Long-run dynamics of sulphur dioxide emissions, economic growth and energy efficiency in China

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Abstract

This paper estimates the linkages among total Sulphur dioxide (SO_2) emissions, total GDP and energy efficiency using China's provincial panel data from 2002 to 2015. We investigate total emissions rather than per capita emissions or ambient concentrations, since it is total emissions that the environment cares about. Energy efficiency is estimated using stochastic frontier analysis and decomposed into both persistent and transient efficiency. We then investigate the long-run dynamics among SO_2 emissions, economic growth and energy efficiency by employing the panel-based error correction model and taking the effects of cyclical variations into account. Our analysis shows that GDP has a positive impact on total SO_2 emissions in the *short* run and gains in energy efficiency have a significant negative effect on emissions in the *long* run. By controlling the effects of business cycle, the effects of GDP on emissions remain positive in both short and long run. Cross-sectional analysis provides similar insights. We argue that economic growth itself is an emission generator. Therefore, the government needs to establish a long-run strategy to curb the emissions by improving energy efficiency.

Keywords: Sulphur dioxide emissions; energy efficiency; stochastic frontier analysis; error-correction model

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1. Introduction

The consumption of fossil energy has resulted in environmental degradation both locally and globally. Since environmental protection has been perceived as obstacles to sustainable economic development worldwide, especially for developing countries, the issue of effectively balancing the environmental pollution and economic growth has been extensively studied both theoretically and empirically.

As the largest developing country, China has enjoyed the highest economic growth rate in the world in the last decade; meanwhile it has also suffered from severe environmental degradation and turned out to be the largest emitter for carbon dioxide (CO_2) since 2006, which is around 11 billion tones in 2013. For the Sulfur dioxide (SO_2), although China has achieved significant reduction since 2007 from 36.6 megaton to 8.4 megaton at 2016, it is still the world second largest emitter (Li et al., 2017). On the other hand, along with consecutive years of double-digit economic growth, energy consumption has also drastically increased in China. The annual average growth rate of energy consumption is 9.5 per cent from 2000 to 2008, which is 3.8 times higher than the world average. Although the growth rate of energy consumption began decreasing in recent years as it moves to the regime of "new normal" growth, China remain the largest consumer of energy worldwide.

More importantly, due to the heavy dependence on fossil-based energy sources, China's massive use of energy directly leads to grave environmental problems, especially air pollution. It seems that the largest developing country has fallen into a dilemma and been asked to choose between a prosperous economy and a clean environment. The question of how to realize sustainable development has therefore become prominent on the central policy agenda.

In this paper, we hope to offer some new perspectives to address China's environmental problems. By employing the error-correction model to the aggregate level of data, we show gross domestic product (GDP) has a positive impact on total SO_2 emissions in the *short* run, and gains from energy efficiency have a negative effect on emissions in the *long* run. By controlling the effects of business cycle, the effects of GDP on emissions remain positive in both short run and long run. This suggests economic growth itself is emission generator. Only with the improvement in energy efficiency, the emissions will eventually begin to decrease as the inverted U-shaped EKC predicts.

This paper contributes to the literature in several aspects. Firstly, we question the argument of the inverted-U shaped relationship between economic growth and environmental quality, the so-called EKC hypothesis. In theory, it says environmental quality decreases as the economy develops at the early stage; the trend reverses as rising income per capita passes beyond the turning point. The earliest empirical study of EKC was a paper written by Grossman and Krueger (1991). Subsequent studies have extended growth-environment literature by including other explanatory factors for pollution, new methodologies and different pollutants. One of the rationales behind the EKC is the improvement in energy efficiency. However, the empirical evidence has been largely mixed in the literature of the EKC hypothesis for SO_2 for the case of China (Hai et al. 2005; Shen 2006; Llorca and Meunié 2009; Wang et al. 2016); there is no study that directly investigates the effects of energy efficiency on SO_2 emissions in China. Therefore, instead of including both scale and technical effects in GDP as the traditional way of EKC, we capture the technical effect separately by using energy efficiency as explanatory variable. In another paper, Agras and Chapman (1999) estimated EKC by including the price of energy as explanatory variable and found income was not a significantly relevant indicator of environmental quality. In this paper, we will control energy price as an explanatory variable for energy efficiency.

Secondly, we offer an integrated three-dimensional analysis of the energy-growth-pollution nexus. Granger causality between total energy consumption and growth has been studies extensively. These studies have been mostly confined to a bivariate model with energy use and GDP, such as Yuan et al. (2008), Ozturk (2010), Belke et al. (2011), and Yildinm et al. (2014). However, some studies questioned the potential bias of bivariate model by omitting relevant key variables such as energy price (Zachariadis, 2007; Costantini and Martini, 2010; Belke et al., 2011).

In addition to a bivariate model, a number of studies also investigate the relationship between energy consumption, economic development and environmental pollution, particularly CO_2 emissions. Mixed empirical results have been found due to different econometric methods and datasets have been adopted by these studies (Ramanathan 2008; Alam et al., 2011; Ghosh, 2010; Jayanthakumaran et al., 2012; Vidyarthi, 2013). In general, economic growth is positively associated with energy use and in turn emissions of air pollutants if not controlled properly. Instead of using data at national level, Yuan and Zuo (2014) employed provincial data in China to study the relationship of energy consumption, economic development and environmental pollution. They found the economic growth and pollution reduction can achieve simultaneously if reasonable energy and industrial structure and improved energy efficiency are put into place. However, energy efficiency is calculated as energy consumption per GDP in this paper, and no sound econometric method to rigorously estimate the impact of energy efficiency on growth and pollution.

Instead of using energy consumption, in this paper, we investigate the linkage through a two-step approach. In the first step, we develop an energy demand model to estimate energy efficiency through stochastic frontier analysis (SFA). Particularly, we distinguish between transient energy efficiency in the short run and persistent energy efficiency in the long run. The estimated efficiency is then used in the second step to analyze its impact on SO_2 emissions. We choose total SO_2 emission as the indicator for environmental damage since it persists as contaminant and directly leads to respiratory illness and acid rain, compared to CO_2, which is not a direct threat to human health. Another distinction between previous studies and ours is that we consider total amount of emissions rather than per capita emissions. The main reason that the environment cares about is total emissions. The variables at the per-capita level may result in over-optimistic and misleading conclusions. Since total emission is the major determinant to the environmental effect, it is informative to investigate the environmental issue at the aggregate level.

Thirdly, we bridge the technical energy efficiency with economic development and investigate the energy efficiency-growth-pollution nexus empirically. Although at macro level, numerous papers have explored the casual relationship between total energy consumption and economic growth as reviewed above, empirical evidence on the relationship between energy efficiency and economic growth or pollution is thin. One paper directly linked emission efficiency to pollution is Hanley et al. (2009), who simulated the impact of improving energy efficiency on pollution in Scotland by using a computable general equilibrium model. They found that an improvement in energy efficiency ultimately increased energy use due to the lower energy price. However, in their paper, energy efficiency is not directly calculated by an econometric method. In addition, the case of China investigated by this paper has both rapid economic growth and high pollution at the same time, which is in different development stage compared with Scotland. Lastly, the energy market in China is controlled by the central government, so the price of energy is not or only partly determined by the market. Therefore, the findings of this paper may provide different insights for the world largest developing country. Another related paper (Rajbhandari and Zhang, 2017) studied the impact of energy efficiency on economic growth based on a panel data of 56 countries, where energy efficiency is proxied by energy intensity, measured as energy use per unit of economic output.

In this paper, we estimate energy efficiency by SFA approach for several reasons. First and most importantly, it has been widely discussed in the literature that energy intensity is not a good indicator for energy efficiency, as energy intensity is a complex outcome of a set of factors including energy efficiency (Filippini and Hunt, 2011; Filippini and Zhang, 2016). SFA offers a way to estimate the underlying energy efficiency. Second, it is able to deal with measurement errors. Our data is based on provincial statistics which may suffer from measurement errors. Third, omitted variable bias problem can be mitigated in SFA while this may create significant bias by using other non-parameter methods. Therefore, SFA provides more precise estimation of energy efficiency compared to other methods (Zhang and Adom, 2018). Recent development of SFA also allows us to distinguish between persistent and transient energy efficiency. Furthermore, we suggest the use of an error correction model (ECM) for the econometric specification, which follows the tradition of Narayan (2010). Finally, we decompose the short-term fluctuations of cyclical effects from the long-term trend effects by employing the method suggested by Hodrick and Prescott (1997). As macroeconomic variables are usually correlated with business cycle, we need to remove the effects of business cycle in the data to allow for a precise estimation of the long-term effects of energy efficiency and GDP on total emissions. The true effect can be buried in the unfiltered data due to cyclical fluctuations.

The rest of this paper is organized as follows: in section 2, we describe the energy demand model to be used for stochastic frontier analysis, the error-correction model, and the Hodrick-Prescott approach. In section 3, the data descriptive statistics is presented and the unit-root and co-integration tests are discussed. Section 4 shows the results for energy efficiency by using stochastic frontier analysis. Section 5 presents the empirical results of error-correction model. Section 6 introduces structural break and cross-sectional analysis for robustness check. Section 7 concludes the paper and provides several policy implications.

2. Methodology and econometric specification

2.1 Stochastic frontier analysis

Stochastic frontier analysis is one of the common practices for estimating energy efficiency. As confirmed from previous empirical studies (Hunt and Filippini, 2011; Filippini and Zhang, 2016; Zhang, 2017;) that energy intensity or energy productivity is not a good indicator to describe energy efficiency of an economic entity, estimation of energy efficiency using a rigorous econometric method is essential for future policy advice. In this paper, we apply the aggregate energy demand for Chinese provinces as suggested by Filippini and Zhang (2016) with the specification of Pitt and Lee (1981), and Greene (2005a,b) to estimate the provincial transient and persistent energy efficiency in China.

The provincial energy demand frontier function is given by:

$$E_{it} = E(X_{it}, DT_t, EF_{it}) \quad (1)$$

In the equation, E_{it} is the energy consumption at the aggregate level for province *i* at time *t*. X_{it} is a vector of control variables that affect the energy demand, including P_{it}, GDP_{it}, POP_{it}, HS_{it}, CLM_{it}, TRN_{it}, SHI_{it}, SHS_{it}, DT_t, and EF_{it}.

P_{it} is the index for the energy price; GDP_{it} denotes the provincial real GDP in billion Chinese Yuan. POP_{it} and HS_{it} are two demographic variables to capture the total population and average household size. The climate change effect is captured by CLM_{it}, the total number of heating degree days and cooling degree days. TRN_{it} represents the effect of transport sector on energy demand using the total number of public and private cars. SHI_{it} and $SHS_{i,}$ are the variables to capture the economic structure of a province. SHI_{it} is the share of the industrial sector in provincial GDP, and SHS_{it} the share of the service sector in provincial GDP. DT_t reflects general technological progress, which assumes to be a function *t* and t^2. EF_{it} is the level of energy efficiency for province *i* at year *t*. One difference between our model and Filippini and Zhang (2016) is that we use only HS_{it} to capture the potential economies of scale effects derived from demographic changes, while Filippini and Zhang (2016) consider two types of economics of scale.

By log-log transformation of equation 1 as suggested in Filippini and Hunt (2011), we have the following equation to be estimated:

$$\ln E_{it} = \alpha + \alpha^P P_{it} + \alpha^Y GDP_{it} + \alpha^{HS} HS_{it} + \alpha^{POP} POP_{it} + \alpha^{CLM} CLM_{it} + \alpha^{TRN} TRN_{it} + \alpha^{SHI} SHI_{it} + \alpha^{SHS} SHS_{it} + \alpha^T T + \alpha^{T2} T^2 + v_{it} + u_{it} \quad (2)$$

v_{it} is the normally distributed error term. u_{it} indicates the inefficiency levels with half-normal distribution.

SFA family is composed of a wide range of model specifications. We follow the argument of Filippini and Zhang (2016) to estimate the persistent energy efficiency using Pitt and Lee (1981) and transient energy efficiency using Greene (2005a, b). However, both models suffer from potential bias due to unobserved heterogeneity (Farsi et al., 2005a, b). Therefore, Pitt and Lee (1981) tend to underestimate the energy efficiency as it considers the individual random effects as inefficiency; while Greene (2005a, b) tends to overestimate the energy efficiency as the individual random effects are considered as unit-specific heterogeneity. To address these issues, we adjust the model by adding the Mundlak components as proposed by Farsi et al. (2005a, b), which is an auxiliary equation expressed by the group-means of the explanatory variables.

$$\alpha_i = \gamma \overline{X_i} + \delta_i, \quad \overline{X_i} = \frac{1}{T}\sum_{t=1}^{T} x_{it}, \quad \delta_i \sim iid(0, \sigma_\delta^2) \quad (3)$$

By integrating equation 3 into equation 2, we can estimate the following energy demand frontier function:

$$\ln E_{it} = \alpha + \alpha^P P_{it} + \alpha^Y GDP_{it} + \alpha^{HS} HS_{it} + \alpha^{POP} POP_{it} + \alpha^{CLM} CLM_{it} + \alpha^{TRN} TRN_{it} + \alpha^{SHI} SHI_{it} + \alpha^{SHS} SHS_{it} + \alpha^T T + \alpha^{T2} T^2 + \gamma \overline{X_i} + \delta_i + v_{it} + u_{it} \quad (4)$$

The efficiency score, either persistent or transient, for each province can be calculated by using the conditional mean of the inefficiency term $E[u_{it}|u_{it}+v_{it}]$. According to Jondrow et al. (1982), the level of energy efficiency (EF_{it}) can be expressed in the following way:

$$EF_{it} = \frac{E_{it}^{F}}{E_{it}} = \exp(-\hat{u}_{it}) \tag{5}$$

where E_{it} is the energy consumption values from statistics and E_{it}^{F} is the minimum demand of the i^{th} province at time t. The value of EF_{it} ranges between 1 (100% efficient), and 0 (100% inefficient). The overall energy efficiency is calculated by multiplying the persistent with the transient energy efficiency.

2.2 Error correction model and the aggregate estimation

The error correction model is a dynamical system with the characteristics that the deviation of the current state from its long-run relationship will be fed into its short-run dynamics. The error-correction of SO_2 emission model has two parts. The first part is a long-run equilibrium SO_2 emission function given by

$$\ln SO_{2_{it}} = \beta_0 - \beta_1 \ln GDP_{it} - \beta_2 EF_{it} + \epsilon_{it} \tag{6}$$

where $\ln SO_{2_{it}}$ is the natural logarithms of SO_2 emissions at time t in province i. ϵ_{it} is the white noise. The second part represents the short-run dynamics of error-correction equation:

$$\Delta\ln SO_{2_{it}} = \alpha_1 + \alpha_2 \Delta\ln GDP_{it} + \alpha_3 \Delta EF_{it} + t + \lambda u_{i,t-1} + \varepsilon_{it} \tag{7}$$

where all variables are as defined above and ε_{it} is the short-run random disturbance term. Δ is the operator for first difference; and $u_{i,t-1}$is the lag of the random disturbance term. Equation (7) gives the determinants of SO_2 emissions in the short run, which include current and past changes in the scale and technology cost variables and the lag of the residual from the long-run SO_2 emission level. The parameter λ that appears on $u_{i,t-1}$ in equation (7) is the error-correction coefficient, reflecting the speed of adjustment. The presence of $u_{i,t-1}$ in equation (7) reflects that actual SO_2 emissions do not always equal the optimal level defined by the long-run factors specified in equation (6). Therefore, in the short run, the economy adjusts its emission levels to correct any deviation from the long-run equilibrium. The larger λ is, the greater response to the previous period's deviation from long-run equilibrium. Specifically, if $\ln SO_2$is greater than its long-run equilibrium solution, a negative λ is required to make the system back to equilibrium. At the opposite extreme, it also necessitates a negative λ to increase $\Delta\ln SO_2$ when $\ln SO_2$ is less than its long-run equilibrium.

By integrating equation (6) and (7), an elementary error correction model for this study could be represented as follows, which could be used to estimate the short-run and long-run parameters jointly.

$$\Delta\ln SO_{2_{it}} = \alpha_1 + \alpha_2 \Delta\ln GDP_{it} + \alpha_3 \Delta EF_{it} + \lambda\left[\ln SO_{2_{i,t-1}} - \beta_0 - \beta_1 \ln GDP_{i,t-1} - \beta_2 EF_{i,t-1}\right] + \varepsilon_{it} \tag{8}$$

2.3 The Hodrick-Prescott filter and the decomposition estimation

As macroeconomic variables are usually correlated with business cycle, we need to remove the effects of business cycle in the data to allow for a precise estimation of the long-term effects. Hodrick and Prescott (1997) proposed a procedure to decompose a time series as the sum of a smoothly varying trend component and a cyclical component. In order to further study the dynamics among emissions, economic growth and energy efficiency; we first apply the Hodrick-Prescott filter to separate the trend component from cyclical component of the three interested series. The Hodrick-Prescott filter solves the following minimization problem:

$$\min_{C_{it}, Y_{it}} \sum_{t=1}^{T} (C_{it})^2 + \rho[\Delta^2(Y_{it} - C_{it})]^2 \qquad (9)$$

where Y_{it} is the observed variable, C_{it} is the cyclical component, the trend component (T_{it}) can be calculated as the difference of the two, namely $Y_{it} - C_{it}$. $\rho = \sigma_T^2/\sigma_C^2$ is the smoothing coefficient, where σ_T^2 and σ_C^2 are the variances of the trend and cyclical component respectively.

After applying the Hodrick and Prescott procedure, each of the observed variables, namely SO_2 emissions, real GDP and energy efficiency, are decomposed into two parts: the cyclical component C_{it} and the trend component T_{it}. We then apply the ECM, by using the T_{it} values for each of the variables in equation (8), to the trend component as it is now absent from the effects of business cycle.

3. Data

In this paper, we use annual data on the total volume of SO_2 emissions, total real GDP, and total consumption of energy. Our data cover 29 provinces for a period of 13 years, from 2002 to 2014, from China Statistical Yearbook, 60 years of statistical compilation of new China and Wind database. The data does not include Hong Kong, Macau and Tai Wan due to missing information. Descriptive statistics of the variables used in our study are presented in Table 1.

Table 1: Descriptive Statistics of the data

Variable	Obs	Mean	Std. Dev.	Min	Max
Energy consumption	377	0.0133	0.0074	0.001	0.0389
Real Price index (year2002=1)	377	1.6719	0.4388	1	2.7409
Real GDP (billion RMB)	377	928.67	847.25	34.065	5030.99
Average household size	377	3.1696	0.3503	2.33	4.06
Total population (million)	377	44.987	25.981	5.29	107.24
Heating and cooling degree days	377	646.02	715.49	0	7704.9
Number of vehicles	377	3.9199	4.2801	0.121	25.419
Share of industry sector (%)	377	48.145	6.7713	21.3	61.5
Share of service sector (%)	377	40.062	8.0917	28.6	77.9
Total SO_2 emissions (k Tons)	377	767.40	431.17	32	2003

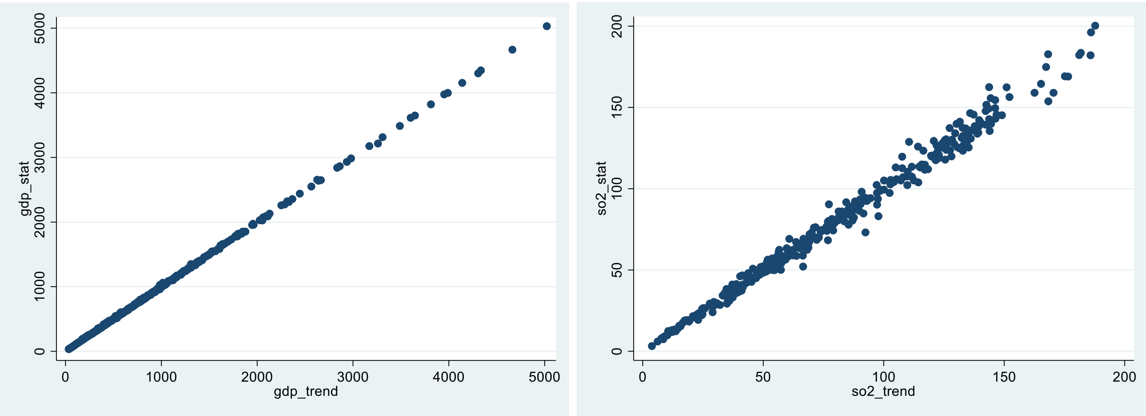
Note: Data on Energy consumption are obtained from China Energy Statistical Yearbook, and other data are obtained from China Statistical Yearbook (various years).

For time-series data and panel data, unit-root tests are required before proceeding with regression analysis. Use of classical regressions to estimate the econometric relationship among variables requires that the data are stationary, otherwise it may lead to the "spurious regression" problem. Some non-stationary series contain common trends but essentially have no correlation. Regression based on such non-stationary data is meaningless even if it exhibits a high R-square. As suggested by Maddala and Wu (1999), we apply the Fisher test for panel unit root using an augmented Dickey-Fuller test (ADF).[‡] The results imply that Ln(SO_2) and Ln(GDP) have a unit-root since the unit-root tests are statistically insignificant even at 10 per cent level. Therefore, it is reasonable to conclude that the two variables are non-stationary. However, stationarity could be achieved by some simple transformation, such as first difference. The test results show that the series of Ln(SO_2) and Ln(GDP) are said to be integrated of order one denoted as I(1).

An important assumption implicit in the ECM is that the random disturbance term u_t is stationary. This implies that actual SO_2 emission levels do not permanently drift away from what is determined by long-run factors specified in equation (1). Since the levels of the variables in equation (1) are generally nonstationary, the stationarity of u_t requires that these non-stationary variables be co-integrated as discussed in Engle and Granger (1987). Since our unit-root tests above indicate that all variables are I(1), we perform the panel cointegration test developed by Pedroni (1999, 2001). The tests indicate a co-integrating relationship between the variables.

Figure 1 is a scatter plot of the statistical values of the two key variables and its trend components after filtering out the business cycle impacts. This figure shows total emissions present relatively large fluctuations from business cycle, compared real GDP.

Figure 1: The scatter plots of the statistical data and the filtered data for GDP and SO_2 (scaled values)



Panel a: GDP Panel b: SO_2

Note: The vertical axis is the statistical data values and the horizontal axis is the filtered data.

4. Energy efficiency estimation

[‡] In a preliminary version of the paper, we have applied other tests including Levin-Lin-Chu (LLC) test, Breitung test, Im-Pesaran-Shin (IPS) test. The test results come to the same conclusion that panels contain unit roots.

The estimation results of the SFA models are given in Table 2. Overall, most of the estimated coefficients and lambda have the expected signs and are statistically significant. The estimated values of coefficients for the two models are similar.

Table 2: Estimation results of SFA

VARIABLES	(1) Persistent	(2) transient
Price	-0.036	-0.019
	(0.027)	(0.043)
ln *GDP*	0.652***	0.694***
	(0.097)	(0.066)
ln *Population*	0.096	0.113
	(0.081)	(0.119)
ln *Household size*	-0.473***	-0.394***
	(0.119)	(0.142)
ln *Transport*	0.183***	0.133**
	(0.040)	(0.055)
ln *Climate*	-0.001	0.003
	(0.005)	(0.004)
%Service	-0.004**	-0.003
	(0.002)	(0.003)
%Industrial	0.000	0.001
	(0.002)	(0.002)
T	0.030**	0.045*
	(0.013)	(0.023)
T2	-0.005***	-0.005***
	(0.000)	(0.001)
Constant	9.609***	8.319***
	(2.493)	(0.758)
Mundlak adjustment	yes	yes
Log likelihood	412.2	419.2
lambda	4.578***	2.644***

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

We find that price does not influence energy demand as the coefficient of price is insignificant. This may be due to the low variation in price and state-controlled price system. The income elasticity (coefficient of GDP) is around 0.7 and statistically significant in all two models. The coefficients of household size and population show the effect of demographics on energy demand. We find that population has positive impact for both models. Household size is shown to negatively impact the energy demand, suggesting the existence of economies of scale. This is reasonable as it is very unlikely that one family will purchase air conditioners by the number of family members.

The sign of the estimated coefficients of transport is positive and statistically significant, which implies that the energy use for transport is one of the driving forces of the energy demand in China. The estimated coefficients of climate are small and insignificant in all models. The energy use for comfortable environment has no significant impact due to both low penetration rates of heating systems and the small share of electricity use for cooling, as shown in Zhang (2013).

The economic structure factors (the share of industrial sector to GDP and the share of service sector to GDP) have the expected signs. The *DT* is captured by the coefficients of T and T^2 combined. The positive sign of T and the negative sign of T^2 together suggest that the declining trend of energy use occurs only in the later period.

In Table 3 we provide the descriptive statistics of the estimated persistent and transient energy efficiency scores. As expected, the average persistent efficiency is lower than the average transient efficiency. The overall efficiency is around 0.73.

Table 3: Descriptive statistics of the estimated efficiency

Variable	Obs	Mean	Std. dev.	Min	Max
Persistent	377	0.80	0.15	0.47	0.98
Transient	377	0.92	0.05	0.60	0.99
Overall	377	0.73	0.14	0.39	0.94

5. Empirical results of ECM and discussion

Table 4 presents our empirical estimations with four model specifications. Model 1 and 2 consider only GDP and the underlying energy efficiency into account, while model 3 and 4 include additional controls. In model 1, the coefficient of "D.lnGDP" is positive. It shows that GDP will have positive and statistically significant effects on SO_2 emissions in the short run, however, such effect becomes insignificant in the long run. This is consistent with the EKC literature. The coefficient of λ is negative as required.

Although there is a time trend of declining emissions through general technological development, efficiency seems to be less helpful in curbing the emissions in the short run. We find that efficiency can contribute to the emission reduction in the long run as it shows in the result. This may suggest that the inverted-U shape of EKC is the result of efficiency improvement. GDP itself is no magic for turning down the ever-increasing emissions. Model 2 is almost the same as model 1. The only difference is that in the short run equation we use the first difference of transient efficiency instead of overall efficiency, as transient efficiency reflects the short-run variations of energy efficiency. The results are more or less the same as in Model 2 except that the coefficient of *D.efficiency* is slightly higher.

Moreover, we introduce additional controls in our model. Specifically, we introduce price variable to capture the price effect, two structural variables to capture the structural change of provincial economy, and one variable to capture the population change. As shown in model 3 and 4. The sign of all coefficients are the same as in model 1 and 2. The only difference is that the positive effect of GDP on SO_2 emission becomes statistically significant, which further proves that inverted U shape will never happen if the government cares only GDP growth while ignoring other measures such as efficiency improvement.

Table 4: Error Correction Model results

VARIABLES	Model 1	Model 2	Model 3	Model 4
Long-run Error-correction				
ln*GDP*	0.112	0.112	1.151***	1.151***
	(0.195)	(0.195)	(0.111)	(0.111)
Efficiency	-1.688***	-1.688***	-2.408***	-2.408***
	(0.294)	(0.294)	(0.113)	(0.113)
Short-run				
λ	-0.533***	-0.533***	-0.474***	-0.474***
	(0.055)	(0.055)	(0.105)	(0.105)
*D.*ln*GDP*	1.343***	1.343***	2.186***	2.186***
	(0.409)	(0.409)	(0.782)	(0.409)
D.efficiency (overall)	0.126	---	-0.041	---
	(0.347)		(0.957)	
D.efficiency (transient)	---	0.170	---	0.256
		(0.222)		(0.534)
t	-0.016***	-0.016***	-0.068***	-0.068***
	(0.004)	(0.004)	(0.017)	(0.017)
Constant	1.269***	1.269***	-11.848***	-11.848***
	(0.146)	(0.146)	(2.660)	(2.660)
Additional controls	No	No	Yes	Yes
Log likelihood	582.4	582.4	819.9	819.9

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

As we have discussed earlier, that long-run estimation may be affected by the cyclical fluctuations. We first remove the cyclical component of GDP by applying the Hodrick-Prescott filter. The filtered GDP is used in the long-run part of the ECM model. We re-run Model 1 and 2, the results are shown in Table 5.

As seen from Table 5, almost all the results hold. The only difference is the effects of GDP in the long run. The coefficients of GDP in the long-run error correction component is positive and statistically significant after removing the cyclical variations. This suggests that in the long run, GDP will increase SO_2 emission, although with small magnitude as compared to the short run. This confirms that economic growth itself cannot solve the problem of environmental degradation.

6. The structural break and cross section analysis

In this section, we conduct an analysis to capture the potential structural break. Several reasons support our hypothesis. First, the financial crisis in 2008 affected the global economy, and China was no exception. Second, the central government put great efforts to fight for pollution and emission mitigation. Related policies can cause behavioral change in production and consumption and therefor affect energy demand and emissions. For example, strict environmental regulation might alter production behavior of firms by changing the input mix away from pollution-intensive inputs to less pollution-intensive inputs. In this regard, the environmental policies would cause behavior to change that firms will to either invest and improve the productive use of dirty energy or switch to cleaner energy types. It is expected that there was significant technological update, leading to a jump in terms of technology level rather than a smooth transition.

Table 5: Error Correction Model results after Hodrick-Prescott filter

VARIABLES	Model 1'	Model 2'	Model 3'	Model 4'
Long-run Error-correction				
ln*GDP (filtered)*	0.543***	0.543***	1.150***	1.150***
	(0.173)	(0.173)	(0.024)	(0.024)
Efficiency (overall)	-1.822***	-1.822***	-2.426***	-2.426***
	(0.260)	(0.260)	(0.025)	(0.025)
Short-run				
λ	-0.543***	-0.543***	-0.489***	-0.489***
	(0.060)	(0.060)	(0.106)	(0.106)
*D.*ln*GDP*	1.119***	1.119***	2.236***	2.236***
	(0.409)	(0.409)	(0.771)	(0.771)
D.efficiency (overall)	0.121	---	0.031	---
	(0.342)		(0.943)	
D.efficiency (transient)	---	0.167		0.310
		(0.220)		(0.529)
t	-0.044***	-0.044***	-0.070***	-0.070***
	(0.005)	(0.005)	(0.017)	(0.017)
Constant	-4.801***	-4.801***	-12.235***	-12.325***
	(0.539)	(0.539)	(2.684)	(2.684)
Additional control	No	No	Yes	Yes
Log likelihood	584.1	584.1	842.1	842.1

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We first calculate the average GDP, energy efficiency and SO_2 level over time and perform the tests of structural break in both GDP and energy efficiency. We use the Quandt-Andrews unknown breakpoint test, as it is able to test for multiple structural breakpoints, selecting the maximum breakpoint location based on different statistical tests (Zhang et al., 2018). Table 6 shows the result. According to the results and various statistics in the table, we find a significant structural break in both GDP and energy efficiency in the year 2008. This structural break point coincides well with the start of financial crisis in 2008. Therefore, it makes sense to interact the time dummy and GDP and energy efficiency. This section presents the results of such models through a cross-sectional analysis.

Since we have relatively large panels and relatively few years, a cross-sectional regression in which we simply average over the time periods in each province is feasible. We divide the sample into two separate time segments and calculate the average for each variable for the 29 provinces in each of the time segments. According to our structural break test, we divide the sample into following two periods, first period from 2002 to 2007, second period from 2008 to 2014. We create a time dummy variable, D_1, which equals to zero for period one, and equals to one for the second period.

Table 6: the results of structural break tests

(1) Test for GDP		
Statistic	Value	Prob.
Maximum LR F-statistic (2008)	8.208116	0.0600
Maximum Wald F-statistic (2008)	8.208116	0.0600
Exp LR F-statistic	2.783237	0.0201
Exp Wald F-statistic	2.783237	0.0201
Ave LR F-statistic	3.752267	0.0234
Ave Wald F-statistic	3.752267	0.0234
(2) Test for energy efficiency		
Statistic	Value	Prob.
Maximum LR F-statistic (2008)	8.216325	0.0598
Maximum Wald F-statistic (2008)	8.216325	0.0598
Exp LR F-statistic	2.760063	0.0207
Exp Wald F-statistic	2.760063	0.0207
Ave LR F-statistic	3.709833	0.0243
Ave Wald F-statistic	3.709833	0.0243

Note: Null Hypothesis for the test is no breakpoints within 15% trimmed data.

In this section, we then estimate the following new equations. First, we consider a simple time dummy in the model as follows:

$$\ln SO_{2it} = \alpha_1 + \alpha_2 \ln GDP_{it} + \alpha_3 EF_{it} + \alpha_4 D_1 + \varepsilon_{it},$$

$$i=1,2,\dots,29;\ \ t=1,2;$$

$$D_1 = 0 \ \mathit{if}\ t=1;\ D_1 = 1 \ \mathit{if}\ t=2 \qquad (10)$$

Furthermore, we would like to assess how the level of SO_2 is affected by economic growth and energy efficiency over time. The interaction terms between the period dummy variable and ln(GDP), EF are used to replace the dummy variables. The model used to estimate the effects of GDP is then written as follows:

$$\ln SO_{2it} = \beta_1 + \beta_2 \ln GDP_{it} + \beta_3 EF_{it} + \beta_5 D_1 * \ln GDP_{it} + \varepsilon_{it} \quad (11)$$

And the model used to estimate the effects of energy efficiency is written as follows:

$$\ln SO_{2it} = \beta_1 + \beta_2 \ln GDP_{it} + \beta_3 EF_{it} + \beta_6 D_1 * EF_{it} + \varepsilon_{it} \quad (12)$$

We do not include two interaction terms in one equation because the interaction terms are highly correlated. The correlation coefficient between $D_1 * \ln GDP_{it}$ and $D_1 * EF_{it}$ is 0.97. The regression results of our cross-sectional analysis are presented in Table 9. The second column demonstrates the results of equation (11) and the third column shows the results of equation (12).

From Table 7, the coefficients for *GDP* and *Efficiency* are significant in almost all three cross-sectional models. Additionally, the signs of ln*GDP* and *Efficiency* are positive and negative, respectively, as expected. These outcomes illustrate that the impact of GDP on SO_2 is positive while the impact of energy efficiency on SO_2 is negative. The time dummy variable is significant at 5 per cent, implying the SO_2 emission of later period in the 29 provinces is significantly less than that of the earlier period.

Table 7: Cross-sectional analysis

VARIABLES	1	1a	2	2a	3	3a
ln*GDP*	0.408***	0.513***	0.415***	0.522***	0.405***	0.507***
	(0.089)	(0.078)	(0.111)	(0.092)	(0.108)	(0.093)
Efficiency	-1.375**	-1.670***	-1.373*	-1.668***	-1.144	-1.392***
	(0.681)	(0.455)	(0.769)	(0.489)	(0.713)	(0.395)
Time dummy D1	-0.331**	-408***	---	---	---	---
	(0.152)	(0.103)				
*D1**ln*GDP*	---	---	-0.012**	-0.015***	---	---
			(0.005)	(0.004)		
*D1*Efficiency*	---	---	---	---	-0.434**	-0.516***
					(0.179)	(0.155)
Constant	-5.744**	-4.232**	-5.930*	-4.454**	-5.861**	-4.333*
	(2.293)	(1.853)	(3.029)	(2.243)	(2.878)	(2.608)
Additional controls	No	Yes	No	Yes	No	Yes
R-squared	0.317	0.701	0.318	0.703	0.315	0.693

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

The results in the last two columns of Table 7 provide interesting results. The coefficients of the interaction terms are statistically significant and negative. It shows that in the second period, GDP has relatively lower impacts on SO_2 emissions, as in the second period, the effects of GDP on emission is the sum of the coefficients of β_2 and β_5 . Since β_5 is negative , this suggests that the GDP increases SO_2 emissions at an decreasing rate.

The results of the last column show the time effects of energy efficiency on SO_2 emissions. In the first period, the impact of energy efficiency on SO_2 emission is the coefficient of efficiency, namely -1.144. The effects of energy efficiency on SO_2 in the second period is the sum of the coefficients of β_3 and β_6 , namely -1.578, according to the definition of equation 12. This implies that the energy efficiency reduces SO_2 emissions at an increasing rate.

For a robustness check, we again introduce additional controls in all the three models including variables to capture the price effects and economic structural change. The results are presented in column 1a, 2a and 3a. All the results confirm our main conclusions.

7. Conclusions and policy implications

In this paper, we have revisited the classical nexus among total Sulphur dioxide emission, total real GDP and energy efficiency, using a panel database of 29 provinces in China. We first estimate energy efficiency by employing stochastic frontier analysis, which has been proved to be a rigorous econometric approach for future policy advice. The error correction model is then applied to study the short-run and long-run relationships among SO_2 emissions, economic growth and energy efficiency. Particularly, we have separated the business cycle effects from the macro data to ensure a robust estimation of the relationships. In addition, we consider the potential structural break and explore the relationship between SO_2 and GDP or energy efficiency via the cross-sectional analysis.

Both panel and cross-sectional analyses offer similar insights for us. Total real GDP has a positive impact on total SO_2 emissions, even after removing the cyclical component, which suggests that economic growth alone cannot solve pollution issues. In the long run, we find that an increase in energy efficiency has significant negative impact on SO_2 emissions, whatever the cyclical component is included or not.

The above results offer several important policy implications. Firstly, reduction in energy intensity proposed by Chinese government to curb climate change and other pollutants may not work. Our empirical results show that the increase in total GDP causes non-decreasing trend of total SO_2 emissions, so reduction in energy intensity cannot alleviate the pollution issues without preventing its increasing trend. Therefore, it is necessary to devise appropriate energy efficiency measures to eventually decrease the total pollution in the long term.

In addition, it is beneficial for the government to encourage green research and development of environment-friendly technology. Our analysis shows that the increasing size of transportation has significant impact on driving up the energy demand. Emission from transport is one of the major sources for environmental pollution in China. The transformation towards green transport system with renewable-powered cars is an important outlet for reducing pollutions. Currently, China has invested hugely in the development of electric cars, and even hydrogen transportation.

Thirdly, some literature indicated there may exist significant energy rebound effect due to lower energy price resulted from improving in energy efficiency (Hanley et al., 2009), our SFA estimation show that the impact of energy price on energy demand is insignificant, probably because low variation in price resulted from state-controlled price system. A deep reform in the price system will stimulate the power of market by reducing the energy demand and inducing innovations for efficiency improvement. Although there have been several rounds of market reform, the rigidity of energy price remains a big challenge. Since 2018 the Chinese government has initiated the environmental tax and national carbon trading, which implicitly increases the cost of using dirty energy sources. It is a strong signal that the government is moving a step towards marketable mitigation of pollution rather than command-and-control approach.

Fourthly, to alleviate the pollution issues in China, one of the core strategies adopted by the central government was to switch from coal to natural gas. The first kind of plan was released by Beijing government in 2010. Beijing's four remaining coal-burning power plants were due to switch over to natural-gas combined heat and power (CHP) systems by the winter of 2014 at the latest. Other cities followed similar approaches. However, energy is essential input for economic growth and more than 70% of energy reserve is coal and natural gas reserves are limited in China, so it is not easy to lower its dependency on coal in the short run. When economy booms, we cannot simply shut down the coal power plant to curb pollution; as economic growth slows, many previous closed small coal power plants reopen again due to the higher cost of natural gas. Our empirical results show even in the short run the improvement in energy efficiency can contribute emission reduction whatever the cyclical effects are included or not, so improving energy efficiency can be useful for a developing country to balance between economic growth and pollution control in both the short and long run. Therefore, with high volatility of energy supply market in the world and energy structure of Chinese economy, policies of enhancing energy efficiency could offer more sustainable win-win balance between the environment and economy.

Finally, from a global perspective, as China is becoming a world leader in energy efficiency development and we have confirmed that efficiency indeed has powerful effect for the environment, China can export such expertise to other developing or undeveloped countries as part of its aid. This will not only show its strong leadership, but also regenerate the positive benefit of energy efficiency in other regions, and contribute to the global flight for the climate change.

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