Energy efficiency in transition economies

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Energy Efficiency in Transition Economies: A Stochastic Frontier Approach

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Abstract

This article outlines and estimates a measure of underlying efficiency in electricity consumption for an unbalanced panel of 27 transition economies and 6 European OECD countries between 1994 and 2007. A Bayesian Generalized True Random Effects stochastic frontier model with persistent and transient inefficiency is considered by estimating an aggregate electricity demand function that leads to consumption efficiency scores, giving further insights than a simple analysis of energy intensity. There is evidence of convergence between the CIS countries and a block of Eastern European and 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, as issues such as energy security, energy supply, carbon emissions and climate change get increasing focus from policy makers, the media and society. The topic has been approached from multiple perspectives, from renewable energies to changes in consumer behaviour, spanning a large spectre of research on technical aspects and policy making. However, transition economies have their own challenges and peculiarities which deserve special attention. 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 Organisation for Economic Co-operation and Development (OECD), slowing down the growing patterns of energy demand that were ongoing since World War II (Cooper and Schipper, 1992). Eastern Europe and the Soviet Union 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 more than 25 years of transition, 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 Soviet Union often experienced rapid decreases in energy and electricity intensities as market reforms alleviated problems such as resource misallocation and price distortions. This article models electricity demand and estimates a measure of underlying electricity consumption efficiency, as it is separated from some changes in intensity caused by economic collapse or other deep structural changes in the economy. This is achieved through recent developments in the estimation of Stochastic Frontier models, using the Generalized True Random Effects model (Colombi, Martini and Vittadini, 2011) and its Bayesian implementation approach of Makiela (2017). Both time-varying and persistent inefficiency measures in an electricity demand (cost frontier) equation approach are estimated, 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 often subject to extreme 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 and public conscience on energy consumption in both households and the industrial sector. Selected OECD countries are also added to the sample, due to their large role in the European Union (EU) and their starting points and economic conditions. While there is an undeniable decrease in energy intensity in transition economies in the 1990s (Cornillie and Fankhauser, 2004), that can be attributed to de-industrialization and the collapse of economic activity, and not necessarily due to actual improvements in the use of energy in existing activities at a given time. Therefore, the purpose of this article 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.

While past research has focused heavily on using energy intensity as a proxy for energy efficiency, few attempts to discuss and identify mismatches between the two concepts have been done. Section 2 highlights key facts and peculiar aspects of transition economies along with a literature review of relevant studies of energy efficiency in transition economies and stochastic frontier studies. Section 3 presents a conceptual framework which discusses energy intensity and energy efficiency further. Section 4 presents the Bayesian model to be estimated and the priors of the model, along with a data description. Section 5 shows results which 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. This section also discusses some challenges and related robustness checks. Section 6 concludes.

2. Energy in Transition: key facts and literature review

Key differences separated the Western economies from the centrally planned economies within the FSU and Former Yugoslavia spheres of influence. Planning and energy policy were also fundamentally different, as 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 examples of countries where the main electricity generation firm has remained 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, Taube and Tsyvinski, 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). 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 Commonwealth of Independent States (CIS) (Kennedy, 2003). Removing this distortion maximizes economic benefits. Another major issue is general under-pricing in the power sector, as prices were well below Long Run Marginal Cost (LMRC), a level that needs to be surpassed to allow recovery of past accumulated energy debt, which is a major component of total sovereign or quasi-sovereign debts in some CIS economies. While countries have heterogeneous marginal costs, data from the European Bank for Reconstruction and Development (EBRD) shows 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.

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). The authors decompose energy data to identify the factors driving energy intensity using data from 1992 to 1998. Main conclusions point towards the importance of energy prices and enterprise restructuring as the causes of more efficient energy use (through less energy intensity). Markandya, Pedroso-Galinato and Streimikiene (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, Jamasb and Tisdell (2014) take an institutional approach to explain changes in energy efficiency using dynamic panel data (Bias Corrected Least Square Dummy Variable method) and energy intensity as a dependent variable. The authors find that market liberalization, financial sector and infrastructure industries (excluding the power sector) improved energy intensity 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 and is not used here.

The seminal work of Aigner, Lovell and Schmidt (1977) in Stochastic Frontier modelling introduces the specification of the error term into two separate components, one that is normal and another one with a (one-sided) half-normal distribution and contains information on technical or cost efficiency. 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 (TFE) and the true random effects model (TRE). The methodology of this article will rely on an extension of the true random effects model with an additional one-sided time-invariant component (Colombi, Martini and Vittadini, 2011). However, this is done using Bayesian estimation techniques, as in Makiela (2017). This extension allows the consideration of both time-varying and time-invariant inefficiency, unlike the TRE and TFE models which implied information losses. 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, Greene and Masiero, 2016). Further information on this approach is explained in Section 4.

A major methodological and conceptual influence for estimation of aggregate energy efficiency scores is the approach of Filippini and Hunt (2011). The approach 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 find "underlying energy efficiency" after controlling for income and price effects, climate, technical progress and other exogenous factors, using a pooled model (Aigner, Lovell and Schmidt, 1977) and the TRE model (Greene, 2005) as econometric tools. More detail on Stochastic Frontier modelling tools will be presented in Section 4. 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 as an 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. The authors overlook the issue of heterogeneity among countries by analysing results from an estimation method that might suffer from heterogeneity bias. It also has a simplified approach on accounting for climate and the structure of the economy, which will be discussed in further detail in subsequent sections. 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. This article has two departures from the aforementioned research. Firstly, it considers final consumption only and attempts to remove sectors such as mining, gas and oil extraction from the analysis, along with losses. This implies that the energy industry is excluded from the analysis to focus on the final consumption side of the economy. Secondly, the analysis is based on electricity exclusively and not on total energy consumption.

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 United States. 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, Filippini and Kuenzle (2005) in order to tackle the problem of correlation between the individual effects and the explanatory variables.

Stern (2012) analyses energy 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 article has two important differences from Filippini and Hunt (2011). First, 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. 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. More importantly, 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 of the previous work in the literature, this article will tackle the issue of economy-wide energy efficiency in the specific context of electricity consumption in transition while using up to date Stochastic Frontier techniques. 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 Gross Domestic Product (GDP). This indicator suffered severe but heterogeneous changes in transition economies since 1990. The same happened with electricity intensity, defined as the ratio of electricity consumption per unit of GDP. The Caucasus 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 intensities and didn't manage to considerably bring those levels down by 2006. It is also clear that there is some heterogeneity in efforts bringing down electricity intensity even within the subset of current EU members, which is easy to spot by comparing Latvia and Czech Republic in Figure 1.

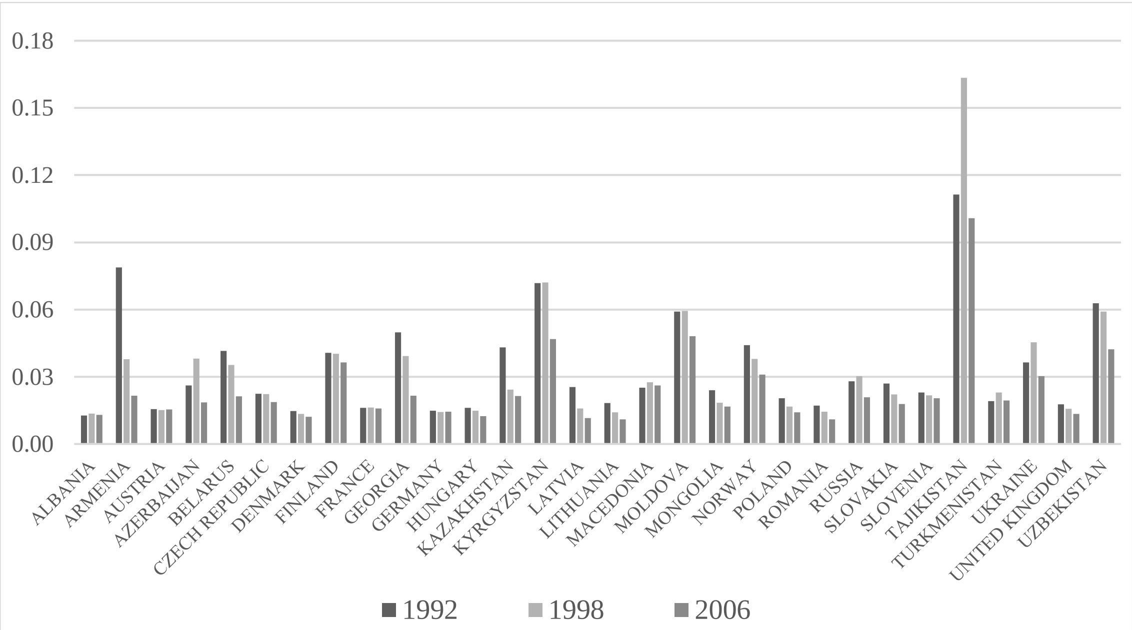

Figure 1. – Electricity use (tonnes of oil equivalent) per $1,000 GDP (constant 2005 PPP). Data source: World Bank

Energy efficiency is a more complex concept than energy intensity, 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 driven mentality and also gave an incentive for more efficient use of energy through government policies, price signals and improved management practices.

The outlined framework points for several theoretical and estimation challenges. 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 due to its reduced energy consumption.

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 makes use of aggregate final electricity consumption for the each economy. Demand relates to several energy services such as heating, manufacturing and lighting. 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). Note that the use of final consumption means that components of total consumption such as energy industry own use and losses are excluded from this analysis. Unlike the analysis of Filippini and Hunt (2011) on OECD countries, there is no readily available data for prices of multiple fuels in ex-Soviet countries, which also justifies the focus of the analysis on electricity consumption exclusively. Electricity is a widely available source of energy for households and businesses with limited substitution effects, which is provided in a standardized manner. To estimate other fuel prices and include them in the analysis would mount to concerns of measurement error.

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 purchase 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 important aspect is the consideration of persistent sources of inefficiency, which can be particularly large in transition economies due to the economic legacy 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 data gaps increases the danger of measurement error. Finally, 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 the output and input mix or if it produces the maximal level of output given inputs (Cornwell and Schmidt, 2008). In this context, Stochastic Frontier Analysis has been used often in empirical research to estimate firm level technical efficiency. It can be argued that an approach that uses electricity consumption as a dependent variable given a set of inputs can retrieve economy-wide efficiency scores which represent national aggregate efficiency.

A neo-classical framework for the frontier approach is considered, although it 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 electricity 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, Llorca and Filippini, 2014) – and the functional form is chosen to achieve estimation simplicity.

A typical cost frontier as originally developed by Aigner, Lovell and Schmidt (1977) can be described as the following logarithmic model:

$$y = \beta_0 + x'\beta + u + v \tag{1}$$

y is the (log) observed cost, while x is a set of (log) inputs. u is a proportional measure of how much y falls short of the (cost) goal, leading to the interpretation of $\exp(-u)$ as percentage or proportional efficiency, bounded between 0 and 1. This stems from the fact that $x'\beta + v$ is the frontier goal or the minimum attainable cost. A popular extension of this model is the True Random Effects model (Greene, 2005), which adds a zero-mean random effect α to equation (1). 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 of the parameters of the cost function so that the frontier is estimated correctly. However, any time-invariant inefficiency which was present in u is now absorbed by α, which changes the interpretation of efficiency scores to a time-varying measure which does not capture persistency.

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-invariant inefficiency from country heterogeneity and the approach of Aigner, Lovell and Schmidt (1977) fails to account for technological heterogeneity, the Generalized True Random Effects (GTRE) approach of Colombi, Martini and Vittadini (2011) is followed to address 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 following cost frontier model accounts for persistent sources of long-run inefficiency and variable sources of inefficiency:

$$y_{it} = x'_{it}\beta + \alpha_i + \eta_i + u_{it} + v_{it} \tag{2}$$

$$\alpha_i \sim i.i.d.N(0;\sigma_\alpha^2) \qquad v_{it} \sim i.i.d.N(0;\sigma_v^2) \tag{3}$$

$$u_{it} \sim i.i.d.N^+(0;\sigma_u^2) \qquad \eta_i \sim i.i.d.N^+\left(0;\sigma_\eta^2\right) \tag{4}$$

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). Here, the frontier gives the minimum level of final electricity consumption attainable by a country. The frontier concept is applied to estimate the baseline electricity demand, with 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 (the model also has a constant). α_i captures latent heterogeneity through a random effect and v_{it} is an idiosyncratic error component which typically present in linear regressions. 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 a random effects model, the effects cannot be correlated with the explanatory variables, as it leads to bias in estimates. Since that problem is often likely to appear, a Mundlak (1978) transformation can be conducted to account for correlation between the time-varying explanatory variables and country-specific effects:

$$\alpha_i = \gamma\bar{X}_\imath + \varphi_i \quad \text{Where} \quad \bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it} \quad \text{and} \quad \varphi_i \sim N(0,\sigma_\varphi) \tag{5}$$

Cross-section means for variables with little variation are not added, such as population and urbanization rate. 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.

In a scenario of differences in technology across countries, the GTRE model presumably performs well in finding true measures of cost efficiency. One could consider that this raises a problem related to the use of random effects models with large enough T to raise concerns about what is indeed time-invariant, 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 model is estimated using Bayesian techniques. This usually implies better small-sample properties and more flexible approaches towards efficiency measurement through the use of prior distributions. Tsionas and Kumbhakar (2014) initially proposed a reparameterization of the model for the joint estimation of some of the components of the model to retrieve more accurate estimates and less correlation between draws of the parameters. The authors argue that this is preferred to a "naïve" approach where the model is not reparameterized before being estimated. However, Makiela (2017) revisited the GTRE "naïve" Bayesian estimation approach, and finds that a different prior distribution which changes the prior assumptions on the sizes of the variances of the error components leads to much better performance and numerical efficiency. The model is therefore estimated without any reparameterization and with the following prior:

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

Where the prior for β is uninformative, and:

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

Equation (7) implies that a sum of squares $\overline{\mathrm{Q}}_{\mathrm{k}}$ is assumed for $\overline{\mathrm{N}}_{\mathrm{K}}$ prior samples. In this case, $\overline{\mathrm{N}}_{\mathrm{K}}$ is always defined as 1 (one prior sample). For the priors of the inefficiency components, a flexible prior that is easier to tune to fit the needs of the researcher is introduced:

$$\frac{1}{\sigma_{\mathrm{k}}^2} \sim f_G(5, 10 \ln^2(r_K^*), for\ K = \eta, u \tag{8}$$

Equation (8) implies that a prior efficiency level r^* is assumed for the inefficiency components. The assumed prior efficiency levels can be different for transient and persistent inefficiency. Because variables are log-transformed as is usual in Stochastic Frontier modelling, the efficiency scores will have to be calculated taking that into account. In any of the aforementioned cases, the following measure of proportional efficiency (bounded between 0 and 1) is used to measure efficiency:

$$Eff_{it} = \exp(-u_{it} - (\eta_i \otimes lt)) \tag{9}$$

To incorporate uncertainty of estimations, 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 $\tilde{\eta}_i{}^{(s)}$:

$$Eff_{it} = S^{-1} \sum_{s=1}^{S} \exp[-\tilde{u}_{it}^{(s)} - \tilde{\eta}_i{}^{(s)} \otimes lt] \tag{10}$$

All estimations are conducted using own code in R 3.1.1.

4.2. Data and modelling

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 (excl. ISIC sectors C and E)
P	Electricity Price Index
CW	Climate Variable
STRUCTURE	Structure of the economy (manufacturing, construction and primary sector)
POP	Population
URBRATE	Urbanization rate (%)
T	Time dummies

Table 1. 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, gas and oil extraction and electricity, gas and water supply activities), with Purchasing Power Parities (PPP) and constant prices. This allows to consider the economic activity that is deeply linked to final electricity consumption. This is preferred to GDP as some of the considered economies have large shares of value added from extractive activities and the energy sector.

Further control variables are necessary to account for factors that influence electricity consumption. CW is a weather 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:

$$CW_{it} = \sum_{m}^{12} (|16 - AMT_{it}|) \tag{11}$$

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 and 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 preferred approach to control for weather effects when compared to a climate dummy because a dummy fails to control for annual variation in climate that can be particularly extreme and affect time-varying inefficiency estimates. A dummy variable can also soak up other effects unrelated to weather that belong to a particular set of countries. 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.

It is also necessary to account for variables that consider 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 of manufacturing (ISIC D), construction (ISIC F) and primary sector (ISIC A and B) are included as separate variables[1]. 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 transition economies, the need to separate energy intensive from less intensive activities and also to consider the quick transition towards a service based economy. Note that after the exclusion of sectors C and E from the total value added that is used for the calculation of shares, the category that is left out amounts to a wide set of service activities. POP is the population of the country at a given year, and URBRATE is the urbanization rate as a percentage of population. T is a set of time dummies which can be interpreted as technological change but can also capture other common time effects. The price of electricity (P) constitutes one of the key estimation issues. Prices are reported in US dollars (mostly sourced from multiple EBRD Transition Reports[2]) and transformed to an index with base 2005=100. The price data is extended using a variety of sources[3] 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 and reduce the possibility of measurement errors. This approach also implies a simplification in the sense that possible

[1] 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 (total with sectors C and E removed from calculations).

[2] 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.

[3] 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).

asymmetric effects in prices and income are not considered. For details on such asymmetries, see Gately and Huntington (2002).

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).

The empirical approach 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. The choice of timeframe is mostly associated to the availability of electricity price data and also the necessary information to deflate it. 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). Descriptive statistics follow on Table 2.

	Mean	**Std. Dev.**	**Min**	**Max**
Final Electricity Cons. (ktoe)	7175.63	12947.63	158	60281
Value Added	2.73e+11	6.74e+11	1.89e+08	3.07e+12
Elec. Price Index	106.11	51.51	37.44	514.38
Climate	114.65	33.38	68.50	263.69
% Manufacturing	18.17	5.53	2.41	35.21
% Primary Sector	10.65	9.73	0.57	36.25
% Construction	7.26	3.38	2.63	28.78
Population	1.89e+07	2.93e+07	1342330	1.47e+08
Urbanization Rate	61.03	13.84	26.4	86.29

Table 2. Descriptive Statistics

5. Results and Discussion

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

The Makiela (2017) Bayesian approach detailed in Section 4.1 is used to estimate the cost frontier. 1,300,000 draws are taken, with a burn-in of 400,000 and taking one in each twenty of the remaining draws. 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 rely on point estimates and group averages 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%, which includes Norway as the seventh non-transition economy of the sample, and another where Norway is excluded. 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, so the results that include Norway as an extremely inefficient country are not the target of analysis and are relegated to Appendix 2. Parameter estimates and efficiency estimates are presented under multiple priors to assess the robustness of the results. In all cases, 95% Bayesian credible intervals are presented in square brackets. The analysis of results is focused on the case where prior and posterior persistent inefficiency are rather close, which is the case of $\mathrm{r}_{\eta} = 0.6$, as seen in Table 3.

	$\overline{Q}_v$=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 $r_\eta = 0.5$ $r_u = 0.85$
$\beta_{Intercept}$	**-15.083** [-21.50;-8.72]	**-16.023** [-22.86;-8.81]	**-15.794** [-22.55;-8.96]
$\beta_{Value\ Added}$	**0.2080** [0.15;0.27]	**0.2054** [0.15;0.26]	**0.2042** [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]
$\beta_{Weather}$	0.0492 [-0.11;0.21]	0.0483 [-0.11;0.21]	0.0479 [-0.11;0.21]
$\beta_{Urb.Rate}$	**1.0470** [0.64;1.45]	**1.0970** [0.70;1.47]	**1.1357** [0.73;1.55]
$\beta_{Population}$	**0.7581** [0.53;0.96]	**0.7340** [0.51;0.98]	**0.7215** [0.45;0.98]
$\beta_{Manuf.\ Share}$	**0.0951** [0.02;0.17]	**0.0888** [0.02;0.16]	**0.0838** [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]
$\beta_{Primary\ Share}$	-0.0006 [-0.08;0.08]	-0.0021 [-0.09;0.08]	-0.0034 [-0.09;0.08]
Mean(η_i)	0.484	0.552	0.608
Mean(u_{it})	0.099	0.098	0.098
σ_v	0.0177 [0.010;0.028]	0.0176 [0.010;0.028]	0.0176 [0.010;0.028]
σ_u	0.1348 [0.123;0.147]	0.1346 [0.123;0.147]	0.1344 [0.123;0.147]
σ_η	0.5912 [0.401;0.828]	0.7018 [0.510;0.942]	0.8217 [0.634;1.073]
σ_α	0.1896 [0.046;0.424]	0.1573 [0.046;0.383]	0.1237 [0.041;0.307]
Mean Efficiency (0-100%)	**59.6%**	**56.7%**	**54.1%**

Table 3. Key regression results (excl. Norway)

All results 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. 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. The effect of the construction sector is also significant at a higher significance level.

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. Past research shows that in such complex models results can be severely affected if the underlying signal-to-noise ratio is weak. 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. 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 and interpretation of results.

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 group averages are considered there are clear signs of convergence. This is an indication 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 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, divergent exception.

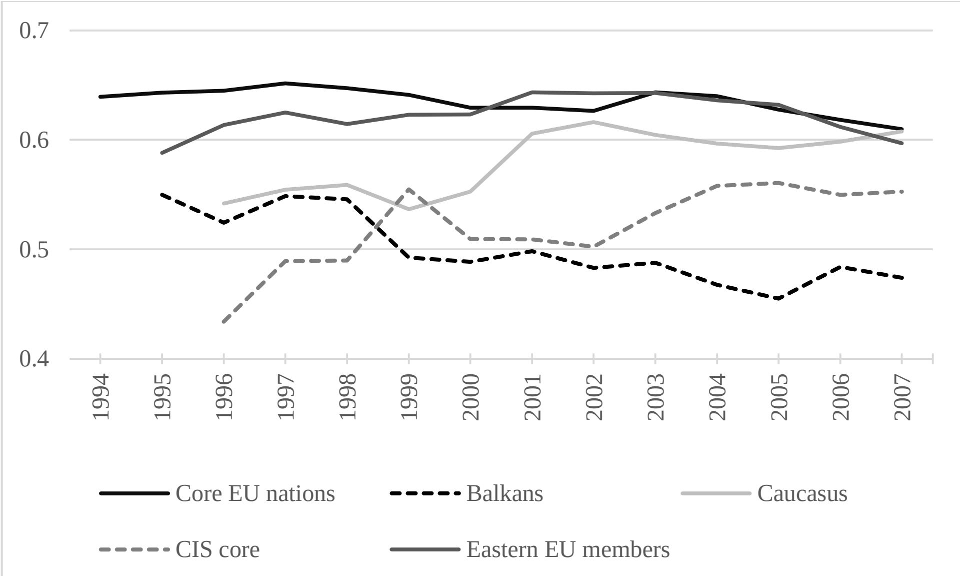

Figure 2. Efficiencies across time and country groups

The convergence behaviour seen in Figure 2 is compatible with the removal of central planning 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. Gomułka (2000) 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 electricity consumption 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 can be visible in the time-varying efficiency results.

The group that stands out as divergent 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 instability in the late 1990s that seems 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 to the one in Eastern Europe or the CIS, as there was already a significant private sector role in the 1990s. The results point that this region failed to capitalize as much in terms of efficiency gains as others, although the starting point was relatively comparable to other economies in the mid-1990s.

There are three other country groups of countries not displayed in Figure 3. 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 article. Appendix 1 shows a detailed list of average, minimum and maximum efficiency levels for each country in the sample.

An issue to have in mind is that the size of the shadow economy in many of these countries is rather large (Schneider, Buehn and Montenegro, 2010). The underestimation of economic activity 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 electricity. However, this theory is somewhat in conflict with the obtained results. Uzbekistan is one of the least efficient countries but was also one of the countries in the FSU 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 that this is distorting results. There are also some further examples to support this perspective in the time dimension. 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 peaked around 2000 but the decrease in efficiency levels is very stable and does not follow the pattern of the size of the shadow economy.

Countries with shy reform efforts 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 a clearly slow paced and gradualist approach towards economic reform. The efficiency scores for this country are volatile but consistently low.

Another possible issue to consider is a correlation between efficiency scores and domestic fuel availability. If an economy has abundant or cheap gas supply, that might influence electricity consumption. Gas is the fuel with the highest substitution potential to electricity. 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 coal. 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 virtually non-existent at -0.02.

Possible endogeneity issues might require further work in the stochastic frontier literature. Mutter et al. (2013) point that it is important to consider if the endogeneity is present in the idiosyncratic error or in the inefficiency component, 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 extremely complex to address a possible endogeneity issue as the modelling approach does not allow for that, and finding and using appropriate instruments would also be difficult in this framework of data availability. This also makes it extremely complex to test for endogeneity. Two key questions are posed in this context. First, the prices might be set as a function of inefficiencies in electricity use. As discussed in Section 2, the energy sector revolved around the issues of broader economic conditions, fiscal issues, subsidies and break-even points of the energy industry. Therefore, it is extremely unlikely that prices were endogenously set with efficiency of consumption in mind. Secondly, the levels of electricity prices might be dependent from the prices of other fuels, which in turn can impact electricity consumption. However, as discussed in the paragraph above, there are no strong and clear correlations between efficiency scores and variables related to other fuels, so this danger related to substitution effects appears to be mitigated. Both questions would also be validly raised for the analysis of Filippini and Hunt (2011), but with further complications due to the existence of multiple fuels, a combined fuel price index which is not disaggregated by fuel, and a much longer time frame in the analysis which could encompass several visions and plans for energy policy.

Finally, the concept of rebound effect is not modelled explicitly but is worthy of discussion. 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, Llorca and Filippini (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 here implicitly imposes the restriction of a zero rebound effect, which according to the evidence from past research from other regions is possibly 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.

In general, all the issues considered above point for a very complex set of possible issues when using Stochastic Frontier models for analysis of electricity consumption efficiency, and it is highly recommended that future research considers these issues and takes them into account in the interpretation of any obtained results from frontier models.

6. Conclusions

This article 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 relatively unexplored in energy economics, even if it displays a growing literature on technical and estimation aspects. The Bayesian approach of Makiela (2017) is chosen to carry out estimation of this model as it allows for flexible priors. 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 size of persistent inefficiency is particularly strong in the results and reinforces the need to choose a modelling approach which allows its measurement. The results and their analysis are an important contribution to the energy efficiency and applied econometrics literature as there is very scarce 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.

This article 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. Many of these difficulties can be the target of future research in the field. 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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Appendix 1. Detailed list of efficiency scores

Country	*Average Efficiency*	*Minimum Efficiency*	*Maximum Efficiency*
MONGOLIA	0.797	0.773	0.820
TURKMENISTAN	0.779	0.731	0.846
ROMANIA	0.776	0.658	0.811
LITHUANIA	0.776	0.681	0.839
LATVIA	0.771	0.660	0.835
DENMARK	0.755	0.709	0.788
HUNGARY	0.749	0.726	0.789
ARMENIA	0.720	0.608	0.789
GERMANY	0.708	0.655	0.742
GEORGIA	0.682	0.578	0.767
CROATIA	0.652	0.570	0.709
UNITED KINGDOM	0.651	0.626	0.677
FRANCE	0.650	0.633	0.664
BELARUS	0.646	0.617	0.662
POLAND	0.632	0.603	0.652
UKRAINE	0.599	0.551	0.633
AUSTRIA	0.532	0.479	0.556
BULGARIA	0.529	0.491	0.554
CZECH REPUBLIC	0.519	0.497	0.531
ESTONIA	0.496	0.435	0.526
BOSNIA	0.479	0.446	0.530
MACEDONIA	0.476	0.405	0.518
ALBANIA	0.476	0.341	0.595
MOLDOVA	0.460	0.390	0.511
RUSSIA	0.455	0.432	0.471
SLOVENIA	0.407	0.369	0.437
SLOVAKIA	0.404	0.370	0.437
UZBEKISTAN	0.383	0.367	0.404
KYRGYZSTAN	0.370	0.265	0.422
KAZAKHSTAN	0.369	0.286	0.410
FINLAND	0.360	0.347	0.375
AZERBAIJAN	0.351	0.330	0.400
TAJIKISTAN	0.207	0.182	0.222

Note: OECD Non-Transition Economies in bold.

Appendix 2. Results with the inclusion of Norway or Area as an additional regressor

	Dataset including Norway $\mathbf{\bar{Q}_v = 0.001}$ $\mathbf{\bar{Q}_\alpha = 0.01}$ $\mathbf{r_\eta = 0.6}$ $\mathbf{r_u = 0.85}$	**Dataset excl. Norway, with area as a regressor** $\mathbf{\bar{Q}_v = 0.001}$ $\mathbf{\bar{Q}_\alpha = 0.01}$ $\mathbf{r_\eta = 0.6}$ $\mathbf{r_u = 0.85}$
$\beta_{Intercept}$	**-18.840** [-26.69;-12.27]	**-17.747** [-27.75;-8.69]
$\beta_{Value\ Added}$	**0.2138** [0.16;0.27]	**0.2053** [0.16;0.25]
$\beta_{Elec.\ Price}$	**-0.0578** [-0.09;-0.03]	**-0.0497** [-0.08;-0.02]
$\beta_{Weather}$	0.0767 [-0.08;0.23]	0.0488 [-0.08;0.18]
$\beta_{Urb.Rate}$	**0.9978** [0.61;1.36]	**1.0981** [0.76;1.43]
$\beta_{Population}$	**0.6435** [0.34;0.89]	**0.7258** [0.49;0.97]
$\beta_{Manuf.\ Share}$	**0.1062** [0.04;0.18]	**0.0881** [0.02;0.15]
$\beta_{Constr.\ Share}$	0.0390 [-0.00;0.08]	**0.0388** [0.00;0.08]
$\beta_{Primary\ Share}$	-0.0042 [-0.09;0.08]	-0.0019 [-0.07;0.07]
β_{Area}	-	-0.0478 [-0.25;0.14]
Mean(η_i)	0.601	0.604
Mean(u_{it})	0.098	0.098
σ_v	0.0172 [0.010;0.027]	0.0181 [0.011;0.026]
σ_u	0.1339 [0.122;0.146]	0.1347 [0.125;0.145]
σ_η	0.7495 [0.537;1.037]	0.7550 [0.568;0.966]
σ_α	0.1659 [0.043;0.407]	0.1513 [0.050;0.264]
Mean Efficiency (0-100%)	**54.3%**	**53.9%**