Convergence of Operational Efficiency in China's Provincial Power Sectors

Vishal Chandr Jaunky and Lin Zhang***

ABSTRACT

To analyze the operational efficiency of Chinese power sector at the provincial level, this paper studies the convergence of technical efficiency and productivity growth of electricity across 29 Chinese provinces during the period 1996–2008 using several convergence models. Depending on the model being employed, we find evidence of convergence of operational efficiency towards either a national steady state or towards their own steady states, with the latter process occurring more rapidly. In essence, our study provides evidence of negative effects of government intervention. Additionally, we use the nonparametric distribution dynamics approach to analyze intra-distributional dynamics of technical efficiency and productivity. We find some support for productivity convergence while technical efficiency does not converge for provinces with relatively low levels. We discuss policy implementations based on our model results and highlight several aspects for policy making in the power sector reforms currently being undertaken.

Keywords: Convergence, Electricity, Operational efficiency, Productivity

http://dx.doi.org/10.5547/01956574.37.SI1.vjau

1. INTRODUCTION

China's electricity generation market experienced unprecedented expansion in the past decade as the country worked to ensure sufficient and secure levels of electricity supply for sustained and high-speed economic growth. From 1996 to 2008, the annual average growth rate of power capacity was approximately 12.5%, boosted by the acceleration of industrialization and urbanization. China now owns 960 GW of installed generation capacity, second only to the United States' 1075 GW. Yet, electricity generation mainly occurs in coal-fired power plants. For the improvement of efficiency and reduction of emissions, the power sector faces a series of market reforms from the 1980s initiated by the government. Even though some reforms have taken place in the power sector, relative monopoly is still surviving and hampering the development of the liberalized economy (Wang and Chen 2012), indicating lower effectiveness of the reforms in improving the efficiency and productivity from the perspective of market structure.

The government also provides a number of technological initiatives to promote energy efficiency and pollution abatement. These measures mainly focus on the closure of older, less efficient plants and the construction of new plants with advanced technologies, for instance super-

* Department of Business Administration, Technology and Social Sciences, Luleå University of Technology, Sweden, and Faculty of Law & Management, Department of Finance and Accounting, University of Mauritius. E-mail: vishal.jaunky@ltu.se.

** Corresponding author. Center of Economic Research at ETH Zurich, Zurichbergstrasse 18, 8092 Zurich, Switzerland. E-mail: linzhang@ethz.ch.

critical and ultra-supercritical coal plants. As summarized in Zhou et al. (2010), massive attention is devoted to energy efficiency measures with focus on the so-called "top ten priorities" and "Ten key Projects". The largest energy-consuming power plants signed agreements to improve their energy performance through the "Top 1000 Program" (IEA 2010c). Several targets have also been announced officially for the increase of generation capacity and the promotion of renewable energy.[1] However, the rapidly expanding generating capacity in China cannot meet the even faster growth of electricity demand.[2] Lack of unified national grid system and limited access to the most advanced technologies cause the generating and transmission systems to remain underdeveloped and inefficient in spite of substantial investment. An even more challenging target has been set in the 12th Five-Year-Plan, which clearly mentions the reduction of energy consumption per Yuan 10,000 of GDP by 32% compared to the 2005 level. China also promises to reduce its CO_2 emission intensity by 40–45% in 2020 compared to 2005 in the United Nations Framework Convention to Climate Change (UNFCCC).

China's electricity sector is particularly important for achieving these targets, as it accounts for nearly half of greenhouse gas emissions (Steenhof and Fulton, 2007). Around 80% of electricity generation in China comes from coal-fired power plants (NBS, 2013). The energy intensity and CO_2 emissions in China is highly dependent on coal consumption. Any inefficient use of coal in electricity generation results in higher coal consumption, which keeps the energy intensity and CO_2 emissions at a higher level. Despite the importance of the electricity industry in China, very few studies have investigated the trend in the efficiency of electricity generation at the provincial level. For this purpose, we have to understand the status-quo of the electricity efficiency across Chinese provinces.

In this paper, we first estimate the operational efficiency using DEA method. In the second stage, several convergence models are employed to investigate the change of operational efficiency over time and across provinces.[3] We examine the dynamic changes in operational efficiency from two perspectives: the change in technical efficiency and the change in productivity. There are reasons to study operational efficiency and its change. The level of operational efficiency provides us with information on individual provincial power sectors' performance. As this study distinguishes inefficient and efficient provinces in terms of operational variables, we can identify suitable models for less efficient provinces to emulate. Policies and regulations used in efficient provinces may also be suitable role models for inefficient provinces in order to improve their performance. Moreover, operational efficiency tells us how much more electricity can be produced to fulfill our demand. This is particularly important for the government in terms of energy supply security.

Nevertheless, changes in efficiency can only reflect the development of performance of individual provinces and cannot account for the degree of effectiveness of the energy policies across provinces. With convergence analysis we can explore the cross-province disparities[4] in electricity generation performance and relate it with the effectiveness of the provincial energy policies. If the electricity efficiency gap among provinces diminishes over time, then the Chinese government may

1. To reach the target for installed capacity in 2020, 70GW of nuclear, 100GW of wind, 1.8GW of solar are needed according to IEA (2010c). A new Renewable Energy Law and many regulations are designed to support the development of renewable energy industries.

2. China has faced a severe electricity crisis since 2000. In 2004, 26 out of 31 provinces experienced electricity shortages. The total shortage was about 35 GW. This gap remained or even increased since then.

3. The decision-making unit (DMU) in this study is the provinces.

4. Cross-operational efficiency convergence can crop up from diminishing returns of capital, economies of scale, convergence in the quality of coal, etc.

be less concerned about the effectiveness of their regional energy policies especially with regards to the power sector. If, on the other hand, the gap tends to persist over time, then the Chinese government should "introspect" on areas it is lagging behind and enact policies to enhance the efficiency of provincial power sectors. Our results reveal a converging pattern across Chinese provinces. Specifically these provinces are found to converge faster to their own operational efficiency long-run growth paths than to a common one. We also find evidence that reform of pricing system, unity of the grid distribution network, urbanization and economic structural change, avoidance of government intervention, are necessary to increase efficiency. This paper is organized as follows. Section 2 reviews the convergence literature with special reference to the power sector. Section 3 describes the methodologies. Section 4 summarizes the data. Section 5 presents efficiency models and results. Section 6 shows various convergence models and our main findings. Section 7 provides some policy implementations and concludes the paper.

2. REVIEW OF LITERATURE

The concept of convergence is borrowed from the neoclassical growth literature (Solow, 1956). It essentially prophesies a catching-up of the poor countries with the rich ones in terms of income. Income convergence is achieved if differences in relative income are falling over time. Recently, the convergence concept has also been applied to the field of energy. So far, the literature has focused on carbon dioxide (CO_2) emissions. Nguyen Van (2005) makes use of principally non-parametric distribution dynamics techniques to study CO_2 emissions for 100 countries over the period 1966–1996. His results reveal a tendency for CO_2 emissions in industrialized countries to converge even as he discerns little evidence of convergence for the whole sample. Romero-Ávila (2008) uncovers both stochastic and deterministic convergence of CO_2 emissions, occurring in 23 developed countries over the period 1960–2002. Westerlund and Basher (2008) find indication of stochastic convergence for a group of 28 developed and developing countries over the period 1870–2002. Jobert et al. (2010) report further evidence of absolute convergence in CO_2 emissions for 22 European countries over the period 1971–2006. Marrero (2010) finds evidence of conditional convergence of greenhouse gases (GHG) emissions for 27 European countries over the period 1990–2006.

From the electricity perspective, the convergence phenomenon has also been investigated. Robinson (2007) tests for β-convergence hypothesis by using annual electricity price data for 9 European Union members over the period 1978–2003. The hypothesis holds for most of the countries in his sample. Using several parametric and non-parametric concepts, Jaunky (2008) uncovers evidence of electric power consumption divergence for 22 African countries for the period 1971–2002. Using non-parametric techniques, Maza and Villaverde (2008) test the residential per capita electricity consumption convergence for 98 countries over the period 1980–2007 and report weak evidence of such convergence. Zachman (2008) investigates whether a common European market for electricity for 11 European countries over the period 2002–2006 is emerging. He finds evidence of stochastic convergence for some countries only.

Liddle (2009) detects both σ-convergence and γ-convergence in electricity intensity of 22 IEA/OECD countries. He also supplies evidence of commercial electricity intensity convergence toward a bell-shape distribution while industry electricity intensity is converging toward two groups such as one with relatively high electricity intensity and another with relatively low electricity intensity. Jaunky (2010) provides evidence of a divergence pattern for electric power consumption among the Southern African Power Pool (SAPP) members over the period 1995–2005. Jaunky (2013) finds some mixed evidence of neoclassical convergence of TE for the SAPP members over the period April 2003-March 2010. His study especially reveals the occurrence of club-formation and γ-divergence.

Recently, Jiang and Wu (2008) analyze the electricity productivity convergence of 30 Chinese provinces over the period 2000–2006. They define electricity productivity as output divided by final electricity use. They use the panel data model to test the conditional convergence and introduce province-specific factors such as electricity price, investment ratio, FDI, technologies, and international trade. Their panel data estimation results show that the gap between the eastern China and western China is decreasing, but there is no absolute convergence in electricity-productivity levels. Furthermore, the influence of electricity price, investment, FDI, technologies and openness on province-specific electricity-productivity growth rates are found to be limited, though the industrial structure negatively influences the electricity productivity growth. We investigate the provincial differences explicitly instead of the general trends in regional level. To conduct a complete analysis both parametric and non-parametric convergence models are employed for this study.

3. METHODOLOGY

To analyze the operational efficiency convergence of the Chinese provinces, both technical efficiency and productivity change indices are computed. The electricity efficiency scores across provinces are initially calculated. Non-parametric approaches using data envelopment analysis (DEA) is employed to compute the technical efficiency scores. In literature, both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are extensively used for efficiency analysis. We use DEA to compute the technical efficiency scores with following reasons. Firstly, SFA uses specific assumptions about the population distribution and will yield biased estimates if these fail to hold. Instead, DEA does not account for statistical noise and can be sensitive to outliers. In this paper, no assumption is made with respect to the population distribution; the data are left to speak for themselves. Secondly, SFA relies on detailed information about the institutional characteristics, cost and price information in order to adequately specify a production function (Paxton, 2006). In the case where limited data on inputs, prices and costs are available, the DEA method is preferred. Furthermore, the productivity changes have also been studied by computing the Malmquist index, which is based on the DEA[5] approach as well.

We next use the efficiency scores obtained from the DEA approach to examine the convergence patterns. For this purpose, both parametric[6] convergence models and non-parametric ones are employed. As in Barro (1991), parametric convergence models mostly refer to the conventional neoclassical convergence approaches, such as β-convergence and σ-convergence.

These classical approaches fail to reveal some key features of the intra-distributional dynamics which might characterize the convergence process such as polarizations, stratifications or clustering of regions with similar patterns of local development. As argued by Pellegrini (2002),

5. We use the SFA approach with the assumption of Cobb-Douglas production to calculate the efficiency scores in a preliminary version of the paper, and find the results (both efficiency scores and rankings) are highly correlated with those using DEA. Since this paper also studies the productivity changes and computes the Malmquist index, we use the DEA approach as the main body of the efficiency analysis. Besides, SFA models cannot directly estimate the Malmquist index (Pantzios *et al*., 2011).

6. Bernard and Durlauf (1995) advocate another parametric convergence approach which studies the stochastic properties of a series. It differs from β-convergence since it does not look at the catching-up process but focuses on how persistent global shocks and variations among states can be. Stochastic convergence occurs if the series follows a trend stationary process. But since T is only 13, unit root test is not a viable option.

these approaches cannot effectively capture individual variability and heterogeneity and also hide phenomena which much concern some groups of regions, especially those located in the distribution tails. Quah (1997) suggests employing non-parametric distribution dynamics technique to study such mobility in order to determine the degree of convergence. Alternatively, the so-called γ-convergence can also be used for testing convergence dynamics. Eventually, several parametric and non-parametric convergence approaches are applied to assess whether a common trend in operational efficiency prevails across provinces.

4. DATA

Our primary data sources are the China Statistical Yearbook and China Energy Statistical Yearbook. These are the main sources published by the National Bureau of Statistics China and used for energy related studies in China. Several studies have questioned the reliability and accuracy of economic statistics especially in an authoritarian economy. According to Chow (2006), China's economic indicators are for most part reliable and it is difficult for any falsifications of official statistical documents to happen. He especially studies the Chinese GDP over the period 1996–2005. Koch-Weser (2013) also notes that there has been an improvement in the consistency of the Chinese statistics mainly due to both higher quality standards for data collection and anti-corruption measures.[7] We collected data for all provinces from 1996–2008. Our study relies on a balanced panel. Hainan and Tibet are excluded due to missing statistical data. However, none of them are large producers of electricity. Hence, we believe the final dataset used for the study is in good quality without hurting the coverage and representativeness.[8]

Table 1 shows the descriptive statistics of the economic indicators used in the paper, which are electricity generation, number of employees, transmission system losses (TSL), average household size, GDP share of industry sector, GDP share of service sector, real energy price index, real government consumption expenditure (in constant 1996 CNY) and the degree of government intervention. TSL can be due to both technical and non-technical reasons. Examples of technical losses are improper earthing at customer end, overloading of electricity mains, poor equipment standards, etc. Non-technical ones are illegal line tapping and connections, vandalization of equipment, non-payment by customers, etc. Government consumption expenditure is mainly indicative about the size of the government and may not adequately reflect the degree of intervention. Following Wei et al. (2009), the share of government financial expenditure in GDP is used as a proxy for the degree of government intervention. On average, the annual electricity generation growth rate accounts to 12.49%. Within the provincial sample, Qinghai and Heilongjiang have the highest and lowest annual growth rate of electricity generation, 41% and 5.2% respectively.

5. THE EFFICIENCY-PRODUCTIVITY ANALYSIS

The DEA technique employs piecewise linear programming to calculate the efficient or best-practice frontier. Assuming data are available on P inputs and M outputs for each of the D decision-making unit (DMU), the input and output vectors can be denoted by x_{it} and y_{it} respectively

7. We conducted "external consistency check" as suggested in Koch-Weser (2013) by comparing provincial GDP to provincial energy uses. There exists a relatively high correlation (more than 0.8) between the two, providing an evidence of data consistency.

8. Hong Kong, Marco, Taiwan are excluded from the study of mainland China as usual.

Table 1: Annual Average of Economic Indicators used in the study from 1996 to 2008

Region	Electricity Generation (100 million kWh)	Number of Employees (per 10,000)	Transmission System Losses (%)	Household Size	GDP share of Industry Sector (%)	GDP share of Service Sector (%)	Real Energy Price Index	Govt. Consumption (100 million CNY)	Degree of Govt. Intervention (%)
Anhui	538.176	8.668	8.258	3.172	44.431	33.931	110.058	210.723	12.042
Beijing	173.497	4.896	19.048	2.762	34.915	62.154	112.760	234.945	17.791
Chongqing	219.878	5.679	12.369	2.980	42.662	40.115	109.302	136.945	13.889
Fujian	548.461	7.745	13.575	3.128	46.054	38.923	109.105	321.199	13.304
Gansu	363.642	6.634	8.611	3.652	45.454	35.508	122.849	111.540	15.593
Guangdong	1649.319	19.048	10.074	3.559	51.269	39.462	102.601	527.732	11.065
Guangxi	347.151	7.985	19.394	3.536	37.531	37.054	105.115	285.371	18.523
Guizhou	586.522	5.780	7.171	3.484	40.346	35.062	110.222	105.245	17.361
Hebei	1064.904	16.207	6.208	3.223	50.769	33.077	115.542	325.764	11.767
Heilongjiang	509.339	14.858	3.066	2.971	54.985	31.700	127.150	261.348	14.134
Henan	1079.758	21.075	7.735	3.379	49.738	29.800	111.754	415.408	13.350
Hubei	817.742	12.475	10.869	3.146	46.762	36.177	111.291	264.943	12.013
Hunan	477.120	10.810	17.216	3.155	40.162	38.162	114.318	357.097	14.908
Inner Mongolia	835.243	8.861	8.258	2.986	44.438	34.138	114.529	156.877	16.197
Jiangsu	1471.113	13.042	7.752	2.974	53.423	35.938	105.876	525.742	11.345
Jiangxi	290.057	9.233	10.195	3.374	42.785	35.523	111.167	170.074	12.876
Jilin	352.449	8.251	8.258	3.043	43.331	35.923	118.761	133.175	13.896
Liaoning	785.047	17.808	6.452	2.930	49.708	38.677	117.358	419.600	13.701
Ningxia	227.532	2.725	5.877	3.554	46.415	37.500	128.795	34.447	21.534
Qinghai	150.358	1.544	12.908	3.685	45.769	39.700	120.045	38.715	23.117
Shaanxi	429.529	8.634	8.052	3.368	47.031	37.554	113.006	224.376	12.519
Shandong	1488.724	19.759	8.258	2.887	52.315	34.123	104.974	1034.888	13.485
Shanghai	611.871	5.921	6.060	2.663	49.115	49.323	108.017	290.745	11.294
Shanxi	982.732	10.883	5.258	3.355	55.038	35.654	118.148	187.477	14.376
Sichuan	722.505	15.005	21.335	3.032	42.223	35.192	105.445	341.979	13.076
Tianjin	271.678	3.518	6.480	2.931	52.754	43.208	107.869	130.426	13.757
Xinjiang	241.717	5.442	7.329	3.411	42.985	35.777	133.508	166.769	20.652
Yunnan	444.528	7.083	20.412	3.560	43.662	35.315	116.667	148.520	17.771
Zhejiang	1010.517	9.617	9.287	2.790	53.269	37.415	103.458	810.310	13.887
Mean	644.521	9.972	10.199	3.196	46.529	37.658	113.438	288.703	14.801

for the i^{th} DMU in the t^{th} time period. The data for all the DMUs can be denoted by $P \times D$ input matrix (X) and $M \times D$ output matrix (Y). An input-oriented DEA model is applied since the DMUs or Chinese provinces have more control over electricity inputs rather than outputs. Since the input quantities (particularly labor and capital are the major resources for production, the other two are also important since transmission loss reflects the levels of technologies, and government intervention providing information on the possibility to attract more investment from capital market) are the primary decision variables for DMUs in electricity generation, power utilities are bound by legal obligations to serve all clients in their respective provinces so they may not be able to control outputs i.e. volume of power generated. According to Le Lannier and Porcher (2014), the adoption of an input-oriented framework is preferred for public utilities as demand can be seen as exogenous. We follow such routine and select input-oriented model in our analysis.[9]

The envelopment form of an input-oriented DEA with constant returns-to-scale (CRS) model can be denoted as follows:

$$\begin{aligned} &\min_{\theta,\lambda}\theta, \qquad (1a)\\ &\textit{subject to}:\\ &-y_{it} + Y\lambda \geq 0,\\ &\theta x_{it} - X\lambda \geq 0,\\ &\lambda \geq 0, \end{aligned}$$

where θ is the input TE score and λ is a $D \times 1$ vector of constants which reflects the linear combination of the i^{th} DMU in the t^{th} time period. If $\theta = 1$, then the DMU is said to be technically efficient. Efficiency scores from the DEA with variable returns-to-scale (VRS) model can also be computed by adding a convexity constraint $DI'\lambda = 1$ (where DI is a $D \times 1$ vector of ones) to equation (1a). A fixed level of output and strong disposability in both inputs and outputs are assumed. The disposability assumption indicates that a rise in inputs does not result in a decline in outputs, and that any decline in outputs can still be produced with the same amount of inputs.

Choosing a model between the CRS or VRS model depends on the degree of control a utility has on the scale of its operations. If a utility cannot control its scale and is not operating at its optimal level, then the VRS model would be more appropriate (Nillesen and Pollitt, 2008). Factors such as labor shortage, oligopolistic competition and financial constraints can cause a sub-optimal performance. The VRS model does not account for size variation and compares utilities only within similar sample size. Utilities are not free to choose or adapt their size. Conversely, CRS models require an optimal operation level and the scale of such operation can be assumed to be under the control of the utilities (Hirschhausen von et al., 2006). If the Chinese utilities can adapt their sizes and scales of operation through mergers and by spreading fixed costs, then the CRS model is appropriate. This will allow them the possibility to adjust their sizes and scales of operation. For the sake of completeness both VRS and CRS models are applied in the paper.

When panel data are available, the most common approach in the DEA literature is to apply the Malmquist productivity growth index as outlined by Färe et al. (1994). The index can be decomposed into technical efficiency and technical change indices. Technical efficiency arises when a DMU moves towards a given efficiency frontier while technical change occurs when a DMU

9. Actually, given that linear programming cannot suffer from such statistical problems as simultaneous equation bias, the choice of an appropriate orientation is not as crucial as it is in the econometric estimation case. In fact, many studies tend to choose input orientation model for their analysis.

moves to a new technically efficient frontier from period from period t to $t+1$. We can also analyze how efficient province i is when using input x^{t-1} to produce y^{t-1} while comparing province using year t technology in year $t-1$. The Malmquist input-based index for a particular country can be defined as:

$$M_0(x^{t+1},y^{t+1},x^t,y^t)=\left[\frac{D_0^t(x^{t+1},y^{t+1})}{D_0^t(x^t,y^t)}\times\frac{D_0^{t+1}(x^{t+1},y^{t+1})}{D_0^{t+1}(x^t,y^t)}\right]^{1/2} \tag{1b}$$

Changes in the Malmquist index can be attributed to either efficiency change of particular regions or shifts in the production frontier depicting technical change. Put differently, it allows us to disentangle, for a given province, a change in efficiency from a change in technology. Equation (1b) represents the productivity of production point (x^{t+1}, y^{t+1}) relative to production point (x^t, y^t). D_0 denotes the distance functions from the frontier. If the Malmquist index is above unity, this will indicate positive productivity growth from period t to $t+1$.

The selection of input and output variables for the DEA models is a crucial task. Similar to Yadav et al. (2009), we consider inputs such as number of employees, capital stock and TSL. It is also important to control for the influence of provincial governments in determining the differences in the level of investment and operation of electricity generation. As an extra input, real provincial government consumption expenditure is included. To some extent, it measures how much provincial governments can spend to intervene in the electricity market and affect the final investment and electricity generation. For the output, the electricity generation is used. Homogeneity of technology can be assumed across provinces.

Let K_{it} denotes the capital stock of a province i at time t and is estimated using the perpetual inventory method:

$$K_{it}=I_{it}+(1-\delta_i)K_{it-1},\ \text{with}\ K_{initial}=\frac{I_{initial}}{r_i+\delta_i} \tag{2}$$

where I_{it} and δ_i denote real investment in the electricity industry (in constant 1996 values) and the depreciation rate of province i at time t respectively. $K_{initial}$ and $I_{initial}$ are initial capital stock and real investment in 1996 respectively. r is the long-run real investment growth rate. There is variation in selecting of the value for the depreciation rate in existing literature. Perkins (1998), Wang and Yao (2003 and Qian and Smyth (2006) all assume a rate of depreciation of 5%. We adopt this depreciation rate for our analysis.[10]

Table 2 shows the efficiency score, Malmquist index and ranking using above three models. The spearman correlation coefficient between DEA-CRS and DEA-VRS is about 0.88, which shows the results using both approaches are highly correlated. The ranking shows interesting results on the levels of energy efficiency across province. In general, it only illustrates the efficiency in the electricity generation and distribution industry across regions.

Three factors contribute to the major provincial differences. Firstly, resource abundant provinces tend to exhibit higher efficiency scores. For example Shanxi, which is rich in coal reserves, ranks 1. Inner Mongolia, which is also a resource-exporting province, ranks 4 in DEA-CRS. Ningxia owns the sixth largest coal reserves in China and ranks in top 3 in all the three rankings. Since these provinces are close to the resource, the effects of economies of scale and economies of

10. We used different values for robustness check and the final results are similar to the ones reported in the paper.

Table 2: Annual Average Technical Efficiency Scores and Productivity Change Indices

	DEA-CRS		DEA-VRS		Malmquist	
Region	Score	Ranking	Score	Ranking	Score	Ranking
Anhui	0.6092	18	0.6677	20	0.6043	19
Beijing	0.3438	29	0.4808	28	0.3423	29
Chongqing	0.4377	26	0.5885	25	0.4459	26
Fujian	0.5862	21	0.6131	21	0.5927	21
Gansu	0.6062	19	0.7000	18	0.6079	18
Guangdong	0.8646	8	0.9438	8	0.9016	8
Guangxi	0.4215	28	0.5069	26	0.4303	28
Guizhou	0.8746	6	0.9146	10	0.9366	6
Hebei	0.8723	7	0.8808	12	0.9080	7
Heilongjiang	0.8485	10	0.9669	6	0.8474	10
Henan	0.7008	15	0.7108	16	0.7178	15
Hubei	0.5923	20	0.6085	22	0.5916	22
Hunan	0.4469	25	0.4692	29	0.4540	25
InnerMongolia	0.9538	4	0.9708	5	0.9938	4
Jiangsu	0.9992	2	0.9992	4	1.0221	3
Jiangxi	0.4592	24	0.6008	23	0.4607	24
Jilin	0.6485	16	0.7054	17	0.6603	16
Liaoning	0.7815	12	0.7985	14	0.7817	12
Ningxia	0.9915	3	1.0000	1	1.0488	2
Qinghai	0.7369	13	1.0000	1	0.7406	13
Shaanxi	0.6192	17	0.6954	19	0.6227	17
Shandong	0.8608	9	0.9523	7	0.8658	9
Shanghai	0.9131	5	0.9385	9	0.9377	5
Shanxi	1.0000	1	1.0000	1	1.1293	1
Sichuan	0.4315	27	0.4915	27	0.4402	27
Tianjin	0.7285	14	0.9131	11	0.7319	14
Xinjiang	0.5808	22	0.7954	15	0.5933	20
Yunnan	0.5462	23	0.5946	24	0.5598	23
Zhejiang	0.8300	11	0.8492	13	0.8349	11
Mean	0.6995	—	0.7709	—	0.7173	—

scope reduce capital investment and labor requirement for the extraction of resources for electricity generation. With the same level of output, these provinces enjoy higher productivity of inputs. The level of efficiency score and productivity index are relatively higher compared to other regions.

Secondly, the disparity in technology varies according to the economic level of the regions. Since most of the power plants are invested and operated by the government, advanced economies are able to invest more for efficient technologies. For example, Jiangsu, Shanghai and Guangdong are among the top in terms of GDP, they also ranked among the top in terms of efficiency as well, which shows developed regions can utilize their production by investing in efficiency improvement. This is because on one hand, these regions enjoy less government intervention (in terms of government consumption expenditure), the negative effects of intervention is low and thus the government-initiated investments have less influence in these regions; on the other hand they are able to attract more investment from capital market which can be used for capacity expansion and technology advancement.

Thirdly, the size (or capacity) of the power sector also has positive impact on the efficiency level. Guangdong and Shandong are the top two provinces in terms of electricity generation; they are ranked in Top 10 in efficiency. Economies of scale in production reduces the production cost and indirectly improves the operational efficiency.

The only exception is Beijing[11] which is ranked 29 when computing the DEA-CRS efficiency scores and productivity indices. One explanation for this is that most of the administrative offices of the energy sectors are located in Beijing which is not related to the generation and distribution industry. These offices occupy physical capital investment and demand for labors from electricity sector and do not contribute to the pure productivity. We observe from the data that Beijing has high figures for labor and capital in the electricity sector and yet yields low electricity output. Nevertheless, we are not able to exclude this part from original data which results in lower rank of Beijing. The Malmquist index reflects similar patterns. As we can see from the table, Jiangsu, Ningxia and Shanxi have the score above 1, representing the significance of resource distance and economic level in determining the total productivity scores. The ranking using Malmquist index provides almost the same results as the ones using efficiency scores.

6. THE CONVERGENCE ANALYSIS

In this section we consider both parametric convergence models and non-parametric ones. As in Barro (1991), parametric convergence models mostly refer to the conventional neoclassical convergence approaches, such as β-convergence and σ-convergence. Non-parametric convergence models include distribution dynamics analysis and the so-called γ-convergence.

6.1 Absolute β-convergence

β-convergence hypothesis postulates efficiency convergence across provinces occurs if those provinces with low efficiency levels experience higher growth rates than the relatively more technically efficient ones. It can be absolute and conditional. Efficiency absolute convergence occurs if provinces with a low level of efficiency and those with a high efficiency level have similar determinants of efficiency steady state or long-run level, such as physical and human capital stock, population growth, saving rate, etc., irrespective of the initial conditions. Thus, provinces with low efficiency levels will grow faster than those with high efficiency levels. All provinces will be converging to the same efficiency steady state level. Conditional convergence occurs when provinces converge to their own steady state level of efficiency instead of a common level, regardless the initial conditions. The lower the initial efficiency level relative to its steady state position, the faster will be efficiency growth rate. Such convergence happens due to diminishing marginal returns to capital as provinces with less initial capital per worker relative to their steady state will have greater returns on capital and so a higher rate of efficiency growth.

Following Barro and Sala-i-Martin (1992) the absolute or unconditional β-convergence hypothesis can be examined by estimating the following reduced-form equation for the pooled model:

$$\Delta \log RE_{it} = \zeta + \beta_a \log RE_{it-1} + e_{it} \tag{3a}$$

where RE_{it} denotes the relative efficiency (RE) of province i at time t. It captures $RDEAC_{it}$, $RDEAV_{it}$ and $RMALMQ_{it}$ variables, denoting the relative efficiency scores from the DEA-CRS, DEA-VRS

11. To check for the robustness of the DEA estimations, Beijing is removed from the dataset, and the efficiency and productivity scores are recomputed. No major difference is to be found and the DEA models do not seem to suffer from the influence of an outlier such as Beijing.

Table 3: Absolute β-Convergence Models

	Dependent Variable		
Coefficient	Δ ln $RDEAC_{it}$	Δ ln $RDEAV_{it}$	Δ ln $RMALMQ_{it}$
β_a	−0.122	−0.105	−0.088
	(0.021)***	(0.020)***	(0.015)***
ζ	−0.003	−0.002	0.0004
	(0.008)	(0.006)	(0.006)
R^2	0.092	0.070	0.094
	348	348	319
Number of Observations	0.131	0.110	0.092
λ	(0.024)***	(0.023)***	(0.017)***
	5.310	6.278	7.541
Half-Life	(0.959)***	(1.298)***	(1.380)***

Note: The standard errors are in parenthesis. ***, ** and * denote 1%, 5% and 10% levels respectively.

and productivity growth models respectively. RE_{it} is computed as the efficiency score of province i at time t divided by the sample average $\overline{\text{RE}}$ at time t. ζ is the constant term and e_{it} is the error term. Δ denotes the change in RE_{it}. RE_{it-1} represents RE of province i in the previous period $t-1$ and is utilized as initial efficiency level to endogenize varying steady state of RE. β_a denotes the absolute convergence in efficiency. According to Islam (1995), $\beta_a = -(1-\exp^{-\lambda\tau})$ where τ is the length of the period and λ is the speed of convergence, defined as speed at which a Chinese province move from its initial efficiency to the balanced efficiency growth or steady states. If the estimated β_a is negative and statistically different from zero, then absolute β-convergence hypothesis is supported. Chinese provinces with a low efficiency level are deemed to be growing faster than those with a high efficiency level while they are all converging to the same steady state or potential level of efficiency.

From equation 3(a), the half-life can be estimated from the β-convergence equation. It is the time needed to reach halfway of the steady state. The formulation can be applied as:

$$1-e^{-\lambda\tau} = 1/2 \Rightarrow \tau = -(\ln(1/2))/\lambda = \ln 2/\lambda \qquad (3c)$$

The delta method is utilized to compute standard errors of λ and half-life respectively. This indeed allows for a statistical assessment of the accuracy and precision of those computed values.

As shown in Table 3, the β_a coefficient is found to be negative and statistically significant at conventional levels. Provinces with a low efficiency level are deemed to be evolving faster than those with a high efficiency level and are all converging to a common level of efficiency. The three models tend to yield a rather similar statistically significant λ value. The λ and half-life range from an annual 0.09 to 0.13 and 5.03 to 7.54 years respectively. Absolute β-convergence across Chinese provinces seems to be a fairly rapid process in terms of both electricity technical efficiency and productivity growth.

6.2 Conditional β-convergence

Subsequently, conditional β-convergence can be studied by extending equation 3(a) to control for provinces with different steady states. The following reduced-form equation can be run as follows:

$$\ln RE_{it} = a + \beta_c \ln RE_{it-1} + \alpha_1 \ln H_{it} + \alpha_2 \ln M_{it} + \alpha_3 \ln S_{it} + \alpha_4 \ln P_{it} + \alpha_5 \ln G_{it} + f_i + \eta_t + \varepsilon_{it} \quad (3b)$$

where H_{it}, M_{it}, S_{it}, P_{it} and G_{it} represent average household size, GDP share of the industry sector, GDP share of service sector, real energy price index (constant 1996) and government intervention respectively of province i at time t. f_i denotes the province-specific fixed effects component which captures unobserved heterogeneity such as level of technology, managerial constraints, etc. η_t is a period-effect[12] component to control for specific temporal shocks such as decreasing quality-adjusted technological cost, increasing non-renewable raw materials costs, etc. a is the constant term and ε_{it} is the error term.

A rise in average household size (H_{it}) will fuel electricity demand and therefore affect electricity efficiency adversely if there is limited access to the grid. Yet, such positive growth can also induce the deployment of fuel saving devices and lead to greater energy efficiency. Increased GDP share of both industry and service sector (M_{it} and S_{it}) can be expected to influence relative efficiency positively as China has been moving up along the development ladder from an agricultural-based economy towards an industrialized one. Despite the fact that China's manufacturing sector is renowned to be energy intensive, the energy consumption in the service sector is growing much faster over the last decade. The stringent energy efficiency policies in the service sector can contribute to a reduction in energy consumption and subsequently to a decline in energy intensity (Zhang, 2013). Rising energy price (P_{it}) can adversely affect efficiency as cost of input rises. Finally, government intervention (G_{it}) can cause a positive impact on efficiency and productivity especially with the implementation of policies to close of inefficient facilities and provide financial incentives for energy efficient investment. But if intervention is not efficient, then the upshot could be a decline in efficiency and productivity. Government intervention can be accompanied by a large government bureaucracy, rents for public employees and corruption (Acemoglu and Verdier, 2000). As a result, the impact of intervention can also be negative.

Conditional β-convergence occurs if $0<\beta_c<1$. Similarly we can also calculate the speed of convergence and the half-life for the conditional β-convergence models. As maintained by Islam (1995), the formula is now $\beta_c = e^{-\lambda\tau}$. λ measures the speed at which the efficiency of a Chinese province approaches its own steady state level. One crucial econometric issue to be considered before estimating using the above described models is endogeneity. Panel data models may yield biased estimates due to the correlation and endogeneity issues arising from the lagged dependent variable. Arellano and Bover (1995) and Blundell and Bond (1998) advocate the use of a system generalized method of moments (GMM) estimator which is designed for large N and small T. In our sample, both N and T are rather small. GMM estimators can be unstable when N is small and generate biased estimates for small samples. Furthermore, since T is small, the use of instrumental variables can be problematic. Kiviet (1995) proposes the use of the least squares with dummy variables bias-corrected (LSDVC)[13] version which is found to be quite accurate even when N and T are small.

The regression results are reported in Table 4. The coefficient β_c is generated by the LSDVC approach. Since $0<\beta_c<1$, conditional β-convergences of efficiency and productivity across provinces are confirmed. The λ and half-life range from a yearly 0.16 to 0.24 and 2.87 to 4.28 years respectively. The Chinese provinces are converging rapidly to their individual steady

12. The η_t component is usually excluded from the model as it tends to become irrelevant as τ increases.

13. One criticism of the LSDVC estimator is its failure to deal with the endogeneity of other explanatory variables apart from the lagged dependent one.

Table 4: Conditional β-Convergence Models

	Dependent Variable		
Coefficient	ln $RDEAC_{it}$	ln $RDEAV_{it}$	ln $RMALMQ_{it}$
β_c	0.785	0.807	0.851
	(0.017)***	(0.057)***	(0.011)***
α_1	0.108	0.066	0.091
	(0.100)	(0.083)	(0.028)***
α_2	0.335	0.134	0.122
	(0.061)***	(0.037)***	(0.183)
α_3	0.268	0.169	0.094
	(0.258)	(0.191)	(0.040)**
α_4	−0.080	−0.029	−0.039
	(0.058)	(0.042)	(0.027)
α_5	−0.071	−0.053	−0.053
	(0.043)*	(0.031)*	(0.010)***
Number of Observations	319	319	290
λ	0.242	0.214	0.161
	(0.021)***	(0.070)***	(0.013)***
Half-Life	2.870	3.244	4.281
	(0.255)***	(1.063)***	(0.349)***

Note: The standard errors are in parenthesis. ***, ** and * denote 1%, 5% and 10% levels respectively.

state efficiency level. GDP share of the industry have a significant and positive impact on relative technical efficiency. The industrial sector remains a major economic pillar for the Chinese economy and its expansion will enhance technical efficiency convergence. The average household size and the service sector are found to impact significantly and positively on total productivity change (ln $RMALMQ_{it}$). As the increase in the average household size drives up demand, it also boosts the disposable income of the household. Energy saving devices can now be deployed and the access to grids can also be expanded. These will contribute to both the advancement of technical efficiency and technical change.

The degree of government intervention is found to have a negative impact on both relative efficiency and productivity growth, i.e. higher degree of government intervention lowers the relative efficiency level. This is in line with the concept of government intervention introduced by Acemoglu and Verdier (2000). One interpretation may be that the Chinese government expenditures have not efficiently been invested on cost-saving and updated technologies. In fact, following Fisher-Vanden and Ho (2007), the Chinese government has invested a large share of its capital unproductively in pursuit of non-economic objectives. Indeed, China still relies on coal-fired power plants which employs inefficient technologies and emit high amount of carbon dioxide. Furthermore, higher degree of intervention also restricts the inflow of foreign investment and sets barriers for technology transfer, which limit the advancement of technology not only in the electricity sector but also other industrial sectors.

Although energy price does have the expected negative sign, overall it has a statistically insignificant impact. There are several reasons which could explain this result. In an emerging economy, the demand for energy, particularly electricity is high in order to fuel the fast economic growth. However, the prices of energy are relatively low compared with other commodity goods. This is true in the case of China. The energy prices are fully controlled by the government. Even though the liberalization of the energy market starts 1990s, it is still far lagged behind of other market reform. The energy prices stay far below the market prices and energy sectors enjoy the subsidies from the government. Hence, the prices would send a wrong signal to the market. Another reason for the insignificant effects of price may come from export growth. The export rises significantly and more than half of the energy demand increase in the period of 2002 to 2007 was to produce exported goods or service. Firms can make profits from production (or producing more in order to keep the same level of profits as before) even the prices of energy increase. Finally, even though the general demand of electricity decreases as the price of energy increase, the higher demand from the exporting firms drive up the electricity supply partly.

6.3 σ-convergence

Static efficiency dispersions among provinces can be studied by testing the σ-convergence hypothesis. This approach revolves around the cross-provincial standard deviation σ, over time trend. σ can simply be formulated as:

$$\sigma_t = \sqrt{\left(\frac{1}{N-1}\right)\sum_{i=1}^{N}(\ln efficiency_{it} - \ln \overline{efficiency_t})^2} \tag{4}$$

where $efficiency_{it}$ is the efficiency score for province i at time t and $\overline{efficiency_t}$ is the mean value of efficiency scores at time t. If σ_t is following a downward trend towards zero, then σ-convergence of efficiency is supported. With respect to the Galton's Fallacy,[14] the neoclassical β-convergence is a necessary but insufficient requirement for σ-convergence.

The σ-convergence results are presented in Figure 1. The σ of the all three RTE measures tends to exhibit a downward trend over time, although there seems to be a slight upward movement around 2002–2003.[15] As presented in Table 5, the RE measures have been experiencing a negative annual growth rate. These provide evidence of σ-convergence. Overall, the two neoclassical approaches confirm the notion of a β- and σ-type of TE convergence across the 29 Chinese provinces over the period 1996–2008.

6.4 Nonparametric Distribution Dynamics

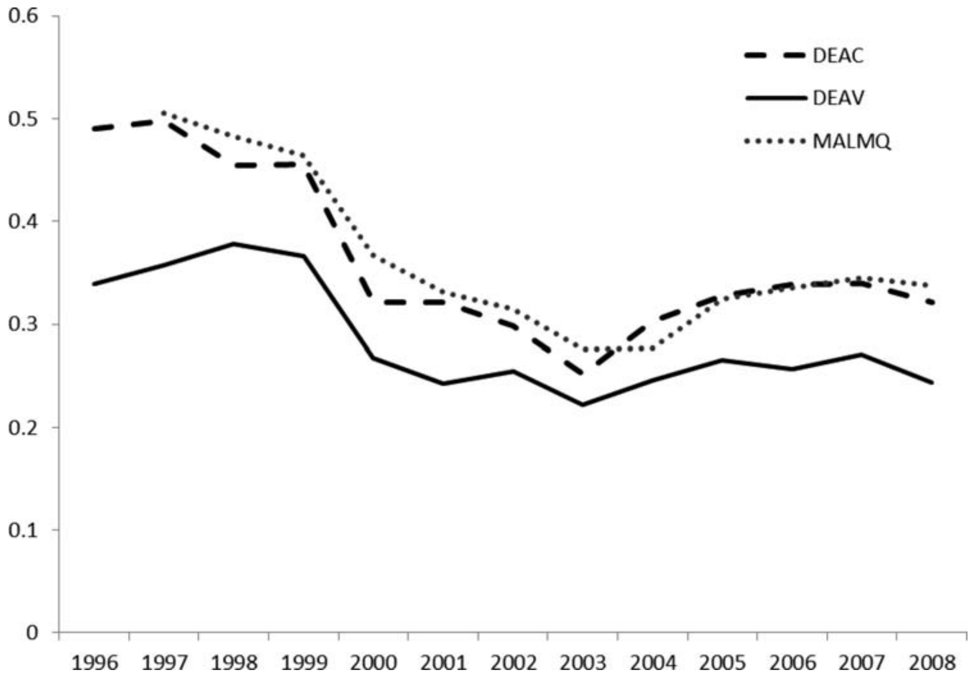
According to Bianchi (1997), σ-convergence analysis alone is not sufficient to study convergence unless more information is gained on how units move within the distribution. As suggested by Quah (1997), we employ the non-parametric distribution dynamics technique to reveal the intra-distributional dynamics of the various provinces over time. Though this approach may offer a rough view of convergence, empirical regularities such as persistence, polarization and club-formation [16]

14. Barro and Sala-i-Martin (2004) provide a formal proof of the Galton's Fallacy.

15. This upward rising is in line with many studies showing the rising of energy intensity between 2002 and 2005.

16. To a certain extent the concept of club-convergence can be related to conditional convergence where the latter allows for sub-groups to converge to a common steady state though the whole group may diverge. This approach differs from conditional convergence as initial conditions of individual countries are assumed to be the same. The formation of clubs takes place when for instance, two provinces with high and low efficiency relative to a certain threshold, have the propensity to build distinct groups at the same time as those with average efficiency are inclined to fade away. This may give rise to the process of polarization whereby provinces converge towards two distinct basins of attractions, resulting in the formations of clubs. Provinces with a low efficiency level do not catch up with those with a high level of efficiency if the initial conditions of similar steady state exist. These conditions will establish whether a province with a low level of efficiency gets caught in a development trap or will break free to match the performance of those provinces with a high efficiency level.

Figure 1: σ of Efficiency Indices



can be determined. The manifestation of convergence relates to a progressive budge towards a single-peak distribution whereby the probability mass will be concentrated around a certain value. Within the club-convergence concept, a twin-peak or multiple-peak distribution is equivalent to polarization or formation of club-convergence. Simply put, this is denotes divergence.

Let $\varphi_t(x)$ be the cross-provincial distribution of a RE series at time t and the density at time $t+\tau$ for $\tau > 0$, is $\varphi_{t+\tau}(y)$, where y denotes RE level of a province at time $t+\tau$. Under the time-invariant process assumption, the link between $\varphi_t(x)$ and $\varphi_{t+\tau}(y)$ is:

$$\varphi_{t+\tau}(y) = \int_0^{+\infty} f_\tau(y|x)\varphi_t(x)dx \tag{5a}$$

where $f_\tau(y|x)$ is the conditional density of y. Assuming $q = |x,y|$, and $f_{t,t+\tau}(q)$ designates the joint distribution q, the joint distribution at point q_0 can be defined as:

$$f_{t,t+\tau}(q_0) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{q_0 - q_i}{h}\right) \tag{5b}$$

where $K(.)$ is a bivariate kernel function assumed to follow the Epanechnikov function, $K(q) = (2/\pi)(1-q'q)I(q'q \le 1)$ where $I(.)$ is the indicator function. Equation (5b) describes the transition over one year from a given RE level in period t. It explains how the cross-provincial distribution at t evolves into $t+1$. The bandwidth h determines the degree of smoothness of the estimates It is selected according to the cross-validation criterion (Nguyen Van, 2005). So, $\varphi_t(x) = \int f_{t,t+\tau}(q)dy$ can be estimated. The conditional distribution is:

$$f_\tau(y\,|\,x) = \frac{f_{t,t+\tau}(q)}{\varphi_t(x)} \tag{5d}$$

Convergence can be studied by computing the surface and contour of the conditional density $f_\tau(y\,|\,x)$ of equation 5(d) for the three relative efficiency scores as measured for DEA-CRS, DEA-VRS and Malmquist approaches. Figures 2(a), 2(b) and 2(c) present the snapshots of these distributions. With respect to the ln(*RDEAC*) and ln(*RDEAV*) series h is computed to be 0.935 and for ln(*RMALQ*), it is equal to 0.949.

As shown in Figures 2(a), the surface plot of ln(*RDEAC*) shows characteristics of nascent multi-peakedness and a tendency of club formations among provinces. The contour plot below represents the bird eye's view of the surface plot and indicates various levels of iso-probs i.e. the probability of a province moving between t and $t+1$. A peak below (above) the 45° line[17] implies a tendency for the Chinese provinces to have lower (higher) electricity efficiency. Club-convergence occurs when distinct peaks lie along this line. A major part of the probability mass is clustered along this line. A prominent peak with a proportion of 2% and relative technical efficiency of about 14 can be distinguished below from the diagonal line. Some provinces with high efficiency values tend to have a decreasing relative efficiency over time while the general tendency for the Chinese provinces is to remain in the same initial position. In this sense the technical efficiency convergence is only half-full or half-empty since the highly efficient provinces are catching up with the low ones while the latter remain where they started.

Referring to Figure 2(b), a more or less similar pattern is observed with a multi-peak distribution of ln(*RDEAV*) where most of the peaks are found on the 45° line, implying again no signs of mobility among Chinese provinces. A few peaks in the lower tail of the distribution, especially those with relative technical efficiency scores less than zero, are found lying on the 45° line. Thus, inefficient provinces do not change from from their initial position. At the upper tail of the distribution, several peaks are found below the diagonal line, especially at relative efficiency levels of 6, 8, 10 and 13. Therefore, highly efficient provinces tend to have a decreasing relative efficiency over time. Once more, the technical efficiency convergence is found to be half-full or half-empty. Overall, no concrete evidence is found in support of the technical efficiency convergence hypothesis among Chinese provinces.

Figure 2(c) shows the distribution dynamics of relative productivity of ln(*RMALMQ*). As opposed to Figures 2(a) and 2(b), the surface plot shows a clear tendency towards a single ridge. As shown in the contour plot, a prominent peak with a proportion of 4% and relative productivity of about 2 which lies on the 45° line can be detected around the middle of the distribution. This rather implies some support for electricity productivity convergence.

To summarize, although some evidence of club-convergence is found, the above findings imply that the efficiency convergence hypothesis is only half-full or half-empty in the sense that technical efficiency does not converge for Chinese provinces while a persistence process on productivity is detected with a tendency towards convergence. The difference observed between trends in efficiency and productivity can be explained by technical progress included in the productivity analysis. Intensive technical progress moving towards advanced technologies is taking place with

17. The dotted diagonal 45° line represents persistence properties and illustrates the position of province i in the distribution which does not change from where it began. Any peak which is either above or below the diagonal line signifies a tendency for RTE to either increase or decrease respectively.

Figure 2(a): Surface and Contour Plots of the Conditional Function of the ln *RDEAC* from 1996 to 2008

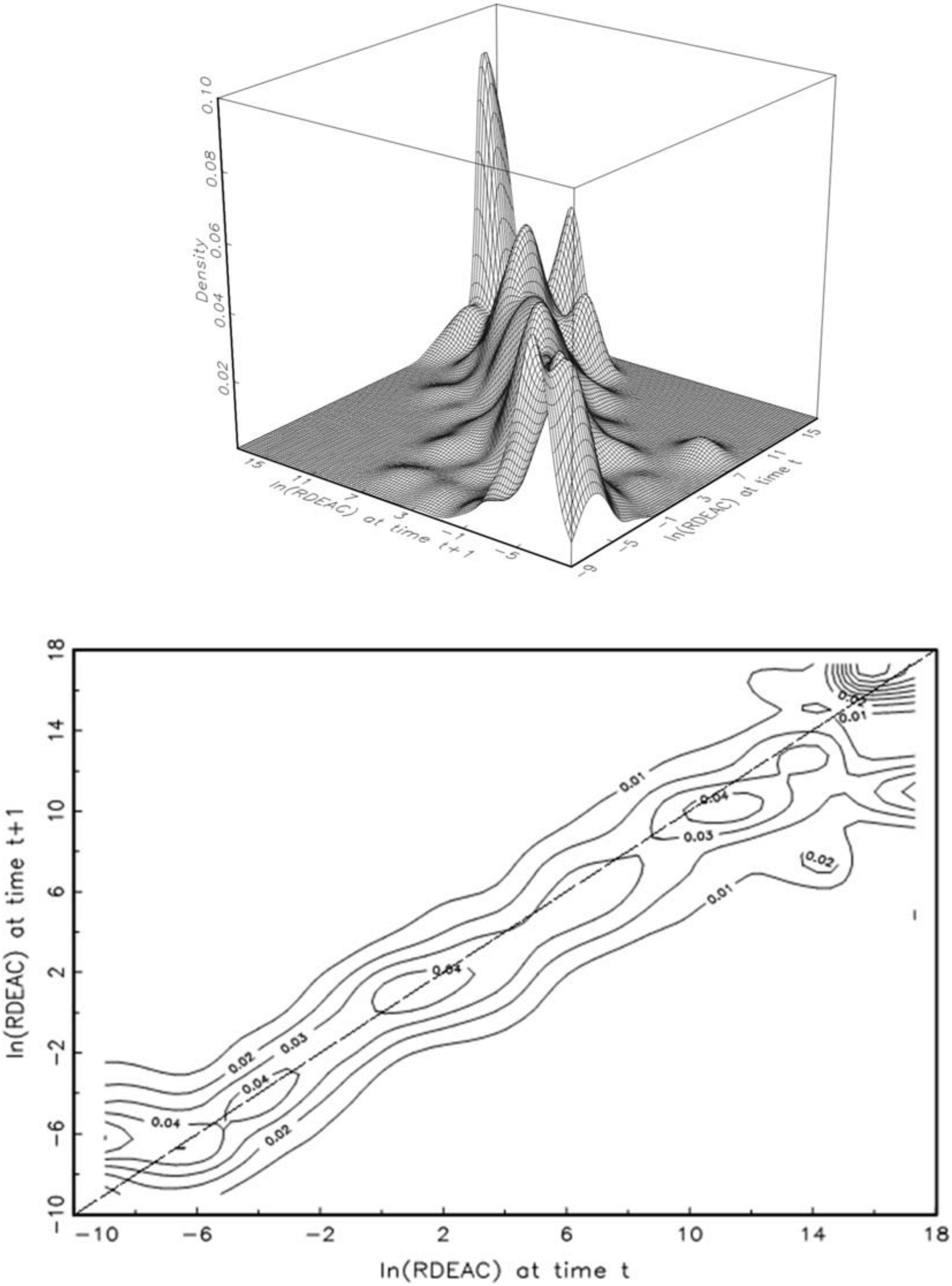
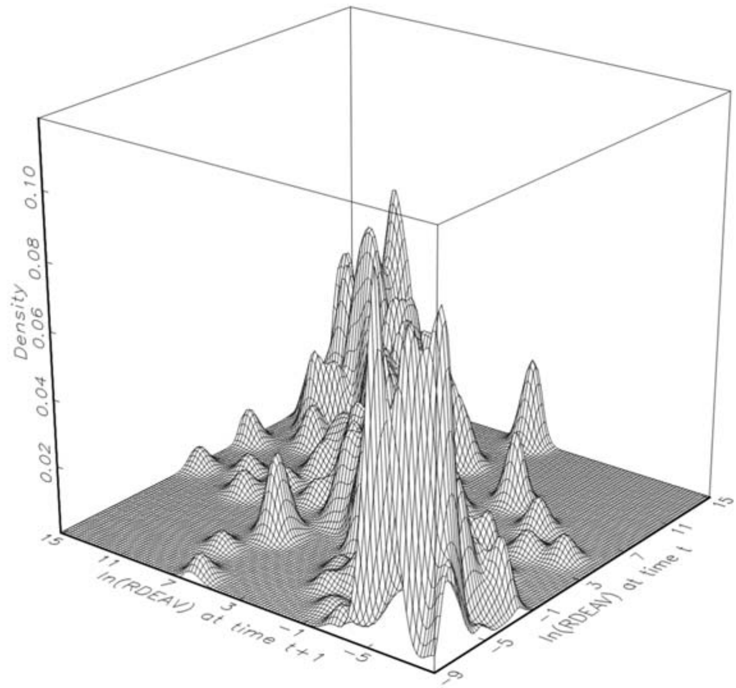


Figure 2(b): Surface and Contour Plots of the Conditional Function of the ln *RDEAV* from 1996 to 2008



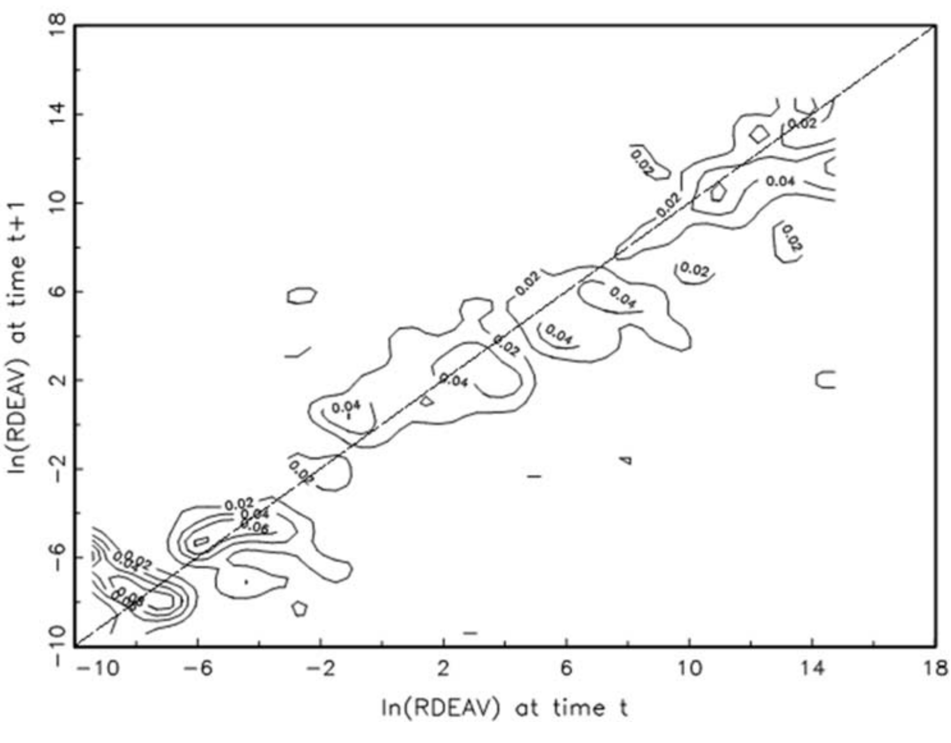


Figure 2(c): Surface and Contour Plots of the Conditional Function of the ln *MALMQ* from 1997 to 2008

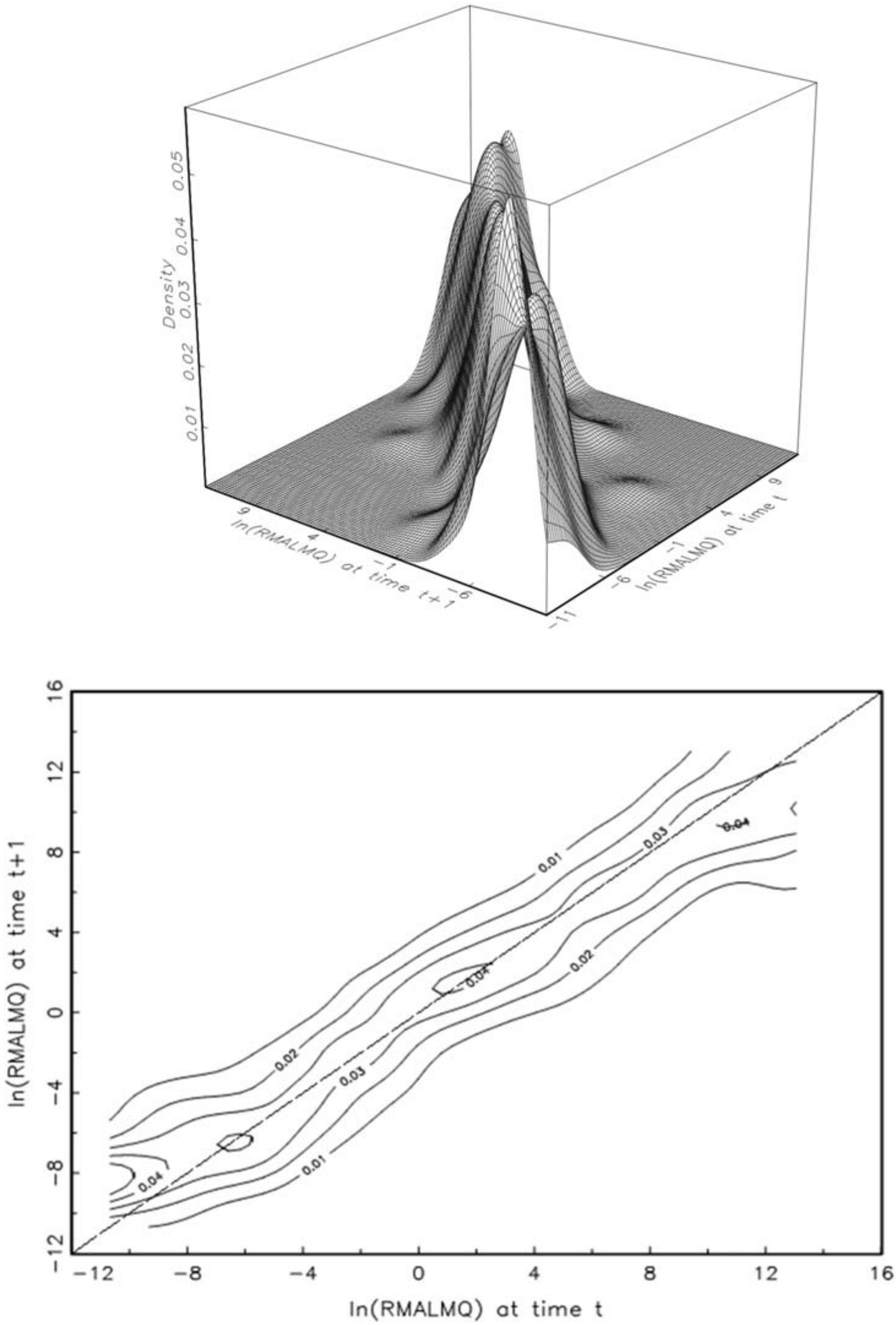


Table 5: Annual Average Growth Rate (%) of σ and RCa

Variable	σ	RCa
DEAC	−2.7049	−2.4750
DEAV	−2.0972	−1.4190
MALMQ	−3.1443	−1.0285

the development of the regional economy, which leads to the convergence tendency in productivity. Efficiency policies seem to have limited effects in most regions.

6.5 γ-convergence

For a reliable estimation of multivariate kernel densities, a large sample size is arguably required. This is due to the curse of dimensionality. It can be rather challenging to interpret distributions with dimensions higher than two especially when the number of observations is relatively small. Boyle and McCarthy (1997) propose an alternative measure known as γ-convergence to measure intra-distributional mobility over time. To test for γ-convergence, the binary version of the non-parametric Kendall's index of rank concordance (RCa) is calculated. The equation as proposed by Boyle and McCarthy (1997) is:

$$RCa_t = \frac{\mathrm{var}(ARo(efficiency)_{it} + AR(efficiency)_{i0})}{\mathrm{var}(2AR(efficiency)_{i0})} \tag{6}$$

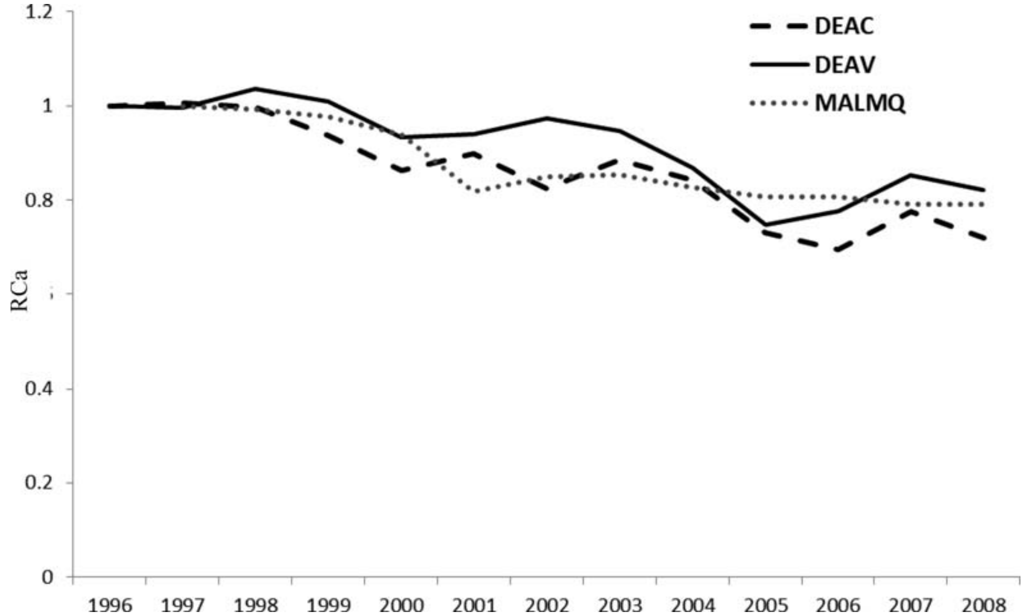
where RCa_t denotes the RCa at time t. $AR(efficiency)_{it}$ is the actual rank of province i's efficiency at time t. $AR(efficiency)_{\mathrm{it}}$ is the actual rank of province i's efficiency at time t. $AR(efficiency)_{i0}$ is the actual rank of province i's efficiency in the initial period 0. RCa_t captures the evolution of the ordinal ranking over a time interval and takes on a value between 0 and 1. The closer the value of the index is to zero, the greater the extent of intra-distributional mobility and as a consequence the greater the efficiency convergence.

In Table 5, the reported average negative growth rates of both RCa and σ tend to be rather close, especially when referring to DEAC. In general, Figure 3 exhibits the trends for all RE series which are decreasing trend towards zero over time. The γ-convergence hypothesis is confirmed and this provides further evidence of efficiency convergence across the Chinese provinces.

7. POLICY IMPLEMENTATION AND CONCLUDING COMMENTS

This study has shed light on the convergence pattern of operational efficiency among 29 Chinese provincial electricity generations over the period 1996–2008. DEA method is exploited to compute the efficiency scores for each province. We then apply both parametric and non-parametric models to examine convergence patterns. Parametric convergence models confirm the prevalence of β-convergence and σ-convergence. These results are further supported by the non-parametric convergence models. Distribution dynamics reveals that technical efficiency convergence is only half-full or half-empty while some support for productivity convergence hypothesis is found. In addition, the γ-convergence hypothesis is found to hold. Overall, operational efficiency is converging across the Chinese provinces. The convergence both unconditional and conditional is related to four reasons: the fast growth of economy of all provinces; government policies towards energy

Figure 3: RCa of Efficiency Indices



saving and efficiency improvement, nationally and locally; the growing awareness of environmental concerns, not only government pressure but also public attention; the advancement of clean technologies and green energy resources.

Furthermore, since conditional β-convergence is found to be greater than the absolute β-convergence in terms of the speed of convergence λ, the operational efficiency of Chinese utilities is converging faster to their own efficiency steady state than to a common one. This outcome is encouraging for supporting the current policies at a provincial level even though it does not necessarily guarantee a steady state with higher efficiency level for the respective utilities. Put differently, there is still scope for active interventions and policy reforms from the government to boost the steady state at utility level. Nevertheless, as in Kostka and Hobbs (2012), not all local governments have achieved the national energy saving and emission reduction targets. Some regions' last minute response by energy cuts and production limitation may harm not only the regional economy but also the public service. Local protectionism and individual interests can lead to a misalignment between central and local government in energy policies. For instance, large amounts of small-sized power plants are inefficient and heavy polluters, but their revenues contribute to a significant part of local fiscal income. That is why the central government met resistance when it shut them down. Laws and regulatory system are needed to separate government departments from intervention.

Another example is that the central government develops the strategy of transmitting power from western to eastern China in order to balance such mismatch between electricity supply and demand. However, market, technical[18] and administrative barriers, and also the financial system

18. Most government investment in the power sector was biased towards generator installation; there has long been insufficient investment in grid construction. The dispatch and delivery network is less developed and so this limits the use of rich energy resources in western China to satisfy soaring energy demand in eastern regions, which aggravates the electricity crisis. In this regard, future investment should promote the unity of the national network. To achieve the energy and emission target, it is also necessary to increase interprovincial and inter-regional trading and power plant dispatch.

between local and central authorities, impede the implementation of this strategy (Xu and Chen, 2006). Such barriers and local protectionism result in self-balance of supply and demand, which are a waste of resource. To overcome such barriers, the Scheme of the Reform for Power Industry started in 2002. Before 2002, more than half of the nation's capacity and 90% of transmission asset belongs to the State Power Corporation. Since the reform of power industry, the State Power was dismantled into five independent electricity generating and two transmission companies (Wang and Chen, 2012). The purpose of such division by the government is to foster competition in an attempt to improve efficiency and guarantee that inter-provincial trade of power can be implemented through market. However, according to Wang and Chen (2012) the state still owns more than 60% of total installed capacity by 2010.

Specifically, we also highlight several factors which can affect the energy efficiency and productivity both in the short- and long-term, pointing out the priorities to policymakers in tackling the difficulties in power sector reforms. The positive effect of household size provides evidence of economies of scale for electricity productivity growth. It is costly to build new grids and improve electrification penetration rate. Provinces can promote urbanization to exploit the economies of agglomeration. Because of concentrated economic activity and more dense population, utilities will benefit from large-scale electricity production with lower average cost of production and higher productivity. Low cost-operating utilities can also improve their productivity by taking advantage of the regional network. Urbanization speeds up the rate of industrialization of the Chinese economy. Industrial and service sector also contribute to the efficiency improvement as illustrated in our results. This is the "double dividend" from urbanization.

The price effects are insignificant. Our results suggest that energy price may not be contributing substantially to convergence of electricity productivity across Chinese provinces. This is due to the opaque and economically irrational pricing system in China. Resources can be allocated effectively through the market if there is a sound price mechanism. Nonetheless, the electricity price was set administratively rather than decided by the supply-and-demand conditions. The National Development and Reform Commission (NDRC) determines the electricity prices based on the generation costs estimations. Adjustments to electricity prices are allowed, though not implemented properly.[19] A reform in electricity pricing system is one priority of the government concerns for the efficiency improvement.

In the latest 12th Five-Year-Plan, the reform toward reducing greenhouse gas emissions requires very large investment in renewable energy and energy efficiency. Grid expansions to accommodate the new mix of clean resources also require substantial investment. The negative effect of government intervention from the result suggests the government financial expenditures do not contribute to the improvement of efficiency. Accordingly, the government needs explicit policies for expenditures towards green technologies and efficiency advancement, for instance, introducing capacity payments or emission performance standard to quantify the output from new investment. However, generation and gird assets are mostly controlled or with policies influenced by the government. Inertia on strong government influence on the reform of the electricity market makes directing new investment to meet the long-term efficiency and environmental goals a big challenge.

The distribution dynamics study reveals some persistence process at play for relative inefficient provinces while the highly efficient ones tend to have a reduction in efficiency over time. One means of assisting the convergence process is to benchmark best practices, such as measuring

19. According to Ma (2011), the electricity prices have been adjusted only three times since 2004, despite the generation costs increase more than 10 times.

a province's productive efficiency of electricity generated against a reference performance. In order for the provinces to keep track of their operational efficiency performance, it is imperative that the central government disseminates provincial-level data in both quality and quantity on a timely basis. This will enable provinces to smoothly track the evolution of their energy performances.

ACKNOWLEDGMENTS

The authors would like to thank the two anonymous referees and the Editor-in-Chief of this journal, Prof. Adonis Yatchew, for providing insightful and constructive comments, which have greatly improved the quality of the paper. We would also like to thank Lucas Bretschger, Robert Lundmark, Patrik Söderholm, Filippo Lechthaler and Aryestis Vlahakis for valuable comments on a previous draft of this paper. Errors, if any, are the authors' own.

REFERENCES

Acemoglu, D. and T. Verdier (2000). "The choice between market failures and corruption." *American Economic Review* 90(1): 194–211. http://dx.doi.org/10.1257/aer.90.1.194.

Arellano, M., and O. Bover (1995). "Another Look at the Instrumental Variables Estimation of Error Components Models." *Journal of Econometrics* 68(1): 29–51. http://dx.doi.org/10.1016/0304-4076(94)01642-D.

Barro, R. J. (1991). "Economic growth in a cross section of countries." *Quarterly Journal of Economics* 106(2): 407–443. http://dx.doi.org/10.2307/2937943.

Barro, R, J. and X. Sala-i-Martin (1992). "Convergence." *Journal of Political Economy* 100(2): 223–251. http://dx.doi.org/10.1086/261816.

Bianchi, M. (1997). "Testing for convergence: evidence from non-parametric multimodality tests." *Journal of Applied Econometrics*, 12, 4, 393–409. http://dx.doi.org/10.1002/(SICI)1099-1255(199707)12:4<393::AID-JAE447>3.0.CO;2-J.

Blundell, R., and S. Bond (1998). "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87(1): 115–143. http://dx.doi.org/10.1016/S0304-4076(98)00009-8.

Boyle, G. E. and T. G. McCarthy (1997). "A simple measure of beta-convergence." *Oxford Bulletin of Economics and Statistics* 59(2): 257–264. http://dx.doi.org/10.1111/1468-0084.00063.

Chow, G. (2006). "Are Chinese official statistics reliable?" *CESifo Economic Studies* 52(2) 396–414. http://dx.doi.org/10.1093/cesifo/ifl003.

Färe, R., S. Grosskopf, M. Morris and Z. Zhang (1994). "Productivity Growth, Technical Progress, and Efficiency in Industrialized Countries." *American Economic Review* 84(1): 66–82.

Fisher-Vanden, K. and S. Ho (2007). "How do market reforms affect China's responsiveness to environment policy?" *Journal of Development Economics* 82: 200–233. http://dx.doi.org/10.1016/j.jdeveco.2005.06.004.

Hirschhausen von C, A. Cullmann and A. Kappeler (2006). "Efficiency Analysis of German Electricity Distribution Utilities, Nonparametric and Parametric Tests." *Applied Economics* 38(21): 2553–2566. http://dx.doi.org/10.1080/00036840500427650.

International Energy Agency (2007). *World Energy Outlook 2007—China and India Insights.* IEA, Paris.

International Energy Agency (2010c). *Energy Technology Perspectives—Scenarios & Strategies to 2050.* IEA, Paris.

Islam, N. (1995). "Growth empirics: A panel data approach." *The Quarterly Journal of Economics* 110(4): 1127–1170. http://dx.doi.org/10.2307/2946651.

Jaunky, V. C. (2008). "Divergence in per capita electric power consumption: An African perspective." *Applied Econometrics and International Development* (8): 137–151.

Jaunky, V. C. (2010) "Divergence of Electric Power Consumption: Evidence from the SAPP." *The Journal of Developing Areas* 44(1): 123–147. http://dx.doi.org/10.1353/jda.0.0080.

Jaunky, V. C. (2013). "Divergence in Technical Efficiency of Electric Utilities: Evidence from the SAPP." *Energy Policy* 62: 419–430. http://dx.doi.org/10.1016/j.enpol.2013.07.113.

Jiang, M. H. and Y.-M. Wu (2008): "Electricity Productivity Convergence: A Study Based on Panel Data Model." *Communication of Urban & Regional Development* 2(1): 1–10.

Jobert, T., F. Karanfil, A. Tykhonenko (2010). "Convergence of per capita carbon dioxide emissions in the EU: Legend or reality?" *Energy Economics* 32: 1364–1373. http://dx.doi.org/10.1016/j.eneco.2010.03.005.

Kiviet, J. F. (1995). "On bias, inconsistency and efficiency of various estimators in dynamic panel data models." *Journal of Econometrics* 68(1): 53–78. http://dx.doi.org/10.1016/0304-4076(94)01643-E.

Koch-Weser, I. N. (2013). "The reliability of China's economic data: An analysis of national output" *U.S.-China Economic and Security Review Commission Staff Research Project Report.*

Kostka, G. and W. Hobbs (2012). "Local energy efficiency policy implementation in China: Bridging the gap between national priorities and local interests." *The China Quarterly* 211: 765–785. http://dx.doi.org/10.1017/S0305741012000860.

Le Lannier, A. and S. Porcher (2014). "Efficiency in the public and private French water utilities: Prospects for benchmarking." *Applied Economics* 46(5): 556–572. http://dx.doi.org/10.1080/00036846.2013.857002.

Liddle, B. (2009). "Electricity intensity convergence in IEA/OECD countries: Aggregate and sectoral analysis." *Energy Policy* 37: 1470–1478. http://dx.doi.org/10.1016/j.enpol.2008.12.006.

Ma, J. (2011). "On-grid electricity tariffs in China: Development, reform, and prospects." *Energy Policy* 39: 2633–2645. http://dx.doi.org/10.1016/j.enpol.2011.02.032.

Marrero, G. A. (2010): "Greenhouse gases emissions, growth and the energy mix in Europe." *Energy Economics 32*(6): 1356–1363. http://dx.doi.org/10.1016/j.eneco.2010.09.007.

Maza, A. and J. Villaverde (2008). "The world per capita electricity consumption distribution: Signs of convergence?" *Energy Policy* 36: 4255–4261. http://dx.doi.org/10.1016/j.enpol.2008.07.036.

National Bureau of Statistics. *China statistical Yearbook (1997–2009, 2013)*. NBS, Beijing, China.

National Bureau of Statistics. *China Energy Statistical Yearbook (1997–2009).* NUBS, Beijing, China.

Nillesen, P. and M. Pollitt (2008). "Using Regulatory Benchmarking Techniques to Set Company Performance Targets: The Case of Us Electricity." *Cambridge Working Paper in Economics CWPE0834 / Electricity Policy Research Group EPRG0817*, Faculty of Economics, University of Cambridge.

Nguyen Van, P. (2005). "Distribution dynamics of CO_2 emissions." *Environmental and Resource Economics* 32(4): 495–508. http://dx.doi.org/10.1007/s10640-005-7687-6.

Pantzios, C. J., G. Karagiannis and V. Tzouvelekas (2011). "Parametric decomposition of the input-oriented Malmquist productivity index: With an application to Greek aquaculture." *Journal of Productivity Analysis* 36(1): 21–31. http://dx.doi.org/10.1007/s11123-010-0202-2.

Paxton, J.A. (2006). "Thechnical efficiency in the rural financial sector: Evidence from Mexico." *The Journal of Development Areas* 39(2): 101–119. http://dx.doi.org/10.1353/jda.2006.0010.

Pellegrini, G. (2002). "Proximity, polarization, and local labor market performances." *Networks and Spatial Economics* 2(2) 151–173. http://dx.doi.org/10.1023/A:1015313212056.

Perkins, D.H. (1988). "Reforming China's economic system." *Journal of Economic Literature* 26(2): 601–645.

Qian, X. and R. Smyth (2006). "Growth Accounting for the Chinese Provinces 1990–2000: Incorporating Human Capital Accumulation." *Journal of Chinese Economic and Business Studies* 4(1): 21–37. http://dx.doi.org/10.1080/14765280600551216.

Quah, D. (1997). "Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs." *Journal of Economic Growth* 2(1): 27–59. http://dx.doi.org/10.1023/A:1009781613339.

Robinson, T. (2007). "The convergence of electricity prices in Europe." *Applied Economics Letters* 14(7): 473–476. http://dx.doi.org/10.1080/13504850500461597.

Romero-Ávila, D. (2008). "Convergence in carbon dioxide emissions among industrialized countries revisited." *Energy Economics* 30(5): 2265–2282. http://dx.doi.org/10.1016/j.eneco.2007.06.003.

Solow, R. M. (1956). "A contribution to the theory of economic growth." *Quarterly Journal of Economics* 70(1): 65–94. http://dx.doi.org/10.2307/1884513.

Steenhof, P. A. and W. Fulton (2007). "Scenario development in China's electricity sector." *Technological Forecasting & Social Change* 74(6): 779–797. http://dx.doi.org/10.1016/j.techfore.2006.09.004.

Wang, Q. and X. Chen (2012). "China's electricity market-oriented reform: From an absolute to a relative monopoly." *Energy Policy* 51: 143–148. http://dx.doi.org/10.1016/j.enpol.2012.08.039.

Wang, Y. and Y. Yao (2003). "Sources of China's economic growth 1952–1999: incorporating human capital accumulation." *China Economic Review* 14(1): 32–52. http://dx.doi.org/10.1016/S1043-951X(02)00084-6.

Wei, C., Ni, J. and M. Shen (2009). "Empirical analysis of provincial energy efficiency in China." *China & World Economy* 17(5): 88–103. http://dx.doi.org/10.1111/j.1749-124X.2009.01168.x.

Westerlund, J. and S. A. Basher (2008). "Testing for convergence in carbon dioxide emissions using a century of panel data." *Environmental and Resource Economics* 40(1): 109–120. http://dx.doi.org/10.1007/s10640-007-9143-2.

Xu, S. and W. Chen (2006). "The reform of electricity power sector in the PR of China." *Energy Policy* 34: 2455–2465. http://dx.doi.org/10.1016/j.enpol.2004.08.040.

Zachmann, G. (2008). "Electricity wholesale market prices in Europe: Convergence?" *Energy Economics* 30(4): 1659–1671. http://dx.doi.org/10.1016/j.eneco.2007.07.002.

Zhang, L. (2013). "Model projections and policy reviews for energy saving in China's service sector." *Energy Policy* 59: 312–320. http://dx.doi.org/10.1016/j.enpol.2013.03.045.

Zhou, N., M. D. Levine and L. Price (2010). "Overview of current energy-efficiency polices in China." *Energy Policy* 38: 6439–6452. http://dx.doi.org/10.1016/j.enpol.2009.08.015.