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Effects of One-Sided Fiscal Decentralization on Environmental Efficiency of Chinese Provinces

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Abstract

China's actual fiscal decentralization is one-sided: while public expenditures are largely decentralized, fiscal revenues are recentralized after 1994. One critical consequence of the actual system is the creation of significant fiscal imbalances at sub-national level. This paper investigates empirically effects of fiscal imbalances on environmental performance of Chinese provinces. First, environmental efficiency scores of Chinese provinces are calculated with SFA for the period from 2005 to 2010. Then, these scores are regressed against two fiscal imbalance indicators in a second stage model. Finally, conditional EE scores are calculated. This paper finds that effects of fiscal imbalances on EE are nonlinear and conditional on economic development level. Fiscal imbalances are more detrimental to environment in less developed provinces. These results suggest that the one-sided fiscal decentralization in China may have regressive environmental effects and contribute to regional disparity in terms of sustainable development.

JEL Classification: Q56; H76; R51

Key Words: Chinese provinces, Decentralization; Environmental efficiency; SFA

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1. Introduction

The Tax Sharing System (TSS) reform of 1994 in China has recognized the dominant role of the central government in intergovernmental fiscal system and recentralized fiscal revenues. However, expenditure responsibilities have been unrevised and remained largely decentralized. In 2009, 80% of national expenditures were spent by sub-national government.[1] Decentralization is even more remarkable in environmental expenditures. In 2007, more than 95% of national expenditures on environmental protection were spent by sub-national governments, of which more than a half was realized at sub-provincial level.[2] In fact, the one-sided expenditure decentralization without revenue-side counterpart has created huge fiscal imbalances in China. Sub-national, in particular sub-provincial governments have excessively heavy expenditure responsibilities which are mismatched with their revenue assignments (World Bank, 2002). These governments depend largely on intergovernmental transfers, which are not always transparent or adequate.

Several factors can explain why environmental protection services would be underprovided under such a system.

First, local governments may be obliged to maintain weak environmental enforcement due to fiscal incapacity. It is argued that, in many poor regions, fiscal resources are so insufficient that public finance is reduced to some kind of “dining finance” (*chi fan cai zheng*), which means the payment of civil servants’ wage (Jing and Liu, 2009). Given the severe budgetary pressures, certain local governments, especially those of poor localities, can fail to provide sufficient environmental services or inspection due to lack of funding, quality personnel and (or) equipment.

Secondly, weak environmental enforcement is also likely to arise due to unwillingness. Qian and Roland (1998) argue that in the inter-jurisdiction competition for foreign capital and grants from the central government, local governments will have incentives for too much infrastructure investment and too few local public goods for a given budget. As a result, when taking budget priority decision, local governments may have reluctance to spend money in “unproductive” areas such as environmental protection. Moreover, it seems that this unwillingness for more stringent environmental enforcement can be reinforced by the severe

[1] Author’s calculation based on China Statistical Yearbook (2010).

[2] Author’s calculation based on China Statistical Yearbook (2008).

local budgetary pressures. On one hand, mismatched revenues and expenditure responsibilities force local governments to trade off between different functions (e.g., infrastructure and environmental protection.) On the other hand, in order to fulfill their responsibilities, local governments struggle to enlarge revenue resources. In particular, they are likely to set lax environmental stringency to attract polluting capital or to engage in other short-sighted activities that may compromise environmental protection.[3]

Finally, mismatched expenditures and revenues can also affect environmental through corruption. On one hand, as argued by Fisman and Gatti (2002), vertical fiscal transfers may allow local officials to ignore the financial consequences of mismanagement. Moreover, transfers may attenuate the direct accountability of a politician in his locality. The authors find that larger federal transfers are associated with higher rates of conviction for abuse of public office in the U.S.; On the other hand, corruption is found in many studies to be an important factor of bad environmental governance and environmental deterioration (Lopez and Mitra, 2000; Welsch, 2004). As a result, one may expect that the Chinese one-sided fiscal decentralization may contribute to ineffective enforcement of environmental regulations due to enlarged corruption.

In summary, it seems that the current one-sided fiscal decentralization imposes important constraint on sub-national governments' enforcement capacity. More importantly, under the strong fiscal pressure, sub-national governments are incentivized to neglect environmental protection or to save enforcement efforts.

The actual effect of fiscal decentralization on environment is an empirical question with important political implications. However, very few studies have investigated this question in the Chinese context with only two exceptions: Jiang (2006) explores with a case study why post-reform decentralization in China has failed to bring about environmental sustainability; Cai and Liu (2010) show that the increase of the disposable financial resources of local governments helps to control pollution sources with small externalities. This paper tries to contribute to this part of literature in another approach, in estimating the effect of the one-sided fiscal decentralization on environmental efficiency at provincial level. It is straight forward to consider that, if the one-sided decentralization in China affects local environmental

[3] A concrete case of the short-sighted activities is the sale of farmland to real estate developers by Chinese local governments. It is estimated that about 40 million farmers have been stripped of their land by local governments. http://www.china.org.cn/learning_english/2011-11/08/content_23852110.htm.

services provision and local environmental stringency, it is high likely to affect localities' environmental efficiency by modifying their pollution abatement efforts or polluting behaviors.[4]

Precisely, I estimate the environmental efficiency (*EE*) scores of the gross regional product (*GRP*) of Chinese provinces and examine whether provinces with larger fiscal imbalance have higher (or lower) *EE* scores. As defined later in the paper, *EE* is the efficiency of environmental detrimental variables in a production process. *EE* is chosen as the environment indicator because it allows measuring environmental performance conditional on levels of the output and other inputs. Two types of fiscal imbalances are considered: The first one is the share of central transfers (*TR*) in provincial expenditures. It measures to which degree a province is dependent on transfers from the central government; the second one is fiscal gap (*FG*) at sub-provincial level. It measures to which degree sub-provincial fiscal revenues and expenditures are mismatched in a province.

The rest of paper is organized as follows. After a brief literature review on *EE* models in section 2, a two-stage *EE* model is presented in Section 3. Section 4 is devoted to empirical analysis of the two-stage *EE* model. Conditional *EE* are calculated in section 5. At last, conclusions and political implications are formulated in Section 6.

2. Literature Review

2.1. Environmental efficiency models

To investigate the effect of fiscal decentralization on environment, a comprehensive environmental performance index must be developed and computed appropriately. In incorporating environmental variables into a traditional production function, environmental efficiency calculates have been proposed by a variety of studies. Based on adjustments of conventional measures of technical efficiency (*TE*), these estimation methods can be classified according to two criteria. The first criterion distinguishes deterministic models from stochastic models, and the second criterion differentiates non-parametric models from parametric models. In the literature, two families of methods are widely employed, namely

[4] Several studies show that environmental stringency in China has an important effect on polluting firms' behavior (Dasgupta *et al.*, 2001; Wang and Wheeler, 2005) and on local industrial pollution level (Wang and Wheeler, 2003).

Stochastic Frontier Analysis (SFA) (Aigner *et al.*, 1977; Meeusen and Broeck, 1977) and Data Envelopment Analysis (DEA) (Charnes *et al.*, 1978). SFA is a parametric stochastic model based on economic theories, while DEA is a nonparametric deterministic model dispensable of specification forms. Each approach has its advantages and shortcomings (Hjalmarsson *et al.*, 1996). The present study will choose the SFA approach because industrial production is a specifiable process and more importantly, SFA is able to distinguish statistical noise from inefficiency and allows for a formal statistical testing of hypotheses. Moreover, to my knowledge, most existing studies on Chinese *EE* have adopted the DEA approach (Zhang *et al.*, 2008; Yuan and Cheng, 2011; Zhang, 2009; Yang and Pollitt, 2009) except one (Wu, 2010). The present study will thus allow a comparison with their results.

Jointly produced with conventional desirable outputs, environmentally detrimental variables are particular because of their undesirable nature. In other words, in order to be efficient, a producer must maximize his conventional desirable outputs and minimize his environmental detrimental factors as well as his conventional inputs. Given this particularity, two groups of technologies have been proposed to introduce environmentally detrimental variables into the production function. The first group treats them as undesirable outputs, while the second group considers them as inputs. Since DEA allows treating multiple output models, it is widely used in the first group technologies. [5] Interesting attempts with SFA within the first group are realized by Cuesta *et al*. (2009) and Wu (2010), both of which rely on distance function models. The second group technologies can be found in both DEA[6] and SFA studies. In the SFA approach, Reinhard *et al.* (1999; 2000) treat the environmentally detrimental variables as inputs to estimate the *EE* of Dutch dairy farms and estimate a stochastic production function. This measure has been later adopted in numerous agricultural *EE* studies (Mkhabela, 2011; Reinhard *et al.*, 2002; Zhang and Xue, 2005).

2.2. Models of environmental efficiency determinants

Determinants of *TE* can be consistently estimated by the one-stage model proposed by Battese and Coelli (1995). However, this model isn't applicable to estimate the determinants of *EE*

[5] A comprehensive survey of such studies is made by Zhou *et al.* (2008).

[6] For exemple, Hailu and Veeman (2001) consider pollution as production input to study the efficiency of Canadian pulp and paper industry. Yang and Pollitt (2009) consider SO_2 emission as input to estimate the efficiency of the Chinese coal-fired power sector.

because *EE* is an adjusted measure of *TE*. To overcome this problem, a two-stage model is proposed by Reinhard *et al.* (2002) to analyze the sources of environmental efficiency variation: In the first stage, they use SFA to estimate *EE* scores of producers; in the second stage, they use again SFA to regress environmental efficiency scores obtained in the first stage against a set of underground variables. According to the authors, a frontier approach in the second stage offers both economic and statistical advantages over an OLS or a TOBIT approach. The reason is as follows. First, conditional estimates of environmental efficiency scores can be derived from the one-sided error of the second stage SFA; secondly, while neither OLS nor TOBIT allows estimating conditional *EE* scores, they are also biased and inconsistent if the conditional inefficiency exists.[7]

3. Two-stage SFA Model

The two-stage model of Reinhard *et al.* (2002) is chosen as the benchmark model for empirical analysis of this paper. In this section, first I illustrate the definition of *EE*. Secondly, *EE* estimation is developed in the framework of SFA. Finally, I present the second-stage model to estimate *EE* determinants and conditional *EE*.

3.1. Definition of *EE*

As defined by Reinhard *et al.* (2000), *EE* is the ratio of minimum feasible to observed use of environmentally detrimental inputs, conditional on observed levels of output and the conventional inputs. This definition is formulated in (1)

$$EE = \min\left\{\theta : F(X_k^R, \theta Z_l^R) \geq Y^R\right\} \tag{1}$$

where X_k^R and Y^R are observed vectors of conventional inputs and output. k is the number of conventional inputs. Z_l^R is the vector of observed environmentally detrimental inputs. l is the number of environmentally detrimental inputs. $F(\bullet)$ is the best practice production frontier. The *EE* measure θ is calculated as a radial contraction of the Z_l^R, conditional on $F(\bullet)$, X_k^R and Y^R.

[7] If the conditional inefficiency exists, disturbance term is skewed with non-zero mean.

3.2. Estimation of *EE* with SFA

EE defined in (1) can be estimated with a stochastic production frontier (2):

$$Y_{it} = f(X_{kit}, Z_{lit}, \beta, \gamma, \zeta)\exp(V_{it} - U_{it}), \quad t = 1,...,T, \quad i = 1,...,I \tag{2}$$

where for all producers indexed with a subscript i and for all years indexed with a subscript t,

Y_{it} denotes the output level;

X_{kit} is a vector of conventional inputs;

Z_{lit} is a vector of environmentally detrimental inputs;

$\beta,\ \gamma$ and ζ are parameters to be estimated;

V_{it} is a symmetric random error term, independently and identically distributed as $N(0,\sigma_v^2)$, intended to capture the influence of exogenous events beyond the control of the industrial sector;

U_{it} is a non-negative random error term, independently and identically distributed as $N(0,\sigma_u^2)$, intended to capture time-variant technical inefficiency in production.[8]

A functional form has to be defined for the production function estimation. In order to avoid excessive misspecification, the commonly employed flexible translog function[9] developed by Christensen *et al.* (1971) is used. Writing (2) in translog form gives (for convenience subscripts i and t are suppressed in (3), (4) and (5)):

[8] In this paper, TE is measured with an output orientation.

[9] Compared to a Cobb-Douglas function whose output elasticities and RTS of inputs are constant, the translog function allows variable elasticities and RTS of inputs, which depend on input levels. Another reason to prefer a translog function to a Gobb-Douglas one is explained by Reinhard et *al.* (1999). In fact, if output elasticities of inputs are constant (as in a Cobb-Douglas function), a ranking by environmental efficiency scores would add no information to the technical efficiency measure because the two rankings would be identical. The two rankings can differ, and the environmental efficiency measure can add independent information of its own, only if output elasticities are variable (e.g. in a translog function).

$$\ln Y = \beta_0 + \sum_j \beta_j \ln X_j + \sum_k \gamma_k \ln Z_k + \frac{1}{2}\sum_j \sum_l \beta_{jl} \ln X_j \ln X_l$$
$$+ \frac{1}{2}\sum_k \sum_m \gamma_{km} \ln Z_k \ln Z_m + \sum_j \sum_k \zeta_{jk} \ln X_j \ln Z_k + V - U \quad (3)$$

where $\beta_{jl} = \beta_{lj}$; $\gamma_{jl} = \gamma_{lj}$. The logarithm of the output of a technically efficient producer is obtained by setting U_{it} = 0 in (3). Since the environmental efficiency implies technical efficiency (Reinhard *et al.*, 1999), the logarithm of the output of an environmentally efficient producer is obtained by replacing Z with $EE \cdot Z$ and setting U = 0 in (3), which gives (4):

$$\ln Y = \beta_0 + \sum_j \beta_j \ln X_j + \sum_k \gamma_k \ln(EE \bullet Z_k) + \frac{1}{2}\sum_j \sum_l \beta_{jl} \ln X_j \ln X_l$$
$$+ \frac{1}{2}\sum_k \sum_m \gamma_{km} \ln(EE \bullet Z_k) \ln(EE \bullet Z_m) + \sum_j \sum_k \zeta_{jk} \ln X_j \ln(EE \bullet Z_k) + V \quad (4)$$

Setting (3) and (4) equal permits the isolation of *lnEE* in (5):

$$\ln EE = \left[-b \pm (b^2 - 2U \sum_k \sum_m \gamma_{km})^{1/2} \right] / \sum_k \sum_m \gamma_{km} \quad (5)$$

where b is equal to the sum of the output elasticities with respect to the environmentally detrimental inputs. The b term is positive if the monotonicity conditions are fulfilled. In this function, the "+√" is applied because if U = 0, only when the "+√" is used, the *lnEE* is equal to "0". U can be calculated from (6), the stochastic version of the output-oriented *TE*:

$$0 \le TE_{it} = \frac{Y_{it}}{f(X_{it}, Z_{it}, \beta, \gamma, \zeta)\exp(V_{it})} = \exp(-U_{it}) \le 1,$$
$$t = 1,\ldots,T,\ i = 1,\ldots,I \quad (6)$$

TE can be calculated using the Battese and Coelli (1988) estimator (7):

$$TE_{it} = E\left[\exp\{-U_{it}\} / (V_{it} - U_{it})\right] = \left[\frac{1-\Phi(\sigma_* - \mu_{*it}/\sigma_*)}{1-\Phi(-\mu_{*it}/\sigma_*)}\right] \bullet \exp\left\{-\mu_{*it} + \frac{1}{2}\sigma_*^2\right\}$$
$$t = 1,\ldots,T, \quad i = 1,\ldots,I \quad (7)$$

where $\Phi(\bullet)$ is the standard normal distribution function, $\sigma_* = \sigma_u \sigma_v / (\sigma_u^2 + \sigma_v^2)^{1/2}$, and $\mu_{*it} = \left[-(V_{it} - U_{it})\sigma_u^2 + \mu\sigma_v^2 \right] / (\sigma_u^2 + \sigma_v^2)$. Parameters $(\beta, \sigma_u^2, \sigma_v^2, \mu)$ are estimated using maximum likelihood techniques.

3.3. Estimate *EE* determinants and conditional *EE*

In order to examine effects of fiscal decentralization on *EE*, the second-stage SFA model proposed by Reinhard *et al.* (2002) has to be estimated. SFA is preferred here because it allows calculating environmental inefficiency with the one-sided error term, even after accounting for the underground variables (Greene, 1999). Conditional *EE* scores can thus be calculated. The second-stage frontier regression model can be expressed in the following general form:[10]

$$EE_{it} = G(W_{it} \bullet \delta) \bullet \exp\left\{ V_{it}^* - U_{it}^* \right\}, \quad t = 1, ..., T, \quad i = 1, ..., I \tag{8}$$

where W_{it} is a vector of observed explanatory variables expected to influence EE_{it}, δ is a vector of parameters to be estimated, $V_{it}^* \sim N(0, \sigma_{V_{it}^*}^2)$ and $U_{it}^* \sim N^+(\mu^*, \sigma_{U_{it}^*}^2)$. In (8), the EE_{it} is assumed to be determined by three sources: (i) inefficiency explained by the observed underground variables captured by $G(W_{it} \bullet \delta)$; (ii) statistical noise reflected in V_{it}^* ; and (iii) an unexplained environmental inefficiency reflected in U_{it}^* . Thus, as defined in (9), the conditional (adjusted) environmental efficiency CEE_{it} can be defined as TE_{it}*, the technical efficiency of (8), once effects of underground variables are taken into account.[11]

$$CEE_{it} = TE_{it}^* = EE_{it} / \left[G\left(W_{it}; \delta\right) \cdot \exp\left\{V_{it}^*\right\} \right] = \exp\left\{-U_{it}^*\right\} \leq 1,$$

$$t = 1, ..., T, \quad i = 1, ..., I \tag{9}$$

[10] A Cobb-Douglas function is used in this stage.

[11] Consider two producers with the same unadjusted *EE* scores. Assume that one produces under a more favorable external background than the other and that the background has an effect on both producers' performance. Then it is reasonable to think that the real *EE* score of the former would be inferior to that of the latter if external background variables are controlled. The same reasoning can be found in background variable models in the DEA framework (Fried *et al.*, 2002; Cooper *et al.*, 2006)

4. Empirical analysis

In this section, empirical data are used to estimate *EE* of Chinese provinces' GRP and the effect of the one-sided fiscal decentralization on *EE*.

4.1. Data and variables

Using data published in various issues of China Statistical Yearbook, China Statistical Yearbook for Regional Economy, Finance yearbook of China and China Population Statistical Yearbook, the present study is based on a panel dataset of 30 Chinese provinces (and centrally administrated municipalities, Hongkong, Macao and Tibet excluded). China conducted a comprehensive national economic survey in 2004 and subsequently revised the country's GDP and GRP figures. As a result, the year 2004 marks a break in the time series of Chinese data. In order to avoid the bias caused by this break in *EE* estimation, I decide to base the first-stage estimation (of *EE* scores) on the period 2005-2010. The second-stage estimation (of decentralization effect) is base on the period 2005-2009, due to the data unavailability of several explicative variables in 2010.[12]

The output (Y) of the first-stage SFA model is the GRP of each province at constant price. The choice of this added value indicator as output indicator is conventional in macroeconomic efficiency such as total factor productivity (TFP) studies. Provincial capital stock (K) in constant prices,[13] total employment in each province (L) and the time trend (T) are three conventional inputs. T aims to capture technological progress. The environmentally detrimental input introduced in the model is the total energy consumption of each province. The reason for the choice of energy consumption rather than other pollutants e.g. carbon dioxide (CO2), sulfur dioxide (SO2) or chemical oxygen demand (COD) is the following. First of all, emission data of CO2 (the major greenhouse gas, which contributes to global warming) are not published in China. Although SO2 and COD are relevant pollution in wastewater and waste gas, their statistics published in China Statistical Yearbook suffer from inaccuracies. In fact, China publishes a combination of survey data for all key industrial enterprises and estimation data for non-key enterprises,[14] both of which can be easily biased.

[12] When the first draft of this paper was completed, 2010 statistics of several indicators (e.g. sub-provincial budgetary expenditures) in the 2nd-stage estimation were not yet published.

[13] Calculated by author following Zhang (2004).

[14] China Statistical Yearbook (NBSC, 2011)

That's why I consider an alternative input- the total energy consumption: Energy is an indispensable input of production. Moreover, it is also a proxy for CO2 emissions. It is often believed that energy intensity of businesses is a major determinant for CO2 pollution, which is especially true in China where power generation still depends primarily on coal.[15] Finally, energy consumption data published in China Statistical Yearbook come from the energy balance sheets. Total energy consumption covers the energy consumption of the whole society, including that of village industries. These sheets are elaborated based on the law of conservation of energy, thus more reliable than pollution data.

In the second-stage model, *EE* scores obtained in the first stage are regressed against transfer's rate (*TR*) and fiscal gap (*FG*) respectively, as well as a set of control variables. The indicator of *TR* is calculated as follows in equation (10):

$$TR_{it} = Transfers_{it} / Expenditures_{it} \quad t = 1,\dots,T, \;\; i = 1,\dots,I \qquad (10)$$

where i denotes the province, t denotes the year, $Transfers_{it}$ denotes the total fiscal transfers that province i receives from the central government in year t, and $Expenditures_{it}$ denotes the consolidated budgetary expenditures spent by province i in year t. The construction of *TR* is inspired by cross-country decentralization indicators proposed by IMF's Government Finance Statistics (GFS), where vertical imbalance of a country is measured as transfers to sub-national governments as a share of sub-national government expenditures. In this paper, *TR* indicates the degree to which a province relies on transfers to support its expenditures.[16] The indicator of *FG* is measured as follows in equation (11):

$$FG_{it} = \left(\sum_{1}^{j} Expenditures_{ijt} - \sum_{1}^{j} Revenues_{ijt}\right) / \sum_{1}^{j} Expenditures_{ijt}$$

$$t = 1,\dots,T, \;\; j = 1,\dots,J, \;\; i = 1,\dots,I \qquad (11)$$

where i denotes the province, t denotes the year, j denotes prefectures in province i, $Expenditures_{ijt}$ denotes consolidated budgetary expenditures spent by prefecture j of province i in year t. $Revenues_{ijt}$ denotes consolidated budgetary revenues raised by prefecture j of province i in year t. Default of transfers data at sub-provincial level, *FG* can also be

[15] In 2010, more than 70% of energy consumed in China was from coal (NBSC, 2011).

[16] Following the GFS indicator, VI doesn't distinguish conditional transfers versus general purpose transfers, due to data unavailability.

considered as a proxy of vertical imbalance within a province, because prefectures need transfers to meet the gap between their expenditures and revenues.

Besides decentralization, a set of control variables which are likely to affect *EE* is also introduced. These variables include income per capita (*Dev*), population density (*Density*), trade openness (*Open*), foreign direct investment (*FDI*), education (*Edu*), urbanization (*Urban*), unemployment rate (*Unemployment*), state-owned sector importance (*State*), coast dummy (*Coast*) and year dummies (*D2006*, *D2007*, *D2008* and *D2009*). These variables are selected because, first, they are commonly used in micro, sectoral or macro studies as TFP determinants (Isaksson, 2007; Li and Hu, 2002; Beeson and Husted, 1989; Söderbom and Teal, 2004); Moreover, some of these variables, e.g. income per capita, population density, trade openness, foreign direct investment and education, are also frequently used as control variables in Environmental Kuznets Curve (EKC) studies (Gangadharan and Valenzuela, 2001). It seems that if these variables have effects on either productivity or environment, they are very likely to affect *EE*. Definitions and descriptive statistics of all variables are presented in Appendices I and II.

4.2. Technical efficiency and non-adjusted environmental efficiency scores

Technical efficiency scores are maximum likelihood estimates computed with the software package *Frontier 4.1* developed by (Coelli, 1996). First, the time-variant translog stochastic production frontier with a normal-truncated normal error distribution was estimated. Tests of hypothesis for parameters are presented in Table 1. According to likelihood ration (LR) tests, the null hypothesis of absence of technical inefficiency $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2) = 0$ is strongly rejected. Nevertheless, the null hypothesis of half-normal distribution $\mu = 0$ and the null hypothesis of time-invariance cannot be rejected. Thus, the specification of time-invariant half-normal stochastic frontier is adopted to estimate the 1st-stage model.

All estimated parameters are summarized in Table 2, which are used in the following to generate the *TE* and non-adjusted *EE* scores.

Table 1: Tests of hypothesis for parameters

Specification	Null hypothesis	Tested against	Log likelihood	Likelihood ratio	$Prob > \chi^2$	Decision
1. Truncated-normal stochastic			313.671			
2. Absence of U_{it}	$\gamma = 0$	1	-2.215	631.771	0.000	rejected
3. Half-normal	$\mu = 0$	1	323.305	0.732	0.694	accepted
4. Time-invariant	$\mu = 0, \eta = 0$	3	312.035	2.540	0.111	accepted

Table 2: Parameter estimates

Parameter	coefficient estimate	standard error	Parameter	coefficient estimate	standard error
β_0	24.469	8.528	β_{lt}	-0.013	0.009
β_k	0.998	0.575	γ_{ee}	0.089	0.040
β_l	-0.229	0.737	ζ_{ke}	-0.049	0.035
β_t	0.312	0.188	ζ_{le}	0.029	0.052
γ_e	-2.211	1.078	ζ_{te}	-0.011	0.012
β_{kk}	0.003	0.015	σ^2	0.402	0.113
β_{ll}	-0.011	0.029	σ_u^2 / σ^2	0.999	0.000
β_{tt}	0.002	0.001	μ	0	
β_{kl}	-0.004	0.030	η	0	
β_{kt}	0.004	0.005			

Note: The subscripts *k, l, t* and *e* refer to capital, labor, time trend, and energy consumption, respectively.

Table 3 reports elasticities of output with respect to each input. The sum of the mean output elasticities of four inputs indicates the presence of increasing returns to scale. The monotonicity assumption is violated for none of the inputs.

Table 3: Output elasticities

	Capital	Labor	Time	Energy	Total
Mean	0.123	0.079	0.051	0.856	1.108
Minimum	0.064	0.034	0.024	0.486	0.879
Lower quartile	0.096	0.065	0.038	0.786	1.064
Median	0.122	0.079	0.048	0.870	1.119
Upper quartile	0.143	0.094	0.059	0.947	1.161
Maximum	0.234	0.121	0.092	1.036	1.231
S.D.	0.034	0.020	0.016	0.115	0.071

Estimated *TE* and *EE* are summarized in Tables 4 and 5. *TE* scores vary from 27.4% to 98.8%, with a mean of 63.4%, in line with the findings of Zhang (2009). Ningxia (27.4%), Guizhou (31.8%) and Qinghai (31.8%) have the lowest *TE* scores, all in west China. Meanwhile, Guangdong (98.8%), Beijing (98.1%) and Shanghai (97.6%), the most economically developed regions in China, have the highest *TE* scores. *EE* scores vary from 3.6% to 98.8%, with an overall mean of 57.3%. Over the period 2005-2010, Ningxia (7.3%), Qinghai (7.4%) and Gansu (21.1%) have the lowest mean *EE* scores, while Guangdong (98.8%), Beijing (97.4%) and Shanghai (97.0%) have the highest mean *EE* scores. Nevertheless, these *EE* scores will be further adjusted.

Table 4: Estimates of *TE* and non-adjusted *EE*

	Technical efficiency	Environmental efficiency
Overall mean	63.4%	57.3%
Overall minimum	27.4%	3.6%
Overall lower quartile	45.1%	41.0%
Overall median	61.2%	56.3%
Overall upper quartile	81.2%	76.4%
Overall maximum	98.8%	98.8%
Overall Standard Deviation (S.D.).	0.213	0.254
Overall observation number	180	177

Note: Three *EE*s cannot be solved.

Table 5: Estimates of non-adjusted *EE* by year

	2005	2006	2007	2008	2009	2010
Mean	57.2%	57.5%	56.4%	57.5%	57.1%	58.2%
Minimum	3.6%	4.9%	5.0%	8.9%	7.4%	8.5%
Lower quartile	47.6%	48.1%	40.1%	41.0%	40.5%	50.1%
Median	55.5%	55.9%	56.0%	56.9%	56.7%	57.7%
Upper quartile	75.3%	75.6%	76.0%	76.7%	76.4%	76.6%
Maximum	98.7%	98.7%	98.8%	98.8%	98.8%	98.8%
S.D.	0.255	0.253	0.263	0.256	0.259	0.258
Observation number	29	29	30	30	30	29
Dropped province	Qinghai	Qinghai	Na	Na	Na	Xinjiang

4.3. Effects of fiscal imbalance

Based on the second-stage *EE* model, *EE* scores are regressed against *TR* and *FG*. Among the set of control variables, income per capita (*Dev*) and population density (*Density*) are put in logarithm. In order to be in line with EKC studies, cubed and squared income per capita (Dev^3 and Dev^2) are included.

4.3.1. Linear effects of *TR* and *FG*

First, linear effects of *TR* and *FG* are tested for. I start with a time-variant model where the distribution of the one-sided error is normal-truncated. Specification tests statistics are summarized in Table 6. According to the LR tests, for both *TR* and *FG*, the null hypothesis of $\gamma = 0$ is strongly rejected, indicating the presence of stochastic errors and the necessary of the SFA model. The null hypothesis $\mu = 0$ can't be rejected at 5% level of significance. The null hypothesis of $\eta = 0$ is strongly rejected. As a result, the time-variant model with half-normal distribution is adopted for the second-stage SFA.

Table 6: Specification tests for the 2nd-stage linear effect model

Indicator	Specification	Null hypothesis	Tested against	Log likelihood	Likelihood ratio	$Prob > \chi^2$	Decision
TR	1. Truncated-normal stochastic			456.362			
TR	2. Absence of U_{it}	$\gamma = 0$	1	94.290	724.144	0.000	rejected
TR	3. Half-normal	$\mu = 0$	1	456.006	0.712	0.399	accepted
TR	4. Time-invariant	$\mu = 0, \eta = 0$	3	450.870	10.271	0.001	rejected
FG	5. Truncated-normal stochastic			456.970			
FG	6. Absence of U_{it}	$\gamma = 0$	5	91.816	730.307	0.000	rejected
FG	7. Half-normal	$\mu = 0$	5	456.621	0.698	0.403	accepted
FG	8. Time-invariant	$\mu = 0, \eta = 0$	7	451.012	11.218	0.001	rejected

Estimation results are presented in Tables 7. Both *TR* and *FG* have positive and non-significant coefficients. These results suggest that fiscal imbalance don't have any significant effects on *EE*, which seems to go against the prediction. However, insignificant linear effects of *TR* and *FG* are not surprising because it is reasonable to think that fiscal imbalance may have different effects on *EE* under different circumstances. For example, poor localities may be more vulnerable facing fiscal pressures and sacrifice more easily environment. As a result, in the following, nonlinear effects of *TR* and *FG* on *EE* will be considered. Concerning control variables, most of they have expected signs, among which squared income per capita, trade openness, population density and Coast dummy have positive and significant coefficients, while income per capita, cubed income per capita, FDI, illiterate rate and year dummies have negative and significant coefficients.

Table 7: Estimation with linear *TR* and *FG* effects

	With *TR*		With *FG*	
Constant	1.377*	(1.758)	1.407*	(1.797)
TR	0.006	(0.259)		
FG			0.019	(1.151)
Dev^3	-0.004**	(-2.356)	-0.004**	(-2.359)
Dev^2	0.088**	(2.268)	0.090**	(2.292)
Dev	-0.610**	(-1.990)	-0.626**	(-2.034)
Open	0.021**	(2.336)	0.019**	(2.171)
FDI	-0.194**	(-2.237)	-0.173**	(-1.966)
Edu	-0.113*	(-1.818)	-0.115*	(-1.938)
Unemployment	-0.165	(-0.595)	-0.164	(-0.622)
Urban	-0.056	(-0.925)	-0.062	(-1.035)
State	-0.097	(-1.441)	-0.098	(-1.489)
Density	0.127***	(5.850)	0.131***	(6.078)
Coast	0.127***	(11.114)	0.133***	(10.871)
D2006	-0.010***	(-4.384)	-0.010***	(-4.627)
D2007	-0.018***	(-4.355)	-0.018***	(-4.771)
D2008	-0.024***	(-3.464)	-0.025***	(-3.839)
D2009	-0.036***	(-4.246)	-0.038***	(-4.701)
σ^2	0.084***	(3.899)	0.085***	(4.052)
γ	1.000***	(13148.850)	1.000***	(13592.846)
μ	0		0	
η	0.006***	(3.126)	0.006***	(3.249)
Log likelihood function	456.006		456.621	

Note: *t-student* statistics between parentheses, *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

4.3.2. Nonlinear effects of *TR* and *FG*

In order to examine potential nonlinear effects of *TR* and *FG*, interactions between fiscal imbalances and income per capita are created, namely $TR*Dev$ and $FG*Dev$. These interactions allow testing whether effects of fiscal imbalances on *EE* in a province depend on its economic development level.[17] The LR test statistics strongly reject the null hypothesizes that the coefficients β_{TR*DEV} and β_{FG*DEV} (associated respectively to $TR*DEV$ and $FG*DEV$) are equal to zero. This means that the specifications with interactions are more fit than those without interactions. Once again, the time-variant model with half-normal distribution is adopted. Specification tests statistics are summarized in Table 8. Regression results are presented in Table 9.

Table 8: Specification tests for the 2nd-stage nonlinear effect model

Indicator	Specification	Null hypothesis	Tested against	Log likelihood	Likelihood ratio	$Prob > \chi^2$	Decision
TR	1. Truncated-normal with nonlinear *TR*			464.771			
TR	2. Truncated-normal with linear *TR*	$\beta_{TR*DEV} = 0$	1	456.362	16.818	0.000	rejected
TR	3. Absence of U_{it}	$\gamma = 0$	1	94.405	740.732	0.000	rejected
TR	4. Half-normal	$\mu = 0$	1	464.675	0.193	0.661	accepted
TR	5. Time-invariant	$\mu = 0, \eta = 0$	3	459.907	9.536	0.002	rejected
FG	6. Truncated-normal with nonlinear *FG*			463.607			
FG	7. Truncated-normal with linear *FG*	$\beta_{FG*DEV} = 0$	6	456.970	13.274	0.000	rejected
FG	8. Absence of U_{it}	$\gamma = 0$	6	92.182	742.850	0.000	rejected
FG	9. Half-normal	$\mu = 0$	6	463.529	0.156	0.693	accepted
FG	10. Time-invariant	$\mu = 0, \eta = 0$	9	458.074	10.910	0.001	rejected

It is notable that when interactions are included, both *TR* and *FG* as well as their interactions with income per capita have significant coefficients, suggesting the significant nonlinear effects of fiscal imbalances on *EE*. Precisely, the marginal effects of *TR* and *FG* are conditional on income per capita. Their marginal effects are offset by economic development level, i.e., the more a province is affluent, the less fiscal imbalances are detrimental to *EE*,

[17] An important issue worth considering is the potential endogeneity of income per capita in the 2nd-stage model (Stern, 2004). Several alternative models i.e., IV estimator, lagged endogenous variables and control function method have been estimated in order to control the potential bias. All of these models give consistent results with what are reported in the paper. The nonlinear effects of fiscal imbalance found in the paper are thus robust.

vice versa. These results seem to confirm the hypothesis that fiscal imbalances have more serious environmental consequences in poorer localities than in richer ones. In these two nonlinear-effect models, control variables have the same signs as in previous linear effect models, although different orders of income per capita become non-significant in *TR* regression.

Table 9: Estimates with nonlinear *TR* and *FG* effects

	With *TR*		With *FG*	
Constant	0.882	(1.203)	1.958***	(2.708)
TR	-0.529***	(-4.340)		
$TR * DEV$	0.071***	(4.478)		
FG			-0.362***	(-3.595)
$FG * DEV$			0.047***	(3.841)
Dev3	-0.001	(-0.910)	-0.004***	(-3.038)
Dev2	0.038	(1.020)	0.103***	(3.018)
Dev	-0.320	(-1.119)	-0.783***	(-2.883)
Open	0.011	(1.256)	0.004	(0.420)
FDI	-0.153**	(-1.890)	-0.170**	(-2.048)
Edu	-0.078	(-1.402)	-0.115**	(-2.109)
Unemployment	-0.126	(-0.497)	-0.091	(-0.363)
Urban	-0.006	(-0.126)	-0.031	(-0.872)
State	-0.088	(-1.432)	-0.097	(-1.577)
Density	0.144***	(11.681)	0.141***	(22.243)
Coast	0.142***	(12.449)	0.143***	(12.057)
D2006	-0.007***	(-3.208)	-0.007***	(-3.613)
D2007	-0.011***	(-2.914)	-0.013***	(-3.418)
D2008	-0.015**	(-2.337)	-0.017***	(-2.617)
D2009	-0.028***	(-3.648)	-0.031***	(-3.914)
σ^2	0.085***	(3.954)	0.084***	(3.813)
γ	1.000***	(15223.715)	1.000***	(15304.738)
μ		0		0
η	0.005***	(3.085)	0.005***	(3.907)
Log likelihood function	464.675		463.529	

Note: *t-student* statistics between parentheses, *** significance at 1% level, ** significance at 5% level, * significance at 10% level.

4.3.3. Marginal effects of *TR* and *FG*

Overall marginal effects of *TR* and *FG* are reported in Table 10. Critical values of income per capita below which the marginal effects are negative are also reported. It is notable that while both indictors have positive mean marginal effect on *EE*, an increase in fiscal imbalance is still detrimental to environment in a considerable number of the least affluent provinces (27% for *TR* and 43% for *FG*).

Table 10: Overall marginal effects of fiscal imbalances

	With *TR*	With *FG*
Mean	0.028	0.008
Minimum	-0.073	-0.060
Lower quartile	-0.004	-0.014
Median	0.026	0.006
Upper quartile	0.051	0.022
Maximum	0.137	0.079
S.D.	0.042	0.028
Critical value of income per capita	1726.152	2190.907
% of observations with negative marginal effects	27.0%	43.2%
Observation number	148	148
Dropped province	Qinghai	Qinghai

Note: Critical value of income per capita is in 2005 USD.

5. Conditional environmental efficiency

In this subsection, *CEE* scores are calculated using results of the second-stage SFA. Although consistent results have been found regarding nonlinear effects of *TR* and *FG*, the model with *TR* has higher log likelihood value. According to the Akaike information criterion (AIC), this model is preferred because it has a smaller AIC value. Thus, the adjusted environmental efficiency scores are calculated based on the two-stage SFA with *TR.* Summary of overall provincial *CEE* scores by region is presented in Table 11. It is remarkable that Chinese provinces have on average relatively higher *EE* scores once external variables are controlled. *CEE* scores vary from 10.2% to 99.6% with an overall mean of 69.3%. Among the seven regions, East China has the highest mean scores (84.2%), followed by South China (75.0%) and Northeast China (74.9%). Northwest China has the lowest mean scores (51.2%), far behind the others. Summary of *CEE* by year is presented in Table 12. It seems that *CEE* scores are relatively stable over this period. The three provinces with the highest mean *CEE* scores are Beijing (99.6%), Fujian (99.5%) and Jiangxi (99.5%). The three provinces with the lowest mean CEE scores are Ningxia (11.0%), Qinghai (27.0%) and Guizhou (30.6%). The concordance between *EE* ranking and *CEE* ranking is positive and significant. The Spearman rank correlation coefficient between the two measures is 0.715. The null hypothesis that the two rankings are independent can be strongly rejected. The entire rankings list of *EE* and *CEE* scores can be found in Appendix III.

Table 11: Summary of overall and regional *CEE* scores

	Overall	North	Northeast	East	Center	South	Southwest	Northwest
Mean	69.3%	63.2%	74.9%	84.2%	69.4%	75.0%	63.3%	51.2%
Minimum	10.2%	32.0%	53.6%	56.7%	62.3%	58.8%	29.9%	10.2%
Lower quartile	57.4%	40.8%	54.2%	75.4%	62.9%	59.4%	47.2%	26.7%
Median	71.8%	68.2%	72.0%	88.9%	70.9%	70.9%	66.6%	40.0%
Upper quartile	89.6%	74.5%	98.8%	99.5%	74.6%	94.8%	79.7%	73.4%
Maximum	99.6%	99.6%	98.8%	99.5%	75.0%	94.9%	89.7%	95.5%
S.D.	0.233	0.246	0.191	0.141	0.052	0.154	0.218	0.321
Nb. of ob.	148	25	15	35	15	15	20	23
Dropped province	Na	Na	Na	Na	Na	Na	Na	Qinghai

Table 12: Summary of *CEE* by year

	2005	2006	2007	2008	2009
Mean	69.9%	70.1%	68.7%	68.9%	69.1%
Minimum	10.2%	10.6%	11.0%	11.5%	11.9%
Lower quartile	58.8%	59.0%	57.1%	57.3%	57.5%
Median	71.7%	71.8%	71.4%	71.6%	71.7%
Upper quartile	89.5%	89.5%	89.6%	89.6%	89.7%
Maximum	99.6%	99.6%	99.6%	99.6%	99.6%
S.D.	0.232	0.231	0.240	0.239	0.237
Observation number	29	29	30	30	30
Dropped province	Qinghai	Qinghai	Na	Na	Na

6. Conclusion

Decentralization has been promoted by major international institutions. Proponent arguments defending the merits of decentralization are abundant. However, many studies show that decentralization may be inefficient for environmental protection. China's one-sided fiscal decentralization has shown an example. After 1994, public expenditures are largely decentralized while fiscal revenues are recentralized. Sub-national, in particular sub-provincial governments have excessively heavy expenditure responsibilities which are mismatched with their revenue assignments. Sub-national governments have huge fiscal imbalances and depend basically on transfers to fulfill their expenditure responsibilities. It seems that this critical situation may have negative effects on environmental protection. Localities, especially poor ones, are likely to under-provide environmental protection service either due to incapacity or incentive to develop economy at the cost of environment.

In this paper, I study empirically the environmental effect of this one-sided fiscal decentralization. Precisely, I examine whether fiscal imbalances caused by this decentralization improve or reduce environmental efficiency of Chinese provinces. Following the two-stage *EE* model of Reinhard *et al.* (2000), I first calculate with *EE* scores of Chinese provinces' gross regional product over the period 2005-2010. After that, *EE* scores are regressed against two fiscal imbalance indicators, *TR* and *FG*, in order to test the linear and nonlinear effects of the latter. Finally, adjusted *EE* scores are calculated conditional on fiscal imbalances and other underground variables.

The empirical results are interesting to interpret. During the period of study, fiscal imbalances have nonlinear effects on *EE* of Chinese provinces. Moreover, these effects seem to be conditional on economic development level, i.e., fiscal imbalances seem to be more detrimental in less affluent provinces, which confirm the vulnerability of poor localities in face of severe fiscal pressures. In at least 27% of the cases, larger fiscal imbalances reduce *EE*. Once external factors are controlled, Chinese provinces have on average an adjusted *EE* score of 69.3%, considerably higher than 57.3% before the adjustment. This increase suggests that the overall external context in China contributes to environmental inefficiency. If all provinces had the same external context as the most advantageous one, mean *EE* would increase from 57.3% to 69.3%.

Results obtained in this paper call for attention to the potential negative environmental effects of the one-sided fiscal decentralization in poor provinces. Too many responsibilities without adequate revenues can lead to inefficient resource allocation; severe fiscal pressures may encourage poor localities to engage in short-term behaviors, e.g. developing economy at the cost of environment. Moreover, since the effects are nonlinear, it seems that this fiscal decentralization has regressive environmental effects in contributing to disparity across regions in terms of sustainable development. Although the choice between more revenue autonomy and less expenditure responsibilities is still a political debate in China, it is certain that the balance between expenditure responsibilities and revenue assignments need to be redressed for a more sustainable regional development in this country.

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Appendices:

Appendix I: Name and description of variables

Variable	Description
Y	Gross regional product (10000 USD at 2005 price)
K	Provincial capital stock (10000 RMB at 1952 price)
L	Total provincial employment at the end of year (10000 persons)
T	Time trend
E	Total energy consumption (ton of Standard Coal Equivalent)
TR	Share of central transfers in provincial expenditures
FG	Fiscal gap
Dev	Income per capita (2005 USD)
Open	(Exportation + Importation)/ Gross regional product
FDI	Foreign direct investments/ Gross regional product
Edu	Illiterate rate
Unemployment	Unemployment rate
Urban	Non-agricultural population/total population
State	Employment of state-owned sector/total employment
Density	Population /km^2
Coast	1 if coast province, 0 otherwise
D2006	1 if the year of 2006, 0 otherwise
D2007	1 if the year of 2007, 0 otherwise
D2008	1 if the year of 2008, 0 otherwise
D2009	1 if the year of 2009, 0 otherwise

Appendix II: Summary statistics of variables

Variable	Obs.	Mean	S.D.	Min	Max
Y	180	14300000	12900000	663023	69500000
K	180	54300000	49100000	3714443	263000000
L	180	2423.416	1602.439	267.619	6041.557
T	180	3.500	1.713	1	6
E	179	138000000	94900000	8221845	497000000
TR	148	0.509	0.183	0.141	0.857
FG	148	0.478	0.182	0.078	0.818
Dev	148	3102.874	2125.191	616.500	11862.610
Open	148	0.359	0.410	0.045	1.668
FDI	148	0.026	0.020	0.001	0.082
Edu	148	0.088	0.046	0.028	0.223
Unemployment	148	0.038	0.006	0.014	0.056
Urban	148	0.367	0.164	0.158	0.880
State	148	0.111	0.048	0.053	0.245
Density	148	411.474	534.697	7.667	3029.969
Coast	148	0.372	0.485	0	1
D2006	148	0.196	0.398	0	1
D2007	148	0.203	0.403	0	1
D2008	148	0.203	0.403	0	1
D2009	148	0.203	0.403	0	1

Appendix III: Ranking lists of mean *EE* and *CEE* scores

Province	CEE ranking	EE ranking	mean CEE score	mean EE score	Region
Beijing	1	3	0.996	0.937	North China
Fujian	2	10	0.995	0.704	East China
Jiangxi	3	24	0.995	0.300	East China
Heilongjiang	4	21	0.988	0.363	Northeast China
Xinjiang	5	26	0.954	0.294	Northwest China
Guangdong	6	1	0.949	0.946	South China
Yunnan	7	4	0.896	0.935	Southwest China
Anhui	8	14	0.896	0.566	East China
Zhejiang	9	9	0.889	0.732	East China
Jiangsu	10	11	0.792	0.625	East China
Shanghai	11	8	0.753	0.876	East China
Hunan	12	28	0.747	0.263	Center China
Inner Mongolia	13	6	0.744	0.916	North China
Shaanxi	14	17	0.732	0.484	Northwest China
Jilin	15	29	0.720	0.248	Northeast China
Guangxi	16	30	0.709	0.116	South China
Hubei	17	19	0.709	0.384	Center China
Sichuan	18	25	0.696	0.298	Southwest China
Tianjin	19	5	0.682	0.925	North China
Chongqing	20	13	0.636	0.576	Southwest China
Henan	21	15	0.627	0.548	Center China
Hainan	22	27	0.592	0.291	South China
Shandong	23	2	0.571	0.937	East China
Liaoning	24	7	0.540	0.914	Northeast China
Hebei	25	16	0.411	0.510	North China
Gansu	26	22	0.397	0.362	Northwest China
Shanxi	27	18	0.326	0.424	North China
Guizhou	28	12	0.306	0.616	Southwest China
Qinghai	29	20	0.270	0.372	Northwest China
Ningxia	30	23	0.110	0.341	Northwest China