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Energy Efficiency in Transition Economies: A Stochastic Frontier Approach

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Abstract

The paper 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, by estimating a Bayesian Generalized True Random Effects (GTRE) stochastic frontier model that estimates both persistent and transient inefficiency. The properties of alternative GTRE estimation methods in small samples are explored to guide the estimation strategy. The paper 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 heterogeneous structural economic changes, an aggregate electricity demand function is estimated to obtain efficiency scores that give new 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.

JEL Classification: C23, Q49, P20

Keywords: Electricity Consumption, Transition Economies, Energy Efficiency, Stochastic Frontier

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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 spectre 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 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 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 Stochastic Frontier models, using the Generalized True Random Effects model (Colombi et al., 2011) and exploring the Bayesian reparametrized estimation approach of Tsionas and Kumbhakar (2014) and particularly the simpler Gibbs sampling approach of Makiela (2016) as competing solutions. Simulation results 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 paper estimates 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. 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 paper 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.

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 bankrupt 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 1. – Power Sector 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. 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 random 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 meant 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).

A major methodological and conceptual influence for estimation of energy efficiency scores of this paper is the 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. 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 paper (Hungary, Poland and Slovakia). This 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 paper. The size of the T dimension of the panel also raises some concerns about the stationarity of the data and therefore the validity of the obtained results. 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) in order to tackle the problem of correlation between the individual effects and the explanatory variables.

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 (Cornwall 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 paper 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. 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.

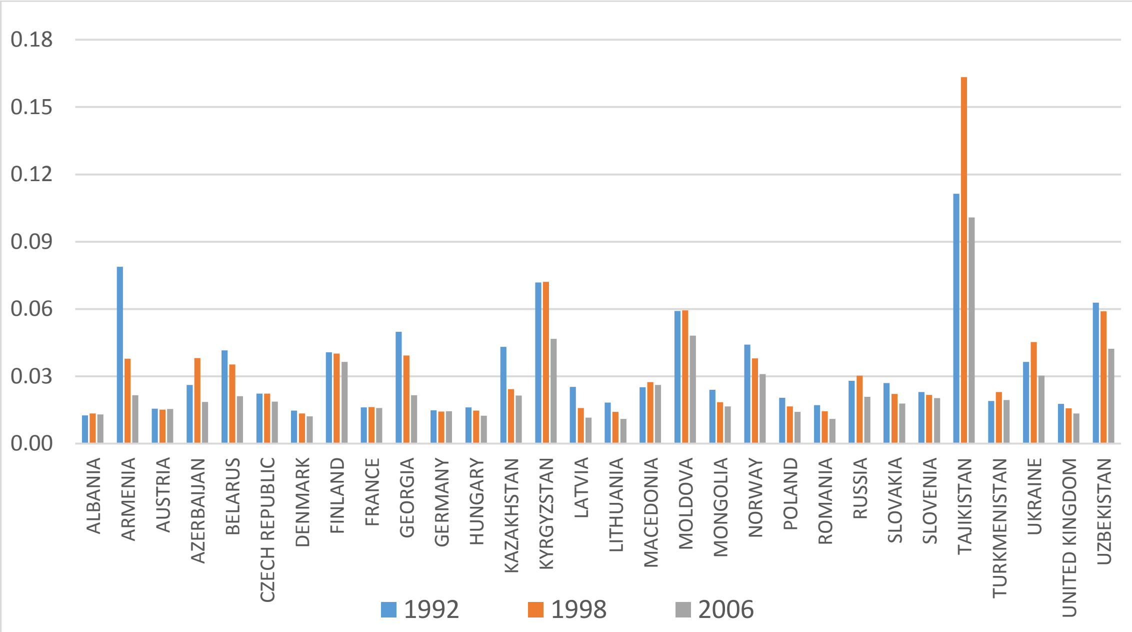

Figure 1. – Electricity use (tonnes of oil equivalent) per $1,000 GDP (constant 2005 PPP). Data source: World Bank

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).

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 the each economy. Demand 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 trying to fill the gaps with approximations increases the danger of measurement error. 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 a strong reform effort 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.

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

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 a cost frontier.

A neo-classical 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. As such, the following model accounts for persistent sources of long-run inefficiency and variable sources of inefficiency:

$$y_{it} = x'_{it}\beta + \alpha_i + \eta_i + u_{it} + v_{it} \tag{1}$$

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

$$u_{it} \sim i.i.d.N^+(0;\sigma_u^2) \qquad \eta_i \sim i.i.d.N^+\left(0;\sigma_\eta^2\right) \tag{3}$$

This is a cost frontier model. Note that the 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). 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). 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)[1], as it adds another time-invariant random effect to capture persistent inefficiency (φ_i). 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:

$$\alpha_i = \gamma \bar{X}_\iota + \varphi_i \quad \text{Where} \quad \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it} \quad \text{and} \quad \varphi_i \sim N(0, \sigma_\varphi) \tag{4}$$

Cross-section means for variables with very low variation are not added, such as population and urbanization rate, as recommended by STATA 14.1 statistical package “mundlak”.

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:

$$y_i = (\alpha_i + \eta_i) \otimes l_T + x'_i\beta + (u_{it} + v_{it}) = \delta_i \otimes l_T + x'_i\beta + \varepsilon_{it} \tag{5}$$

[1] 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.

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:

$$p(\beta, \sigma_e, \sigma_u, \sigma_\varphi, \sigma_\alpha) = p(\beta)p(\sigma_v)p(\sigma_u)p(\sigma_\eta)p(\sigma_\alpha) \tag{6}$$

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[2] $A = 10^{-4}.I_K$. Therefore, there is very little information in the prior about the coefficients of the regressors. For scale parameters, it is assumed that:

$$\frac{\overline{\mathrm{Q}}_{\mathrm{k}}}{\sigma_{\mathrm{k}}^2} \sim \chi^2(\overline{\mathrm{N}}_{\mathrm{K}}), for\ K = v, u, \eta, \alpha \tag{7}$$

And setting $\overline{\mathrm{N}}_{\mathrm{K}} = 1$ which represents the length of a prior sample from which a sum of squares $\overline{\mathrm{Q}}_{\mathrm{k}}$ is obtained. For posterior consistency, $\overline{\mathrm{Q}}_{\mathrm{k}}$ 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 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[3] 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 paper. 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 paper. To reduce the natural correlations among parameters in the Markov Chain Monte Carlo (MCMC) scheme, reparametrizations are implemented. First, a δ -

[2] 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 of Makiela (2016)

[3] 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).

Parametrization[4] is conducted, with $\delta_i = \alpha_i + \eta_i$, grouping firm-specific effects and persistent inefficiency, which would be grouped implicitly in Greene (2005) True Random Effects 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 paper, even for a similar DGP, with estimation of inefficiencies easily collapsing when signal to noise rations are not large unless some particular tuning of the priors is applied.

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:

$$p(\beta, \sigma_v, \sigma_u, \sigma_\eta, \sigma_\alpha) = p(\beta)p(\sigma_v)p(\sigma_u)p(\sigma_\eta)p(\sigma_\alpha) \tag{8}$$

Where the prior for β as in the aforementioned paper is uninformative, and:

$$\frac{\overline{\mathrm{Q}}_{\mathrm{k}}}{\sigma_{\mathrm{k}}^2} \sim \chi^2(\overline{\mathrm{N}}_{\mathrm{K}}), for\ K = v, \alpha \tag{9}$$

[4] 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 paper, adaptive-rejection sampling is used to draw δ.

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:

$$\frac{1}{\sigma_k^2} \sim f_G(5{,}10\ \ln^2(r_K^*), for\ K = \eta, u \tag{10}$$

In any of the aforementioned cases, the following measure of total efficiency (bounded between 0 and 1) is used to measure efficiency:

$$Eff_{it} = \ \exp(-u_{it} - (\eta_i \otimes lt)) \tag{11}$$

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

$$Efficiency = S^{-1} \sum_{s=1}^{S} \exp[-\tilde{u}_{it}^{(s)} - \tilde{\eta}_i{}^{(s)} \otimes lt] \tag{12}$$

All estimations are conducted using own code in R 3.1.1.

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

Table 2. Explanatory variables of electricity demand model

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.

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:

$$CW_{it} = \sum_{m}^{12} (|16 - AMT_{it}|) \tag{13}$$

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 variations in weather. 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 use 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 (hereby "MAS" – ISIC D), construction ("CON" – ISIC F) and primary sector (ISIC A and B) as separate variables[5]. 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[6]).

However, one needs to consider the complicated issue of deflation and the overall issue of data quality. The data is extended using a variety of sources[7] and is deflated using CPI when the OECD real energy price index is not available. 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[8].

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

[5] 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 (i.e. sectors C and E are removed from calculations).

[6] Average tariffs are used, but when data is missing, residential tariffs or an average of the year before and after are used. The latter issue affects a very small part of the sample.

[7] 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).

[8] For details on such asymmetries, see (Gately and Huntington, 2002).

provide a measure of efficiency from 0 to 1 (fully efficient). This can be translated into a score from 0 to 100%.

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, 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 (Non Transition OECD members).

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 $\sigma_v, \sigma_u, \sigma_\eta, \sigma_\alpha$, with 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: $\sigma_v = 0.1, \sigma_u = 0.2, \sigma_\eta = 0.2, \sigma_\alpha = 0.5$. This scenario is the same as the case N=50 of 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 (hereby "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 have 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 $r_\eta = 0.7$ $r_u = 0.85$		$\bar{Q}_v$=$\bar{Q}_\alpha$=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	0.400	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. 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 $r_\eta = 0.7$ $r_u = 0.85$		$\bar{Q}_v$=$\bar{Q}_\alpha$=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	0.402	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 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 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 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 $r_\eta = 0.7$ to $r_\eta = 0.85$ (0.15 change in prior median efficiency)	0.197	0.143	0.105	0.051
Change in mean η_i from change in $r_\eta = 0.7$ to $r_\eta = 0.6$ (0.1 change in prior median efficiency)	0.095	0.044	0.022	0.016

Table 7. Key results from prior changes in simulations

The summary table shows how the prior drives results in a small sample when there is little data to draw from with low signal-to-noise ratios. With $r_\eta = 0.85$ the prior is tightened into intervals of low inefficiency that are incompatible with the underlying DGP and results suffer severely as a result. With $r_\eta = 0.6$ 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), and witnessed 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 a change in priors is greatly reduced.

There are three key conclusions to take from these results. The first conclusion 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 the 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 puzzling how their results are close to the true values, as the chosen prior would lead to very irregular results in the simulations above.

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 might give less pessimistic insights about some scenarios, particularly in smaller samples.

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 pursuit this modelling approach.

Both Makiela (2016) approach and Tsionas and Kumbhakar (2014) approach (hereby “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 takes about an hour[9].

[9] 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.

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[10]. For each case, parameter 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 analysis of results is focused on the column where prior and posterior persistent inefficiency are rather close, with $\mathrm{r}_{\eta} = 0.6$, as explained below.

[10] 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. For results summary with Norway included, see Appendix 2.

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_{GDP}	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 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 (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 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 plausible. Deviations from an average temperature level also show a positive effect on 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. 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 changes with different priors. As seen in Section 3.5., in comparable sample sizes the results will be severely affected if the underlying signal-to-noise ratio is not strong enough (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), 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. This makes 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 method gives reassurance about the robustness of results as they are reasonably similar. 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 "naïve" approach and two priors under the TK approach. 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 $\mathrm{r}_\eta = 0.6$.

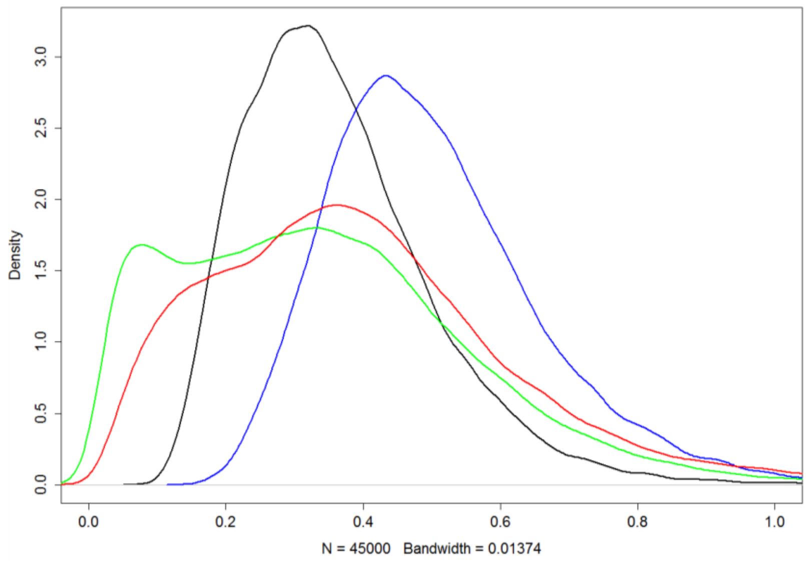

Figure 3.2. Posterior densities of ${\sigma_\eta}^2$ under different priors and approaches. $r_\eta = 0.7$ (black), $r_\eta = 0.6$ (blue) , $\overline{Q}_\eta$=0.1 (green), $\overline{Q}_\eta$=0.25 (red).

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.

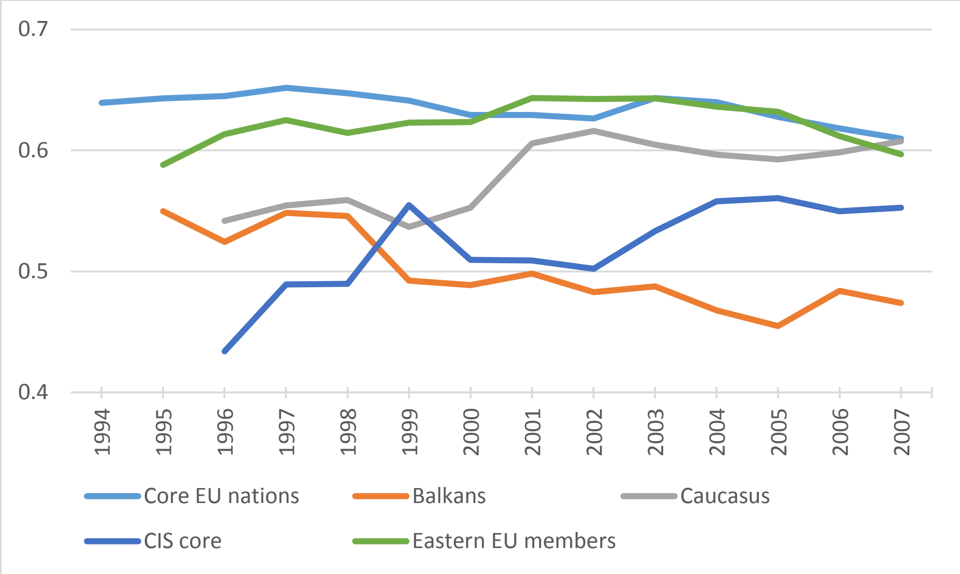

Figure 3.3. Efficiencies across country groups

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 relatively 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 interlinked. 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 of the one in Eastern Europe or 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 the figure. Kazakhstan and Kyrgyzstan, who 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 a claim falls out of the scope of this paper.

One of the most noticeable decrease 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 significance.

Some complications arise when discussing this partial convergence behaviour. There is possibly some measurement error measurement 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 GDP 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 country 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 energy consumption. There is no clear correlation between shadow economy sizes and levels of efficiency and there is no empirical argument supporting that this is distorting results. Regarding changes throughout time, 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 the year of 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. 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 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 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. In this case, it would be hard to solve a possible endogeneity issue (i.e. finding and using appropriate instruments) but preliminary regressions with true random effects approach (not accounting for inefficiency) do not show the significance of lags of prices or GDP. Tran and Tsionas (2013) present an alternative for estimation of a simple stochastic frontier model with GMM and endogenous regressors. 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 price reduction that results from a unit cost decrease 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 paper implicitly imposes the restriction of a zero rebound effect, 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.

7. Conclusions

This paper 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 apparent 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 paper 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.

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APPENDICES

Appendix 1. Geweke convergence diagnostic z-scores for each parameter

Dataset 2 (excluding Norway)	$\bar{Q}_v$=0.001 $\bar{Q}_\alpha$=0.01 $r_\eta = 0.7$ $r_u = 0.85$	**$\bar{Q}_v$=0.001** **$\bar{Q}_\alpha$=0.01** $\mathbf{r_\eta = 0.6}$ $\mathbf{r_u = 0.85}$	$\bar{Q}_v$=0.001 $\bar{Q}_\alpha$=0.01 $r_\eta = 0.5$ $r_u = 0.85$	TK: $\bar{Q}_v$=0.001 $\bar{Q}_\alpha = 0.01$ $\bar{Q}_u$=0.01 $\bar{Q}_\eta$=0.25
β	-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	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	-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	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
σ_v	-1.255	1.159	-0.05584	1.918
σ_u	-0.1887	0.864	-0.6302	-1.228
σ_η	-0.7133	0.07871	0.5243	-2.461
σ_α	1.233	-1.341	-0.2224	1.496

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 5th percentile instead of the 10th. That makes all z-scores within the interval of -2 and 2.

Appendix 2. 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%**