Role of FDI in Decomposing of Scale and Technique Effects on China's Energy Consumption

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Abstract: This study contributes to the literature of energy economics by divulging the nature of scale and technique effects on energy consumption, considering foreign direct investment (FDI) as one of considerable factors of energy demand. The Chinese provincial data over the period of 2000–2018 are used for empirical analysis. In doing so, we have applied the Westerlund and Edgerton (2008) cointegration test using cross-sectional dependence and structural breaks, and bootstrapped quantile regression to decompose scale and technique effects. The empirical results show the presence of cointegrating association among the model parameters, in the presence of cross-sectional dependence and structural breaks. The quantile regression results indicate that the scale effect exerted by FDI is negative at lower quantiles of energy consumption, and positive at upper quantiles. Moreover, scale and technique effects exerted by FDI are positive and negative, respectively, at lower quantiles of energy consumption, and negative and positive, respectively, at higher quantiles. The results of this study are expected to help in designing the energy policies in China, keeping the quantum of energy consumption at various provinces in mind, and, thereby, ensuring the sustainability in energy consumption.

Keywords: Income Effect, Scale effect, Energy Consumption, Quantile Regression, China

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Highlights

- We analyze the scale and technique effects on energy consumption from FDI.
- Chinese provincial data over the period of 2000–2018 are used.
- Bootstrapped quantile regression is used.
- Scale effect exerted by FDI reverse with quantiles.

Abbreviations

BRICS:	Brazil, Russia, India, China, and South Africa
CD:	Cross-Sectional Dependence
CO2:	Carbon Dioxide
DOLS:	Dynamic Ordinary Least Square
EKC:	Energy Kuznets Curve
FDI:	Foreign Direct Investment
FMOLS:	Fully Modified Ordinary Least Square
GCC:	Gulf Cooperation Council
GDP:	Gross Domestic Product
IEA:	International Energy Agency
LM:	Lagrange Multiplier
MENA:	Middle East and North Africa
MINT:	Mexico, Indonesia, Nigeria, and Turkey
OECD:	Organisation for Economic Co-operation and Development
OLS:	Ordinary Least Square
SDG:	Sustainable Development Goal
UN:	United Nations
UNDP:	United Nations Development Programme
USA:	United States of America
VIF:	Variance Inflation Factor

I. Introduction

Global warming has become the most important issue over the years and ever-increasing carbon dioxide (CO2) emissions have accelerated the debate among practitioners, international agencies, policy makers and academicians to discuss the strategies and collective action on how to reduce CO2 (Benjamin & Lin, 2020; Skytt, Nielsen, & Jonsson, 2020; Wang & Su, 2020). The growing population and increased use of energy in the world has made the environmental mitigation task even more difficult. This dilemma has prompted practitioners, policy makers and researchers to develop better understanding about energy consumption and environmental degradation to overcome the issue. This necessitates exploring new techniques and ways how energy efficiency can be improved to reduce the ecological footprints resulting from consumption of energy derived from fossil fuels. Despite the several efforts to mitigate the global warming issue, the rising trends of CO2, as a result of increased economic activities mostly in Asia, are posing a serious threat to the planet. According to the United Nations (UN), energy-related CO2 emissions have increased to a record level globally, up to 415 parts per million in May 2019 (UNDP, 2019). Increased use of coal in power generation, particularly, in China, India and the US has contributed 85 % of the net increase in emissions (IEA, 2018). These ever-increasing CO2 emissions have drawn considerable attention among international agencies, practitioners, academicians and policy makers in both developed and developing economies. Being the second largest economy of the world, China is a leading emitter of CO2, accounting for 18–35 % of global emissions (BP, 2019; Hoesly et al., 2018; Shuai et al., 2018; Zheng et al., 2018). The rapid growth in the Chinese economy has increased energy consumption and CO2 emissions, which is a great policy concern. It is crucial to find the ways how to reduce CO2 emissions to combat environmental pollution and global warming challenges faced by the people living in one of the fastest growing economy in the world (Zhang & Cheng, 2009).

The Chinese energy sector and its emissions have global implications both in the short run and the long run (Andrews-Speed & Zhang, 2019). The short-run policy implications are viewed in terms of its role in affecting the global demand and supply of energy raw materials, energy technologies and the rising levels of pollution as a result of energy consumption whereas the long-run implications emphasize the need of CO2 emissions reduction. Being the largest commercial energy consumer in the world with 23 % of the world's total consumption in 2017, China has become the main actor in the international energy sector so far this century (BP, 2019). The changing composition of the Chinese economy due to the continuous growth in gross domestic product (GDP), expansion in trade volumes, increase in FDI, shifts in economic structure, and the ongoing urbanization in the country seem the main factors contributing to CO2 emissions. The increased greenhouse gas emissions as a result of economic growth are causing global climate change. A substantial literature has documented the relationship between CO2 emissions and economic growth. However, the evidence suggests that the development and economic growth lead to structural transformation in energy production (Grossman and Krueger, 1995). The use of energy and CO2 emissions are influenced by various factors such as the level of FDI, the use of efficient techniques or technologies, capital and labor among others. A considerable literature focuses on the effects trade and FDI on energy consumptions and CO2 emissions (Shahbaz & Sinha, 2019; Bu, Li, & Jiang, 2019; Wang, 2017; Yildirim, 2014). Likewise, increased economic output is also one of the driving factors contributing to emissions (Ma et al., 2019; Sinha et al., 2018, 2019). Several studies have focused on structural decomposition approach that relies on input-output tables and index decomposition approach based on aggregation methods such as mean Divisia Index (Sinha, 2017; Chong, Ma, Li, Ni, & Song, 2015; Cornillie & Fankhauser, 2004; Ramachandra & Shwetmala, 2012). However, few studies have focused on detailed decomposition analysis by accounting for multiple factors simultaneously.

The change in structural composition of the Chinese economy is influencing the energy demand of the country. It is important to explore what factors are causing the increased pollution as a result of CO2 emissions (Sharif et al., 2020c; Liobikienė & Butkus, 2019; Shahbaz, Gozgor, Adom, & Hammoudeh, 2019; Tsurumi & Managi, 2010). The question is whether the shifting economic structure is helping to reduce emissions or not? What kind of technologies and innovations can help to reduce emissions? What are the impacts of adoption of CO2 emissions reduction technologies on the economy? What could be the policy response and implications of energy consumption in the short run and the long run? These important policy questions need to be addressed explicitly for effective climate change mitigation policies. This paper contributes to the energy literature on four issues: (i) The income and technique effects are estimated by considering FDI and composition effect as determinants of energy demand in China; (ii) The unit root analysis is conducted by applying the Weak Cross-Sectional Dependence unit root test (Chudik and Pesaran, 2015); (iii) The Westerlund and Edgerton (2008) cointegration approach is applied considering cross-sectional dependence and structural breaks to examine cointegration between energy demand and its determinants; and (iv) Bootstrapped quantile regression is applied to examine the impact of the scale effect, the technique effect, the composition effect and the FDI effect on energy consumption. Our empirical analysis reveals the presence of cointegration between energy demand and its determinants. Moreover, the quantile regression analysis confirms that the scale effect and the technique effect exerted by the income effect on energy demand negatively and positively, simultaneously. The composition effect declines energy demand at the lower (medium) quintiles but increases it at higher quintiles. The scale and the composition effects exerted by FDI change with the level of quantiles, i.e., the scale effect has a positive impact and the composition effect has a negative impact on energy demand until the median, and the impacts are reversed beyond the median. The detailed decomposition using provincial data allows us to examine the underlying factors explaining Chines energy consumption precisely.

The remainder of the paper is organized as follows. Section II provides an overview of the literature on energy consumption and economic growth (and *FDI*) issues. Section III presents details about the empirical modelling and the data collection. The empirical methods are described in Section IV. The empirical results and their discussion are provided in Section-V. Section-VI presents conclusions with policy implications.

II. Literature Review

The relationship between energy consumption and economic growth has been extensively studied both in developing and developed economies (Al-mulali, Weng-Wai, Sheau-Ting, & Mohammed, 2015; Apergis & Payne, 2009; Gozgor, Lau, & Lu, 2018; Salahuddin & Gow, 2019; Shahbaz, Hye, Tiwari, & Leitão, 2013; J.-H. Yuan, Kang, Zhao, & Hu, 2008; Sharif et al., 2020 a, b). The literature on energy consumption and economic growth mostly focused on testing the causal relationship between the two variables. However, the findings of these studies have been mixed and inclusive from a policy perspective due to diverse political, institutional and economic settings (Ozturk, 2010). Most of the studies on causality between energy and economic growth (also called the energy-growth nexus) rely on testing the four main hypotheses: i) growth hypothesis, i.e., energy promotes economic growth; ii) the conservation hypothesis, i.e., economic growth leads to energy use; iii) the feedback hypothesis i.e., two-way causality between energy and economic growth; and iv) the neutrality hypothesis, i.e., no relationship in either way between energy and growth (Ahmad et al., 2020). Yet, there is no unanimous consensus on the direction of causality between energy consumption and economic growth. These causal relationships between environmental pollutants and economic growth, and/or the link between energy consumption and economic growth, are generally drawn on the validity of the energy Kuznets curve (EKC) hypothesis. The EKC hypothesis postulates the inverted-U relationship between energy consumption and economic output (e.g., GDP) which was first discussed by Nobel Laureate Simon Kuznets (Kuznets, 1955). The relationship between energy consumption and economic growth was first tested on USA data (Kraft & Kraft, 1978). Since the seminal paper of Kraft and Kraft, an abundant literature has focused on the EKC hypothesis testing using data from different countries and a detailed survey can be found in (Dinda, 2004; Özokcu & Özdemir, 2017; Ozturk, 2010; Stern, 2004).

The controversy in the role of energy in economic growth has been a long-standing issue in the energy and growth nexus literature. Since the seminal work of Kraft and Kraft (1978), there has been exponential growth in the empirical evidence on energy consumption and economic growth. Grossman and Kruger (1995) examine the relationship between per capita income and different environmental indicators; however, they did not confirm any evidence on environmental quality deterioration with economic growth. Stern (2004) provides a chronology of EKC studies of both past and recent developments. A number of studies raised theoretical issues of EKC implementation (Arrow et al., 1995; Cole & Elliott, 2003; Dinda, 2005; Lucas, Wheeler, & Hettige, 1992; Stern, Common, & Barbier, 1996). For instance, Arrow et al., (1995) argue that the environmental damage does not have negative repercussions on future income because of absence of the feedback assumption. Further, based on the Heckscher-Ohlin theorem, they argued that the reduction in environmental pollution in developed countries and further increase in environmental pollution in developing economies may be the result of specialization. On the other hand, Cole and Elliot (2003) argue that the capital-intensive production activities in the developed world comparatively pollute more in the absence of regulation differentials. On similar lines, various studies investigated the energy-environmental Kuznets curve using time-series and panel data, which also provided mixed results. For example, in case of 76 developing economies, Van Benthem (2015) applied ordinary least squares regression for examining the relationship between energy intensity and economic growth. The empirical evidence confirms the existence of an S-shaped association between energy intensity and economic growth. Using the Arellano-Bond-Bover model, Menegaki et al. (2015) reported that economic growth declined energy intensity initially but that it increased after a threshold level of real GDP per capita (i.e., U-shaped association between energy intensity and economic growth). Pablo-Romero and Jesús (2016) applied panel data methods using Latin American and the Caribbean data to investigate association between energy consumption and economic growth and validated the absence of an energy Kuznets curve. Burke and Csereklyei (2016) used panel data of 132 countries and noted the existence of a U-shaped relationship between energy consumption and economic growth. Pablo-Romero et al. (2018) applied Dynamic OLS (DOLS) and Fully Modified OLS (FMOLS) approaches to examine the presence of an energy Kuznets curve using data for transition economies. Their empirical results indicated that an energy Kuznets curve was not valid.

Dong and Hao (2018) used China's provincial data for the period of 1996–2013 to investigate the association between energy (electricity) consumption and economic growth by considering the role of urbanization and trade openness in an energy demand function. By applying the Generalised Method of Moments, they confirmed that the association between energy consumption and economic growth was inverted U-shaped, i.e., an energy Kuznets curve. Chai et al. (2019) unveiled the relationship between energy (coal) consumption and economic growth by applying the Logarithmic Mean Divisia Index decomposition method. Their empirical findings showed the validation of the energy Kuznets curve between coal consumption and economic growth. Dong et al. (2019) added capital, population density and FDI as additional factors affecting energy consumption in an energy demand function for the Chinese economy. They noted that an energy Kuznets curve was not present in China. We note that empirical evidence is mixed on the presence of an energy Kuznets curve in China.

Recently, there have been significant developments in EKC analysis, which can be classified into three main categories (Stern, 2004). First, the empirical evidence on environmental performance in developing economies and policy issues have been discussed by relating the environmental quality with economic development, which is based on the "pollution heaven hypothesis" (Dasgupta, Laplante, Wang, & Wheeler, 2002). For example, in case of the Gulf Cooperation Council (GCC), Al-mulali and Tang (2013) applied the Pedroni cointegration approach and reported the existence of a pollution heaven hypothesis. Similarly, Shahbaz et al. (2015) used data for high-, middle- and low-income countries to examine the association between FDI and CO_2 emissions by applying the FMOLS approach. They found the existence of a positive relationship between FDI and CO_2 emissions which further confirmed the pollution heaven hypothesis. For the Turkish economy, Koçak and Şarkgüneşi (2018) applied cointegration (that was suggested by Maki, 2012) and the DOLS approaches and found that FDI contributes to CO_2 emissions, thus, confirming the presence of the pollution heaven hypothesis. Using data from Chinese cities, Lui et al. (2018) applied a spatial lag model and a spatial error model for examining the association between FDI and CO_2 emissions. They noted that the effect of FDI on CO_2 emissions depends on environmental pollutants but the pollution heaven hypothesis and the pollution halo hypothesis were present. Shao et al. (2019) revisited the pollution heaven hypothesis in the case of BRICS and MINT countries by applying the panel vector correction method. They found that FDI has negative impact on CO_2 emissions which validated the absence of pollution heaven hypothesis. Finally, Liu et al. (2019) used data for 29 Chinese provinces to examine the presence of an environmental Kuznets curve by including FDI as an additional determinant in CO_2 emissions function. They applied parametric econometric approaches and reported the validation of EKC in Chinese. Their empirical evidence also suggested an inverted N-shaped association between FDI and CO_2 emissions. The second development was based on improved econometric methods that further took into account four issues, namely: i) heteroscedasticity; ii) simultaneity; iii) omitted variable bias; and iv) co-integration issues (Holtz-Eakin & Selden, 1995; Stern & Common, 2001; Stern et al., 1996). The third development focused on decomposition analysis (Liobikienė & Butkus, 2019; Shahbaz et al., 2019; Stern, 2002). For example, Tsurumi and Managi (2010) decomposed an environmental Kuznets curve into scale, technique and composition effects for using data of 205 developed and developing countries by considering energy consumption as an additional factor affecting CO_2 emissions. They noted that the scale effect was positively linked with CO_2 emissions but the technique effect was indifferent. Liobikien and Butkus (2019) examined the scale, technique and composite effects of economic growth, urbanization, trade and FDI on carbon emissions by applying a GMM estimator on data from 147 countries over the period, 1990–2012. They noted that the scale effect GDP (urbanization) had positive (no) impact on CO_2 emissions. Their empirical results showed insignificant impacts of the technique and the composite effects of FDI on CO_2 emissions. In the case of the US economy, Shahbaz et al. (2019) applied bounds testing approach and vector error correction model (VECM) Granger causality for decomposing the effect of economic growth, FDI and trade openness on CO_2 emissions for the period, 1965–2016. Their empirical results indicated a positive impact of the scale effect exerted by real GDP and FDI on CO_2 emissions but the technique and the composite effects negatively affected environmental degradation.

An intensive literature has investigated the relationship between energy consumption and economic growth both at the national and provincial levels. These studies have investigated different factors affecting energy consumption and economic growth, including international trade, labor, capital, technology and industrialization (Chang, 2010; Hao, Wang, Zhu, & Ye, 2018; Sattich & Freeman, 2019; Shuai et al., 2018; J.-H. Yuan et al., 2008; J. Yuan, Zhao, Yu, & Hu, 2007; M. Zhang, Bai, & Zhou, 2018; X.-P. Zhang & Cheng, 2009; B. Zheng et al., 2018; W. Zheng & Walsh, 2019). For instance, Zhang and Cheng (2009) investigated the direction of causality between energy consumption, CO_2 emissions and economic growth using annual Chinese data on 30 provinces and concluded that there was a unidirectional causality in the long run. They confirmed that CO2 emissions and energy consumption did not affect economic growth. Zhang et al. (2018) analyzed the relationship between Chinese coal consumption and economic growth. Their decomposition analysis suggests that technological innovation and efficient utilization of coal technology, coupled with development of the modern energy industry, can help energy conservation and reduction in environmental pollution.

III. Empirical Modelling and Data

The empirical investigation of determinants of energy demand is as old as the energy-growth nexus. For empirical investigation of influencing factors to energy demand, researchers have applied econometric approaches by using time-series and panel data at regional and provincial levels. By employing an energy demand function, an energy environmental Kuznets curve is also empirically investigated but obtained mixed results. For example, Van Benthem (2015) noted S-shaped, Menegaki et al. (2015) and Burke and Csereklyei (2016) found U-shaped, Dong and Hao (2018) noted inverted-U shaped linkages between economic growth and energy consumption.[2] Dong et al. (2019) indicated the importance of FDI while investigating the relationship between economic growth and energy consumption. FDI is also one of the important factors influencing energy demand by stimulating economic activity, resulting an increase in real GDP per capita, which is termed the scale effect. Emerging and developing countries introduce flexible economic policies to attract FDI for reaping positive externalities that, in turn, may have effects on per capita income (Shahbaz and Rahman, 2012). FDI has positive externalities such as improvements in productive efficiency, technological advancements, and enhancements in human and managerial skills, increasing learning-by-doing capacity, introduction of methods for increasing production and providing access to global markets. Hence, such positive externalities not only affect domestic production but also impact energy demand via the scale effect (Rahman and Shahbaz, 2011, Shahbaz et al., 2018). FDI introduces advanced technology in the host country, thus, increasing production. The adoption of new energy efficient technology not only affects domestic production but also energy demand, which is also termed as the technique effect (Shahbaz et al., 2018; Cole, 2006; Antweiler et al., 2001; Arrow, 1962). We note that the use of advanced technology produces more output with reduced energy consumption compared with obsolete technology.

The production pattern for energy intensive goods is fostered by the dynamic structural changes in an economy. Due to the sequential patterns of this dynamism, the economies initially move from the traditional to the industrial sector. This phenomenon is the outcome of economies of scale in term of skill base, transaction costs, and production, which may lead to a more efficient, but less energy-intensive economies, through the negative composite effect (Stern, 2004; Lee, 2013) which, therefore, leads to a net comparative advantage of the economies across the international markets (Cole, 2006). The major factors influencing the comparative advantage such as the capital-labor ratio, environmental sustainability regulations and availability of skilled human capital drives the effective localization of economies for a higher steady state. Moreover, if sectoral composition of economy is gauged through industrial contributions in the GDP, we may trace the composite effects of FDI on structural dynamism of an economy. Therefore, the composition effect also has an important implication for energy consumption in the energy

[2] Dong et al. (2019) introduced capital and population density in energy demand function by inserting FDI as well and noted that the energy Kuznets curve is not valid for the Chinese economy.

demand function. The composition effect increases energy demand if the capital-labor ratio is energy-intensive but declines energy demand if the capital being used for production is energy efficient. The impact of the composition effect depends on the value of the capital-labor ratio. The general form of the energy demand function is modeled as follows:

$$E_{it} = f(Y_{it}, Y_{it}^2, K_{it}, F_{it}) \tag{1}$$

For empirical analysis, we transformed all the variables into natural-log form. The natural-log linear-specification provides empirically efficient and reliable empirical results compared with a simple linear specification. The transformation of the variables into natural-logs directly provides elasticity estimates with respect to the independent variables. The empirical model for the energy demand function is modelled as follows:

$$ln\, E_{it} = \alpha_0 + \alpha_1\, ln\, Y_{it} + \alpha_2\, ln\, Y_{it}^2 + \alpha_3\, ln\, K_{it} + \alpha_4\, ln\, F_{it} + \varepsilon_{it} \tag{2}$$

Where ln, E_{it}, Y_{it}, Y_{it}^2, K_{it} and F_{it} represent the natural-log, energy consumption, the scale effect, the technique effect, the composition effect and *FDI*, and ε_{it} is the residual error that is assumed to be normally distributed. We have included squared terms of *FDI* in augmented the energy demand function to examine whether the association between *FDI* and energy consumption is inverted U-shaped or U-shaped. The relationship between *FDI* and energy demand is inverted U-shaped if the scale effect is dominated by the technique effect, otherwise it is U-shaped. It is argued that *FDI* increases energy demand by boosting economic activity and, later on, energy consumption declines due to adoption of advanced and energy efficient technology for production (Dong et al., 2019, Dong and Hao 2018). The revised augmented energy demand function is modelled as follows:

$$ln\, E_{it} = \beta_0 + \beta_1 ln\, Y_{it} + \beta_2 ln\, Y_{it}^2 + \beta_3 ln\, K_{it} + \beta_4 ln\, F_{it} + \beta_5 ln\, F_{it}^2 + \varepsilon_{it} \tag{3}$$

Following Cole (2006), Ling et al. (2015) and Shahbaz et al. (2019), we measure the scale effect and the technique effect using real GDP per capita and the square of the real GDP per capita. The composition effect is measured by the capital-labor ratio as suggested by Cole (2006), Tsurumi and Managi (2010) and Ling et al. (2015).[3] It is argued that the scale effect increases energy demand if $\beta_1 > 0$ otherwise it decreases energy consumption. If $\beta_2 < 0$ then this shows the presence of negative association between the technique effect and the energy consumption, i.e., the technique effect decreases energy demand, otherwise the technique effect increases energy consumption, i.e., $\beta_2 > 0$ if the technology used is energy intensive. If $\beta_3 > 0$, then this indicates that the composition effect increases energy consumption, otherwise it declines if $\beta_3 < 0$. The relationship between *FDI* and energy consumption is inverted U-shaped if $\beta_4 > 0, \beta_5 < 0$, otherwise it is U-shaped if $\beta_4 < 0, \beta_5 > 0$.

[3] Panayotou (1997) suggested that the "industrial contribution to GDP" was an appropriate measure for the composition effect.

The data for provincial energy consumption, GDP, gross fixed capital formation measure of capital, labor, *FDI* from China Statistical Yearbook[4]. We use total population for transforming all the variables into per capita units. The log-linear specification is used for our empirical study.

VI. Methodological Framework

VI.I. Cross-Sectional Dependence Test

The examination of cross-sectional dependence (CD) in the panel data is of utmost important, because the presence of the same might produce biased and inconsistent empirical results (Phillips and Sul, 2003). In reality, countries are connected with each other via different channels, e.g., economic, social, political, bilateral trade, and board sharing[5]. These forms of associativity among the countries might result in CD among the model variables. The significance of this test lies in determining the generation of unit root and cointegration tests. The first-generation unit root and cointegration tests assume the presence of cross-sectional independence that might not be true in the present geopolitical scenario. To address this issue, we use the CD test developed by Chudik and Pesaran (2015). The following equation is used to examine the presence of CD in the data:

$$CD = \sqrt{2T/N(N-1)}\left\{\sum_{i=0}^{N-1}\sum_{j=i+1}^{N}\rho_{ij}\right\} \tag{4}$$

where N indicates the cross-sections in the panel data; T represents the time span; and $\rho_{ij}$is the correlation coefficient between units i and j. Under the null hypothesis of weak cross-sectional dependence, this statistic weakly converges to normal distribution and the CD statistic of equation (4) validates the applicability of the first-generation unit root and cointegration tests, whereas rejection of the null hypothesis indicates the applicability of the second-generation unit root and cointegration tests.

VI.II. Cointegration Test with Structural Breaks

The cointegration test of Westerlund and Edgerton (2008) accommodates structural breaks along with cross-sectional dependence and employed the procedure involved in the LM unit root test, devised by Schmidt and Philips (1992). The significance of this test is in determining the possible structural breaks persisting in the cointegrating association, in the presence of cross-sectional dependence. These structural breaks might bring forth significant insights regarding the nature of cointegrating association among the model parameters. The null hypothesis of this test is the absence of cointegration among the data, against the alternate hypothesis of cointegration in the presence of structural breaks. The model involved is given by:

$$y_{it} = A_i + \mu_i t + \alpha_i D_{it} + x_{it}^{'} B_i + (D_{it}x_{it})^{'} b_i + \varepsilon_{1it} \tag{5}$$

$$x_{it} = x_{it-1} + \varepsilon_{2it} \tag{6}$$

where cross-sections are denoted by $i = 1, \ldots, N$; periods in the time series are denoted by $t = 1, \ldots, T$; $x_{it}$is the set of independent covariates; D_{it} is the dummy variable indicating the presence of structural break; (A_i, a_i) and (B_i, b_i) are model intercepts and slopes before and after the

[4] http://www.stats.gov.cn/english/Statisticaldata/AnnualData/

[5] It signifies to be in the board of directors of firms from other nations.

structural break, respectively; and ε_{it} is independent and identically distributed (i.e., *i.i.d*) allowing the cross-sectional dependence among the unforeseen conjoint factors C_t.

$$\varepsilon_{2it} = \rho_i^{'} C_t + m_{it} \tag{7}$$

$$C_{it} = \omega_j C_{jt-1} + n_{it} \tag{8}$$

$$\phi_i(L)\Delta m_{it} = \phi_i \Delta m_{it-1} + \rho_{it} \tag{9}$$

where $\phi_i(L) = 1 - \sum \phi_{i,j} L_j$ is a scalar polynomial with lag length L; and ρ_i is the vector of factor loading parameters. Therefore, the test statistics, reported by Westerlund and Edgerton (2008) are given by:

$$LM_\phi(i) = T\hat{\phi}_i(\gamma_i/\delta_i) \tag{10}$$

$$LM_\tau(i) = T = \hat{\phi}_i/SE(\hat{\phi}_i) \tag{11}$$

where $\hat{\phi}_i$is the estimated value of ϕ_i with standard error of $\hat{\sigma}_i$, and $\hat{\gamma}_i^2$ is the estimated long-run variance of m_{it}.

VI.III. Quantile Regression Test

To estimate the long-run association among the model parameters, we have employed the quantile regression test of Koenker and Hallock (2001). This method is used to curtail the sum of squared residuals through an optimization function across the quantiles. Following the central limit theorem, objective of the optimization problem is the unconstrained minimization of the quantile-wise weighted median.

$$min_{\varepsilon \in R} \sum_i \sum_t q_t(y_{it} - \varepsilon_{it}) \tag{12}$$

In Equation (12), the term $q_t(y_{it} - \varepsilon_{it})$ denotes the quantile regression function. Similarly, the minimization of the quantile-wise weighted mean can be carried out in the following manner:

$$min_{\mu \in R} \sum_i \sum_j (y_{it} - \mu)^2 \tag{13}$$

Now, this function provides the unconditional distribution of the sample mean that is spanned across x_{it} sample points of β_i to be the sample mean for each cross-section. In the quantile regression function, the central tendency of the residual errors and the sample mean theoretically coincides at the median, i.e., at median, $\mu \rightarrow \varepsilon$. In this view, Equation (13) can be written as follows:

$$min_{\mu \in R} \sum_i \sum_j q_t(y_{it} - \varepsilon_{it})^2 \tag{14}$$

This optimization problem consists of the set of regressors x_{it}, that have sample mean and residual errors coinciding at ε, i.e., $\mu \rightarrow \varepsilon$. Through the bootstraps, iterations of the quantile regression try to reduce the value of ε.

V. Empirical Results and Discussion

As the first step towards the empirical analysis, we have computed the summary statistics of model parameters, and results are noted in Table-1. All the model parameters are log-transformed. The volatility in energy consumption is lower than scale effect, i.e., $\ln Y_{it}$ and composition effect, i.e., $\ln K_{it}$. The volatility in *FDI* i.e., $\ln F_{it}$ is less than volatility occurs in squared of real GDP per capita i.e., $\ln Y_{it}^2$ and *FDI* i.e., $\ln F_{it}^2$. The correlation matrix shows that the model parameters are highly correlated. For instance, positive (negative) correlation is found between scale effect (technique effect) and energy consumption. Composition effect is negatively correlated with energy consumption. The correlation between *FDI* (squared of *FDI*) and energy consumption is positive (negative). The high correlation between the variables gives an impression that there might be a problem of multicollinearity in the data, and owing to that, we have computed variance inflation factor (VIF) for all the model parameters. The computational outcomes are reported in Table-2. We find that the model parameters suffer from multicollinearity in the base form, and it is evident from the low tolerance values. To rectify this issue, all the model parameters are orthogonally transformed. After the transformation, the tolerance values become unity, which indicates that the model parameters no longer suffer from the issue of multicollinearity. The rest of the analysis has been carried out on the orthogonally transformed dataset.

<Place for Table 1>
<Place for Table 2>

For assessing the integrating properties of the variables, we need to conduct panel unit root tests. However, before conducting these tests, we need to consider the possibilities of cross-sectional dependence in the data, and therefore, applicability of these tests can be ascertained. Henceforth, we have conducted Chudik and Pesaran (2015) weak cross-sectional dependence test, and empirical results are described in Table-3. The empirical evidence shows that there is cross-sectional dependence among all variables. This empirical evidence is significant in terms of assessing the integrating properties of the variables. Moreover, this empirical analysis elucidates that the regions under consideration of the present study are associated through several channels, and any shock given to the variables in any of the regions might affect the one in the other regions. Owing to this phenomenon, for inspecting the integrating properties, we use the panel unit root tests, which assume cross-sectional dependence in the data. To inspect the integrating properties of the variables, we have employed Herwartz and Siedenburg (2008) and Herwartz et al. (2017) panel unit root tests, which account for the cross-sectional dependence in the testable hypotheses. The empirical results documented in Table-4, show that after the first differentiation, the variables turn out to be first-order integrated i.e. I(1). This integration property can be considered as robust, as the property revealed via this battery of tests take account of the cross-sectional dependence in the data.

<Place for Table 3>
<Place for Table 4>

For proceeding further with the analysis, we need to validate the long run association between energy demand and its determinants, post that we will be able to assess the long run coefficients.

Now, the long run association between the variables can be validated through the cointegration method, and among the available set of techniques under cointegration method, we need to choose the one with the assumption of cross-sectional dependence. Moreover, given the period of the study, it can be assumed that there might be certain socio-economic and political transformations in the regions. Therefore, there might be possible structural breaks in the data. The chosen cointegration technique should be able to take account of those unknown structural breaks in the data. In consequence of these intentions, we have employed Westerlund and Edgerton (2008) cointegration test, which takes into account of unknown structural breaks, as well as cross-sectional dependence. This test is also able to produce robust estimates in presence of heteroscedasticity and serial correlation. The results are reported in Table-5, which are obtained for (a) no shift, (b) level shift, and (c) regime shift. In all the three cases, the test statistics reveal the presence of significant cointegration association between energy demand and its determinants during 2000-2017 for Chinese provinces.

<Place for Table 5>

While conducting the Westerlund and Edgerton (2008) cointegration test, we have also found several structural breaks appearing across the provinces under consideration (see Table 6). We will try to analyze these structural breaks, from both Chinese and global perspective. In 2002, Chinese economy experienced a shift in political regime, when Hu Jintao became the head of the Communist Party of China by substituting Jiang Zemin. This shift in the leadership had an impact on the overall socio-economic structure of the nation (Scobell, 2003). Moreover, since 2002, the world started experiencing nearly double-digit growth in oil consumption. However, in 2014, global crude oil prices experienced a sharp descent, and the impact of this descent was visible in Chinese economy. Similarly, 2014 was also the year, when China hosted several international sports events, which also influenced the economic operations via several channels. These events caused shocks in economic growth and its drivers, and therefore, these years have appeared as potential structural breaks in the model parameters.

<Place for Table 6>

After asserting the long-run association between energy consumption and its determining factors, we employed bootstrap quantile regression to assess the impact of scale effect and technique effect, composition effect and FDI on energy consumption. The empirical results are reported in Table-7 and the plots of empirical models are shown in Figure-1 and 2. Let us begin with Model-I. We find that, except for 9^{th} quantile, scale effect increases the energy consumption, implying that a 1% rise in scale effect is exerted by real GDP per capita increases energy consumption by 1.185-3.068%, given ceteris paribus. The positive scale effect implies that economic expansion is generating more demand for energy, which is in turn being translated into higher energy consumption. This phenomenon might be warranted by considering the nature of economic growth in an industrialized economy, which is characterized by high-energy demand. On the flipside, except for 9^{th} quantile, technique effect decreases energy consumption, i.e., a 1% rise in technique effect is exerted by square of real GDP per capita decreases in energy consumption by 0.0182-0.1056%, given ceteris paribus. The negative technique effect implies that technologies employed to boost industrial output are effective in bringing down the level of energy consumption, and thereby ensuring energy efficiency. However, while mentioning this, it should also be observed that the turn-around points for the inverted U-shaped EKCs achieved in Model-I are much higher compared with the maximum real GDP of the sample. It signifies that the achievement of lowered energy consumption might not be possible in near future, as the provinces under consideration might take several years to reach the turn-around points. It also depicts the inefficacy of environmental regulations in reducing environmental damages done through ambient air pollution and loss of energy efficiency. This segment of results is similar to Shahbaz et al. (2016), who found that scale and technique effects are exerted on energy demand, which follow an inverted U-shaped pattern for Malaysia, thereby indicating their unsustainable energy-led growth pattern. When we observe this scenario in comparison with the results obtained for 9th quantile, it becomes clearer that provinces with higher energy consumption fail to internalize the negative externalities via economic growth trajectory. Perhaps that is the reason the scale effect exerts negative impact on energy consumption in this case, whereas the impact of technique effect is positive.

By looking into the FDI effect, we find that it has a negative impact on energy consumption for lower quantiles, and the effect turns out to be positive in higher quantiles. This segment of the results is in line with the findings of Doytch and Narayan (2016), where they found the impact of FDI on nonrenewable energy consumption for low-income countries, and positive impact for high-income countries. If energy consumption is considered as a proxy for economic growth, then the result of this study complies with our finding. If we discuss the results obtained for real GDP and FDI, then we can see that the results converge towards the intrinsically developed and imported environmentally degrading production technologies being used in China. While boosting industrial growth, the policymakers in China are bringing forth negative externalities by degrading environmental quality, and the existing policies are proving to be ineffective in internalizing those externalities. This scenario can be seen in case of the OECD countries, as shown by Pazienza (2019). This work shows an extension of this segment of the results, by demonstrating the negative impact of FDI on environmental quality. This claim is further validated against the impact of composition effect on energy consumption. Composition effect, i.e., capital-labor ratio is negative for lower and medium quantiles, and positive for higher quantiles. This signifies that higher energy consumption is visible for capital-intensive industries, where the labor-intensive industries are prone to be characterized by lower energy consumption. Therefore, production technologies used by capital-intensive industries are not energy efficient, and therefore, they contribute to environmental degradation. This segment of the results contradicts the findings of Apergis et al. (2015), who found the capital-intensive industries to be more energy efficient than labor-intensive industries for OECD countries. The major reason behind this difference in results might lie in the nature of economic growth, level of industrial innovation, and the approach towards sustainable development between the OECD countries and China.

Once, we have analyzed the test outcome for Model-I, we will now proceed with Model-II. The basic difference between these two models is that Model-II captures the technique effect exerted by FDI. In presence of the technique effect, scale effect of FDI has undergone a transformation. The FDI-energy consumption association is inverted U-shaped for the lower quantiles, and U-shaped for higher quantiles. However, the turn-around points of FDI need special mention in this case. For the lower quantiles, in presence of inverted U-shaped association, the turn-around points are quite low, and for the higher quantiles, in presence of U-shaped association, the turnaround points are quite high. For lower quantiles, the results fall in the similar lines with the findings of Shahbaz et al. (2019), who found the similar impacts of scale and technique effects of FDI on environmental quality for the MENA countries. This phenomenon brings forth several insights regarding the technology import perspective. Existing and intrinsically developed production technologies are proving to be environmentally deteriorating, and the negative externalities caused by these technologies can be internalized by the import of green technologies. This is the reason, when the GDP-energy consumption and FDI-energy consumption associations are coming out to be opposite in nature. However, continuous import of green technologies might put pressure on the fiscal balance of the nation, and therefore, policymakers might ignore the environmental aspects for boosting economic growth (see Sinha et al., 2020 a, b). Perhaps that is the reason the coefficients of scale and technique effects exerted by GDP and the coefficient of composition effect are showing the sign of robustness across the two models.

Lastly, as a robustness check, we have employed instrumental variable quantile regression on the two empirical models. The test outcome stated in Appendix 1 demonstrates that the estimated coefficients for both the models are robust and significant.

<Place for Table 7>
<Place for Figure 1>
<Place for Figure 2>

VI. Conclusions and Policy Implications

By far, we have looked into the empirical association between energy consumption, scale and technique effects exerted by GDP and FDI, and composition effect exerted by capital-labor ratio for 30 Chinese provinces over the period of 2000-2018. In empirical pursuit, we have employed the second-generation unit root tests for investigating the integration property of the model parameters. Subsequent to this, long-run cointegrating association among the model parameters was assessed by Westerlund and Edgerton (2008) panel cointegration test. Finally, bootstrapped quantile regression was utilized to examine the impacts of scale and technique effects by GDP and FDI and composition effect by capital-labor ratio on energy consumption. The robustness of long run coefficients has been checked by instrumental variables quantile regression.

The results show that scale effect exerted by GDP stimulates energy consumption, whereas technique effect exerted by the same leads to fall in energy consumption. On the flipside, scale effect exerted by FDI diminishes energy consumption at lower quantiles and stimulates at higher quantiles. However, technique effect exerted by FDI affects energy consumption just in the opposite manner compared with that of scale effect. The composition effect exerted by capital-labor ratio has a negative impact on energy consumption for low and medium quantiles, and the impact becomes positive for high quantiles. Now, based on these model outcomes, we will discuss the suitable policies in pursuit of sustainable development in China, and the policies will be divulged in terms of the Sustainable Development Goals (SDGs).

China is one of the fastest growing industrial economies across the globe, and economic growth pattern of China is reflected in its energy, environment, and trade policies. Achieving economic growth through industrial progression seems to be primary concern in China, and therefore, environmental sustainability issues are gradually taking a backseat. In such a situation, the new economic policies should be designed in such a way that the negative externalities created by the current policies can be internalized, while causing no harm to economic growth pattern. Continuous dependence on the fossil-fuel-based energy consumption might lead towards not only the depletion of nonrenewable natural resources, but also the deterioration of environmental quality by causing ambient air pollution and diminishing the ecological balance. Moreover, the reliance on the imported outdated technologies might give short-run economic benefits at the cost of sustainable long run economic development. Therefore, the policymakers should start investing on the discovery of alternate clean energy solutions, while catalyzing the research and development within the nation for developing cleaner production technologies. While doing this, the policymakers should gradually remove the harmful subsidies on fossil fuel consumption, and restrict the sanctions to captive coal-based power plants. Imposition of environmental taxation policies on industries might discourage them from using the environmental deteriorating technologies. At the same time, the policymakers should also introduce subsidies in interest rates on credits for green projects, and for firms with low CO2 footprint. This will also encourage the industries to implement green technologies in their production processes. While both of these policies will be in place, the industries will look into the import of green technologies, and foreign firms trying to open the plants in China will have to follow the environmental norms, which are set through credit policies to industries. In this way, the trade route will be used for importing of green technologies. When these policies are in place, then China will be able to address the issues of environmental degradation (objective of SDG 13). At the same time, gradual rise in the demand of green energy will allow China to achieve clean and affordable energy for both industry and households (objective of SDG 7). These policy moves need to be devised at the first phase of implementation.

Once the first phase policies are implemented, the second phase of policies need to implemented, to stabilize the policies devised in the first phase. In this phase, it should be remembered that when fossil fuel-based energy consumption will fall, the mining and coal-based power production industry would face a fall in demand, which will be translated into unemployment issues. This problem might appear in the short run. If the policymakers ponder upon encouraging people-public-private partnerships in designing the clean energy solutions at the grassroots level, then it might create several green jobs. Moreover, this move by the policymakers is required, as the demand of renewable energy will gradually rise with the shift from nonrenewable to renewable energy solutions, and the renewable energy infrastructure might not to be able to cater to the rise in demand. Therefore, the surplus labor from the mining and coal-based power production industry might be employed in these places. In this way, the policymakers should be able to tackle the issue of unemployment arising out of the shift of energy solutions. Once these policy measures are implemented, China will be able to provide affordable and clean energy solutions, tackle environmental issues, sustain ecological balance, while providing sustainable jobs to the labors. The policies devised at this phase, will help China in achieving the sustained economic growth (objective of SDG 8).

As a final step to institutionalize the policies devised in the previous two phases, China should move into the third phase of policy implementation. One of the ways to institutionalize the policies is to educate the people about them, and to achieve this at the grassroots level, policymakers should make amendments in the educational curriculum to educate the people about environmental benefits of green energy, and energy efficiency. This educational reform should be complemented by the environmental regulations for protecting public goods and controlling environmental degradation. This move will enhance the quality of education in China (objective of SDG 4).

Data Availability statement: The data that support the findings of this study are available in China Statistical Yearbook at http://www.stats.gov.cn/english/Statisticaldata/AnnualData/ .

Table-1: Summary Statistics and Correlation

Variables	$\ln E_t$	$\ln Y_t$	$\ln Y_t^2$	$\ln K_t$	$\ln F_t$	$\ln F_t^2$
Obs.	510	510	510	510	510	510
Mean	0.8595	9.7278	95.1329	11.3165	8.6904	77.2534
Std. Dev.	0.5684	0.7100	13.8340	0.8417	1.3166	23.5886
Min	-1.1027	7.9165	62.6704	9.4589	5.7966	33.6004
Max	2.1144	11.3933	129.8076	12.9252	12.2137	149.1746
$\ln E_t$	1.0000					
$\ln Y_t$	0.7191	1.0000				
$\ln Y_t^2$	-0.7134	0.9991	1.0000			
$\ln K_t$	-0.6047	0.6124	0.5985	1.0000		
$\ln F_t$	0.4289	0.8193	0.8223	0.2562	1.0000	
$\ln F_t^2$	-0.4206	0.8096	0.8151	0.2217	0.9965	1.0000

Table-2: Variance Inflation Factors (VIF) and Tolerance

Variables	*Before transformation*		*After transformation*	
	VIF	*Tolerance*	*VIF*	*Tolerance*
$\ln E_t$	2.60	0.3852	1.00	1.0000
$\ln Y_t$	1305.25	0.0008	1.00	1.0000
$\ln Y_t^2$	1269.12	0.0008	1.00	1.0000
$\ln K_t$	2.93	0.3415	1.00	1.0000
$\ln F_t$	330.75	0.0030	1.00	1.0000
$\ln F_t^2$	335.45	0.0030	1.00	1.0000

Table-3: Chudik and Pesaran (2015) Weak Cross-Sectional Dependence Analysis

Variables	Test statistic	p-value	Variables	Test statistic	p-value
$\ln E_t$	78.359	0.000	$\ln K_t$	85.945	0.000
$\ln Y_t$	85.987	0.000	$\ln F_t$	85.896	0.000
$\ln Y_t^2$	85.965	0.000	$\ln F_t^2$	85.612	0.000

Table-4: Second-Generation Unit Root Analysis

Variables	Herwartz and Siedenburg (2008)		Herwartz et al. (2017)	
	Level	First Diff.	Level	First Diff.
$\ln E_t$	1.0312	-0.0095[a]	2.1723	-3.4907[a]
$\ln Y_t$	1.0101	0.7707[a]	3.0593	-2.5007[a]
$\ln Y_t^2$	1.0197	0.7722[a]	3.1498	-1.4208[a]
$\ln K_t$	1.0126	0.7808[a]	3.2936	-1.4708[a]
$\ln F_t$	1.0111	0.3183[a]	2.7776	-4.7506[a]
$\ln F_t^2$	1.0204	0.3015[a]	2.7115	-4.9706[a]

Note: a significant value at 1%.

Table-5: Westerlund and Edgerton (2008) Cointegration Analysis

	Model 1		Model 2		Model 3	
Test	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value
LM_τ	-5.870	0.000	-3.452	0.000	-2.448	0.007
LM_ϕ	-8.509	0.000	-3.429	0.000	-3.796	0.000

Note: Model (1): model with a maximum number of 5 factors and no shift.
Model (2): model with a maximum number of 5 factors and level shift.
Model (3): model with a maximum number of 5 factors and regime shift.

Table-6: Structural Breaks in Westerlund and Edgerton (2008) Cointegration Test

Provinces	*No Shift*	*Mean Shift*	*Regime Shift*
Beijing	2002	2004	2004
Tianjin	2002	2004	2005
Hebei	2002	2002	2001
Shanxi	2002	2003	2003
Neimenggu	2002	2001	2001
Liaoning	2002	2001	2001
Jilin	2002	2003	2001
Heilongjiang	2002	2001	2014
Shanghai	2002	2002	2014
Jiangsu	2002	2002	2014
Zhejiang	2002	2002	2014
Anhui	2002	2005	2014
Fujian	2002	2007	2014
Jiangxi	2002	2007	2007
Shandong	2002	2007	2007
Henan	2002	2002	2005
Hubei	2002	2002	2008
Hunan	2002	2002	2002
Gaunggong	2002	2002	2002
Guangxi	2002	2002	2003
Hainan	2002	2002	2004
Chongqing	2002	2001	2003
Sichuan	2002	2014	2003
Guizhou	2002	2014	2005
Yunnan	2002	2014	2014
Shannxi	2002	2014	2014
Gusu	2002	2004	2014
Qinghai	2002	2005	2014
Ningxia	2002	2001	2014
Xinjiang	2002	2003	2014

Table-7: Results of Bootstrap Quantile Regression Analysis

Variables	$Q_{0.1}$	$Q_{0.2}$	$Q_{0.3}$	$Q_{0.4}$	$Q_{0.5}$	$Q_{0.6}$	$Q_{0.7}$	$Q_{0.8}$	$Q_{0.9}$
Model I									
$\ln Y_t$	2.6512[a]	3.0683[a]	2.6104[a]	1.9275[b]	2.6171[a]	1.1994	1.1847[b]	1.5212[a]	-0.9664[a]
$\ln Y_t^2$	-0.0892[a]	-0.1056[a]	-0.0822[a]	-0.0487	-0.1056[b]	-0.0182	-0.0408[c]	-0.0606[b]	0.1004[a]
$\ln K_t$	-0.0478[c]	-0.0786[a]	-0.0737[a]	-0.0280	-0.0389[a]	0.1305[c]	0.1205[a]	0.1998[a]	0.0026[b]
$\ln F_t$	-0.1607[a]	-0.2229[a]	-0.2339[a]	-0.2379[a]	0.0074	0.0296	0.0663[a]	0.0463	0.0003
Constant	-14.8914[a]	-16.3995[a]	-14.0853[a]	-11.0163[b]	-14.6150[a]	-11.3110	-7.9502[a]	-10.1100[a]	-9.5336[a]
Shape of EKC	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	U-shaped
Turnaround Point	28,44,752.27	20,38,929.77	78,68,244.23	Very large	2,40,763.88	Very large	20,19,544.10	2,82,421.27	123.07
Model II									
$\ln Y_t$	6.8672[a]	5.8524[a]	5.6713[a]	4.9262[a]	8.7988[a]	3.9006[a]	4.6062[a]	2.5947[b]	-0.9853[a]
$\ln Y_t^2$	-0.1381[a]	-0.0856[a]	-0.0707[a]	-0.0333[b]	-0.3623[a]	-0.1569[b]	-0.1954[a]	-0.1065[b]	0.0944[a]
$\ln K_t$	-1.0781[a]	-1.0896[a]	-1.1284[a]	-1.1347[a]	-0.1219[a]	0.0451	0.0603	0.1949[a]	0.0460[a]
$\ln F_t$	1.1168[a]	1.1085[a]	1.1414[a]	1.1406[a]	-2.3549[a]	-1.3645[a]	-1.2523[a]	-0.3778	-0.0401[a]
$\ln F_t^2$	-0.1052[a]	-0.1042[a]	-0.1076[a]	-0.1076[a]	0.1074[a]	0.0659[a]	0.0611[a]	0.0172	0.0039[a]
Constant	-32.6273[a]	-27.6524[a]	-26.5795[a]	-22.7841[a]	-39.1212[a]	-15.9015[a]	-19.7860[a]	-14.1985[a]	-9.7614[a]
Shape of EKC (with respect to $\ln Y_{it}$)	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	U-shaped
Turnaround Point	Very large	Very large	Very large	Very large	1,87,770.44	2,50,248.66	1,31,477.58	1,95,182.47	184.70
Shape of EKC (with respect to $\ln F_{it}$)	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	Inverted U-shaped	U-shaped	U-shaped	U-shaped	U-shaped	U-shaped
Turnaround Point	201.94	204.20	201.12	200.37	57,712.07	31,344.91	28,224.74	58,838.88	170.89

Note: regressions have been run with 200 bootstrap replications and 95% confidence level.
a significant value at 1%.
b significant value at 5%.
c significant value at 10%.

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