	VC	Energy	Customers	LoadFactor	SAIDI	CustomerDensity	Capital
Alpine Energy	2000	1	3339661.46	496.52	27828.89	71.50	82.00	7.67	83.45
Alpine Energy	2001	1	3831550.08	537.63	27806.08	72.00	113.00	7.43	89.35
Alpine Energy	2002	1	3832929.69	522.33	28376.03	68.40	81.00	7.70	94.36
Alpine Energy	2003	1	3936844.22	586.73	28248.06	72.70	204.00	7.63	98.02
Alpine Energy	2004	1	4457416.96	589.68	28408.96	69.48	115.00	7.62	103.50
Alpine Energy	2005	1	4638167.91	576.46	28697.06	70.96	79.00	7.60	103.06
Alpine Energy	2006	1	4892627.31	625.91	29163.11	68.80	81.00	7.64	110.79
Alpine Energy	2007	1	8441157.49	659.18	29367.09	68.68	1138.00	7.65	112.78
Alpine Energy	2008	1	9702168.74	665.52	29849.10	61.86	149.50	7.43	129.30
Alpine Energy	2009	1	11312965.33	708.94	30266.90	64.28	200.94	7.45	130.00
Dunedin Electricity	2000	2	8717734.87	1117.40	69494.30	56.50	208.00	16.10	240.40
Dunedin Electricity	2001	2	9733752.08	1159.75	70208.17	55.70	82.00	15.15	252.78
Dunedin Electricity	2002	2	10308403.56	1160.89	71431.20	53.90	89.00	15.06	262.70
Dunedin Electricity	2003	2	11167965.33	1219.48	72794.09	54.60	101.00	14.93	271.85
Aurora Energy	2004	2	11753480.88	1189.39	73971.86	58.88	97.30	14.71	246.19
Aurora Energy	2005	2	12947069.15	1262.62	75116.84	57.52	80.50	14.59	266.86
Aurora Energy	2006	2	14693855.92	1269.26	76400.15	57.19	96.50	14.55	268.98
Aurora Energy	2007	2	17014219.61	1296.68	77712.39	56.33	101.40	14.51	275.53
Aurora Energy	2008	2	23040636.06	1274.41	79811.27	54.47	140.10	14.64	283.19
Aurora Energy	2009	2	27327388.53	1266.22	80685.97	55.84	68.01	14.55	274.83
Buller Electricity	2000	3	1396626.16	40.55	4241.00	65.00	366.00	7.34	7.60
Buller Electricity	2001	3	1161415.41	41.55	4258.00	66.00	314.00	7.19	7.84
Buller Electricity	2002	3	1537026.09	40.24	4108.00	63.00	290.00	6.91	8.06
Buller Electricity	2003	3	1803049.58	37.87	4187.00	63.00	370.00	7.03	7.75
Buller Electricity	2004	3	1814535.37	40.08	4171.00	64.29	256.00	6.85	7.82
Buller Electricity	2005	3	1662544.80	41.17	4178.00	65.91	134.00	6.99	7.90
Buller Electricity	2006	3	2116469.65	40.59	4211.00	66.32	196.00	7.17	7.85
Buller Electricity	2007	3	2351090.92	42.46	4258.00	67.75	355.00	7.22	7.68
Buller Electricity	2008	3	3401509.97	43.54	4320.00	64.43	428.00	7.21	8.38
Buller Electricity	2009	3	2577936.94	45.17	4395.00	64.81	273.26	7.30	8.64
Centralines	2000	4	1080905.85	85.43	7454.00	59.90	746.00	4.83	17.00
Centralines	2001	4	1443122.89	102.25	7432.00	62.56	438.00	4.60	20.29
Centralines	2002	4	1383697.75	102.91	7431.00	30.40	361.00	4.60	41.72
Centralines	2003	4	1391732.59	109.06	7442.00	71.80	260.00	4.81	18.72
Centralines	2004	4	1530278.04	104.34	7457.00	67.22	388.00	4.55	19.02
Centralines	2005	4	1562519.28	106.02	7532.00	68.28	171.39	4.57	19.02
Centralines	2006	4	1723469.55	106.47	7692.00	65.31	153.20	4.61	19.84
Centralines	2007	4	2207077.94	103.64	7775.00	68.34	246.60	4.56	19.01
Centralines	2008	4	2604053.95	105.47	7958.00	63.66	157.09	4.65	20.51
Centralines	2009	4	3701467.79	109.37	7981.00	64.19	198.76	4.51	20.63
Counties Power	2000	5	4959175.23	367.23	30470.06	60.26	124.00	9.70	75.15
Counties Power	2001	5	4602545.14	379.09	30546.03	60.06	132.00	9.13	77.80
Counties Power	2002	5	4392152.57	388.03	30816.95	55.62	62.00	9.10	85.81
Counties Power	2003	5	5238103.17	409.31	31213.94	63.02	92.00	9.44	79.90
Counties Power	2004	5	5289794.73	417.97	32780.86	63.68	96.45	10.10	80.13
Counties Power	2005	5	5921734.77	440.30	33930.85	62.97	59.60	10.50	85.26
Counties Power	2006	5	7339270.44	444.49	34813.13	62.13	61.73	10.68	87.10
Counties Power	2007	5	8258305.67	457.00	35544.83	60.49	109.49	12.00	91.51
Counties Power	2008	5	11732226.32	464.87	35613.14	61.05	167.78	11.97	92.43
Counties Power	2009	5	13475583.82	472.77	35969.98	60.91	171.68	11.95	94.09
Eastland Network	2000	6	5001407.85	264.51	25680.06	56.59	235.00	7.35	54.45
Eastland Network	2001	6	6736358.13	264.92	26127.93	57.99	1043.00	7.38	56.95
Eastland Network	2002	6	4631540.07	269.06	25551.98	58.06	190.00	6.95	57.08
Eastland Network	2003	6	3612389.42	275.20	25264.11	61.11	427.00	6.72	55.46
Eastland Network	2004	6	3803377.33	273.99	24876.03	62.85	356.32	6.85	53.85
Eastland Network	2005	6	4218372.72	287.26	24855.89	62.78	282.53	6.77	55.70
Eastland Network	2006	6	4772686.92	283.16	24864.09	61.75	358.95	6.78	55.89
Eastland Network	2007	6	6148016.09	290.92	24962.00	59.79	261.50	6.84	59.21
Eastland Network	2008	6	6225846.66	283.72	25195.99	59.82	258.13	6.90	57.90
Eastland Network	2009	6	8432720.55	280.74	25300.01	61.19	248.82	6.90	55.95
Electra	2000	7	3721919.17	340.64	36651.15	52.47	100.00	18.60	79.55
Electra	2001	7	4195696.86	352.95	37301.92	54.58	142.00	17.56	79.18
Electra	2002	7	4663701.48	358.38	38292.14	52.24	66.00	18.00	83.89
Electra	2003	7	5002408.23	369.22	39014.94	56.01	61.00	18.30	80.64
Electra	2004	7	4950949.83	368.91	39540.87	54.96	133.47	18.41	82.02
Electra	2005	7	4877434.88	388.34	39905.92	51.92	83.86	18.43	91.41
Electra	2006	7	5295457.84	384.99	40458.01	51.23	93.99	18.57	91.93
Electra	2007	7	6954642.64	406.23	40860.13	50.43	185.26	18.67	98.00
Electra	2008	7	8382694.83	402.37	41512.09	52.03	193.90	16.23	95.00
Electra	2009	7	10999715.87	401.42	41761.08	51.79	683.10	16.31	95.00
Electricity Ashburton	2000	8	2367393.22	270.16	13843.00	53.30	147.00	5.69	62.43
Electricity Ashburton	2001	8	2464402.64	326.09	14285.00	57.49	131.00	5.67	69.29
Electricity Ashburton	2002	8	2330259.05	319.13	14558.00	52.43	229.00	5.64	74.62
Electricity Ashburton	2003	8	3214524.49	413.35	14789.00	55.57	319.00	5.54	83.92
Electricity Ashburton	2004	8	2991483.57	367.10	15049.00	58.33	198.63	5.51	91.21
Electricity Ashburton	2005	8	3469704.54	357.99	15311.00	52.25	132.69	5.52	95.58
Electricity Ashburton	2006	8	4618128.06	471.48	15975.01	56.12	150.20	5.70	104.02
Electricity Ashburton	2007	8	6996565.89	477.20	16090.99	56.97	1918.00	5.67	99.62
Electricity Ashburton	2008	8	6663463.82	477.74	16732.01	47.90	199.27	5.86	123.07
Electricity Ashburton	2009	8	8228711.51	524.92	17218.01	45.95	337.32	5.96	136.00
Electricity Invercargill	2000	9	1763268.95	237.11	16733.00	54.90	34.00	24.08	53.38
Electricity Invercargill	2001	9	2002025.55	244.52	16701.00	51.60	35.00	24.35	57.87
Electricity Invercargill	2002	9	1914180.21	246.36	16847.00	48.60	96.00	24.49	62.11
Electricity Invercargill	2003	9	1716949.97	261.21	16961.00	54.40	21.00	24.44	59.69
Electricity Invercargill	2004	9	1969558.57	253.54	16922.00	52.55	49.60	25.03	60.07
Electricity Invercargill	2005	9	2134685.74	262.53	16842.00	53.41	15.40	24.79	60.61
Electricity Invercargill	2006	9	2628463.47	259.61	16889.00	54.67	19.80	24.78	57.86
Electricity Invercargill	2007	9	3780511.97	280.38	16943.00	51.55	36.70	24.94	63.70
Electricity Invercargill	2008	9	4218625.83	267.48	17012.00	50.92	54.66	26.50	62.40
Electricity Invercargill	2009	9	5202760.98	269.60	17126.00	50.91	51.43	26.29	61.36

Horizon Energy	2000	10	2967706.53	555.27	23061.04	73.30	205.00	10.32	90.23
Horizon Energy	2001	10	2268546.78	562.05	23046.06	76.48	129.00	9.74	87.56
Horizon Energy	2002	10	2755005.51	571.97	23091.96	84.71	258.00	9.69	80.11
Horizon Energy	2003	10	2603507.16	579.47	23303.99	76.71	192.00	9.74	89.57
Horizon Energy	2004	10	2927267.64	559.37	23458.07	76.53	219.00	9.75	86.44
Horizon Energy	2005	10	4132445.83	571.01	23571.89	73.22	987.00	9.85	92.61
Horizon Energy	2006	10	5166107.18	586.66	23887.01	73.35	292.00	9.94	94.07
Horizon Energy	2007	10	7131769.94	587.10	23971.96	74.27	315.00	9.96	94.15
Horizon Energy	2008	10	8194305.34	540.53	24219.90	67.13	345.52	10.34	96.05
Horizon Energy	2009	10	9654068.59	512.09	24254.08	71.59	201.98	10.36	84.78
MainPower	2000	11	3272746.18	334.55	24140.11	59.09	117.00	5.84	68.23
MainPower	2001	11	3840564.81	382.93	25637.98	68.77	152.00	6.01	67.50
MainPower	2002	11	3661377.50	359.18	25047.02	63.84	214.00	5.79	68.34
MainPower	2003	11	4093660.03	396.46	25997.09	62.00	284.00	6.41	77.58
MainPower	2004	11	4797953.35	433.65	29081.86	69.69	99.64	6.96	74.43
MainPower	2005	11	6338546.24	449.60	30282.95	70.84	115.57	7.25	76.62
MainPower	2006	11	6390416.47	460.73	30670.91	69.66	109.17	6.94	79.57
MainPower	2007	11	8600750.29	466.52	31666.04	66.23	236.53	7.07	84.74
MainPower	2008	11	9003104.32	492.00	32545.03	69.02	110.67	7.52	86.00
MainPower	2009	11	12331407.24	509.15	33248.00	69.01	146.16	7.55	89.00
Marlborough Lines	2000	12	3875402.17	270.73	20572.00	58.20	172.00	7.07	52.98
Marlborough Lines	2001	12	4308455.31	289.91	20804.99	62.60	178.00	6.90	56.22
Marlborough Lines	2002	12	4386402.62	286.26	21037.99	62.30	208.00	6.90	55.61
Marlborough Lines	2003	12	4121715.43	303.37	21416.99	73.90	201.00	6.53	55.09
Marlborough Lines	2004	12	5194339.33	306.42	22250.95	67.83	222.40	7.09	54.81
Marlborough Lines	2005	12	6675602.36	320.28	22547.06	67.99	224.90	7.11	57.59
Marlborough Lines	2006	12	8071339.41	331.24	22932.03	68.65	260.20	7.14	58.23
Marlborough Lines	2007	12	9724120.44	332.68	23134.96	64.57	353.10	7.09	63.19
Marlborough Lines	2008	12	17294342.80	348.15	23583.91	60.79	265.30	6.81	70.00
Marlborough Lines	2009	12	19325770.07	353.08	23870.05	60.67	249.88	7.19	70.00
Nelson Electricity	2000	13	646934.29	140.38	8476.00	59.40	77.00	35.46	28.22
Nelson Electricity	2001	13	778987.28	140.84	8579.00	58.70	41.00	35.30	28.80
Nelson Electricity	2002	13	717874.47	143.38	8575.00	55.05	39.00	35.58	30.47
Nelson Electricity	2003	13	1241970.76	142.33	8614.00	57.73	100.00	35.60	29.77
Nelson Electricity	2004	13	1273551.48	137.67	8735.00	56.09	53.20	36.55	29.80
Nelson Electricity	2005	13	1428606.43	146.63	8876.00	58.48	51.00	36.68	30.12
Nelson Electricity	2006	13	1732420.29	145.43	8915.00	56.30	122.00	36.54	31.07
Nelson Electricity	2007	13	2150756.07	149.98	8900.00	56.58	249.90	36.33	31.67
Nelson Electricity	2008	13	2245165.96	150.11	8881.00	52.58	16.93	36.04	34.23
Nelson Electricity	2009	13	2582064.94	148.42	8943.00	54.05	185.40	36.21	32.81
Network Tasman	2000	14	3394577.96	595.03	30246.02	63.65	215.00	9.71	116.52
Network Tasman	2001	14	4190120.29	646.40	30790.15	65.29	173.00	9.86	117.89
Network Tasman	2002	14	3446879.89	661.62	31293.01	63.30	115.00	10.02	123.50
Network Tasman	2003	14	4599738.44	699.36	32205.10	66.12	151.00	10.19	126.10
Network Tasman	2004	14	4973080.38	703.73	33334.89	64.39	164.10	10.28	129.29
Network Tasman	2005	14	5903169.69	742.57	33829.89	65.14	210.15	10.42	134.98
Network Tasman	2006	14	6669663.72	739.98	34399.94	63.21	224.66	10.54	138.75
Network Tasman	2007	14	7554318.92	740.44	34910.05	62.68	285.41	10.58	140.02
Network Tasman	2008	14	8302689.03	594.25	35416.04	48.40	172.00	10.69	147.95
Network Tasman	2009	14	11674879.03	575.23	35828.90	59.71	342.31	10.76	148.40
Network Waitaki	2000	15	1327489.34	164.36	11408.99	69.89	46.00	6.02	28.82
Network Waitaki	2001	15	1311392.36	165.26	11371.99	65.18	72.00	5.98	31.36
Network Waitaki	2002	15	1366481.85	164.58	11341.00	69.15	78.00	5.93	29.03
Network Waitaki	2003	15	1662511.55	183.57	11400.00	71.04	92.00	5.91	31.26
Network Waitaki	2004	15	1821862.71	183.27	11491.00	61.24	187.00	5.94	36.21
Network Waitaki	2005	15	2070084.53	183.37	11974.99	66.03	104.85	6.17	33.56
Network Waitaki	2006	15	2669148.32	190.45	12006.00	67.95	102.31	6.02	33.99
Network Waitaki	2007	15	3270783.12	202.00	11944.00	57.39	505.55	5.96	42.57
Network Waitaki	2008	15	3319052.80	230.00	11970.00	60.74	94.67	6.10	46.42
Network Waitaki	2009	15	4146768.86	233.73	12256.00	59.17	69.36	6.56	47.28
Northpower	2000	16	5876430.04	801.02	44674.14	73.18	131.00	8.46	129.26
Northpower	2001	16	5699961.62	823.09	45588.92	74.85	183.00	8.63	128.09
Northpower	2002	16	6443548.79	813.88	46712.17	74.85	220.00	8.75	129.98
Northpower	2003	16	6547933.10	863.90	47785.14	77.38	182.00	8.80	131.56
Northpower	2004	16	7197900.90	867.72	48851.97	77.87	145.32	9.21	131.88
Northpower	2005	16	8795229.23	876.31	49819.91	76.37	113.24	9.19	135.34
Northpower	2006	16	11461337.81	929.94	50753.20	76.20	119.23	9.09	143.80
Northpower	2007	16	14047851.16	939.05	51668.83	76.67	151.33	9.15	144.01
Northpower	2008	16	18465413.50	970.00	52875.74	74.20	783.08	9.19	154.00
Northpower	2009	16	22023486.28	965.35	53330.84	75.36	254.34	9.48	151.00
Orion New Zealand	2000	17	16929699.43	2601.24	162543.35	57.70	52.00	14.11	541.61
Orion New Zealand	2001	17	18176316.26	2683.34	166556.52	61.30	62.00	14.52	525.65
Orion New Zealand	2002	17	19348781.42	2758.87	168454.34	58.60	46.00	14.64	564.82
Orion New Zealand	2003	17	21187035.09	2914.24	170489.67	58.00	102.00	14.37	603.40
Orion New Zealand	2004	17	23828192.59	2928.91	174449.40	62.44	43.40	13.39	563.12
Orion New Zealand	2005	17	27836815.47	3036.99	177717.41	63.15	52.90	13.36	577.37
Orion New Zealand	2006	17	33424175.05	3097.92	180540.43	62.54	64.00	13.13	594.71
Orion New Zealand	2007	17	40086092.03	3125.02	183199.32	59.55	154.50	12.91	630.03
Orion New Zealand	2008	17	45354048.37	3155.80	186029.40	60.01	53.76	12.92	631.60
Orion New Zealand	2009	17	52076794.27	3263.00	190285.34	62.15	62.85	17.90	625.00
Powerco	2000	19	19747747.65	1893.94	156219.91	63.26	110.00	10.11	243.33
Powerco	2001	19	24464655.47	1941.50	157120.77	63.91	96.00	10.26	372.09
Powerco	2002	19	22981038.02	1955.19	157451.07	63.50	160.00	9.87	373.23
Powerco	2003	19	36382920.30	3775.71	293478.60	71.70	296.00	11.84	466.00
Powerco	2004	19	42718387.24	3796.23	296164.40	67.18	370.41	11.88	692.25
Powerco	2005	19	57575057.36	4052.41	298665.65	67.35	208.32	11.14	727.42
Powerco	2006	19	60424789.45	4235.29	304470.66	75.67	235.80	11.24	677.26
Powerco	2007	19	59722536.32	4106.43	306125.37	67.24	220.60	11.23	753.03
Powerco	2008	19	73123474.37	4430.07	305071.06	66.67	358.76	11.15	776.00
Powerco	2009	19	80218121.41	4376.46	315378.88	67.34	320.09	10.77	764.00

Scanpower	2000	20	1007154.92	79.10	6675.00	67.40	123.00	6.71	14.41
Scanpower	2001	20	1214751.39	81.08	6707.00	67.95	70.00	6.73	14.74
Scanpower	2002	20	1135030.41	82.46	6615.00	67.80	165.00	7.59	14.90
Scanpower	2003	20	1154352.34	86.63	6638.00	70.43	110.00	7.60	15.09
Scanpower	2004	20	973467.77	86.69	6719.00	69.99	185.20	7.80	15.23
Scanpower	2005	20	1117450.15	91.32	6753.00	67.88	71.31	7.84	16.47
Scanpower	2006	20	1441046.29	89.88	6694.00	67.30	68.59	7.74	16.35
Scanpower	2007	20	1461918.25	90.56	6686.00	62.97	46.67	7.68	17.61
Scanpower	2008	20	2352266.76	89.83	6748.00	63.45	58.31	7.64	17.35
Scanpower	2009	20	2539327.91	80.51	6831.99	61.03	35.57	7.65	16.24
The Lines Company	2000	21	2746121.20	265.07	25259.06	60.25	473.00	5.30	53.99
The Lines Company	2001	21	2755997.49	262.90	25845.97	62.81	574.00	5.79	51.58
The Lines Company	2002	21	3072032.65	265.64	25711.92	52.63	564.00	5.59	62.09
The Lines Company	2003	21	3586150.85	276.64	25045.01	51.92	729.00	5.18	65.24
The Lines Company	2004	21	3456855.78	278.08	25196.99	59.77	400.20	5.28	57.32
The Lines Company	2005	21	4728648.55	291.45	25535.12	64.61	305.60	5.84	55.58
The Lines Company	2006	21	5395846.24	294.80	26181.02	65.09	284.90	5.94	55.70
The Lines Company	2007	21	6069033.96	306.39	23359.06	64.35	368.50	5.33	58.44
The Lines Company	2008	21	7018710.01	301.19	23227.91	57.49	267.31	5.33	65.00
The Lines Company	2009	21	9097225.18	293.75	24185.05	59.75	297.13	5.48	61.00
The Power Company	2000	22	4483345.10	493.67	30272.95	65.00	446.00	3.62	97.83
The Power Company	2001	22	4489985.36	526.01	31004.88	66.50	147.00	3.70	101.63
The Power Company	2002	22	4958679.33	546.65	31799.95	60.70	139.00	3.77	114.32
The Power Company	2003	22	6013815.72	602.19	31944.01	68.20	167.00	3.78	110.96
The Power Company	2004	22	6138985.14	601.93	31875.09	67.89	157.30	3.76	110.52
The Power Company	2005	22	7521829.87	615.16	31967.02	68.29	125.50	3.76	112.17
The Power Company	2006	22	8942448.58	621.16	32243.12	67.48	161.20	3.78	114.01
The Power Company	2007	22	11265550.51	646.26	32568.15	69.93	182.90	3.81	113.92
The Power Company	2008	22	11436608.04	629.47	32997.93	64.10	294.78	3.87	121.53
The Power Company	2009	22	14599093.56	649.87	33692.14	64.02	217.34	3.93	128.04
Top Energy	2000	23	3210894.13	255.91	25700.10	62.00	495.00	7.00	52.00
Top Energy	2001	23	3960496.68	273.73	26233.96	63.40	329.00	7.05	55.00
Top Energy	2002	23	3870057.80	286.75	27043.99	62.00	674.00	7.20	58.00
Top Energy	2003	23	4361296.79	302.93	27590.04	63.00	420.00	7.27	59.00
Top Energy	2004	23	5412599.31	313.55	27075.11	65.08	352.90	7.07	59.00
Top Energy	2005	23	7501098.24	322.13	27656.06	67.47	496.20	7.15	59.00
Top Energy	2006	23	9097771.03	324.68	28486.06	67.78	556.10	7.14	59.00
Top Energy	2007	23	9673976.47	336.25	29073.14	64.68	487.80	7.16	64.00
Top Energy	2008	23	10969617.90	323.33	29972.93	63.95	818.30	7.32	62.76
Top Energy	2009	23	13643721.36	324.55	30453.01	64.21	915.16	7.94	63.29
Unison	2000	24	6385880.89	784.13	56594.10	61.13	104.00	14.80	154.59
Unison	2001	24	7395926.99	802.04	57331.19	59.57	385.00	14.81	162.20
Unison	2002	24	6578320.32	819.63	58069.74	58.62	102.00	14.88	168.90
Unison	2003	24	11466725.91	1479.26	102492.00	59.11	97.00	12.77	300.70
Unison	2004	24	13870848.98	1523.88	102299.49	65.81	202.00	11.15	276.88
Unison	2005	24	18174862.21	1581.08	103347.25	63.45	156.00	11.15	302.01
Unison	2006	24	22748732.78	1606.53	104578.16	62.92	134.00	11.22	307.72
Unison	2007	24	24501625.00	1592.51	105819.49	60.13	140.00	11.29	318.88
Unison	2008	24	27735396.30	1569.03	108139.79	56.73	117.80	12.10	332.56
Unison	2009	24	29580916.54	1562.51	107484.29	55.01	129.24	13.61	341.93
Vector	2000	26	30349178.27	4423.65	259577.35	59.26	59.00	29.80	889.90
Vector	2001	26	36207614.50	4765.46	265895.86	62.11	50.00	31.48	917.20
Vector	2002	26	35002148.39	4884.94	273999.07	59.41	56.00	31.94	982.91
Vector	2003	26	79309620.74	9170.54	633756.44	67.43	80.00	25.68	1605.22
Vector	2004	26	91777708.56	9773.77	643997.42	59.81	107.94	23.30	1957.78
Vector	2005	26	112585106.97	10243.03	650996.80	58.81	83.09	23.47	2085.09
Vector	2006	26	129230733.96	10289.03	660346.52	59.13	119.81	23.65	2088.86
Vector	2007	26	151793256.75	10695.86	671675.09	57.17	244.38	23.62	2241.80
Vector	2008	26	146440535.06	10650.12	679613.82	57.59	220.20	23.68	2221.76
Vector	2009	26	128951896.83	8244.00	522144.68	57.37	172.34	29.77	1711.00
Waipa Networks	2000	27	2051455.30	275.76	19824.01	60.33	300.00	10.52	55.77
Waipa Networks	2001	27	2117125.86	281.87	20050.01	62.41	280.00	11.46	55.29
Waipa Networks	2002	27	2136308.72	296.89	20293.01	65.23	375.00	11.50	56.06
Waipa Networks	2003	27	2660434.46	302.88	20510.00	66.79	247.00	11.60	55.21
Waipa Networks	2004	27	2754068.97	303.22	20772.99	64.98	491.04	10.92	56.81
Waipa Networks	2005	27	3374102.77	313.63	21107.00	63.09	278.74	10.47	60.56
Waipa Networks	2006	27	4540510.46	315.16	21538.00	65.38	176.23	11.02	58.73
Waipa Networks	2007	27	4982787.34	321.12	22005.99	67.35	541.43	11.11	58.14
Waipa Networks	2008	27	5007212.85	318.80	22702.04	64.00	497.29	11.30	60.77
Waipa Networks	2009	27	6410706.24	318.48	22896.97	63.83	236.99	11.13	61.14
WEL Networks	2000	28	9004905.12	922.18	70201.85	60.10	116.00	16.55	185.00
WEL Networks	2001	28	9183601.45	912.70	71473.35	59.20	158.00	15.59	186.20
WEL Networks	2002	28	9072242.18	915.23	72942.01	58.50	76.00	15.55	187.87
WEL Networks	2003	28	10553625.41	956.92	73959.28	62.27	94.00	15.60	184.45
WEL Networks	2004	28	9387785.62	971.89	75595.35	57.63	68.48	15.51	202.34
WEL Networks	2005	28	10207976.68	1017.64	77480.38	61.10	132.43	15.86	200.00
WEL Networks	2006	28	12582908.72	1041.70	79195.12	56.41	69.63	15.93	223.00
WEL Networks	2007	28	16154835.91	1102.83	81461.03	57.63	103.43	16.31	231.00
WEL Networks	2008	28	18988232.44	1160.24	81312.09	58.05	80.13	16.09	236.55
WEL Networks	2009	28	22189949.08	1152.54	83714.71	64.35	88.74	16.20	214.27
Westpower	2000	29	3304547.14	185.38	11729.00	65.30	156.00	6.11	185.00
Westpower	2001	29	2655782.78	190.43	11995.99	66.30	235.00	6.11	186.20
Westpower	2002	29	3160434.26	186.90	12072.00	63.40	140.00	6.12	187.87
Westpower	2003	29	3207299.94	201.75	12077.00	63.10	122.00	6.10	184.45
Westpower	2004	29	4126499.39	192.73	11931.00	65.65	205.49	6.03	36.02
Westpower	2005	29	4398965.69	196.82	12031.00	64.22	372.06	6.01	37.17
Westpower	2006	29	5070043.73	210.98	12010.00	65.02	151.12	5.94	39.29
Westpower	2007	29	6530212.22	215.67	12192.00	62.06	309.87	5.85	42.10
Westpower	2008	29	8224022.48	245.12	12414.00	67.71	150.52	5.96	44.00
Westpower	2009	29	9694119.28	271.92	12617.01	69.03	382.47	5.96	47.29