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Measurement of the "Underlying energy efficiency" in Chinese provinces

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Abstract

China is one of the largest consumers of energy globally. The country also emits some of the highest levels of CO2 globally. In 2009, 18% of the world's total energy was consumed in China and the growth rate of energy consumption in China is 6.4% per year. In recent years, the Chinese government decided to introduce several energy policy instruments to promote energy efficiency. For instance, reduction targets for the level of energy intensity have been defined for provinces in China. However, energy intensity is not an accurate proxy for energy efficiency because changes in energy intensity are a function of changes in several socioeconomic factors. For this reason, in this paper we present an empirical analysis on the measurement of the persistent and transient "underlying energy efficiency" of Chinese provinces. For this purpose, a log-log aggregate energy demand frontier model is estimated by employing data on 29 provinces observed over the period 1996 to 2008. Several econometric model specifications for panel data are used: the random effects model and the true random effects model along with other versions of these models. Our analysis shows that energy intensity cannot measure accurately the level of efficiency in the use of energy in Chinese provinces. Further, our empirical analysis shows that the average value of the *persistent* "underlying energy efficiency" is around 0.78 whereas the average value of the *transient* "underlying energy efficiency" is approximately 0.93.

Keywords: Chinese energy demand, Stochastic frontier analysis, Underlying energy efficiency, Energy intensity

JEL Classification: D, D2, Q, Q4, Q5.

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1 Introduction

Emerging economies such as certain Asian and Latin American countries are characterized by relatively high growth rates of energy consumption. The rapid increase of energy consumption in these countries featured by fossil-fuel-based energy system determines local and global environmental problems as well security of supply issues. China, one of the largest energy consumers and emitter of CO2 globally, is also facing these problems. In fact, China has consumed 18% of the world energy in 2009 and the average growth rate of energy consumption is approximately 6% per year. As the most remarkable growing economy in both energy consumption and GDP, China's energy strategy can significantly affect international discussions on climate change.

In order to promote a reduction of CO2 emissions, a reduction of the local pollution and to promote a higher level of security of supply, the Chinese government has decided to introduce several energy policy instruments. Some of these instruments are market oriented. However, others are non-market oriented instruments such as limits, targets and standard. For instance, in 2007 China revised its energy conservation law and emphasized the relevance of the level of energy efficiency in all sectors of the economy. Further, recently the Chinese government introduced the 12th Five Year Plan that clearly states some binding targets at the end of 2015: a reduction of energy consumption per unit of GDP by 16 percent and a decline of CO2 emissions per unit of GDP by 17%, relative to 2005 levels. Therefore, the Chinese provinces received individual targets for reduction of the level of energy intensity.[3]

With the introduction of these targets, the Chinese government would like to promote an increase in the level of efficiency in the use of energy as well a higher degree of security of supply. However, as discussed in a report by IEA (2009) and by Filippini and Hunt (2011), energy intensity is not an accurate proxy for energy efficiency. This is because changes in energy intensity are a function of changes in several socioeconomic and climate factors. Therefore, for the definition of these policy targets, a better understanding and measurement of the level of energy efficiency of these provinces could improve the effectiveness of interventions done by the central government.

[3] In the period 1980-2000 China's energy intensity declined 4.52% annually. Though experienced a slight increase between 2002 and 2005, it continued with a staggering decline of 18% between 2005 and 2010.

The goal of this paper is to perform an empirical analysis on the measurement of the "underlying energy efficiency" of Chinese provinces using an approach proposed by Filippini and Hunt (2011). This approach is based on the stochastic frontier analysis developed in applied production theory and regards energy as an input into a production function to generate an energy service (such as heating and transport).

Some studies have been published on the measurement of the energy efficiency of the Chinese provinces. All these studies use a Data Envelopment Approach (DEA) and not, as in this study, a stochastic frontier approach. Hu and Wang (2006) estimated the level of energy efficiency using a DEA model and employing provincial data in the periods of 1995-2002. They found a U-shape relation between energy efficiency and per capita income. Moreover, the study confirmed the impact of economic growth on improvement of energy efficiency.[4] Wei et al. (2009) used a DEA approach and panel data to estimate the level of energy efficiency of Chinese provinces. Using a two-step approach the authors of this study tried to identify the drivers of energy efficiency. The results suggest presence of inefficiency in the use of energy and the presence of spatial differences in energy efficiency.

These differences are mainly due to the economic structure, energy structure, the type of government intervention, and the level of technology. Hu and Wang (2010) proposed the estimation of a total-factor energy productivity change index using a DEA approach. The analysis is based on provincial data for the period 2000-2004. In a second part of the analysis, Hu and Wang (2010) proposed to decompose the energy productivity index into "energy efficiency" and "shift in energy use technology".

In this paper, as discussed above, we want to use an alternative approach to measure the level of "underlying energy efficiency" based on stochastic frontier analysis. The advantages of this approach in the context of measurement of energy efficiency is the possibility to take into account the presence of unobserved

[4] Many papers have also examined the driving forces for energy intensity decline in China using Divisia decomposition method. For instance, Fisher-Vanden et al. (2004) applied the approach using panel data for 2500 industrial enterprises and identified several forces such as research and development expenditures, changes in China's industrial structure as the principal drivers. Hang and Tu (2007) followed similar approach and showed the asymmetric impacts of energy prices on energy intensity. There are also studies in literature on the structural change effects (Liao et al. 2007; Ma and Stern 2008). Song and Zheng (2012) combined decomposition analysis with econometric model and found the significant impacts of rising income as well as limited effect of energy price on the reduction of energy intensity.

heterogeneity, to distinguish persistent (time-invariant) from transient (time-varying) inefficiency and to take into account through the statistical noise of approximation errors and random behavior. To note, that the estimation and interpretation of persistent and transient inefficiency as complementary parts of the level of productive efficiency is recent.[5]

The paper is organized as follows. Section 2 introduces the specification of aggregate energy demand model and summarizes data. In Section 3, econometric specifications have been explained. Section 4 presents and discusses estimation results. Section 5 summarizes the estimated "underlying energy efficiency". Section 6 concludes the paper.

2 Model specification and data

The analysis of the level of "underlying energy efficiency" of the Chinese provinces is based on the econometric estimation of following aggregate energy demand frontier function:

$$E_{it} = E(P_{it}, Y_{it}, H_{it}, HS_{it}, ISH_{it}, SSH_{it}, HDD_{it}, CDD_{it}, UEDT_t, EF_{it}) \qquad (1)$$

where E_{it} is the aggregate energy consumption for each provinces i over time t in million tonnes of coal equivalent (Mtce); Y_{it} is the real GDP in billion 1996 Chinese Yuan (CNY); P_{it} is the real energy price index (1996 = 100); H_{it} is the number of household units; HS_{it} indicates the household size computed as the ratio between population and household units; ISH_{it} and SSH_{it} are the share of the industrial sector and the share of the service sector in % of the GDP, respectively. $UEDT_t$ captures some important unmeasured exogenous factors that influence all provinces simultaneously, e.g. general technical progress, awareness of emission reduction and climate change. Finally, EF_{it} is the level of "underlying energy efficiency" of each of the Chinese provinces in year t.

[5] Generally, the empirical literature on the measurement of productive efficiency interpret time-varying and time-invariant inefficiency indicators as alternative measures of productive efficiency. See for instance Filippini and Hunt (2012). Only recently Kumbhakar et. al. (2012) introduced a new interpretation of these inefficiency measures based on complementarity. In this paper we decided to follow this approach.

Unfortunately, this level is usually not directly observed for an economic system and, therefore, has to be estimated. As previously discussed, in this paper, following the approach suggested by Filippini and Hunt (2011), we estimate the level of "underlying energy efficiency" of Chinese provinces by using a stochastic energy demand frontier function. This frontier represents the minimum level of energy consumption necessary for each province to produce any given level of energy service (Filippini and Hunt 2011, 2013). Therefore, the frontier function defines a boundary, deviations from which can be interpreted as inefficiency in the use of input energy.

Aigner et al. (1977) proposed the stochastic frontier model as an econometric technique to estimate the level of efficiency in use of inputs. In this econometric model, variation of the dependent variable unexplained by independent variables is split in two parts: statistical noise and productive inefficiency.

Following Filippini and Hunt (2011, 2012) and using a log-log functional form the stochastic energy demand frontier function can be specified as follow:

$$\begin{aligned} e_{it} &= \alpha + \alpha^{p} p_{it} + \alpha^{y} y_{it} + \alpha^{h} h_{it} + \alpha^{hs} hs_{it} + \alpha^{ISH} ISH_{it} + \alpha^{SSH} SSH_{it} \\ &+ \alpha^{hdd} hdd_{it} + \alpha^{cdd} cdd_{it} + \alpha^{t} t + \alpha^{t^2} t^2 + v_{it} + u_{it} \end{aligned} \tag{2}$$

where e_{it} is the natural logarithm of aggregate energy consumption (E_{it}); p_{it} is the natural logarithm of the real energy price (P_{it}); y_{it} is the natural logarithm of of GDP; h_{it} is the natural logarithm of the number of households (H_{it}); hs_{it} is the natural logarithm of the household size (HS_{it}); hdd_{it} and cdd_{it} are the natural logarithm of the heating degree days (HDD_{it}) and the cooling degree days (CDD_{it}), respectively; ISH_{it} and SSH_{it} are as defined above; t and t^2 are used as proxies for $UEDT_t$.[6]

The error terms in equation 2 have two parts. The first part, v_{it}, is the normal noise term assumed to be normally distributed. The second term, u_{it} contains information on the distance between the frontier and the actual input and is interpreted as an indicator of the inefficiency levels. It is a one-sided non-negative random disturbance term that can vary over time. For this term a distributional

[6] As suggested in Filippini and Hunt (2012), time dummies can also be used as an alternative to capture the impacts of UEDT. In a preliminary analysis we also used time dummies and the results were relatively similar.

assumption has to be made. Generally researchers choose the half-normal distribution. However, other assumptions regarding the distribution of inefficiency term can be made such as exponential, truncated-normal and gamma distributions.

Summarizing, in equation 2 the time trend should capture impact on energy consumption due to technological, organizational, and social innovation, whereas u_{it} should capture improvements in the level of efficiency in use of energy. As discussed in more details in Filippini and Hunt (2013), in a more general interpretation the time trend should capture shifts in isoquants, whereas u_{it} should capture the distance from the isoquant.

Based on the values of u_{it} and following Jondrow et al. (1982) it is possible to estimate the level of "underlying energy efficiency" of a province using the conditional mean of the efficiency term $E[u_{it}|u_{it}+v_{it}]$. The level of "underlying energy efficiency" can be expressed in the following way:

$$EF_{it} = \frac{E_{it}^{F}}{E_{it}} = \exp(-\hat{u}_{it}) \qquad (3)$$

where E_{it} is the observed energy consumption and E_{it}^{F} is the frontier or minimum demand of the ith state in time t. A value EF_{it} of one indicates a province on the frontier (100% efficient), while non-frontier provinces are characterized by a level of EF_{it} lower than 100%.

This study is based on a balanced China panel data set for a sample of 29 provinces observed over the period 1996 to 2008 (t = 1996-2008). This paper is restricted to study provinces, autonomous regions, and municipalities in mainland China. Due to incomplete information in statistics, Tibet and Hainan are excluded from this study. For simplicity, thereafter all the units of observations are called provinces. The data set is based on information taken from China National Bureau of Statistics reports "China Statistical Yearbook" (1997-2009)[7] and "China Urban Life and Price Yearbook" (2009). Table 1 presents the descriptive statistics of key variables.

[7] The yearbooks of China always have one-year delay, which means yearbook in 1997 reports the statistics of 1996.

Table 1: Descriptive statistics of explanatory variables

Variables	Description	mean	sd	min	max
E	Energy consumption (Mtce)	70.46	49.78	6.980	305.7
P	Real price index (1996=100)	113.4	22.41	84.65	216.4
Y	Real GDP (billion 1996CNY)	472.5	436.7	18.36	2,599
POP	Population (1000)	43,356	25,176	4,880	97,170
HOUSE	Number of household (1000)	13,717	8,075	1,259	32,948
ISH	Share of industrial sector in % of GDP	46.53	6.042	25.70	61.50
SSH	Share of service sector in % of GDP	37.66	6.544	24.60	73.20
HDD	Heating degree days (base: 18 $^{\circ}$ C)	2,284	1,309	142.6	5,390
CDD	Cooling degree days (base: 24 $^{\circ}$ C)	207.1	190.7	0	751.1
HS	Average household size (persons)	3.19	0.32	2.60	4.13

3 Econometric specifications

The estimation of a stochastic frontier function with panel data can be performed using a number of different SFA model specifications such as the pooled model (PM hereafter), the random effects model (REM hereafter), the true fixed effects model (TFEM hereafter), and the true random effects model (TREM hereafter).[8] Moreover, in some recent studies on the aggregate energy demand by Filippini and Hunt (2012, 2013), part of these stochastic frontier models, have been estimated using an adjustment introduced by Mundlak (1978). This adjustment takes into account a potential unobserved heterogeneity bias and separates transient inefficiency from time invariant unobserved heterogeneity.

[8] For a general presentation of these models, see Greene (2008) and Farsi and Filippini (2009).

As discussed in details in Farsi and Filippini (2009) and Filippini and Hunt (2013), all these models have their relative advantages and disadvantages and the choice of model is not straightforward. It depends upon the goal of the exercise and type of data and variables that are available. Generally, one of the most important issues to consider in estimating energy demand frontier function using aggregate data is to use an econometric specification that takes into account of the presence of time-invariant unobserved heterogeneity variables, time invariant or persistent inefficiency and transient inefficiency. In our case, due to the relatively large size and heterogeneity in the morphology and socioeconomic organization of Chinese provinces, we can expect to observe transient and persistent inefficiency in the use of energy as well a model specification that could suffer from unobserved heterogeneity bias.

Unfortunately, nowadays, there is no satisfactory and relatively straightforward econometric model that can be estimated in order to obtain at the same time information on persistent and transient inefficiency and controlling for unobserved heterogeneity bias. For instance, Kumbhakar et. al. (2012) propose a relatively complex econometric approach based on a three steps estimation procedure and Tsionas and Kumbhakar (2012) proposed an approach based on Bayesian methods and Monte Carlo methods.[9]

In our empirical analysis we decided to follow another approach to measure persistent and time-varying inefficiency based on the estimation of several independent models. For this reason, we estimate the basic version of the REM proposed by Pitt and Lee (1981), a Mundlak version of this model, the TREM proposed by Greene (2005a, 2005b) and a Mundlak version of the TREM. The first two models provide information on the level of persistent inefficiency, whereas the last two models give information on transient inefficiency. Of course, we are aware that this approach based on the estimation of separate models is not completely satisfactory.

In the basic form of REM proposed by Pitt and Lee (1981), individual random effects are considered inefficiency indicators rather than time-invariant unobserved heterogeneity as in the traditional literature on panel data econometric methods. In this model, the individual effects u_i are assumed to be half-normal distributed and to

[9] Filippini and Greene (2013) are developing an approach based on simulated maximum likelihood function that will allow to estimate persistent and time-varying inefficiency.

be uncorrelated with the explanatory variables. As long as this assumption holds, the estimators are not affected by a heterogeneity bias. As discussed by Filippini and Hunt (2012), one problem with the REM is that any time-invariant, province-specific heterogeneity is included in the inefficiency term. Further, the level of inefficiency does not vary over time. Therefore, the REM tends to provide information on the level of persistent inefficiency.

The TREM is obtained by adding to the PM proposed by Aigner et al. (1977) an individual random effect that should capture the time-invariant unobserved variables.[10] The TREM estimates unit-specific constants that are designed to capture unobserved heterogeneity by simulated maximum likelihood, so that the remaining elements in the error term, including inefficiency, vary freely over time. Still, correlation between the individual effects and the explanatory variables might cause a heterogeneity bias. This model has the advantage to be able to differentiate time invariant unobserved heterogeneity from the time varying part of efficiency. This is a clear advantage of the TREM with respect to the basic version of the PM. However, this model tends to underestimate the level of inefficiency because the persistent part of inefficiency is captured by individual random effects. In situations characterized by the presence of persistent inefficiency in the use of resources, the TREM estimates just one part of the level of inefficiency. Therefore, the values of inefficiency in use of energy obtained using TREM tend to represent the transient part of inefficiency.

As discussed by Farsi et al. (2005a, 2005b), both approaches mentioned above (REM and TREM) can suffer from the "unobserved variables bias". To address this issue in the classical linear random effects model, Mundlak (1978) proposed to use the following auxiliary equation that considers possible correlation between the unobserved heterogeneity and the explanatory variables with the group-means of the explanatory variables:

$$\alpha_i = \gamma \bar{x}_i + \delta_i, \quad \bar{x}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} x_{it}, \quad \delta_i \sim iid(0, \sigma_\delta^2) \qquad (4)$$

[10] True RE model of Greene (2005a, 2005b) is a successor of the models of Kumbhakar (1991) and Polachek and Yoon (1996). For a successful application of these models in network industries, see Farsi et al. (2005a) and Farsi et al. (2006).

This auxiliary equation (4) can directly be incorporated into the energy demand model. Equation (4) divides the unobserved heterogeneity term into two components. The first component with the estimators γ absorbs part of the unobserved time-invariant heterogeneity that is correlated with the independent variables. The second component (δ_i) accounts for unit-specific constants.

In order to solve the unobserved heterogeneity bias in the estimation of stochastic frontier models, Farsi et al. (2005a, 2005b) proposed to use the Mundlak adjustment along with estimation of these non-linear models. [11],[12]

In the Mundlak version of REM (hereafter MREM) the correlated components of unobserved heterogeneity are absorbed by the group-means of explanatory variables, whereas uncorrelated components are stuck in individual effects. The additional assumption that underlies in this model is that only uncorrelated, i.e. separable components of unobserved heterogeneity are in the individual effects, which as explained above, in this model are interpreted as inefficiency terms. The correlated, i.e. non-separable components of unobserved heterogeneity are considered in the coefficients of auxiliary equation and thus not interpreted as inefficiency. This assumption is in line with Bagdadioglu and Weyman-Jones (2007) and Cullmann et al. (2012), in that time-invariant non-separable factors are assumed an integrated part of the production process and therefore not inefficiency. We believe that the MREM is an appealing model because it is relatively intuitive, easy to estimate, avoids the unobserved heterogeneity bias and separates the individual effects in two parts - the persistent inefficiency term and the non-separable time-invariant unobserved variables.

Another issue related to the estimation of an aggregate energy demand function is the potential endogeneity problem of the GDP variable, especially in models that try to explain energy consumption in developing or emerging countries.[13]

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[11] This argument holds for RE models, which are based on normality, but does not strictly apply to stochastic frontier models estimated by ML, as these models possess an asymmetric composite error term ε_i. As the model captures the correlation between the individual effects and the explanatory variables at least partly, the resulting heterogeneity bias is expected to be minimal.

[12] The TREM is estimated using a simulated maximum likelihood procedure. To note, that Greene (2005a) proposed also another model for panel data, the true fixed effects model. We decided not to use this model because of the existence of the incidental parameters problem.

[13] To note that in the literature using data for industrialized countries characterized by a relatively small

As recently discussed by Greene (2011) and Mutter et al. (2013), it is difficult to account for endogeneity in SFA models, particularly because of the non-linearity of econometric specification. In fact, no accepted approach exists for SFA models. This is the reason why most of the empirical studies using SFA do not consider this potential econometric problem. Recently, Mutter et al. (2013) investigated the impact of endogeneity on inefficiency estimates using the SFA approach. The results show that the degree of severity of problem depends across model specifications and type of data. As a robustness check, we decided to investigate the endogeneity issue of GDP using residual inclusion approach (2SRI hereafter) for non-linear models suggested by Terza et al. (2008). This approach tries to solve the endogeneity problem by using a two-stage method. In the first stage, the endogenous variable is regressed against instrumental as well exogenous variables. In the second stage, the original equation is estimated by including the residuals obtained in the first stage. Of course, we are aware that this approach based on two separate steps is not completely satisfactory.

Table 2: Descriptive statistics for instrumental variables

Variables	Description	mean	sd	min	max
ILT	Rate of illiterate persons (%)	11.92	6.70	3.11	43.62
ENG	Rate of engineers in total professional personnel (%)	18.15	6.00	8.91	44.31
LIF	Life expectations (years)	70.23	3.66	59.64	78.14
PAK	Area size of green land (km^2)	38,179	46,409	1,041	377,041

The instruments considered in our empirical analysis are illiterate rate (ILT_{it}), the ratio of engineers in professional personels (ENG_{it}), life expectation (LIF_{it}), and the size of green parks (PAK_{it}). Table 2 provides the descriptive statistics of these instruments.

weight of energy to GDP, this potential endogeneity problem is rarely considered.

To test for weak instruments we compute the Cragg-Donald Wald F test statistic. The value of this statistic (11.786) is larger than the critical value at 10% level of significance (10.27) suggested by Stock-Yogo (2003). Therefore, we reject the hypothesis that instruments are weak. The Hansen J statistic for testing the overidentication of all instruments does not reject the null hypothesis of valid instruments (Chi2(3)=4.40, P-Value=0.22). All these results show that we were able to find reasonable instruments. Further, the endogeneity test rejects the null hypothesis of exogeneity of GDP (Chi2(1)=5.31, P-Value=0.02).

Given the discussion above, six models are estimated in this paper: Model I, the REM; Model II, the Mundlak version of the REM (hereafter MREM); Model III, the MREM with 2SRI (hereafter MREM-2SRI); Model IV, the TREM; Model V, the Mundlak version of the TREM (hereafter MTREM); and Model VI, the MTREM with 2SRI (hereafter MTREM-2SRI). As previously discussed, the Mundlak version of REM and TREM are considered the most interesting models for estimation of persistent and transient level of efficiency in the use of energy, respectively. Table 3 summarizes the six models.

Table 3: Econometric specifications of the stochastic cost frontier

	Model I	***Model II***	***Model III***	***Model IV***	***Model V***	***Model VI***
	REM	**MREM**	**MREM-2SRI**	**TREM**	**MTREM**	**MTREM-2SRI**
State effects α_i		$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$	*iid (0, σ_α^2)*	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ *iid (0, σ_α^2)*	$\alpha_i = \gamma \bar{X}_i + \delta_i$ $\bar{X}_i = \frac{1}{T}\sum_{t=1}^{T} X_{it}$ *iid (0, σ_α^2)*
Random error ε_{it}	$\varepsilon_{it} = \alpha_i + v_{it}$ $\alpha_i \sim N^+(0, \sigma_\alpha^2)$ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = \delta_i + v_{it}$ $\delta_i \sim N^+(0, \sigma_\delta^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N^+(0, \sigma_u^2)$ $v_{it} \sim N(0, \sigma_u^2)$
Inefficiency	$E(\alpha_i \mid v_{it})$	$E(\delta_i \mid v_{it})$	$E(\delta_i \mid v_{it})$	$E(u_{it} \mid v_{it})$	$E(u_{it} \mid v_{it})$	$E(u_{it} \mid v_{it})$

4 Estimation results

The estimation results of frontier energy demand models using the six models are given in Table 4. [14] Most of the estimated coefficients and *lambda*[15] have the expected signs and are statistically significant at the 10% level; the only exceptions being in some models some variables such as the price variable and the share of the service sector. Generally, the value of coefficients of REM and TREM are similar but to some extent different from the values of the coefficients of all other models that take into account the problem of unobserved heterogeneity bias. For instance, the values of income elasticity obtained in REM and TREM are much lower than the ones obtained in all other models. The results obtained with MREM, MREM-2SRI, MTREM and MTREM-2SRI models are relatively similar. This similarity in the results confirms that Mundlak adjustment method applied to REM and TREM models can be a valid approach in stochastic frontier analysis. Therefore, MREM, MREM-2SRI, MTREM and MTREM-2SRI models should be preferred to REM and TREM models.

The estimation results indicate that price does not influence energy demand. This result may be due to the fact that in China energy prices are relatively low and fully controlled by the government. Therefore, the variation across provinces of the price is relatively low.

The income elasticity (α^{y}) is around 1 and statistically significant in all four models with the Mundlak corrections (MREM, MREM-2RSI, MTREM, and MTREM-2SRI). This implies that a 1% increase in GDP will lead to a 1% increase in energy demand. Therefore, as expected for emerging countries, the income elasticity is relatively high. To note, that in MREM-2RSI, MTREM-2SRI models where the endogeneity of GDP is taken into account, the values of income elasticities are relatively similar to the values obtained in other models. Moreover, the coefficients of residuals in MREM-2RSI, MTREM-2SRI are not significant. These results could suggest the presence of a weak endogeneity problem.

[14] Given the fact that we are using a log-log functional form, the estimated coefficients can be interpreted as elasticities.
[15] Lambda (λ) gives information on the relative contribution of u_{it} and v_{it} on the decomposed error term ε_{it} and shows that in this case, the one-sided error component is relatively large.

Table 4: Estimation results

VARIABLES	(1) REM Frontier	(2) MREM Frontier	(3) MREM-2SRI Frontier	(4) TREM Frontier	(5) MTREM Frontier	(6) MTREM-2SRI Frontier
P	0.000	0.001	0.002	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Y	0.659***	1.079***	1.002***	0.605***	1.064***	1.007***
	(0.075)	(0.147)	(0.172)	(0.022)	(0.074)	(0.086)
e^{2SRI}			0.107			0.077
			(0.118)			(0.067)
HOUSE	0.085	0.208	0.296*	0.050**	0.261***	0.332***
	(0.080)	(0.128)	(0.164)	(0.023)	(0.030)	(0.057)
HS	-0.422***	-0.376**	-0.359*	-0.436***	-0.357**	-0.332**
	(0.160)	(0.191)	(0.192)	(0.082)	(0.139)	(0.142)
HDD	0.187***	0.097*	0.090*	0.113***	0.100	0.095
	(0.040)	(0.053)	(0.054)	(0.012)	(0.076)	(0.077)
CDD	0.016**	0.019***	0.019***	0.017***	0.021**	0.020**
	(0.006)	(0.006)	(0.006)	(0.004)	(0.009)	(0.009)
ISH	0.012***	0.012***	0.016***	0.009***	0.013***	0.015***
	(0.004)	(0.004)	(0.005)	(0.001)	(0.002)	(0.003)
SSH	-0.004	-0.002	0.002	-0.008***	-0.002	0.001
	(0.004)	(0.004)	(0.006)	(0.002)	(0.002)	(0.003)
T	-0.032***	-0.065***	-0.060***	-0.017***	-0.061***	-0.059***
	(0.010)	(0.013)	(0.014)	(0.006)	(0.009)	(0.010)
T2	0.003***	0.002	0.001	0.002***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
M(P)		-0.011*	-0.011**		-0.005***	-0.005***
		(0.006)	(0.006)		(0.002)	(0.002)
M(Y)		-0.398*	-0.410**		-0.477***	-0.487***
		(0.205)	(0.206)		(0.077)	(0.079)
M(HS)		1.134	1.110		1.220***	1.202***
		(0.870)	(0.853)		(0.197)	(0.201)
M(HDD)		0.161*	0.166*		0.113	0.109
		(0.087)	(0.087)		(0.079)	(0.080)
M(CDD)		-0.097***	-0.094***		-0.084***	-0.083***
		(0.015)	(0.015)		(0.010)	(0.010)
M(ISH)		-0.004	-0.004		0.002	0.002
		(0.009)	(0.009)		(0.003)	(0.003)
M(SSH)		0.019**	0.018**		0.016***	0.016***
		(0.008)	(0.008)		(0.003)	(0.003)
Constant	-2.788	-5.854	-5.251	0.280	-4.760***	-4.377***
	(1.721)	(3.921)	(3.872)	(0.422)	(0.545)	(0.632)
Log likelihood	249.0	268.8	269.3	250.0	266.1	266.4
Sigma_u	0.508***	0.333***	0.335***	0.147***	0.129***	0.124***
Lambda	4.814***	3.237***	3.264***	1.759***	1.123**	0.973**

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The coefficients of the two variables household size (hs_{it}) and number of households ($house_{it}$) represent the impact on aggregate energy demand of demographic variables. As expected, in all models the coefficient of the number of households is positive, whereas the coefficient of the household size is negative. Thus, ceteris paribus, an increase of the household size implies a decrease of energy consumption. This result is due to the presence of 'economies of scale' in the production of some residential energy services. For instance, the size of a fridge is unlikely to vary proportionally with the number of household members. In order to reduce the growth rate of energy demand, the government could introduce policy instruments to encourage families to live together. The traditional Chinese philosophy of life supports this behavior.

As expected, the sign of HDD and CDD coefficients are positive. However, the coefficient of HDD is not always significant. A possible explanation for this result is the relatively low penetration rates of heating systems in some provinces. In reality, only northern and a small part of central region in China are heated legally according to the construction code of China. On the other side, energy consumption for cooling is becoming a major demander for electricity in residential and service sector (Zhang 2013). Due to the relatively hot climate in some Chinese provinces and the increase of income, the use of air-condition appliances increased a lot during the last years.

The estimated coefficients of GDP share in both, the industrial sector and service sector are relatively small. The UEDT is captured by the coefficients of t and t^2 combined. In all models, with the Mundlak adjustment (MREM, MREM-2SRI, MTREM and MTREM-2SRI), the squared term is not significant. Therefore, we can assume the presence of a linear trend with a coefficient of *t* that varies between -0.059 and -0.065 across models. This is an evidence of a continuous improvement of exogenous technical progress, which contributes to the decline in the common underlying energy demand trend.

5 Energy efficiency

Table 5 gives a summary of the energy efficiency scores estimated with all six models. As expected, the scores obtained with REM, MREM and MREM-2SRI are lower

than the scores obtained with TREM, MTREM and MTREM-2SRI. Further, the values of energy efficiency obtained using MREM and MREM-2SRI (0.78) are higher than the values obtained with the basic REM (0.67).

As discussed above, the reason for this difference is due to the ability of MREM and MREM-2SRI to distinguish persistent inefficiency from time-invariant unobserved variables. Finally, the values of energy efficiency calculated with MTREM and MTREM-2SRI are relatively high (0.92-0.93). In this study, as argued before, we propose to interpret the values obtained with MREM and MREM-2SRI as the persistent component of level of energy efficiency and the values from MTREM and MTREM-2SRI as the transient component.

Table 5: Energy efficiency scores of different estimations

MODEL	OBS	MEAN	STD. DEV	MIN	MAX
REM	377	0.6738	0.1718	0.3271	0.9793
MREM	377	0.7831	0.1490	0.4868	0.9747
MREM-2SRI	377	0.7830	0.1509	0.4857	0.9751
TREM	377	0.9051	0.0492	0.7272	0.9744
MTREM	377	0.9270	0.0295	0.8055	0.9738
MTREM-2SRI	377	0.9338	0.0242	0.8316	0.9741

In Table 6 we report the values of Spearman's rank correlation coefficient of the energy efficiency values obtained with all models that consider the Mundlak adjustment. To note, that the rank correlation coefficient between the level of efficiency obtained using MREM and MREM-2SRI is 0.99. Also, the rank correlation coefficient between the level of efficiency obtained using MTREM and MTREM-2SRI is very high (0.99). Further, the correlation coefficients between all MTREM models and all MREM models are relatively low (0.31). This result indicates that *persistent* "underlying energy efficiency" and *transient* "underlying energy efficiency" are not highly correlated. Finally, the Spearman's rank correlation coefficient between the estimated "underlying *persistent* energy efficiency" from the two models MREM and MREM-2SRI and 'energy

intensity is -0.51, whereas the Spearman's rank correlation coefficient between the estimated "underlying *transient* energy efficiency" from MTREM and MTREM-2SRI and energy intensity is -0.35 (see Table 7). This result confirms that energy intensity should not be used as a proxy for energy efficiency.

Table 6: Pair-wise Spearman's rank correlation coefficient between model estimations

	REM	MREM	MREM-2SRI	TREM	MTREM	MTREM-2SRI
REM	1.0000					
MREM	0.7054	1.0000				
MREM-2SRI	0.7059	0.9995				
TREM	0.1064	0.2020	0.1951	1.0000		
MTREM	0.1364	0.3133	0.3074	0.7773	1.0000	
MTREM-2SRI	0.1458	0.3187	0.3128	0.7813	0.9990	1.0000

Table 7: Pair-wise Spearman's rank correlation coefficient between efficency scores from all models and energy intensity (EI)

	REM	MREM	MREM-2SRI	TREM	MTREM	MTREM-2SRI
EI	-0.80	-0.51	-0.51	-0.29	-0.35	-0.35

The values of level of energy efficiency can be used to identify three groups of provinces namely, relatively efficient provinces (average value of the level of efficiency higher than the third quartile of the distribution of efficiency), relatively inefficient states (average value of the level of efficiency lower than the median value) and moderately efficient states (average value of the level of efficiency between the median and the third quartile value).

Table 8: Classification of provinces based on the estimated average energy efficiency over the period 1996-2008

	MREM average	MTREM average
Beijing	**	**
Tianjin	**	*
Heibei	*	*
Shanxi	*	*
Inner Mongolia	*	**
Liaoning	*	*
Jilin	***	*
Heilongjiang	***	*
Shanghai	**	***
Jiangsu	***	***
Zhejiang	**	**
Anhui	**	**
Fujian	***	**
Jiangxi	***	***
Shandong	**	*
Henan	*	***
Hubei	*	*
Hunan	*	*
Guangdong	*	***
Guangxi	**	**
Chongqing	*	*
Sichuan	*	**
Guizhou	*	**
Yunnan	***	*
Shaanxi	*	*
Gansu	**	***
Qinghai	***	***
Ningxia	*	*
Xinjiang	*	**
Mean	0.783	0.927
Median	0.784	0.928
75% percentile	0.944	0.931

NB: The classification in the table are based on the following rules:

Inefficient province: Marked with "*", where a province's average value of estimated "underlying energy efficiency" is lower than the median estimated "underlying energy efficiency". ***Moderately efficient province:*** Marked with "**", where a province's average "underlying energy efficiency" is between the median and the 75% quartile estimated "underlying energy efficiency". ***Efficient province****:* Marked with "***", where a province's average "underlying energy efficiency" is higer than the 75% quartile estimated "underlying energy efficiency".

In Table 8, we report the classification of provinces based on average value of the energy efficiency obtained during the period 1996-2008 and using the results of MREM and MTREM models. From this table it is interesting to observe that: a) there is no clear relationship between the efficiency level and the degree of economic development. For instance, well developed provinces such as Zhejiang, Jiangsu, Fujian, Beijing, Shanghai, Guangdong belong to different efficiency groups; b) some of the provinces show a relatively high level of persistent efficiency but a relatively low level of time varying efficiency, whereas some of the provinces show a relatively low level of persistent efficiency but a relatively high level of transient efficiency; c) it is possible to identify some spatial clusters in the level of energy efficiency.

The maps in figures 1 and 2 illustrate the average level of energy efficiency of all provinces observed during the period of the analysis from model MREM-2SRI and MTREM-2SRI. The greener the color is, the more efficient a province is. Both figures show that there are significant differences between provinces in term of persistent as well transient level of energy efficiency.

Figure 1: Geographic illustration of the level of persistent energy efficiency across provinces (MREM model)

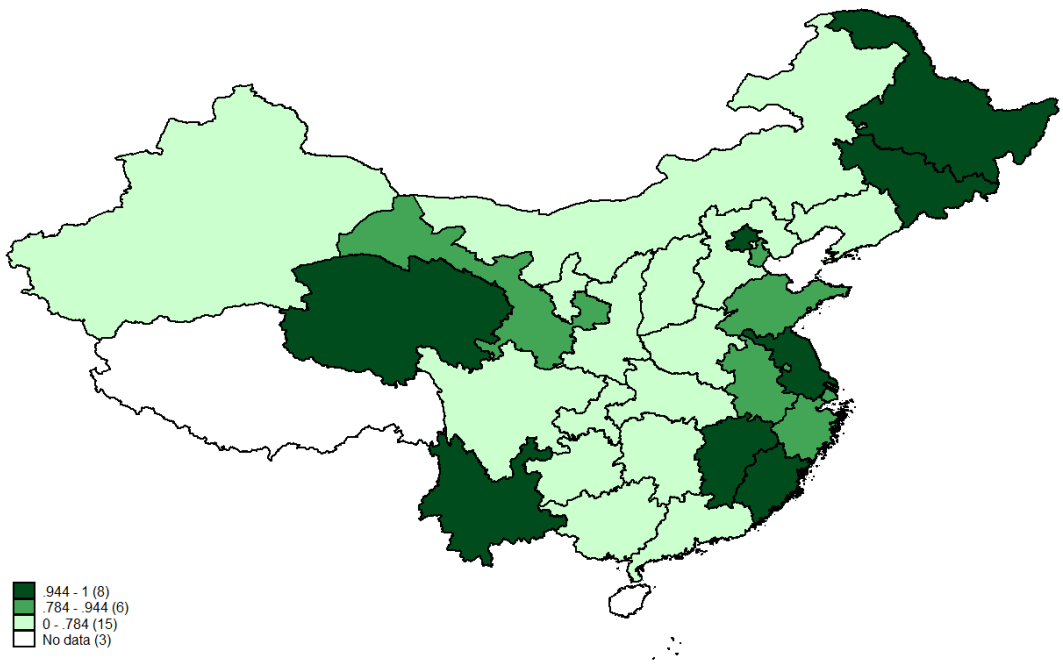
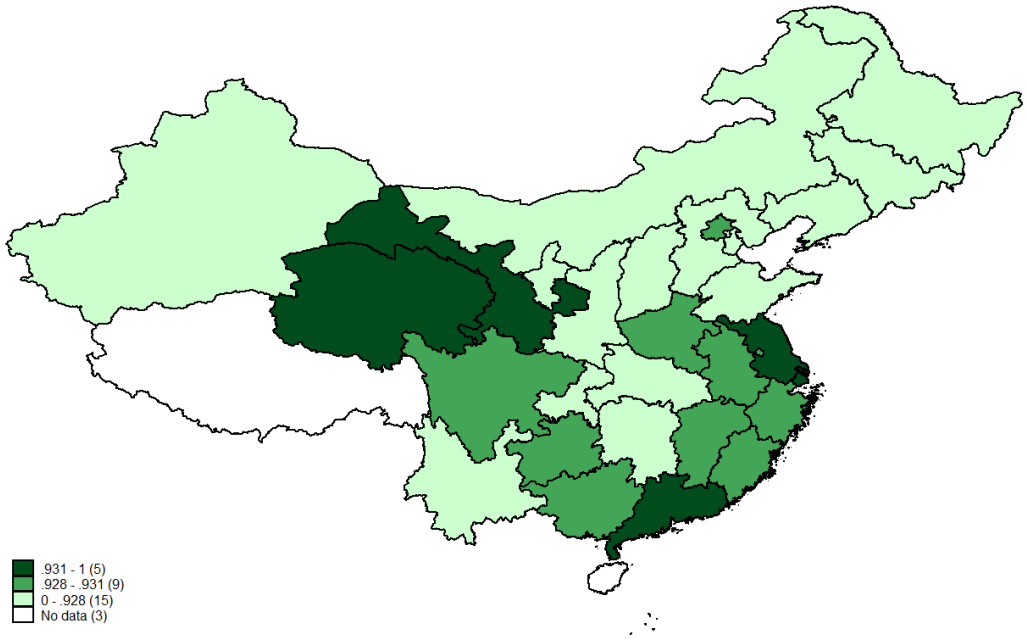


Figure 2: Geographic illustration of level of transient energy efficiency across provinces (average value, MTREM model)



6 Concluding remarks

In this study, we have estimated the level of "underlying energy efficiency" for Chinese provinces. For this purpose, a log-log aggregate energy demand frontier model was estimated employing data of 29 provinces observed between the periods from 1996 to 2008. The frontier model approach used in this study is based on Filippini and Hunt (2011, 2012).

From the econometric point of view, several estimators are possible for panel data frontier models. In the choice of econometric techniques, special attention has been given to the presence of unobserved heterogeneity variables and to the fact that some models provide information on the level of *persistent* "underlying energy efficiency" and some others provide information on the level of *transient* "underlying energy efficiency". In this study, in addition to the widely used REM and TREM, we estimate these models using the Mundlak adjustment (1978).

Our analysis shows that energy intensity cannot measure accurately the level of efficiency in the use of energy in Chinese provinces. Further, our empirical analysis

shows that the average value of the *persistent* "underlying energy efficiency" is around 0.78 whereas the average value of the *transient* "underlying energy efficiency" is approximately 0.93. Finally, the results indicate that exogenous factors such as technical change play an important role in decreasing the consumption of energy.

From an energy policy point of view the empirical analysis reported in this paper shows that energy consumption targets, as the ones introduced recently by the Chinese government, should also be defined by considering the level of "underlying energy efficiency" of single provinces and not only the energy intensity. The energy policy instruments should give on one side incentives to the provinces to be on the frontier. On the other side, the energy policy instruments should be more incentive to adopt new and more efficient technologies.

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