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***JEL Classification:*** *C23, D24, L51, L94*

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# State-Level Electricity Generation Efficiency: Do Restructuring and Regulatory Institutions Matter in the US?

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**Abstract**

This paper examines the impact of deregulation and the political support for it on the electric power industry using a consistent state-level electricity generation dataset for the US contiguous states from 1997-2014. Recent analyses of productivity growth suggests that institutional factors are important and we wish to study the role of deregulation as a state-level institutional change through two measures: (a) restructuring and (b) the political support for it, measured by the majority political affiliation of public utility commissions. We find evidence of positive impacts of deregulation (both restructuring and the political support for it) on technical efficiency across the models estimated. Our preferred model which allows for the control for deregulation variables on the mean and variance of the inefficiency shows an average technical efficiency of 73.1 percent. The results of the marginal effects reveal that the impact of deregulation including its political support on inefficiency is negative and monotonic, with the potential reduction of 8.4 percent in the mean of technical inefficiency, thereby suggesting a compelling evidence for generation efficiency improvement via deregulation.

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## 1. Introduction

The United States electricity sector has been historically dominated by large, vertically integrated, and heavily regulated utilities until recent decades, with firms exercising monopoly in their local service area while subject to control in the form of rate of return regulation. However, studies on the US power sector reform starting with the works of Palmer and Burtraw (1995), Joskow (1997) and Ando and Palmer (1998) report that a series of significant restructuring policies has been implemented since the late 1990s occasioned by the structural transformation and advances in technology which have changed the production characteristics of the industry. The policies are aimed at promoting competition to enhance more efficient electricity supply, lower electricity prices to consumers and boost innovation among wholesale and retail customers. Although, there is no evidence of a mandatory and comprehensive federal electricity restructuring program, a number of state-based restructuring initiatives have emerged, varying considerably from states to state, with many states introducing only limited electricity sector reform.

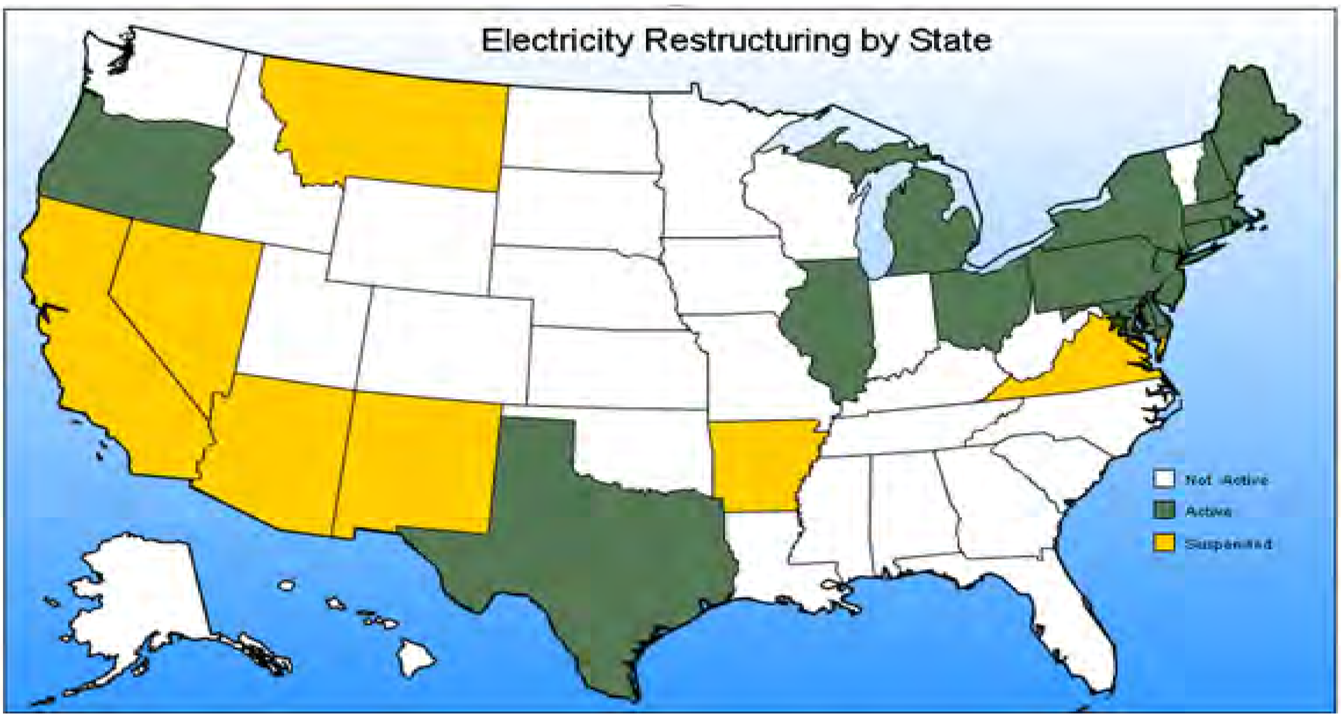
Electricity market restructuring began with the enactment of the Federal Energy Policy Act of 1992 and FERC Order No. 888 in 1996[2]. On the one hand, the former legislation allowed some categories of generators to build or purchase electricity generation sources to sell electricity at the wholesale market and require transmitting utilities to open access to their transmission capacities for wholesale electricity sale to any electric utility, federal power marketing agencies and any person generating electric energy (FERC, 2006, p. 24). On the other hand, the later act facilitates the restructuring process by permitting independent private and other participant entry into the wholesale market. In both cases, restructuring was mainly intended to induce competition to the wholesale market being the starting point of a restructuring program. Competition among independent generators was supposed to create a framework for wholesale power transactions so that retail customers and local distribution utilities could purchase power from a wide range of alternative suppliers in order to lower wholesale costs and thus lower retail prices (Kwoka, 2008).

At the state level, the wave of restructuring in the US was driven mainly by the regional disparity in electricity prices. Retail prices for both residential electricity customers and large industrial electricity consumers were shown to be higher in most of the Northeastern states and California with price variation up as high as 130% across states (See Joskow, 1997 p 126). Indeed, the quest for retail competition was seen as way of lowering prices (Palmer and Burtraw, 1995). Thus in 1996, California became the first state to enact market restructuring legislation that introduced competition into retail market. Meanwhile, the state public utility commissions (PUCs) regulate the electric power industry and set the retail rates for electricity, based on the

[2]The precursor to restructuring legislations is the Public Utility Regulatory Policy Act of 1978 (PURPA) which offered the first organisational departure from the legitimate monopoly franchise of electricity generation by regulated utilities. The main objective is to promote greater use of alternative renewable energy.

cost of service. As the industry restructures, PUC no longer regulate retail rates for generated or purchased power in some states as retail electricity prices open to the market forces of competition. So far, some states have active restructuring activities on-going, spanning complete deregulation and competition in the retail market while others states have partial restructuring involving divestment of some generation or allowing a portion of customers to choose their energy. Some states failed to achieve the expected outcome of deregulation and suspended further restructuring a few years afterwards. However, a majority of the states have so far maintained their original structure with no sort restructuring attempted. Figure 1 shows patterns of restructuring across the U.S., with sixteen states together with District of Columbia have restructuring active as of 2012[3] while other states had either suspended or not activated restructuring according to the Department of Energy's (DOE) of the US Energy Information Administration (EIA)[4].

**Fig. 1.** Electricity restructuring by US states as of 2012




*Source: US Energy Information Administration*

Over all, the key dimension of restructuring in the United States has implications for ownership arrangements, resulting in conversion of some generation capacity from utility status to independent power producer status

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[4]These states are Connecticut, District of Columbia, Delaware, Illinois, Maine, Maryland, Massachusetts, Michigan, New Hampshire, New Jersey, New York, Ohio, Oregon, Pennsylvania, Rhode Island and Texas.

(IPP)[5]. Essentially, this impacted on the generation asset remuneration moving from a rate of return regulation model, in which they were guaranteed to recover a positive return on those capital costs, to a market-based pricing mechanism, under which these assets earned a market price for the output they were able to produce. The aftermath of the restructuring witnessed an unprecedented investment in new generation, especially renewables, with the share of nuclear generation owned by IPP increased from zero in 1997 to almost 50% in 2012, as utilities sold off their nuclear assets (see Borenstein and Bushnell, 2015).

Since the implementation of market reform, there has been proliferation of empirical studies on the effects of restructuring in the electric power industry. One aspect that has attracted much attention is the investigation of the efficiency gains from restructuring. Obviously, the debate has been more intense about how reform has potentially impacted on the operational efficiency of the investor –owned electric utilities. Protagonists of restructuring have earlier advocated that it offers incentives to electricity producers to improve their efficiency; however, controversies remain going by the mixed pictures of the findings from these studies. Previous studies which have established efficiency gains from restructuring in the US electricity sector include Kleit and Terrell (2001), Knittel (2002), Hiebert (2002), Davis and Wolfram (2012), Zhang (2007) and Craig and Savage (2013). Some empirical studies confirmed a negative efficiency impact of deregulation on electric power industry: Delma and Tokat (2005) and Goto and Tsutsui (2008), while Fabrizrio et al (2007) shows both negative and positive impacts of deregulation on efficiency.

Using a Bayesian stochastic frontier model, Kleit and Terrell (2001) examined the potential efficiency gains in electric power generation for 78 steam plants in the year 1996. They find that plants, on average, could reduce production costs by up to 13% by eliminating production inefficiency. Knittel (2002) reveals an increase in efficiency by about two per cent for coal and natural gas fuelled plant. Hiebert (2002) investigated the impact of restructuring on cost efficiency for 633 fossil-fuelled plants from 1988 to 1997. The result shows a mean efficiency increase in the states implementing retail competition to about 50 per cent. Craig and Savage (2013) examine the effects of market restructuring initiatives that introduced competition into the US electricity industry on the thermal efficiency of electricity generation for 950 plants from 1996 to 2006. The authors found that access to wholesale electricity markets and retail choice together increased the efficiency of investor-owned plants by about nine percent and that these gains stem from organizational and technological changes within the plant.

[5] The extent one considers the electric sector to be deregulated," in the United State, it is due to this fundamental shift in the paradigm for compensating owners of generation.

In contrast, Delmas and Tokat (2005) showed that the process of retail deregulation had a negative impact on firms' productive efficiency using data envelopment analysis (DEA) on 177 U.S. electric utilities from 1998 to 2001. Goto and Tsutsui (2008) investigated the impact on technical efficiency change in electric utilities in their generation, transmission/distribution, and general administration functions using the input distance function and stochastic frontier approach. They examined technical efficiency change using annual data for 22 U.S. electric utilities firms from 1992-2000 and found that firms located in states that have enforced deregulation are less efficient. However, Fabrizio et al (2007) shows both negative and positive impacts of deregulation by estimating the input demand functions for 769 fossil fuelled plants from 1981 to1999. They indicate that the labour and non-fuel expenses of plants in the states that implemented restructuring legislation were about 3 to 5 percent lower than plant in non- restructured states while concluding that restructuring yields substantial medium-run efficiency for the investor-owned utilities.

Our paper focuses on electric power industry's performance using consistent state-level electricity generation dataset for the contiguous state from 1998-2014. Why state level aggregation? The focus of the paper is the restructuring of the markets as deregulation and other changes have occurred. This is part of a general focus on the importance of institutions in shaping productivity and growth as suggested by North (1991) and Acemoglu et al (2005). However institutional change and restructuring occur at the state level rather than at the firm level. Therefore, we argue that it is important in the context of this research question to aggregate across firms at the state level. This paper makes a number of distinct contributions to the efficiency and restructuring literature. It adds to the limited number of studies examining the determinants of the inefficiency in the US-state level electricity generation aftermath of restructuring. Moreover, it improves on such previous empirical applications by employing several specifications of stochastic frontier models. which have not been applied previously in the past studies and which has been shown to provide a substantial improvement in model fits. Finally, we provide an evaluation of the non-monotonic marginal effects of restructuring on electricity generation inefficiency in other to provide insights into what could have informed the substantial rollback of restructuring by states that have earlier adopted the policy. Therefore, we adopt the Wang (2002, 2003) approach that allows both mean and variance of the pre-truncated normal distribution to depend on the exogenous variables. Our findings reveal that deregulation (both restructuring and the political support for it) significantly reduces technical inefficiency across the models estimated.

The remainder of the paper is organised as follows. Section 2 provides the methodological approach. Specifically, we present the specification for the estimated models and the non-monotonic marginal effects. In section 3, we explain in detail the data and variables used. Section 4 presents the empirical results from models and the marginal effects. Section 5 presents the concluding remarks.

## 2. Methodology

In this paper, we explore the impact of restructuring electricity generation efficiency by estimating a stochastic production frontier model. The stochastic frontier analysis (SFA) independently proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) SFA is centred on the concept that deviations from the production frontier defined by the ''best practice'' technology might not be entirely under the control of the firm and might be due to measurement errors and other noise upon the frontier. The approach decomposes the error term into two components, a traditional two-sided error term which captures effects of measurement error and a one-sided error term to measure technical inefficiency. The general stochastic production function (ALS, hereafter) is specified as follows:

$$y_{it} = \alpha + x_{it}'\beta + v_{it} - u_{it} \quad (1)$$

$$v_{it} \sim N(0, \sigma_v^2) \quad (2)$$

$$u_{it} \sim N^+(0, \sigma_u^2) \quad (3)$$

The cross-sectional units are indexed $i$ = 1….,$N$ and the time periods are indexed $t$= 1, …,$T$, where N is appreciably large (47) and $T$ is 17. $y_{it}$ is the log of output of each state, $\alpha$ is the intercept, $x_{it}'$ is the vector of log of inputs and $\beta$ the vector of coefficients to be estimated. The $v_{it}$ denotes a two-sided conventional idiosyncratic error term which is assumed to follow an *i.i.d.* $N(0, \sigma_v^2)$ distribution and accounts for measurement sampling and specification error, as well as for the effect of other random shocks. The $u_{it}$ represents one-sided and non-negative random variables which measure technical inefficiency and have an identical and independent half normal distribution. This model was originally developed for cross-sectional data but was later extended to accommodate panel data by the inclusion of a time trend or time dummy in order to capture technical progress. The nexus between inefficiency and exogenous effects has been investigated sequentially using a two-step approach[6] (See Kumbhakar and Lovell, 2000). Subsequently, that approach has been considered to be biased due to misspecification inherent in the first model (Battese and Coelli, 1995, Wang and Schmidt, 2002) and now full maximum likelihood estimation in one stage is used.

[6] The approach estimates the observation-specific inefficiency measure in first step, and goes further to regress the efficiency index on exogenous variables in second step. The shortcoming of the procedure is that if the input variables and the exogenous are correlated, the first step of the two-step procedure is considered biased. In the event that input variables and the exogenous factors are uncorrelated, ignoring the dependence of the inefficiency on the exogenous variable will lead the first step technical efficiency to be underdispersed such that the results of the second stage regression are likely to be biased downward (See Kumbhakar et al, 2015)

Modelling of exogenous effects on inefficiency has followed two flexible approaches. First, Kumbhakar, et al. (1991), Huang and Liu (1994), and Battese and Coelli (1995) (KGMHLBC hereafter) proposed parametrising the mean of the pre-truncated inefficiency distribution.

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_{it}^{2}) \qquad (4)$$
$$\mu_{it} = \boldsymbol{z}_{\boldsymbol{it}}' \delta$$

where $\boldsymbol{z}_{\boldsymbol{it}}$ is the vector of exogenous variables. Second, Reifschneider and Stevenson (1991), Caudill and Ford (1993) and Caudill et al (1995) assume $\mu_{it}$ to be constant but parameterize the variance of the pre-truncated distribution as a function the exogenous variables;

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_{it}^{2}) \qquad (5)$$
$$\sigma_{it}^{2} = \exp(\boldsymbol{z}_{\boldsymbol{it}}' \gamma)$$

Hadri (1999) generalises the second approach by allowing the variance of the two-sided error term to be heteroscedastic by parameterizing the variance of the noise component. A model under this second approach is jointly classed as Reifschneider and Stevenson (1991), Caudill and Ford (1993) and Caudill et al (1995) and Hadri (1999) (RSCFG hereafter)[7]. Given that $u_{it}$ has a truncated normal distribution, its variance is a function of both $\mu_{it}$ and $\sigma_{it}^{2}$. Wang (2002) proposed another model that combines the features of KGMHLBC and RSCFG and allows both $\mu_{it}$ and $\sigma_{it}^{2}$ to be observation specific. The truncated normal distribution WANG model with double heteroscedasticity is parameterised as follows.

$$u_{it} \sim N^{+}(\mu, \sigma_{it}^{2})$$
$$\mu_{it} = \boldsymbol{z}_{it}' \delta \qquad (6)$$
$$\sigma_{it}^{2} = \exp(\boldsymbol{z}_{it}' \gamma)$$
$$\sigma_{vit}^{2} = \exp(\boldsymbol{z}_{it}' \lambda)$$

The determinants vector $\boldsymbol{z}_{it}'$ includes a constant and some other exogenous variables associated with the inefficiency. The $\delta$ and $\gamma$ are the corresponding coefficient vectors. All other notations remain as defined above. It is instructive to note that whether we allow the mean, the variance, or both the mean and the variance

[7] The ALS half normal distribution suffers some drawbacks as it assumes that $u_{it}$ and the pre-truncated $u_{it}$ are homoscedastic i.e. both $\sigma_{u}^{2}$ and $\sigma_{u}^{2}$ parameters are constants. This drawback is also addressed by this approach. Ignoring the heteroscedasticity of $v_{it}$ would not affect the consistency of frontier's function parameters estimates but could bias the intercept downward and also bias technical efficiency. Whereas if heteroscedasticity of $u_{it}$ is ignored both the estimates of the frontier parameters as well as the technical efficiency are biased (See Kumbhakar et al. 2015)

of the pre-truncated normal to depend on exogenous factors, both the mean and the variance of the truncated half normal will always depend on the exogenous factors. Failure to model the exogenous factors appropriately leads to biased estimation of the production frontier model and of the level of technical inefficiency, hence leading to poor policy conclusions (see Liu and Myers, 2009). It is the exogenous variables that give policy makers a means to induce efficiency change.

First, we begin by assuming the general model as the WANG model in which $\delta$ and $\gamma$ are both estimated using maximum likelihood methods as parameterised in Eq. (6). Second, we consider the KGMHLBC model. The model treats the mean of the pre-truncated normal distribution as a function of exogenous variables while assuming homoscedastic variance of the pre-truncated normal distribution as specified in the Eq. (4). Third, we look at the pre-truncated normal distribution RSCFG model in which $\mu = 0$. This model addresses heteroscedasticity by treating exogenous variables as determinants of the variance of the pre-truncated normal variable. This is followed by the RSCFG$-\mu$ proposed by Alvarez et al. (2006) where the mean of distribution is allowed to be different from zero[8]. Lastly, we estimate the homoscedastic half normal ALS in which $\mu = \gamma = 0$. We nest the four other restricted models into the general model and select the appropriate model that provides the best fit for our data using diagnostics tests such as the Likelihood ratio (LR) and Akaike information criterion (AIC). The summary of the general model together with the restrictions of the other competing models is presented in Table 1.

**Table 1:** List of the estimated models

| Variable | Restrictions | $N^+(\mu_{it}, \sigma_{it}^2)$ | |
|---|---|---|---|
| | | Mean | Std Deviation |
| WANG Model | - | $\mu_{it} = z_{it}^{'}\delta$ | $\sigma_{it}^2 = \exp(z_{it}^{'}\gamma)$ |
| KGMHLBC Model | $\gamma = 0$ | $\mu_{it} = z_{it}^{'}\delta$ | $\sigma_{it}^2 = \sigma_u^2$ |
| RSCFG- $\mu$ Model | $\delta = 0$ | $\mu_{it} = \mu$ | $\sigma_{it}^2 = \exp(z_{it}^{'}\gamma)$ |
| RSCFG Model | $\mu = 0$ | $\mu_{it} = 0$ | $\sigma_{it}^2 = \exp(z_{it}^{'}\gamma)$ |
| ALS Model | $\mu = \gamma = 0$ | $\mu_{it} = 0$ | $\sigma_{it}^2 = \sigma_u^2$ |

[8] Alvarez et al. (2006) give a technical discussion on the desirability of the scaling property arising from the non- zero mean assumption of the model which parametrises inefficiency term as a deterministic function of a set of efficiency covariates, i.e. $h(.) = \exp(\boldsymbol{z}_{it}'\gamma)$, times a one-sided random variable that does not depend on any efficiency determinant, $u_{it}^* \sim N^+(0, \sigma_u^2)$.

Given the composed error term $\varepsilon_{it} = u_{it} + v_{it}$, $u_{it}$ is estimated as the conditional expectation of the one-sided error term, $\exp(u)$, given the composed error, $v + u$:

$$\hat{u}_{it} = E[u_{it} | v_{it} + u_{it}] \tag{7}$$

The maximum likelihood residuals are used to replace $\varepsilon_{it} = v_{it} + u_{it}$

The measurement of the technical efficiency is obtained by deriving the probability density function for $u$, conditional on every numerical realization of the composed error term $\varepsilon_{it.}$. This approach is based on conditional expectations which generalize the estimators proposed Battese and Coelli (1988). The technical efficiency index for each state can be estimated from the point estimates of the technical inefficiency ($u_{it}$) as the ratio of observed output to corresponding frontier output.

$$TE_{it} = E[\exp(-(u_{it} | \varepsilon_{it}))] \tag{8}$$

The technical efficiency index lies between 0 and 1. A score of one indicates a fully efficient state is on the frontier, while a non-frontier state receives scores below one.

### 2.1. Marginal effect

We proceed to derive the marginal effect of the z$[j]$, the $j$th variable of the $\mathbf{z}_{it}$ vector in Eq. (6). Wang's (2002) model has the advantage of allowing for the estimation of non-monotonic efficiency impacts which implies that $\boldsymbol{z}_{it}$ can have, within the sample both increasing and decreasing effects on the production efficiency. The conventional stochastic frontier model is built on the implicit assumption that the exogenous variables' impacts on inefficiency are monotonic i.e. the exogenous factors are either strictly efficiency-enhancing or efficiency–impeding in the sample, but not both. However, Wang (2002) demonstrates the exogenous variables can positively (negatively) affect the mean and variance of inefficiency when the values of the $\mathbf{z}_{it}$ vector are within e certain range, and then the impacts turn negative (positive) for values of $\mathbf{z}_{it}$ outside the range.

How do changes in the exogenous variables impact on the inefficiency distribution? In the KGMHLBC, RSCFG models one of the parameters of the basic distribution $f(u_{it})$ changes, i.e., either the mean, $\mu$, or the variance,$\sigma_u^2$. If the mean changes, KGMHLBC, this represents a change of location of the distribution which will be displaced to the right if the change in the exogenous variable raises the mode of the inefficiency, i.e., the most frequently observed level of inefficiency is greater. If the variance changes, RSCFG, this represents an increased spread of inefficiency so that the most frequently observed value does not change but more extreme values of inefficiency are likely to be observed. From an economic policy point of view this means that policy directed towards reducing inefficiency may be targeted at improving the performance of the majority of agents (mean targeted) or lowering the likelihood of extremely inefficient agents (variance targeted). The Wang model assumes that both factors may be important. This captures a wider range of behaviours but on the other hand makes policy design more complex.

The non-monotonicity marginal effects of on $E(u_{it})$ of the $j$th element of $\mathbf{z}_{it}$ can written as;

$$\frac{\partial E(u_{it})}{\partial z[\mathrm{j}]} = \delta[\mathrm{j}]\left[1-\Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]-\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right] + \gamma[\mathrm{j}]\frac{\sigma_{it}}{2}\left[(1+\Lambda^2)\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]+\Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right] \qquad (9)$$

where $\Lambda = \mu_{it}/\sigma_{it}$, $\phi$ and $\Phi$ are the probability and cumulative density functions of a standard normal distribution. $z[j]$ is the $j$th element of $\mathbf{z}_{it}$, $\delta$ and $\gamma$ are associated coefficients of the determinants of mean and variance inefficiency. In the event that the variance $\sigma_{it}^2$ is non- parameterised, $\gamma[j]$ is assumed to be zero, constant for all $j$, and equation (10) would imply a monotonic effect of $\mathbf{z}_{it}$ on $(u_{it})$. The marginal effect takes the sign of $\delta[j]$ which is the same for all values of $\mathbf{z}_{it}$.

The marginal effects of $\mathbf{z}_{it}$ on $V(u_{it})$ can be expressed as follows:

$$\begin{aligned}\frac{\partial V(u_{it})}{\partial z[\mathrm{j}]} &= \frac{\delta[\mathrm{j}]}{\sigma_{it}}\left[\Lambda+\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right](m_1^2-m_2)\\ &+ \gamma[\mathrm{j}]\sigma_{it}^2\left\{1-\frac{1}{2}\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]\left((\Lambda+\Lambda^3+(2+3\Lambda^2)\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]\right)+2\Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right\} \qquad (10)\end{aligned}$$

where $m_1$ $and$ $m_2$ are the first two moments of $u_{it}$ represented as:

$$m_1 = f(\mu_{it,}\sigma_{it}) = \sigma_{it}\left[\Lambda+\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right] \qquad (11)$$

$$m_2 = g(\mu_{it,}\sigma_{it}) = \sigma_{it}^2\left[1-\Lambda\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]-\left[\frac{\phi(\Lambda)}{\Phi(\Lambda)}\right]^2\right] \qquad (12)$$

Equations (9) and (10) reveal that the marginal effects of the non-monotonic inefficiency effects consist of two terms, indicating the impact of the variables on the mean and variance of the inefficiency components.

So far, the analysis has preserved the exact approach to non-monotonic heteroscedasticity suggested by Wang (2002) within a pooled sample. However, recent developments in the literature on panel data stochastic frontier analysis argue that the error term should distinguish between heterogeneity and inefficiency and between persistent and transient inefficiency[9]. Transient or time-varying inefficiency may quickly be eliminated but persistent or time-invariant inefficiency indicates longer term problems in adjusting to changing market conditions. The result is the four-component error model of stochastic frontier analysis, e.g., Kumbhakar et al (2014), and Filippini and Greene (2016) which transforms equation (1) to (13).

$$y_{it} = \alpha + x_{it}'\beta + \varepsilon_{it} \; ; \varepsilon_{it} = v_{0i} + u_{0i} + v_{it} + u_{it} \tag{13}$$

The $v_{0i}$ term represents latent heterogeneity, the $u_{0i}$ term represents persistent or time-invariant inefficiency, the $v_{it}$ term represents idiosyncratic random error, e.g., measurement, specification and observation error, and the $u_{it}$ term represents transient or time-varying inefficiency. The persistent and transient inefficiency error terms are assumed to be non-negative random variables: $u_{0i} \geq 0$, $u_{it} \geq 0$. The latent heterogeneity term $v_{0i}$ may be a random error or a set of random fixed effects while the idiosyncratic random error is a zero mean random variable.

Kumbhakar and Heshmati (1995) and Greene (2005) adopted a fixed effects approach

$$\varepsilon_{it} = \alpha_i + v_{it} + u_{it} \tag{14}$$

The issue is how to interpret the time-invariant effect $\alpha_i = v_{0i} + u_{0i}$. Kumbhakar and Heshmati (1995) interpreted it as $\alpha_i = u_{0i}$, i.e., persistent inefficiency, which requires that each estimated effect is used to construct an index of inefficiency. Greene (2005) interpreted it as $\alpha_i = v_{0i}$, i.e., latent heterogeneity, and used both a 'true' fixed effects approach, TFE, and a 'true' random effects approach, TRE.

Equation [13] however is a generalised true random effects model, GTRE. When the error component density function assumptions are imposed, it can be estimated by full maximum likelihood or by simulated maximum likelihood as in Filippini and Greene (2016), where the time-invariant and the time-varying components are a pair of skew-normal random variables. Neither approach lends itself to incorporating heteroscedasticity in the

[9] We are grateful to a reviewer who suggested we consider the four-component panel model as well.

inefficiency error terms. However, a simpler but less efficient multi-step estimator for the GTRE model has been suggested by Kumbhakar et al (2014). It assumes a deterministic variance for each of the error terms and positive expected values for the inefficiency components and zero expected value for the idiosyncratic error. The advantage lies in the fact that the inefficiency components can be heteroscedastic.

$$y_{it} = \alpha + x_{it}'\beta + r_i + \omega_{it} \tag{15}$$

Step 1 uses a one-way random effects panel data model as in [15]. Step 2 decomposes the estimated random effects, $\hat{r}_i$, by a simple stochastic frontier analysis regressing them on a constant, inefficiency and random error

$$\hat{r}_i = \tau(1) + v_{0i} + u_{0i}$$

so that we can apply the Wang (2002) and other heteroscedastic models, e.g.

$$v_{0i} \sim iid(0, \sigma_{v0}^2);\ u_{0i} \sim N^+(\mu_i, \sigma_{u0i}^2);\ \mu_i = \mathbf{z}_{0i}'\boldsymbol{\delta}_{u0};\ \sigma_{u0i}^2 = exp(\mathbf{z}_{0i}'\boldsymbol{\gamma}_{u0}) \tag{16}$$

Step 3 does the same for the estimated time-varying panel residuals:

$$\widehat{\omega}_{it} = \vartheta(1) + v_{it} + u_{it}$$
$$v_{it} \sim Nid(0, \sigma_v^2);\ u_{it} \sim N^+(\mu_{it}, \sigma_{uit}^2);\ \mu_{it} = \mathbf{z}_{it}'\boldsymbol{\delta}_u;\ \sigma_{uit}^2 = exp(\mathbf{z}_{it}'\boldsymbol{\gamma}_u) \tag{17}$$

Step 4 extracts the conditional efficiency scores from these two stochastic frontier analysis models. These steps can be thought of as applications of the quasi-maximum likelihood estimation based on the concentrated likelihood function that was suggested by Fan et al (1996).

Finally, we could also use the procedure in step 2 of the multi-step quasi maximum likelihood procedure to revisit the True Fixed Effects model of Greene (2005) and, if we can extract the fixed effects, we can decompose these as well as, again using the Wang (2002) and other heteroscedastic models:

$$\hat{\alpha}_i = \tau(1) + v_{0i} + u_{0i}$$
$$v_{0i} \sim iid(0, \sigma_{v0}^2);\ u_{0i} \sim N^+(\mu_{0i}, \sigma_{u0i}^2);\ \mu_{0i} = \mathbf{z}_{0i}'\boldsymbol{\delta}_0\ \ \sigma_{u0i}^2 = \sigma_{u0}^2 exp(\mathbf{z}_{0i}'\boldsymbol{\gamma}_{u0}) \tag{18}$$

## 3. Data and descriptive statistics

The study is based on a US state-level electricity panel data set for a sample of 47 states over the period 1997 to 2014. We feel that this represents a consistent set of state-level developments in the electricity generation industry. The sample period covers the era of the implementation of major electric industry restructuring policy, especially the Electricity Generation Customer Choice and Competition Act which introduces retail competition into the electricity industry in most states between 1998 and 2002. Post 2015 data include the deeply changed nature of the federal and state political direction under the new presidential regime post 2016. Consequently, the post 2015 environment is sufficiently different to represent a structural break, particularly in view of the importance of the Republican Party's approach to deregulation given the deeply changed nature of the Republican leadership after 2015, so we have excluded it. For our purposes, we limit the analysis to the contiguous states (i.e. Alaska and Hawaii are excluded)[10]. The data set is based on information from the U.S. Department of Energy's (DOE) Energy Information Administration (EIA) database and the Bureau of Economic Analysis of US Department of Commerce and the US Census Bureau. Our choice of inputs and output is consistent with the literature such as See and Coelli, (2013) and Ajayi, et al (2017).

The capital input is measured in megawatt (MW) of installed capacity. Installed capacity is commonly used as a standard measure of capital stock as electricity generation in the literature[11]. Installed capacity in this study is defined as the equivalent of a conventional thermal plant's maximum amount of electricity that a station can produce at any given point in time. It describes the maximum capacity that a system is designed to run at. Installed capacity is collected from Form EIA-860 of the US Energy Information Agency (EIA). The labour input refers to the economically active population in electricity generation for each state measured in thousands of employees. Information on the number of people employed for electricity generation is taken from the US Bureau of Labour Statistics. The quantity of energy input is measured as the equivalent total heat content in billion British thermal unit (billion BTUs) for each state, and includes all varieties of energy consumed from different energy sources by the generation plants such coal, petroleum, natural gas, nuclear, geothermal and other gases. Energy consumption at the state level from coal, petroleum and natural gas are reported in physical units in EIA-906, EIA-920 and EIA-923 Forms. The reported heat content information

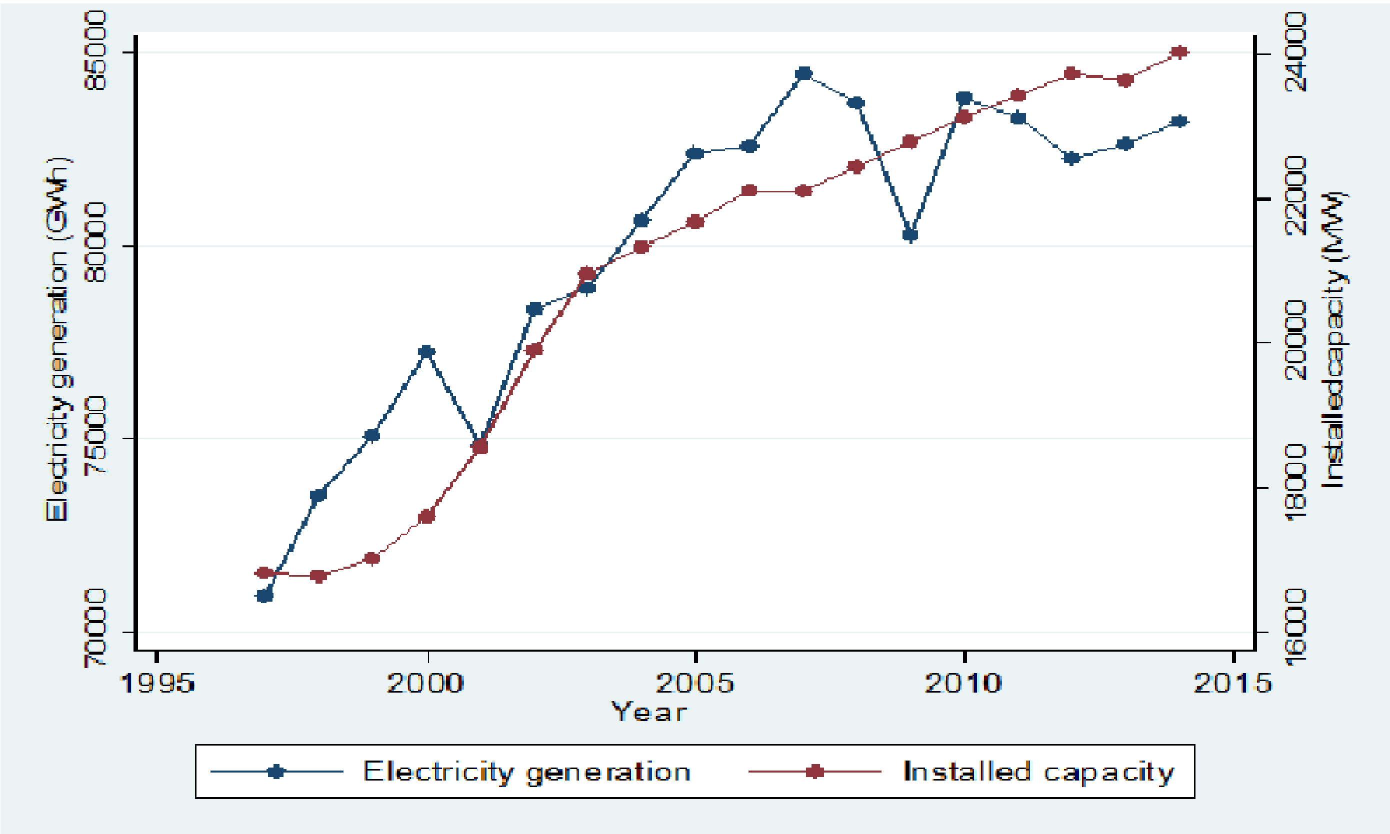
[10] The District of Columbia and Vermont are initially considered in the analysis but were later filtered out as outliers as the data have different distribution of the data.

[11] Installed capital is used as the measure of the services of capital input. The use of installed capital as proxy for capital stock is consistent with literature. Although, a potential issue is that some parts of the installed capital of a generator (conventionally measured as the electrical power rating of the capacity) may not in practice have been part of the 'used and useful' capital stock, as defined by US public service regulators. However, industry wide practice is to use installed capacity in the engineering sense as the comparable measure of the stock of capital services.

for individual fuel is taken from EIA to convert energy consumption into billion BTU. After converting the energy consumption into the same measurement units, we aggregated them into total heat content in billion British thermal unit. All of these variables are available at the state level including those for the non-fossil fuel sources so that our state-level aggregation is feasible.

The output variable is each state's aggregate electric power industry net of generation of electricity for each year from various energy sources such as coal, hydro, natural gas, petroleum etc. Electricity generation is measured in megawatt hours. The total electric power industry net generation derives from the summation of generation by different type of producers such electric utilities generators, Combined Heat and Power and independent power producers including renewables. The data is extracted from Forms EIA-906, EIA-920 and EIA-923 of the US Energy Information Administration (EIA) database. Fig. 2 plots the average annual trend of electricity generation and installed capacity over sample periods. While installed capacity has witnessed a steady increase over the period, electricity generation has largely been driven by US demand, with notable dips in generation experienced occasioned by demand shocks during the recessions in 2001 and 2008.

**Fig. 2.** Annual average trend of the US electricity generation and installed capacity.




*Source: US Energy Information Administration (EIA) database*

Previous studies have identified factors that could shape the operating environment but are not directly related to the performance of the generation plants. These exogenous factors are categorised into political and economic variables that could influence the mean of the inefficiency. First, we consider the market restructuring variables which encompasses different levels of deregulation that utilities face in each state. Of course, several studies in the literature propose broader indicators of market restructuring[12]. For our purpose, we rely on the current restructuring classification originally developed by the Energy Information Administration (EIA) of the US Department of Energy (EIA, 2010). The Energy Information Administration defines restructuring to mean that a monopoly system of electric utilities has been replaced with competing sellers and classifies electricity restructuring into active, not active and suspended. According to the updated restructuring information only fifteen states and the District of Columbia are active in restructuring activities. It is also interesting to observe the spatial clustering of the most restructured states predominantly in the location around the Northeastern region and East North Central, barring Maryland, District of Columbia, Oregon and Texas. Specifically, restructuring activities by state is proxied by deregulation, which is either yes, no or suspended. Therefore, considering this classification, we construct a dummy variable for restructured and non-restructured states. The states where deregulation is yes are assigned the value of one and zero if there is no deregulation or deregulation has been suspended. We construct PUC as a dummy variable that equals one when the majority of the state public utility commission's commissioners are Republican and zero if otherwise using data from the National Association of Regulatory Utility Commissioner (NARUC). On grounds of political ideologies, the Republican PUC members are more likely to promote deregulation and prevent the reversal of deregulation reform. Therefore, we use this affiliation variable to represent the political support for ongoing deregulation and the introduction of competitive entry into generation. A negative coefficient on either of the deregulation variables, restructuring or political affiliation, would mean positive impacts on the technical efficiency.

Finally, we also control for state specific heterogeneity captured by some major observable exogenous variables. The real GDP per capita for each state allows us to assess the impact of economic structure on the mean of inefficiency. The real GDP is measured for each year in thousand US 2009 dollars chained and obtained from the Bureau of Economic Analysis of the US Department of Commerce. Industrial share is the industrial value added as a percentage share of the state GDP, and this measures the extent to which GDP in each state primarily manufacturing industry based. The number of customers is a proxy for the connection

[12] Some of the indicators considered in the literature are as follows; (a) plant access to wholesale electricity market places through an RTO; (b) the date at which formal hearings on restructuring began; (b) the date at which formal hearings on restructuring legislation enacted; (d) the implementation of retail choice under legislation; and (e) complementary aspects of restructuring, such as access to wholesale markets, permit capacity trading, the mandatory divestiture of generation assets and the type of rate of regulation (Fabrizio et al, 2007; Zhang, 2007; Craig & Savage 2013; Davis and Wolfram, 2012).

points for electricity consumption to reflect the way in which a state's population can impact on its generation efficiency. The average real price for electricity across the state is the final exogenous variable.

**Table 2: Summary Statistics**

| Variable | Mean | Sd. Dev. | Min | Max |
|---|---|---|---|---|
| Net electricity generation (MWh) | 8.88e+07 | 7.20e+07 | 5627645 | 4.38e+08 |
| Installed capacity (MW) | 23290.26 | 19721.04 | 1385 | 124214 |
| Energy (million BTU) | 6.17e+08 | 5.89e+08 | 3609378 | 3.93e+09 |
| Labour ('000 people) | 5827.073 | 6673.766 | 10 | 37599 |
| Deregulation (1= yes , 0 = no) | 0.2927 | 0.4553 | 0 | 1 |
| PUC (1= yes , 0 = no) | 0.6530 | 0.4764 | 0 | 1 |
| Retail price (Cents/kwh) | 8.0813 | 2.6273 | 4.010 | 18.070 |
| Per capita GDP (2009 US $(thousand)) | 44.3430 | 7.8557 | 28.3732 | 69.7870 |
| Industrial share of GDP (%) | 13.8762 | 5.7667 | 3.5890 | 30.5949 |
| Number of customer (people) | 3076986 | 2858885 | 263824 | 1.51e+07 |

## 4. Results and Discussions

In this section we focus initially on the pooled heteroscedastic models derived from Wang (2002) in equations (1) to (12), sections 4.1 and 4.2. Then we supplement this analysis by comparing it with the panel data GTRE and TFE models described in equations (13) to (18), section 4.3. We begin with the pooled data approach of Wang (2002) and the other heteroscedasticity literature. The key is that the important determinants of the heteroscedasticity in inefficiency are of two kinds: the deregulation and political affiliation data are time invariant and the contextual macro variables are time varying. Since it is the deregulation variables that we are particularly interested in testing, their impact is the same in a pooled model as in a structured panel.

### 4.1. Empirical Results

We estimate the translog production function with inputs capital, fuel consumption and labour and the exogenous variables[13]. Indexing each input by *j* or *k*, *j* or *k* = 1,.3, the estimated equation can be written as follows:

$$lny_{it} = \beta_0 + \sum_{k=1}^{3} \beta_k ln(x_{ikt}) + \beta_t t + \frac{1}{2}\sum_{k=1}^{3}\sum_{j=1}^{3} \beta_{kj} ln(x_{ijt}) ln(x_{ikt}) + \frac{1}{2}\sum \beta_{tt} t^2$$

$$+ \sum_{j}^{3} \beta_{jt}\, x_{ijt} + \sum_{j}^{3} \theta_j ln(x_{ijt}) t + \delta_{it} z_{it} + v_{it} - u_{it} \tag{19}$$

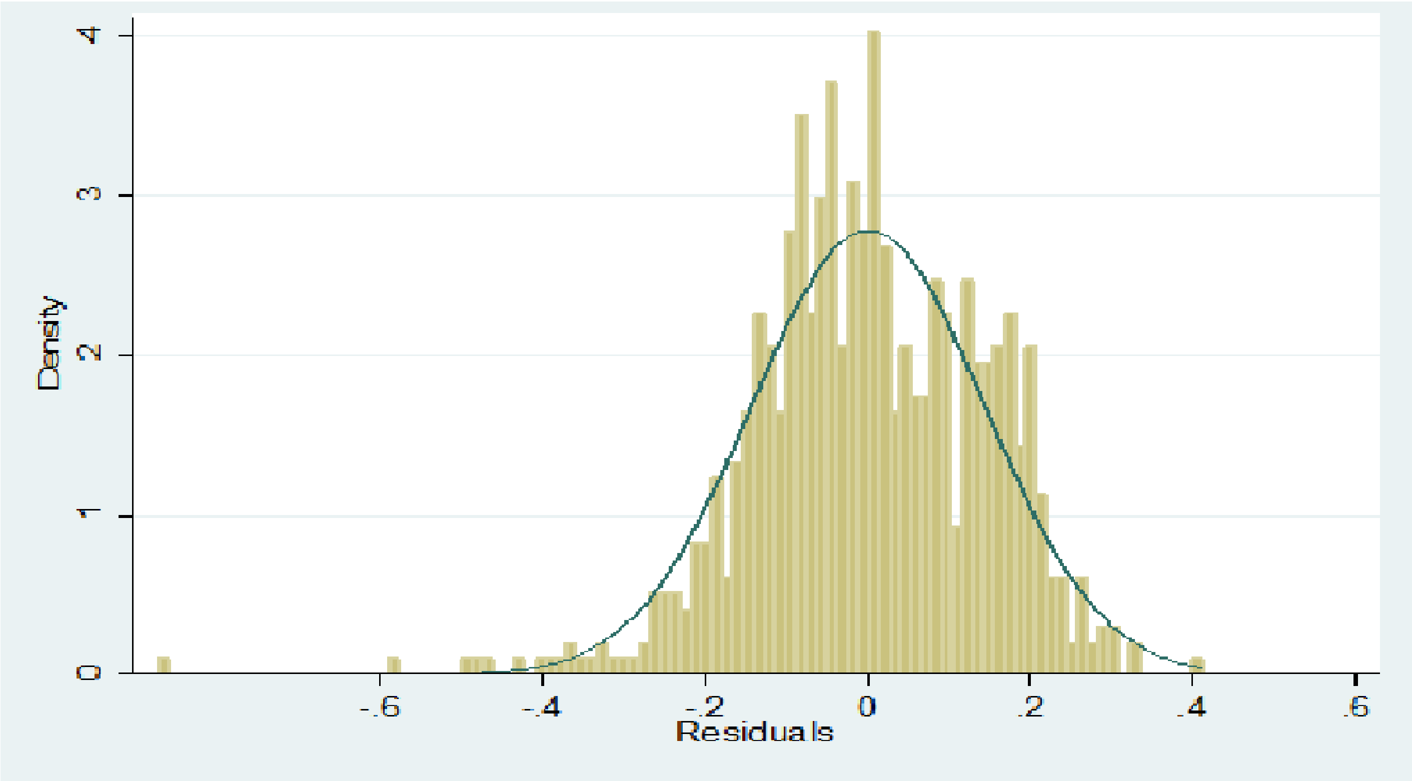
where is $y_{it}$ electricity generation, $x_{it}$ are input variables i.e., energy, installed capital and labour, $z_{it}$ are the environmental variables i.e., deregulation, PUC, per capita GDP, number of customers, industrialisation and electricity retail price. As a preliminary step to our analysis, we estimated a pooled OLS regression of the stochastic production frontier in order to ascertain statistically whether the data contains inefficiency effects. If there were no technical inefficiency, the error term will be symmetric i.e., $u_{it} = 0$, the model reduces to the standard regression model and the composed error term collapses to the two-sided error, i.e. $\varepsilon_{it} = v_{it}$ . Thus, the data will not support the technical inefficiency analysis.

Fig. 3 displays the histogram of the residual following the OLS estimation. However, to avoid distortions due to any unusually large outliers in the data, we first removed observations with OLS standardised residuals greater than 2.5 in absolute value; this reinforces any finding of inefficiency in the remaining residuals. In other words, a finding of inefficiency will not be due to the inclusion of outlier observations. Compared with a normal density distribution, the remaining residuals show a skewed distribution to the left, indicating the presence of inefficiency. In order to demonstrate the skewness more empirically, a skewness test for normality proposed by Coelli (1995) rejects the null hypothesis of normal residual[14]. The computed statistic equals -6.251. The negative sign of statistics reinforces the left skewness of the OLS residual which is consistent with a production frontier specification. Given that it is a normal distribution, the critical value is 1.96, therefore, the result confirms the rejection of the null hypothesis of no skewness in the OLS residual.

[13] Our empirical analysis is programmed in Stata using the maximum likelihood code written by Wang (2002)

[14] Coelli (1995) notes that under the null hypothesis of normal residual, the third moment of the OLS residual is asymptotically distributed as a normal random variable with mean 0 and variance $6m_2^3/N$ . The statistic is given as M3T=$m_3/\sqrt{6m_2^3/N}$.

**Fig. 3: Histogram chart of the OLS residual**




There are eight pooled OLS residuals after filtering that display remaining high negative values (between -2.5 and -0.4). Half of these observations are for states where there has been no deregulation activity and there was no majority political affiliation favouring competitive incentives. Of the remaining four, three were states where there has been regulation but no majority political affiliation favouring competitive incentives. One residual corresponded to a state where there has been deregulation and a majority political affiliation favouring competitive incentives. Since all the remaining residuals are measured prior to modelling the structure of the composed error term there could be several reasons for their relative position on the real line. They may correspond to observations on non-restructured states or states with a political opposition to deregulation or to the impact of the relative income levels, industrial structure differences, customer number differences or electricity retail prices in each state or simply to random error. The subsequent decomposition of the errors into heteroscedastic inefficiency and random error is designed to analyse and test these effects.

Since we are interested in the impact of deregulation on electricity generation efficiency, we have included the deregulation dummy and PUC so as to control for political influence on restructuring while the real GDP per capita and industrial share of GDP are control variables for economic structure. We also control number of customer and electricity retail prices as some states have adopted retail choice which might increase the efficiency of investor-owned plants. We implemented several model selection tests while imposing restrictions in order to obtain the preferred model. Table 3 shows the LR tests for nested models, in which WANG model is nested to the other models using the standard likelihood ratio LR test suggested by Alvarez et al (2006). Since the standard LR test may have the tendency of favouring the model with greater number of parameters since there is no penalty on imposing extra parameters, we estimate the Akaike information criterion (AIC) to further justify our selection decision. The Akaike information criterion is defined as: AIC = $-2$ (ln (likelihood)) + 2K, where likelihood is the probability of the data given the model and K is the number of free parameters in the model. Hence, a model with the smaller value of AIC fits the data better than the one with the larger AIC.

The LR test shows the four other competing models nested in the WANG model. Considering the WANG model as the baseline model, we proceed to test the restrictions that would best fit our data, table 3 below.

**Table 3: Model selection tests**

| Model | WANG | KGMHLBC | RSCFG-m | RSCFG | ALS |
|---|---|---|---|---|---|
| Log-likelihood | 562.465 | 462.19 | 475.696 | 475.358 | 409.936 |
| AIC | -1064.93 | -876.379 | -903.392 | 904.713 | -785.871 |
| BIC | -926.129 | -765.339 | -792.351 | -798.301 | -707.217 |
| LR test[a] | GM | 200.551 | 173.538 | 174.215 | 305.059 |
| # Restrictions | - | 6 | 6 | 7 | 13 |
| 1% critical value[b] | - | 16.704 | 16.704 | 17.755 | 27.026 |
| 5% critical value[b] | - | 11.911 | 11.911 | 13.755 | 21.742 |

[a]In the LR test, GM denotes the general model. All other competing models are nested in the general model.
[b]The critical value of the chi-square is taken from the table in Kodde and Palm (1986, Econometrica)

The likelihood-ratio test shows that KGMHLBC ($\gamma = 0$), RSCFG-$\mu$ ($\delta = 0$), RSCFG ($\delta = 0$) and ALS ($\mu = \gamma = 0$) models are all rejected in favour of the WANG model at one per cent significant level due to the inclusion of exogenous variables in the mean and variance of the heteroscedastic inefficiency term. The table also reports the WANG model as the best frontier specification with the smallest AIC = -1065.139. Undoubtedly, the data favours the WANG model over other simpler alternative models.

Tables 4a and 4b report the maximum likelihood estimates of the technological parameters which seem to be very similar in magnitude, together with the inefficiency parameters. The production and input variables are log mean corrected prior to estimation which enables the estimated coefficients to be directly interpreted as elasticities. The models are well specified with regard to statistical significance, and values of the output elasticities for all the inputs are positive suggesting that the estimated translog production function is a well-behaved function satisfying monotonicity. Specifically, for our preferred model in the first column, the estimated output elasticities with respect to capital, energy and labour are is 0.763, 0.165 and 0.041 respectively. The elasticities indicate that, *ceteris paribus*, a 1% increase in capital will, on average, result in about 0.77% increase in electricity generation. Similarly, a 1% increase in energy use will result in a corresponding increase in electricity generation by 0.17% while output rises by 0.04% for an associated 1% increases in labour. Capital input has the highest impact on production technology, and this is consistent with capital intensive characteristic of the electricity generation industry. Also, the first order coefficient on time is not statistically different from zero, but the second order term confirms that technical progress as measured by the passage of time is important in locating the production function.

**Table 4a: Estimated results of the frontier models: equation parameters**

| Variable | WANG | | KGMHLBC | | RSCFG-μ | | RSCFG | | ALS | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | Std error | Coeff. | Std error | Coeff. | Std error | Coeff. | Std error | Coeff. | Std error |
| Capital | 0.763*** | (0.021) | 0.795*** | (0.017) | 0.754*** | (0.015) | 0.755*** | (0.015) | 0.772*** | (0.014) |
| Energy | 0.165*** | (0.010) | 0.167*** | (0.011) | 0.177*** | (0.011) | 0.178*** | (0.011) | 0.204*** | (0.011) |
| Labour | 0.041*** | (0.008) | 0.022** | (0.009) | 0.030*** | (0.009) | 0.030*** | (0.009) | 0.017** | (0.008) |
| Capital Squared | 0.128*** | (0.022) | 0.038** | (0.016) | 0.069*** | (0.020) | 0.069*** | (0.020) | 0.041** | (0.018) |
| Energy Squared | 0.140*** | (0.011) | 0.105*** | (0.009) | 0.128*** | ((0.010) | 0.129*** | (0.010) | 0.139*** | (0.011) |
| Labour Squared | 0.006** | (0.003) | -0.002 | (0.003) | 0.002 | (0.003) | 0.002 | (0.003) | -0.001 | (0.003) |
| Capital * Energy | -0.240*** | (0.025) | -0.124*** | (0.018) | -0.158*** | (0.021) | -0.159*** | (0.021) | -0.173*** | (0.020) |
| Capital *Labour | 0.072*** | (0.014) | 0.079*** | (0.012) | 0.088*** | (0.014) | 0.088*** | (0.014) | 0.080*** | (0.013) |
| Energy * Labour | -0.107*** | (0.015) | -0.098*** | (0.010) | -0.118*** | (0.014) | -0.117*** | (0.013) | -0.099*** | (0.011) |
| Time | -0.000 | (0.001) | -0.003** | (0.001) | -0.003** | (0.001) | -0.003*** | (0.001) | -0.010*** | (0.001) |
| Time Squared | 0.000** | (0.000) | 0.001*** | (0.000) | 0.001*** | (0.000) | 0.001*** | (0.000) | 0.001*** | (0.000) |
| Capital * Time | -0.008*** | (0.002) | -0.004 | (0.002) | -0.006** | (0.003) | -0.006** | (0.003) | -0.004 | (0.003) |
| Energy *Time | 0.005*** | (0.002) | 0.003* | (0.002) | 0.001 | (0.002) | 0.001 | (0.002) | 0.003* | (0.002) |
| Labour * Time | 0.001 | (0.001) | 0.001 | (0.001) | 0.001 | (0.001) | 0.001 | (0.001) | 0.001 | (0.001 |
| Constant | 0.268*** | (0.028) | 0.193*** | (0.027) | 0.043*** | (0.016) | 0.050*** | (0.014) | 0.092*** | (0.015) |

*Notes: *,**,*** denote statistically significant at 10%, 5% and 1% respectively.*

**Table 4b: Estimated results of the frontier models: inefficiency parameters**

| Variable | WANG | | KGMLHBC | | RSCFG-μ | | RSCFG | | ALS | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | Std error | Coeff. | Std error | Coeff. | Std error | Coeff. | Std error | Coeff. | Std error |
| *Mean function* | | | | | | | | | | |
| Deregulation | -0.110*** | (0.018) | -0.095*** | (0.023) | | | | | | |
| PUC | -0.058*** | (0.012) | -0.014 | (0.016) | | | | | | |
| GDPPC | 0.101** | (0.040) | -0.033 | (0.051) | | | | | | |
| Retail price | -0.024 | (0.019) | -0.007 | (0.016) | | | | | | |
| Industrialization | 0.312*** | (0.032) | 0.363*** | (0.051) | | | | | | |
| Customer | 0.015 | (0.011) | -0.003 | (0.019) | | | | | | |
| $\delta_0$ | 0.389*** | (0.029) | 0.244*** | (0.035) | -0.041 | (0.060) | | | | |
| *Variance function* | | | | | | | | | | |
| Deregulation | 0.888*** | (0.232) | | (0.270) | -0.760*** | (0.281) | -0.768*** | | | |
| PUC | -0.130 | (0.157) | | (0.176) | -0.402** | (0.180) | -0.425** | | | |
| GDPPC | -2.840*** | (0.499) | | (0.539) | -0.991* | (0.550) | -1.075* | | | |
| Retail price | -0.714*** | (0.090) | | (0.149) | -0.694*** | (0.149) | -0.716*** | | | |
| Industrialization | 2.041*** | (0.340) | | (0.619) | 4.295*** | (0.606) | 4.414*** | | | |
| Customer | 0.715*** | (0.179) | | (0.220) | 0.115 | (0.228) | 0.12 | | | |
| $\gamma_0$ | -4.425*** | (0.160) | -3.784*** | (0.102) | -3.566*** | (0.280) | -3.678*** | (0.225) | -3.434*** | (0.177) |
| $\sigma_v^2$ | -7.657*** | (1.155) | -6.242*** | (0.642) | -4.614*** | (0.110) | -4.643*** | (0.113) | -4.738*** | (0.193) |
| # Observation | 755 | | 755 | | 755 | | 755 | | 755 | |
| Log-likelihood | 562.465 | | 462.19 | | 475.696 | | 475.358 | | 409.936 | |

We now turn our attention to the impact of restructuring on electricity production across states, we incorporated several exogenous variables into the heteroscedastic alternative models by allowing the variables to affect the mean and variance of the inefficiency. Since the AIC and LR tests clearly support the WANG model, our discussion is centred on the preferred model which allows both the mean and the variance of the pre-truncated distribution of the inefficiency to depend on the exogenous factors. Tellingly, our preferred model points to the reliability of the variance of the inefficiency to appreciably capture the impacts of the exogenous variables on production inefficiency as most of the environmental variables are insignificant. The preferred model also shows that the estimated restructuring coefficient on the variance of the inefficiency have expected signs and statistically significant.

Focusing on the mean of the inefficiency, overall, our finding shows the importance of restructuring in the electricity generation industry. The coefficient of deregulation is statistically significant at 1% and negatively correlates with technical inefficiency, implying a positive effect on technical efficiency in electricity generation due to restructuring. This particularly holds true for the a priori expectation that deregulation represents a key factor at improving electricity production efficiency. This finding is largely consistent with previous studies such as Kleit and Terrell (2001), Knittel (2002), Hiebert (2002), Zhang (2007) and Craig and Savage (2013). The inclusion of PUC enables us to get better intuition into the political dynamics of restructuring on inefficiency. Interestingly, the coefficient of PUC is also statistically significant and negatively correlated with technical inefficiency. These findings imply an increase in technical efficiency when the majority of the state commissioners on public utility commission are Republican. Intuitively, a plausible explanation to these findings is the tendency of these states controlled by Republicans to influence some political decisions that support restructuring policy in order to promote competition among the electric power generators. Zhang (2007) report a similar positive increasing impact of public utility commission on capacitor factor. However, the findings show that high retail prices and real per capita GDP are associated with technical inefficiency whereas number of customer and industrialisation are not significantly different from zero.

Besides the determinants of the inefficiency, we are also interested in the unit-specific inefficiency to ascertain the distribution of the efficiency. In doing so, we computed the Battese and Coelli efficiency estimates for each observation in all the models. The summary statistics of the efficiency index across competing models are reported for comparison in Table 5. The efficiency index summary statistics shows that our preferred model has an average efficiency of 0.731. This finding means that, on average, states electricity generation is 73.1% of the maximum output. Better still, it implies that the states lost about 26.9% of the potential generation output to technical inefficiency. Interestingly, the findings show that other models overstate average technical efficiency estimates. Figure 2 plots the kernel density estimates of the efficiency scores for the five models.

The kernel density reveals WANG mode as the most rightly skewed distribution, which further reinforces WANG as our preferred model.

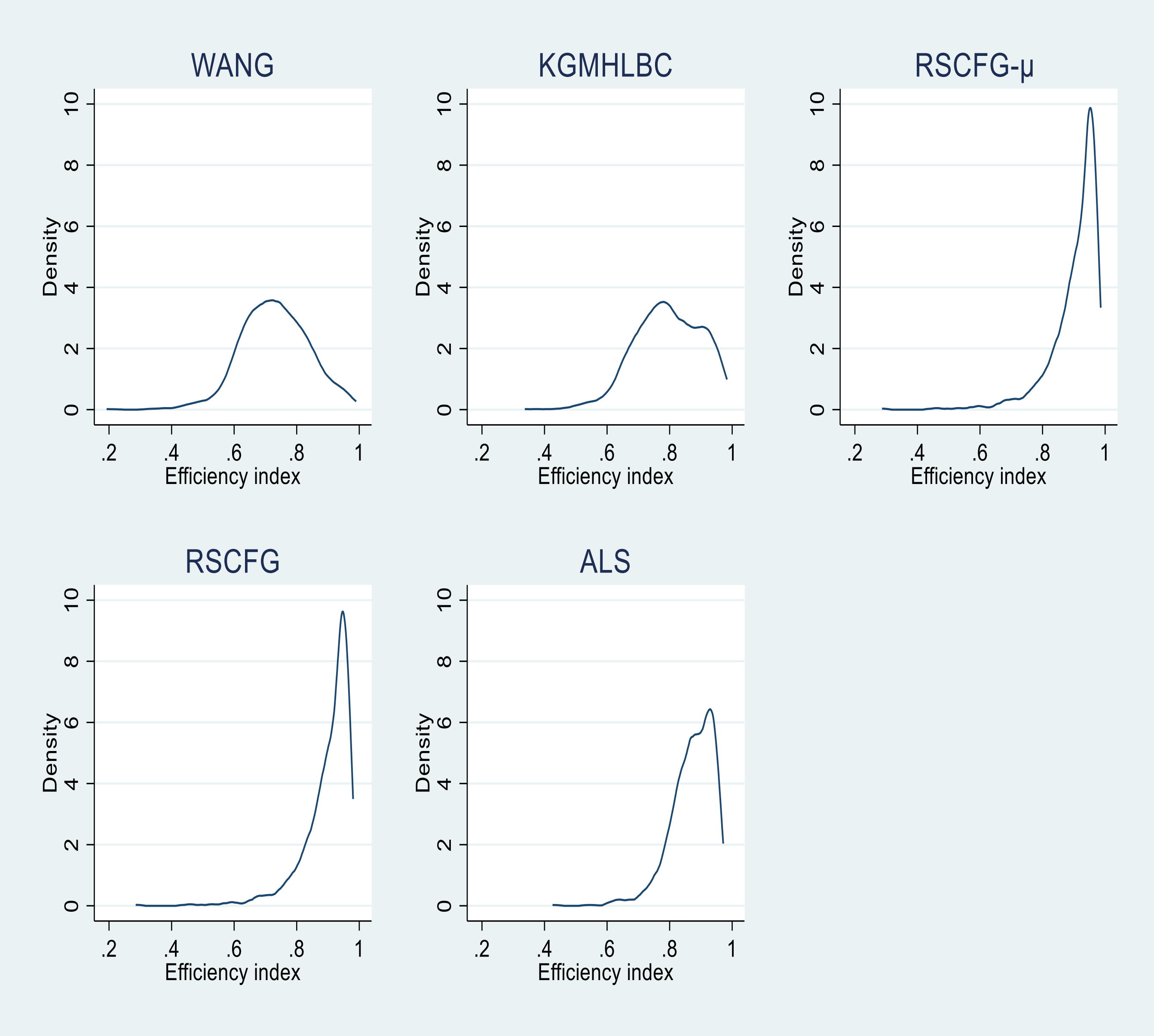
**Table 5**: **Estimate technical efficiency scores**

| Model | Mean | SD | Min | Max |
|---|---|---|---|---|
| WANG | 0.731 | 0.108 | 0.192 | 0.99 |
| KGMHLBC | 0.794 | 0.105 | 0.337 | 0.983 |
| RSCFG-μ | 0.903 | 0.078 | 0.286 | 0.986 |
| RSCFG | 0.897 | 0.078 | 0.285 | 0.98 |
| ALS | 0.872 | 0.068 | 0.426 | 0.971 |

In particular, we note that when the impact of the exogenous variables is monotonic as is the case in the models other than Wang (2002) we can only infer that a change in an exogenous variable will have either a wholly positive or wholly negative effect on, for example, the mean of the inefficiency component, i.e., the value of $\partial E(u)/\partial z[k]$ . The possibility of non-monotonicity means that for some range of the exogenous variable, the effect on the mean of the inefficiency could be positive but for values outside that range the effect could be negative. We can see this in the plot of the mean of the inefficiency effect against one of the exogenous variables, for example number of customers, or average electricity price[15]. This suggests that beyond a certain size of customer base or price level, the effect of further increases changes the sign of the impact $\partial E(u)/\partial z[k]$ . This could give a feasible set of values for a policy change within which movements in an exogenous variable are beneficial and another set of values for which they are not.

[15] We demonstrate this below in figures 5 in the context of a panel data model.

**Fig. 4: Kernel density of efficiency scores of the estimated models**




Although we have established the importance of the deregulation and political affiliation variables the determination of the inefficiency component of the random error, this is not the same as showing whether these variables are associated with the mean overall efficiency scores for each group of states. We used the Battese and Coelli (1988) transformation of the conditional inefficiencies to derive the overall technical efficiency scores, and then we measured the average efficiency scores for different groupings of the states. In order to further explore the heterogeneity between restructuring and non-restructuring states in term of the impacts of restructuring on the states' electricity generation technical efficiency, the efficiency index is first disaggregated into of sub-groups based on states which deregulation has been implemented and currently on-going and their counterparts which have not implemented or suspended deregulation activities. Secondly the efficiency scores are disaggregated into sub-groups where the majority of the state public utility commission's commissioners are Republican and those with a non-Republican majority. We argued above that the two categories may reinforce each other's effects. In fact, we find that the differences in efficiency performance associated with the political affiliation variable are far stronger than the differences associated with deregulation on its own. We find that the t-test of the difference in mean efficiency scores across the two subsamples of only  restructured and non-restructured states fails to reject the null hypothesis that the mean scores are the same, however, the t-tests of the difference in mean efficiency scores across the two subsamples of Republican majority commissioners and non-majority states clearly reject the null hypothesis at the 5 percent significance level that the mean efficiency scores are the same, Table 6. In summary, restructuring does significantly affect the inefficiency error component but not sufficiently to result in higher mean performance compared with non-deregulated states. However the effect of a majority of Republican public commissioners, who are assumed to reinforce the deregulation movement on a continuing basis does result in higher mean efficiency scores at the 5 percent significance level.

**Table 6: Differences in efficiency scores**

test: no difference in mean efficiency score

| Groups | mean Efficiency (1st group) | mean Efficiency (2nd group) | t-value | Satterthwaite's degrees of freedom |
|---|---|---|---|---|
| States with majority Republican commissioners vs non-Republican majority | 0.739 | 0.715 | 2.789 | 464 |

These results further strengthen our earlier finding that political support for deregulation constitutes a major factor in improving electricity production efficiency due to its negative impact on the inefficiency.

### 4.1.Marginal Effects results

Having discussed the slope parameters of the exogenous variables, we now focus on the marginal effects. The marginal effect indicates by how much the technical inefficiency will change if the each of the exogenous variable changes, *ceteris paribus*. The estimation of marginal effects is important to our analysis as the estimated slope parameters of the inefficiency determinants are only indicative of the direction and not the magnitude. Therefore, marginal effects are evaluated for both the mean and the variance of the technical inefficiency i.e. $E(u_{it})$ and $V(u_{it})$ as explained in equation (9) and (10). The mean function marginal effects demonstrate how a change in an exogenous variable affects the expected inefficiency. On the other hand, the marginal effects of the variance function reveal the partial effect of exogenous variables on the dispersion of inefficiency in the electricity generation industry.

We focus on the deregulation and political affiliation, PUC, variables[16]. We find that deregulation has a negative partial effect until the 99$^{th}$ percentile i.e. non-monotonic impact on the mean of inefficiency but positive overall effects on the variance of inefficiency. For the sample average, the partial effect indicates that the increase in deregulation reduces production inefficiency by 8.4 per cent. In addition, the positive marginal effects on the variance reveals that deregulation tends to increase inefficiency dispersion, arguably due to the tendency of the private utilities to scale back generation in face of potential slow demand growth. Meanwhile, the marginal effect of the PUC variable shows an overall negative impact on the mean of inefficiency but has no statistically significant impacts on the variance of inefficiency. On average, PUC has a negative marginal effect of -0.055 in the mean inefficiency function which represents an increase in efficiency by 5.5 per cent. This finding for all the quartiles suggests that the marginal benefit of increasing additional republican commissioners on states' public utility commissions represent the importance of political affiliation in continuing support for competitive incentivisation.

### 4.3 The four component error panel data approach.

In this section we supplement our analysis and check for robustness of the results of the WANG model by re-estimating it in a panel data framework[17], as described in equations (13) to (18). Within the data, we have two groups of states of interest. One group is the restructured states where there is strong political support for competition and entry in the electricity generation industry, and a second group which are not restructured nor where there is political support for moving away from conventional cost of service regulation where efficiency incentives are muted. We might expect therefore that time varying determinants of heteroscedasticity in inefficiency impact mainly on the transient inefficiency component while the time invariant determinants, i.e., our variables of interest: deregulation and political affiliation (PUC), impact mainly on the persistent inefficiency. This is what we find, i.e., that a subset of the time-varying variables determines the heteroscedasticity in the transient inefficiency, while the time-invariant deregulation variables, particularly political affiliation determine the heteroscedasticity in the persistent inefficiency. The detailed results are presented in Tables 7 and 8[18].

[16] Full results with quantile breakdowns are available on Table A1 in the appendix.
[17] To conserve degrees of freedom we did not impose a standardised residual filter on the panel data.
[18] The translog production function elasticities are very similar to those of the pooled data estimation so we report only the inefficiency estimates for the panel approach. Further details of panel elasticities are available from the corresponding author.

**Table 7 Panel data results: transient inefficiency model**

| | | | |
|---|---|---|---|
| GTRE model: Transient Inefficiency. Heteroscedasticity estimated by Wang model | | | |
| step 1: one-way panel random error model, time-varying errors | | | |
| mean of transient inefficiency distribution, $\mu_{uit}$ | | | |
| *variable* | *coeff* | *std err* | *z* |
| number of customers | -13.241*** | 6.527 | -2.03 |
| intercept | -37.252*** | 10.281 | -2.29 |
| variance of transient inefficiency distribution, $\sigma_{uit}^2$ | | | |
| *variable* | *coeff* | *std err* | *z* |
| number of customers | 0.197 | 0.142 | 1.39 |
| intercept | 0.662 | 0.437 | 1.51 |
| $E(\sigma_u)$ | 1.398 | | |
| $\sigma_v$ | 0.082 | | |
| average marginal effect on E(u) is | -0.0149 | | |
| average marginal effect on V(u) is | -0.002 | | |
| NT | 771 | | |
| | | | |
| TFE model: Transient Inefficiency. Heteroscedasticity estimated by Wang model | | | |
| step 1: one-way panel True Fixed Effects model, time-varying inefficiency | | | |
| mean of transient inefficiency distribution, $\mu_{uit}$ | | | |
| *variable* | *coeff* | *std err* | *z* |
| deregulation | -10.480* | 5.676 | -1.850 |
| PUC | -23.691*** | 7.259 | -3.260 |
| number of customers | 3.694*** | 1.150 | 3.210 |
| Share of industrial gdp | 11.858*** | 4.744 | 2.500 |
| intercept | -10.311*** | 2.732 | -3.770 |
| variance of transient inefficiency distribution, $\sigma_{uit}^2$ | | | |
| *variable* | *coeff* | *std err* | *z* |
| deregulation | 0.287 | 0.231 | 1.240 |
| PUC | 0.712*** | 0.276 | 2.580 |
| Number of customers | -0.672*** | 0.108 | -6.210 |
| Share of industrial gdp | -0.284* | 0.173 | -1.640 |
| intercept | 0.1685198 | 0.248 | 0.680 |
| $E(\sigma_u)$ | 1.534 | | |
| $\sigma_v$ | 0.012 | | |
| average marginal effect of deregulation on E(u) is | -0.026 | | |
| average marginal effect of deregulation on V(u) is | -0.006 | | |
| average marginal effect of PUC on E(u) is | -0.054 | | |
| average marginal effect of PUC on V(u) is | -0.012 | | |
| NT | 771 | | |

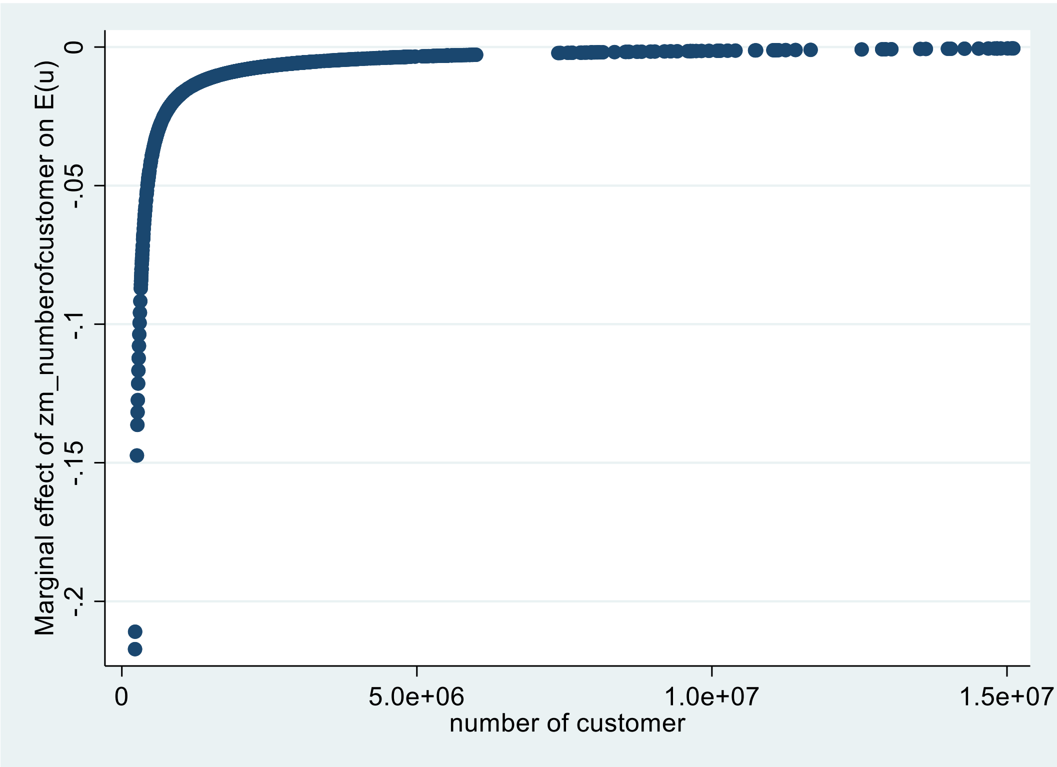
**Table 8 Panel data results: persistent inefficiency model**

| | | | |
|---|---|---|---|
| GTRE model: Persistent Inefficiency | | | |
| step 3: one-way panel random error model, time-invariant RE-effects. Heteroscedasticity estimated by RSCFG model | | | |
| variance of persistent inefficiency distribution, $\sigma_u^2$ | | | |
| *variable* | *coeff* | *std err* | *z* |
| PUC | -1.415*** | 0.482 | -2.94 |
| intercept | 0.25 | 0.351 | 0.71 |
| $E(\sigma_u)$ | 0.781 | | |
| $\sigma_v$ | 0.171 | | |
| N | 49 | | |
| TFE model: Persistent Inefficiency | | | |
| step 3: one-way panel random error model, time-invariant FE-effects. Heteroscedasticity estimated by RSCFCFG-μ model | | | |
| *variable* | *Coef.* | *Std. Err.* | *z* |
| μ | 0.621*** | 0.118 | 5.250 |
| variance of persistent inefficiency distribution, $\sigma_u^2$ | | | |
| variable | coeff | std err | z |
| PUC | -2.224*** | 0.512 | -4.350 |
| intercept | -0.071 | 0.375 | -0.190 |
| $E(\sigma_u)$ | 0.781 | | |
| $\sigma_v$ | 0.171 | | |
| N | 49 | | |

We have fitted the four-component panel data model firstly by the multi-step quasi-ML method of Kumbhakar et al (2014) and then by an extension of the Kumbhakar and Heshmati (1995) fixed effects model in which we decompose the estimated fixed effects from the True Fixed Effects model of Greene (2005) into heteroscedastic persistent inefficiency and latent heterogeneity with the full ML estimator accounting for the transient (time-varying) inefficiency and the idiosyncratic error.

The estimation methods here are not so straightforward nor do they always converge, and not all of the heteroscedasticity models fit equally well, nor are all of the variables statistically significant. Because we are dealing with two different sets of states which differ in their time-invariant characteristics, we expect the pooled models to fit more successfully that the one-way panel data models. We begin with the transient or time-varying inefficiency. In both cases of the GTRE and the TFE model heteroscedasticity in the transient inefficiency component is explained by the time varying variable measuring the number of customers. In the GTRE model, the Wang (2002) heteroscedasticity framework fits successfully and the heteroscedasticity effects are non-monotonic. The average marginal effect of customer numbers on $E(u)$ is -0.0149. Increased customer numbers reduce inefficiency but increase the variance of inefficiency. In the TFE model, the Wang framework fits the time-varying data well; again, customer numbers and industrial share of GDP affect the inefficiency component but, more interestingly our deregulation variables significantly reduce mean inefficiency. We now turn to persistent inefficiency. The GTRE model yields one-way panel random error effects from step 1 and we regress these in a stochastic frontier analysis model against an intercept with a two-component error with the variables determining heteroscedasticity affecting the variance term through the RSCFG framework. The most successful model shows that one of the deregulation variables, PUC representing political affiliation, is a statistically significant explanator of heteroscedasticity in persistent inefficiency, with a coefficient of -1.415. We obtain a very similar result when we use the estimated TFE fixed effects: again, PUC representing political affiliation, is a statistically significant explanator of heteroscedasticity in persistent inefficiency, with a coefficient of -2.224. The average marginal effect of the political affiliation variable PUC on the variance of persistent inefficiency: $\partial V(u)/\partial(PUC)$ is -0.355. One feature of these results is that while the Wang (2002) non-monotonic model fitted the heteroscedasticity in transient inefficiency, the RSCFG model was preferred for the persistent inefficiency. We illustrate in figure 5 the monotonic effect of customer numbers on $\partial E(u)/\partial(PUC)$ for transient inefficiency. The effects of the binary deregulation and PUC variables are step functions in all cases

**Figure 5: Marginal effect of customer numbers on transient inefficiency**



Broadly therefore, the panel data approaches confirm the pooled data analyses about the importance of deregulation-related variables in driving down transient and particularly persistent inefficiency error components in conjunction with other time-varying macroeconomic variables. Nevertheless, there are two differences in the panel data analysis compared with the pooled approach. In the ML estimation fewer of the heteroscedasticity approaches converged and, in the results, the political affiliation support for deregulation and competitive incentives dominated as the explanatory variable associated with deregulation in both transient inefficiency and persistent inefficiency. Why do we observe these factors? Our rationale is this. The purpose of the study is to compare two groups of states, those which have characteristics associated with incentivised deregulation and those which have characteristics associated with the status quo of cost-of-service regulation. The pooled data models suit this comparison of two types of time-invariant state experience better than the panel data models which impose a temporal structure on the data. Our explanation for the finding that PUC, the political affiliation support for deregulation, is dominant is that restructuring although established initially may take time to work through before it generates noticeable efficiency improvements; on the other hand, the political support for incentivised competitive entry and deregulation is an ongoing factor which continually reinforces efficiency gains.

## 5. Conclusions

One area that has attracted much attention in the industrial organisation literature is the debate on the efficiency gains from restructuring. Controversies remain going by the mixed findings from past studies. This paper attempts to analyse the electric power industry's performance using a consistent state-level electricity generation dataset for the contiguous US states from 1997-2014. First, we estimate several specifications of stochastic production frontier models to investigate the impacts of restructuring on technical efficiency in the pooled data in order to find channels for policy adjustment. More specifically, we adopt the Wang (2002, 2003) approach that allows both mean and variance of the pre-truncated normal distribution to depend on the exogenous variables, as well as accounting for heteroscedasticity. Second, we examine the non-monotonic marginal effects of exogenous factors on the technical efficiency. Contrary to earlier studies of the US electricity generation technical efficiency (see Hiebert, 2002), the efficiency scores of this segment were low, indicating wide inter-state differences within the segment, although, other models find higher efficiency scores. The marginal effects were found to show linear effects as the marginal effects of the exogenous variables are monotonic i.e. strictly either strictly efficiency-enhancing or efficiency–impeding across observation percentiles.

Our results indicate a positive impact of deregulation and political support for deregulation on technical efficiency across all the estimated models. The finding is largely consistent with previous studies on deregulation impact on efficiency. In particular, our preferred model reveals that states where deregulation is active and the political support for it is present are more efficient. The results of marginal effects show that deregulation has a mean reducing impact on production inefficiency of 8.4 per cent for the whole sample, which indicates an increased electricity generation output by same size due to deregulation.

Thirdly, we found that the political affiliation within the state public utility commissions affects the level of technical inefficiency. Performance seems improved as when the majority of the state commissioners on a public utility commission are Republican as they are positioned to influence some political decisions that could potentially support and prevent potential reversal of restructuring policy in order to promote competition among the electric power generator. In particular, restructuring through deregulation and continued support for it work together to improve efficient performance is a statistically significant way. We supplemented the analysis of the pooled data by adopting a panel data approach incorporating recent developments in the four component GTRE error model. The results here support our findings with the pooled data approach, in particular emphasising the role of the political support for deregulation in enhancing efficiency. We show that time varying exogenous variables determine transient efficiency, but the time invariant political support for deregulation determines persistent efficiency.

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## Appendix

### Table A1: Marginal effects on inefficiency using WANG Model

| Variable | | Marginal effects on $E(u_{it})$ | | Marginal effects on $V(u_{it})$ | |
|---|---|---|---|---|---|
| | | **observed** | **Standard error** | **Observed** | **Standard error** |
| *Deregulation* | Average | -0.084*** | (0.020) | 0.011** | (0.005) |
| Percentile | 25th | -0.109*** | (0.025) | 0.005** | (0.002) |
| Percentile | 50th | -0.100 *** | (0.025) | 0.008** | (0.003) |
| Percentile | 75th | -0.075*** | (0.031) | 0.012** | (0.005) |
| Percentile | 90th | -0.042** | (0.030) | 0.018** | (0.007) |
| *PUC* | Average | -0.055*** | (0.018) | -0.003 | (0.005) |
| Percentile | 25th | -0.058*** | (0.016) | -0.003 | (0.003) |
| Percentile | 50th | -0.057*** | (0.018) | -0.002 | (0.003) |
| Percentile | 75th | -0.054*** | (0.023) | -0.001 | (0.003) |
| Percentile | 90th | -0.050** | (0.029) | -0.001 | (0.005) |
| *GDPPC* | Average | 0.041 | (0.047) | -0.041*** | (0.013) |
| Percentile | 25th | 0.023 | (0.056) | -0.044*** | (0.013) |
| Percentile | 50th | 0.080 | (0.050) | -0.030*** | (0.008) |
| Percentile | 75th | 0.099 | (0.050) | -0.020*** | (0.005) |
| Percentile | 90th | 0.101 | (0.051) | -0.013*** | (0.004) |
| *Industrialization* | Average | 0.026** | (0.013) | 0.011*** | (0.004) |
| Percentile | 25th | 0.015 | (0.013) | 0.008*** | (0.003) |
| Percentile | 50th | 0.019 | (0.012) | 0.008*** | (0.003) |
| Percentile | 75th | 0.029** | (0.013) | 0.012*** | (0.004) |
| Percentile | 90th | 0.044** | (0.018) | 0.017*** | (0.007) |

| | | | | | |
|---|---|---|---|---|---|
| *Retail Price* | Average | 0.322*** | (0.045) | 0.037*** | (0.008) |
| Percentile | 25th | 0.312*** | (0.047) | 0.017*** | (0.003) |
| Percentile | 50th | 0.313*** | (0.046) | 0.027*** | (0.005) |
| Percentile | 75th | 0.316*** | (0.043) | 0.041*** | (0.008) |
| Percentile | 90th | 0.333*** | (0.043) | 0.062*** | (0.015) |
| *Customer* | Average | -0.035 | (0.026) | -0.011*** | (0.003) |
| Percentile | 25th | -0.037 | (0.023) | -0.012*** | (0.002) |
| Percentile | 50th | -0.027 | (0.027) | -0.009*** | (0.001) |
| Percentile | 75th | -0.024 | (0.031) | -0.005*** | (0.001) |
| Percentile | 90th | -0.024 | (0.033) | -0.003*** | (0.008) |

*Notes: *,**,*** denote statistically significant at 10%, 5% and 1% level respectively. Standard error in parenthesis are based on bootstrapped results of 1000 replications, bias-corrected confidence interval.*