1. Investigate the economic growth-energy consumption relationship.
2. Propose a non-parametric panel data model to this topic.
3. Energy consumption has time-varying impacts on economic growth.
4. Energy consumption promotes the economy differently across provinces in China.
5. Heterogeneous energy policy for industrial sectors with different carbon intensities.

Dynamic impacts of energy consumption on economic growth in China: Evidence from a non-parametric panel data model

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Abstract

To empirically gauge the efficacy of energy policies, we propose a non-parametric method to investigate the relationship between economic growth and energy consumption from both time and space perspectives. Specifically, we rely on the local linear dummy variable estimation (LLDVE) method to explore the time-varying province-specific trends, the common trend, and the coefficients based on panel data from 26 provinces in China from 1995 to 2017. We find that the promotion effect of energy consumption on economic growth changes over time, as evidenced by the inverted U shape of the relationship. Moreover, the non-parametric model captures such an effect better than the parametric model. With the dual goals of sustainable economic growth and carbon emissions reduction in mind, we classify the sample according to the degree of carbon intensity, which indicates that energy efficiency should be improved in high-carbon development areas, while more attention should be paid to investment and innovations in low-carbon development areas.

Keywords: Energy consumption, Economic growth, Time-varying, Non-parametric

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1. Introduction

The last four decades have witnessed tremendous growth in the Chinese economy accompanied by the reform and opening. The rapid economic development is closely related to the energy consumption (see, e.g., Tang & Tan, 2014; Armeanu et al., 2017; Sun et al., 2018; Dong et al., 2021). However, the impact of energy consumption on economic growth may change in time and space (see, e.g., Sun et al., 2018; Chica-Olmo et al., 2020; Radmehr et al., 2021; Wang et al., 2021). As shown in Fig 1, the energy consumption in eastern China is greater than that in western China. The huge cross-sectional heterogeneity among provinces in China motivates us to investigate the complex effect between economic growth and energy consumption in China, to shed light on the future economic and energy policies in different areas.[1]

[Figure 1 about here.]

This study considers a non-parametric model to investigate the time-varying reliance of economic growth on energy consumption across different Chinese provinces. Specifically, based on annual macro data concerning 26 provinces in China over the period 1995-2017, we start with testing the stationarity and cross-sectional dependence of the panel data. Next, as a benchmark, we use a parametric model (i.e., panel data model with fixed effects) to investigate the association between China's energy con-

[1] For example, government agencies have set the goal of achieving carbon neutrality by 2060 to reduce carbon emissions.

sumption and its economic growth, controlling for innovations, labor, and investment as factors that drive economic growth (Youssef, 2020; Chica-Olmo et al., 2020; Ivanovski et al., 2021). Beyond the fixed effect indicated by the benchmark model, we find the promotion effect and the variations in different areas. To capture the time-varying impact of energy consumption on economic growth, we employ the local linear dummy variable estimation method (LLDVE, proposed by Li et al., 2011) to determine the time-varying and province-specific trends, common trend, and coefficient functions. The leave-one-unit-out least-square cross-validation method is used to select the optimal bandwidth, while the bootstrapping method is adopted to determine the confidence interval. Compared with the traditional parametric models, our non-parametric model can better describe the dynamic impacts of energy consumption on economic growth in China.

Our empirical results suggest that energy consumption can significantly promote economic growth for most of the sample period, with its promotion effect being a time-varying effect. Through observing the common trend and the province-specific trend, we find that China's economic growth trend is still increasing, although its growth rate has declined. There are certain differences in terms of the effects of the studied variables on economic growth among the different provinces. Our empirical results also imply that investments and innovations represent the best means of maintaining the growth of the low-carbon economy.

We make three contributions to the existing literature. First, we propose the use of non-parametric models to study the influence of energy consumption on economic growth. Previous studies have mostly used parametric models (Costantini & Martini, 2010; Shahbaz et al., 2020; Radmehr et al., 2021), and they have generally only considered the average effects of certain variables on economic growth. However, time exerts an important influence on the relationships between variables, and such relationships can be time-varying (Magazzino et al., 2021; Wang et al., 2021). Traditional parametric models cannot accurately describe such an effect, since these models often involve strict assumptions. Thus, the LLDVE method with unknown functional forms employed in the present study can provide more insights into the time-varying effects in a more accurate way.

Second, we find the time-varying common trend as well as the province-specific trends in economic growth in China. These time-varying trends and their variations among different provinces cannot be captured by the traditional linear estimations. Moreover, we use panel data concerning the Chinese provinces from 1995 to 2017, whereas most existing studies regarding the impact of China's energy consumption on its economic growth rely on time series data. The use of panel data can increase the degree of freedom and enhance the estimation efficiency (Silvapulle et al., 2017).

Third, we provide more specific suggestions for economic growth policy, comparing the high-carbon subsample with the low-carbon subsample. We divide our full sample into two subsamples based on the carbon emissions intensity and make comparisons. The results show regional differences in the influence among target variables. Policymakers are then recommended to improve energy efficiency in high-carbon development areas to maximize the positive impact of energy consumption on economic growth. For the low-carbon development areas, policymakers should pay more attention to investment level and patent conversion rate.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. In Section 3, we introduce the methodology applied in this study. Section 4 describes the data. The parametric and non-parametric results are discussed in Section 5, while Section 6 further adds robustness. Section 7 concludes.

2. Literature Review

The impact of energy consumption on economic growth is raising more and more attention in academia (see, e.g., Ren et al., 2021; Cheng et al., 2021, and reference therein). The extant literature has not reached a consensus on this issue. Some scholars believe there is a long-run cointegrated relationship between energy consumption and economic growth (Srinivasan & Ravindra, 2015; Shahbaz et al., 2020) while others reckon that economic growth and energy consumption exhibit Granger causality in both short and long run (Tang & Tan, 2014; Sun et al., 2018). For example, Koengkan & Fuinhas (2020) and Radmehr et al. (2021) identified a bidirectional relationship between energy consumption and economic growth. Acheampong et al. (2021) suggested economic growth and energy consumption are interdependent. However, some scholars support the idea that there is no clear connection between energy consumption and economic growth (see, e.g., Narayan, 2016). In a nutshell, the impact of energy consumption and economic growth is complex.

The complex impact of energy consumption on economic growth have been examined by dividing energy into renewable energy and non-renewable energy (Chica-Olmo et al., 2020; Ivanovski et al., 2021). Other variables, such as carbon emissions, have been added to explore the relationships among multiple variables (Cheng et al., 2019; Duan et al., 2021). Some authors have explored different time intervals, such as the short and long term, and observed the influence of time on the relationship between energy consumption and economic growth (Le et al., 2020; Magazzino et al., 2021; Wang et al., 2021). In a similar vein, other authors have considered the variations among different regions when studying the spatial relationship between economic growth and energy consumption (Sun et al., 2018; Chica-Olmo et al., 2020; Radmehr et al., 2021). We investigate such issues associated with the cross-sectional heterogeneity among provinces in China.

In addition to energy consumption, some other factors may also affect economic growth, such as technology innovations, investment, and labor characteristics. As a proxy for technology innovations, patents can effectively promote economic growth (see, e.g., Niwa, 2016; Youssef, 2020). Dang & Motohashi (2015) evaluated the impact of patent subsidy policies on the quality and quantity of patents in China and concluded that patents, R&D input, and financial output are all closely related. For some countries, the investment could promote domestic economic growth (see, e.g., Blomström et al., 1996; Yu, 1998). The labor standards or the age distribution of the population could also affect the economic growth (see, e.g., Bonnal, 2010; Hondroyiannis & Papapetrou, 2001). Thus, we consider technology innovations, investment, and labor as control variables when exploring the key drivers of economic growth.

From the methods point of view, existing studies have adopted different econometric approaches to study the relationship between economic growth and energy consumption, including the generalized method of moments (Omri, 2013; Adams et al., 2016), vector autoregression (Ouyang & Li, 2018; Chen, 2012), vector error correction model (VECM) (Mahadevan & Asafu-Adjaye, 2007; Jian et al., 2019), autoregressive distributed lag (Shahbaz et al., 2012; Chandio et al., 2019). The VECM and cointegration test are the most common methods used to study the relationships between variables. For example, Costantini & Martini (2010) used the VECM for non-stationary panel data. Different from previous literature, panel data is applied to explore the relationship between energy consumption and economic growth. This is mainly because panel data contain time-series and cross-sectional changes, which can enhance the degree of freedom and help to generate more efficient estimates. The present study differs from previous studies in that we investigate the time-varying reliance of economic growth on energy consumption to achieve the dual objectives of sustainable economic growth and lower carbon emissions.

The complexity of this issue may arise due to its dynamic changes in space and time dimensions. To the best of our knowledge, only a few studies have captured the dynamic relationship over a long sample period (Narayan, 2016; Radmehr et al., 2021; Wang et al., 2021). These studies mainly use parametric models, which involve strict parameter-setting conditions. In contrast to the parametric models, we introduce a non-parametric model to estimate the non-linear impact of energy consumption on economic growth, which may change over time. We investigate both the common and province-specific trends of economic growth in China, shedding light on effective energy policies in China. The results could also provide some evidence on energy policies in other countries with heterogeneous areas.

3. Data

We use yearly data concerning 26 provinces in China.[2] Our data cover the period 1995–2017. Thus, there are 26 cross-section units and 23 time-series observations per cross-section unit. We also rely on internationally accepted practices to convert the carbon dioxide emissions from the perspective of total energy consumption. Then, we calculate the average carbon dioxide emissions per unit of GDP based on 23 years of data for each province. The 13 provinces with the lowest carbon dioxide emissions per unit of GDP are considered the low-carbon development areas, while the remainder is

[2]The 26 provinces are Anhui(AH), Beijing (BJ), Fujian (FJ), Gansu (GS), Guangxi (GX), Guizhou (GZ), Hebei (HE), Henan (HA), Heilongjiang (HL), Hubei (HB), Hunan (HN), Jilin (JL), Jiangsu (JS), Jiangxi (JX), Liaoning (LN), Inner Mongolia IM (NM), Qinghai (QH), Shandong (SD), Shanxi (SX), Shaanxi (SN), Shanghai (SH), Sichuan (SC), Tianjin (TJ), Xinjiang(XJ), Yunnan (YN), and Zhejiang (ZJ). We do not choose Guangdong, Tibet, Chongqing, Hainan, and Ningxia because of missing observations during this sample period. Specifically, in terms of total energy consumption, Chongqing lacks data for 1995 and 1996, Ningxia lacks data for 2001, and Tibet lacks all data for the time interval. Hainan and Guangdong lack fixed asset investment price indices before 1999 and 2000, respectively.

considered the high-carbon development areas.

The variables included in Table 1 are the GDP, energy consumption (EC), population (POP), investment in fixed assets (INV), the total number of patents granted (PAT), and the number of utility model patents granted (PAT2). The unit of the GDP and INV is 100 million yuan, while the unit of the POP and EC is 10,000 people and 10,000 tons of standard coal, respectively. We obtain all variables from China Stock Market & Accounting Research (CSMAR) database. The nominal GDP and investment in fixed assets are deflated by the GDP index and fixed asset investment index in the CSMAR database, respectively, to obtain the real values. To render the data more stationary, we take all variables in logs. We derive descriptive statistics based on variables, as shown in Table 1. The mean value of energy consumption is 8.9631. Energy consumption is not heterogeneous in different Chinese provinces, since the coefficient of variation (SD/mean) in terms of energy consumption is just 0.081. The coefficient of variation regarding the number of patents granted is much larger, standing at 0.200. The number of utility model patents granted accounts for a large proportion of all patents. As expected, large gaps are seen concerning economic growth among the different provinces.

[Table 1 about here.]

4. Methodology

To accurately capture how energy consumption affects economic growth, we adopt a non-parametric model with an unknown functional form and use a traditional parametric model as a benchmark.

4.1. Parametric panel data model

In comparison with the non-parametric model, we use the panel data model with fixed effects, which has the following form:

$$\triangle lnY_{it} = \alpha_i + \beta_1 \triangle lnEC_{it} + \beta_2 \triangle lnPOP_{it} + \beta_3 \triangle lnINV_{it} + \beta_4 \triangle lnPAT2_{it} + e_{it}, \tag{4.1}$$

where α_i captures unobserved time-invariant individual heterogeneity, β_1, β_3 and β_4 are coefficients of variables, and e_{it} represents the random error term. After performing the CSD test (cross-sectional dependence test) and unit root test, we build the above model for the stationary data after the difference. We have established three parametric panel models for the total sample, high-carbon development area sample, and low-carbon development area sample, respectively.

4.2. Panel data model with time-varying trend and coefficient functions

Li et al. (2011) proposed a local linear dummy variable estimation(LLDVE) method to estimate time-varying trends and coefficients. In addition, Silvapulle et al. (2017) did further research on the LLDVE method. Due to the excellent performance of this method to describe time-varying relationships, we adopt the LLDVE method to study how energy consumption and patents affect economic growth. Our fixed-effect panel data model is as follows:

$$Y_{it} = f_t + X_{it}^T \beta_t + \alpha_i + e_{it}, i = 1, 2, ...N; t = 1, 2, ...T, \tag{4.2}$$

$$X_{it} = \left(\triangle lnEC_{it}, \triangle lnPOP_{it}, \triangle lnINV_{it}, \triangle lnPAT2_{it}\right), \tag{4.3}$$

$$\beta_t = \left(\beta_{t,1}, \beta_{t,2}, \beta_{t,3}, \beta_{t,4}\right), \tag{4.4}$$

where Y_{it} is the first difference of lnGDP and $f_t = f(t/T)$ is the unknown trend function. $\beta_{t,j}$ and f_t are vectors of time-varying coefficients and trend function. α_i is unobserved individual effects and e_{it} is the error term. To identify the relationship we conjecture, we assume that

$$\sum_{i=1}^{N} \alpha_i = 0. \tag{4.5}$$

We rewrite equation (4.2) as:

$$\tilde{Y} = \tilde{f} + \widetilde{B}(X, \beta) + \widetilde{D}\alpha + \tilde{e}, \tag{4.6}$$

where

$$
\begin{aligned}
\tilde{Y} &= \left(Y_1^\top, \ldots, Y_N^\top\right)^\top, \\
Y_i &= (Y_{i1}, \ldots, Y_{iT})^\top, \\
\tilde{e} &= \left(e_1^\top, \ldots, e_N^\top\right)^\top, \\
e_i &= (e_{i1}, \ldots, e_{iT})^\top, \\
\tilde{f} &= \bar{I}_N \otimes (f_1, \ldots, f_T)^\top = \bar{I}_N \otimes f, \\
\tilde{B}(X, \beta) &= \left(X_{11}^\top \beta_1, \ldots, X_{1T}^\top \beta_T, X_{21}^\top \beta_1, \ldots, X_{NT}^\top \beta_T\right)^\top, \\
\alpha &= (\alpha_1, \ldots, \alpha_N)^\top \\
\tilde{D} &= I_N \otimes \bar{I}_T,
\end{aligned}
$$

$\bar{I}_k$ is a $k \times 1$ vector of ones.

Due to (4.5), we further rewrite equation (4.6) as:

$$
\tilde{Y} = \tilde{f} + \widetilde{B}(X, \beta) + \widetilde{D}^* \alpha^* + \widetilde{e}, \tag{4.7}
$$

where the individual effects α_is are eliminated,

$$
\begin{aligned}
\alpha^* &= (\alpha_2, \ldots, \alpha_N)^\top, \\
\widetilde{D}^* &= \left(-\bar{I}_{N-1}, I_{N-1}\right)^\top \otimes \bar{I}_T.
\end{aligned}
$$

We use the leave-one-unit-out least-square cross-validation method to select optimal bandwidth, which is based on the study of Sun et al. (2009). In addition, following Mammen (1993) and Silvapulle et al. (2017), we adopt a bootstrapping method to construct confidence intervals for the time-varying common trend and coefficient functions. The process is described as follows:

Step 1: Obtain de-trended residuals $\hat{\varepsilon}_{it} = \hat{\mathrm{e}}_{it} - \hat{m}_i(\tau; b)$, where $\hat{\mathrm{e}}_{it}$ is from equation (4.2), b is the bandwidth for the kernel function, and $\hat{m}_i(\tau; b)$ is a province-specific trend. Let $\hat{\varepsilon}_t = (\hat{\varepsilon}_{1t}, \cdots, \hat{\varepsilon}_{Nt})$.

Step 2: Re-sample the de-trended residuals $\hat{\varepsilon}_t^* = \hat{\varepsilon}_{it}\eta_{it}$, where η_t is chosen to be $-\frac{\sqrt{5}-1}{2}$ with a probability of $\frac{\sqrt{5}+1}{2\sqrt{5}}$, $\frac{\sqrt{5}+1}{2}$ otherwise. Generate a bootstrapping sample of Y_{it} through $Y_{it}^* = \hat{f}(t/T) + X_{it}^\top \hat{\beta}_t + \hat{\alpha}_i + \hat{m}_i(\tau; b) + \hat{\varepsilon}_t^*$ for $i = 1, 2, \cdots, N$ and $t = 1, 2, \cdots, T$.

Step 3: Get estimates of time-varying common trend $\hat{f}^*(t/T)$, coefficients $\hat{\beta}_t^*$, and the individual trend $\hat{m}_i^*(t/T)$ by the LLDVE method.

Step 4: Repeat the above steps 1000 times and obtain 90% confidence intervals for the common trend, coefficient functions, and province-specific trend functions.

5. Empirical results and discussion

5.1. Cross-sectional dependence and unit root tests

Breusch & Pagan (1980) introduced a CSD test which has desirable effects when the size of time series T is much larger than the number of cross-sectional units N. A corrected test was proposed by Pesaran (2021) with more desirable properties when $N > T$. In this study, cross-sectional units are more than time series, so we choose the CSD test proposed by Pesaran (2021). Table 2 shows the result of the CSD test. The null hypotheses of its variables are cross-sectional independent, which are rejected significantly in Table 2.

[Table 2 about here.]

Firstly, we use unit root tests such as LLC; HT; Fisher-Pperron proposed by Levin et al. (2002); Harris & Tzavalis (1999); Phillips & Pierre (1988) respectively. The Im et al. (2003) test relaxed the assumptions of a common rho and instead allowed each panel to have its own rho. Additionally, we adopt the second-generation unit root test introduced by Pesaran (2007). The data are nonstationary under the null hypothesis in the tests. The results are shown in Table 3, which means the variables are non-stationary in certain tests. However, all variables are stationary after the first order difference at 1% of significance.

[Table 3 about here.]

5.2. Parametric results

We employ the parametric fixed-effects regression model for the full sample and the two subsamples, and the results are shown in Table 4. For the full sample, both energy consumption and utility model patent grants exert a significant positive impact on economic growth. When compared with the other variables, the effect on economic growth is more significant. The point elasticity of GDP with respect to changes in energy consumption is approximately 0.13, which means that, on average, a 1% increase in energy consumption is associated with a 0.13% increase in GDP for the full sample. Based on the last two columns of Table 4, we find that energy consumption in high-carbon development areas has a more significant effect on GDP than in low-carbon development areas. However, utility model patent grants in high-carbon development areas have less of an effect on economic growth. The R^2 indicates the extent to which an explanatory variable explains the total variation of the explained variable. The R^2 difference of the three samples is relatively small, standing at around 48%, which indicates that 48% of the total variation of economic growth is explained by the model. The rejection of the null hypothesis following the F test indicates that, overall, the three models are significant. In conclusion, on average, energy consumption promotes economic growth significantly, particularly in high-carbon development areas. The results of the parametric model reflect that regions with different carbon emission intensities do have an impact on the relationship between energy consumption and economic growth. However, the shortcomings of the parametric model are also shown.

The parametric panel fixed-effects regression model has several potential problems. First, the model assumptions are strict, and incorrectly setting the model could easily lead to incorrect estimates. There are some insignificant variables in the three models. For example, in the total sample model and the low-carbon subsample model, the total population is not significant in relation to economic growth. Moreover, the model cannot explain the observed variation well. In addition, the parametric model only reflects the average relationships between variables and so cannot capture the time-varying relationships among variables. The relationships between economic growth, energy consumption, and the number of patents granted are complex, which means that the parametric model cannot describe the relevant associations. Thus, the present study applies non-parametric estimation methods to relax the model assumptions and determine more accurate relationships over time.

[Table 4 about here.]

5.3. Non-parametric results

Based on the limits of the above parametric model and the impact of the difference in carbon intensity on the relationship, we adopt a non-parametric model. After applying the LLDVE model, we could better obtain the relationships between variables over time as well as specific trends for each province (Yan et al., 2019). We analyze different results regarding three samples. Figures 2, 3, and 4 present the regression results concerning the full sample, the low-carbon subsample, and the high-carbon subsample, respectively. To ensure that our results are significant, we set 90% confidence bands in each figure. The specific analysis is as follows.

[Figure 2 about here.]

Figure 2 shows that China's economy is still, on average, in a significant growth stage, with the growth rate fluctuating around 0.1 during most stages. Throughout the whole sample period, the economic growth rate experienced two turning points. China's economy began to accelerate after 1999, while its economic growth slowed after 2008, and this trend continued until 2017. These two transitions are also consistent in terms of time with China's experience of the Asian financial crisis in 1997 and the global financial crisis caused by subprime mortgage loans in 2008.

Considering the coefficient of energy consumption in Figure 2, we provide evidence that the effect of energy consumption on economic growth is significantly positive for a long period after 2000, which indicates that an increase in energy consumption can significantly promote China's economic growth. As suggested by Li et al. (2011); Tang & Tan (2014), energy consumption plays a key role in fueling economic growth. Yet, different from previous studies, we observe that this positive impact gradually increases, reaching its highest value of 0.2 in 2007. The economic interpretation is that, on average, a 1% increase in energy consumption leads to a 0.2% increase in economic growth. After 2013, the impact of energy consumption on economic growth weakens, although the coefficient of energy consumption is still above 0. Figure 2 illustrates that the impact of energy consumption on economic growth from 1996 to 2017 changes over time. We consider time, and time certainly has an influence on the relationship (Magazzino et al., 2021; Wang et al., 2021). Unlike the above parametric model, we carry out further research from the dynamic time-varying relationship by the LLDVE method. As the impact of energy consumption on economic growth shows an inverted U shape, our results can fully consider the time-varying relationship throughout the whole sample period, rather than just an average estimate.

Figure 2 also illustrates the role of utility model patent grants in relation to economic growth. The coefficient of the number of utility model patents granted is seen to be significantly positive from 2004 to 2015, albeit below 0.05. Although previous studies support this finding (Crosby, 2010; Niwa, 2016), they ignore the time-varying relationship between patents and economic growth. Moreover, the positive impact of the number of patents on economic growth slowly increases after 2004, and then it slowly weakens after reaching around 0.04. The impact of the number of patents on economic growth is the same as the impact seen concerning the promotion of energy consumption, which also changes over time, although it is not as strong as the effect of energy consumption. These findings suggest that the impacts of energy consumption and the number of utility model patents granted on economic growth are both close to an inverted U shape. Chu et al. (2020) stated that patent protection stimulates economic growth in the short term but reduces economic growth in the long term. Yet, our findings imply that it will continue to promote growth, even though the promotion effect will be weakened, thereby indirectly indicating a low patent conversion rate in China.

To further investigate such relation associated with different areas, we take the provincial heterogeneity of carbon intensity into account (Sun et al., 2018; Le et al., 2020). More specifically, we divide the full sample into two subsamples, namely high-carbon development areas and low-carbon development areas. We compare the high-carbon subsample with the low-carbon subsample, also enhancing the robustness of our time-varying results.

[Figure 3 about here.]

[Figure 4 about here.]

Due to the large variation in terms of regional development in China, there are substantial differences in the carbon emissions intensity among various regions. We divide China's provinces into two groups: high-carbon development areas and low-carbon development areas. Based on the comparison of the two subsamples, we further investigate whether there are differences regarding the effects of energy consumption and utility model patent grants on economic growth under different carbon emission intensity conditions. In Figures 3 and 4, we compare the non-parametric results of the high-carbon development areas with those of the low-carbon development areas. First, in terms of the economic growth trends, the economic growth rate of the low-carbon development areas is slightly higher than that of the high-carbon development areas, although the overall trend is almost the same. This is consistent with the findings of Lin et al. (2020), who suggested the development of a low-carbon economy to promote the regional economy. However, our study differs somewhat because we compare the high-carbon development areas with the low-carbon development areas from the time perspective based on non-parametric models. Second, energy consumption in the high-carbon development areas has a more significant effect on economic growth than in the low-carbon development areas. The coefficient of energy consumption in the high-carbon development areas exceeds 0.2 from 2008 to 2013, while the coefficient remains below 0.2 in the low-carbon development areas throughout the sample period. The impact of energy consumption on economic growth in the low-carbon development areas in 2017 is not significant at the 5% level. This shows that in the high-carbon development areas, energy consumption plays a stronger role in promoting economic growth. Third, the number of utility model patents granted in the low-carbon emission areas has slightly more of an impact on economic growth than in the high-carbon emission areas. In 2008, in the low-carbon development areas, the coefficient of the number of utility model patents reaches 0.05, while the coefficient in the high-carbon development areas does not. This suggests that the patent conversion rate in the low-carbon development areas is slightly higher.

As shown in Figures 2-4, the total population and fixed asset investment significantly promote economic growth during some periods. More specifically, investment in fixed assets significantly affects economic growth throughout most of the period from 1996 to 2017. Different from previous studies that only provide estimates of the average effects of the factors driving economic growth based on parametric models, we capture the time-varying relationships. In the high-carbon development areas, the degree of influence declines year by year, while the impact of fixed asset investment on economic growth in the low-carbon development areas slowly increases, reaching 0.07 in 2017. However, under the combined effect of the low-carbon and high-carbon development areas, China's investment in fixed assets is still weakening in terms of promoting economic growth. The growth of the total population also significantly improves China's economic situation after 2008, and its positive impact gradually increases.

[Figure 5 about here.]

[Figure 6 about here.]

The economic growth trends of each province are similar to the common trend. The trends of each province are shown in red lines in Figures 5 and 6, while the blue line in the figures represents the common trend. The dotted lines represent the upper limit and the lower limit, respectively. The trends of the provinces in the low-carbon development areas are shown in Figure 5. The trends of all the provinces are significantly greater than zero, and the overall trend is downward, which indicates that economic growth has slowed down but is still growing. We find that the individual trends and the common trend of most provinces in the low-carbon development areas are very close to or fluctuate slightly around the common trend. However, Sichuan Province deviates from the common trend after changing from being lower than the common trend to being higher than the common trend. The high-carbon development areas shown in Figure 6 also fluctuate around the common trend, although the range of the fluctuation is higher than seen in relation to the low-carbon development areas. Among the provinces with large deviations, some are initially lower than the common trend and then exceed the common trend (e.g., Inner Mongolia, Guizhou, Yunnan), while some are initially higher than the common trend and then lower than the common trend (e.g., Shanxi).

6. Robustness

We use the total number of patents granted in each province to replace the number of utility model patents granted in the original non-parametric models to conduct robustness checks. The results are shown in Figure 7.

[Figure 7 about here.]

When comparing Figure 7 with Figure 2, we see that the impacts of the variables on economic growth do not obviously change after the replacement, which is likely due to the large proportion of utility model patents. More specifically, our results show that the coefficients of the patents decrease slightly over most of the sample period. Around 2008, the maximum value of the coefficient of the patents is less than that of the original non-parametric model, which reaches 0.05. This indicates that the conversion rate of most patents is low in China, which is known to be true (Fisch et al., 2016). However, the relationship we are concerned with does not change. Energy consumption and the number of patents can both significantly promote economic growth, and the promotion effect initially increases and then weakens over time, appearing close to an inverted U shape. Thus, we believe that the previous model and the results derived from it are relatively robust and that the relationships between the variables are time-varying.

7. Conclusion

To investigate the time-varying reliance of economic growth on energy consumption, we adopt both parametric and non-parametric models using data concerning 26 Chinese provinces from 1995 to 2017. The non-parametric LLDVE method helps to accurately estimate the relationships among variables over time as well as the economic growth trends of all provinces.

The common trend of economic growth across different provinces suggest that the Chinese economy is still growing, although its rate is slowing down. The economic growth rate peaked close to 0.11 around 2017. The province-specific economic growth trends in most provinces exhibit similarities with the common trend. Throughout most of the sample period, both energy consumption and the number of patents significantly promote economic growth, and the promotion effect shows an inverted U-shaped change over time. The high-carbon and low-carbon development areas exhibit similar economic growth trends and variable relationships. Yet, the energy consumption of the high-carbon development areas has a stronger effect on economic growth than that of the low-carbon development areas, while the effects of investments and patents on economic growth are slightly weaker than the low-carbon development areas.

Our results carry several important policy implications. First, it is important to improve energy efficiency and develop new energy sources. Compared with control variables, energy consumption can significantly promote economic growth. Second, it is vital to increase investment in innovations to stimulate economic growth, especially the patent conversion rate. The achievement of the high-quality development of the Chinese economy will require effective innovations. Third, policymakers should fully consider regional variations when formulating economic policies. They should pay more attention to innovations in low-carbon development areas. In terms of high-carbon development areas, increasing energy consumption can more significantly promote the regional economy. The implementation of these recommendations will make the achievement of the dual goals of economic growth and carbon emissions reduction more likely.

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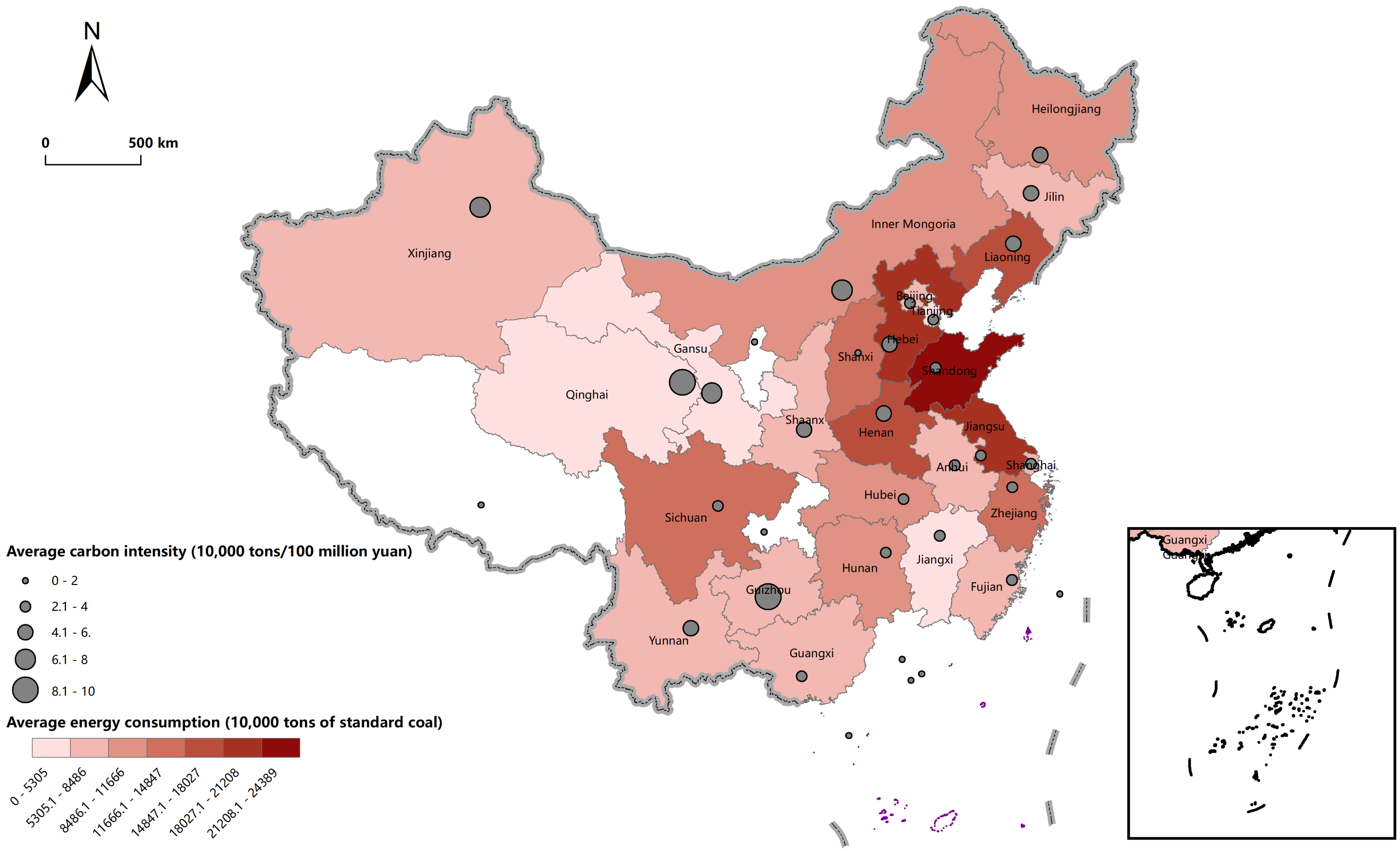

Figure 1: *Spatial characteristics of carbon intensity and energy consumption in China(Data source:CSMAR)*

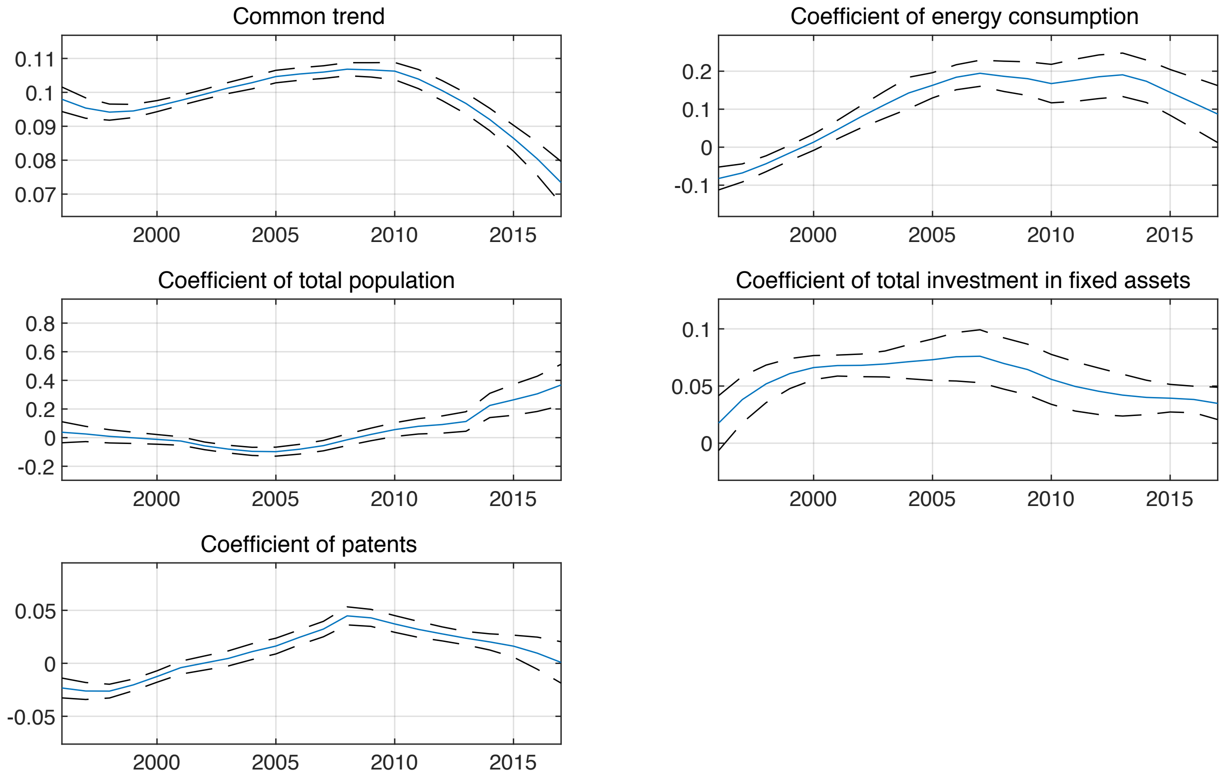

Figure 2: *LLDVE panel estimates of common trend and coefficients (solid blue lines), and their confidence intervals (dashed black lines) over the full sample.*

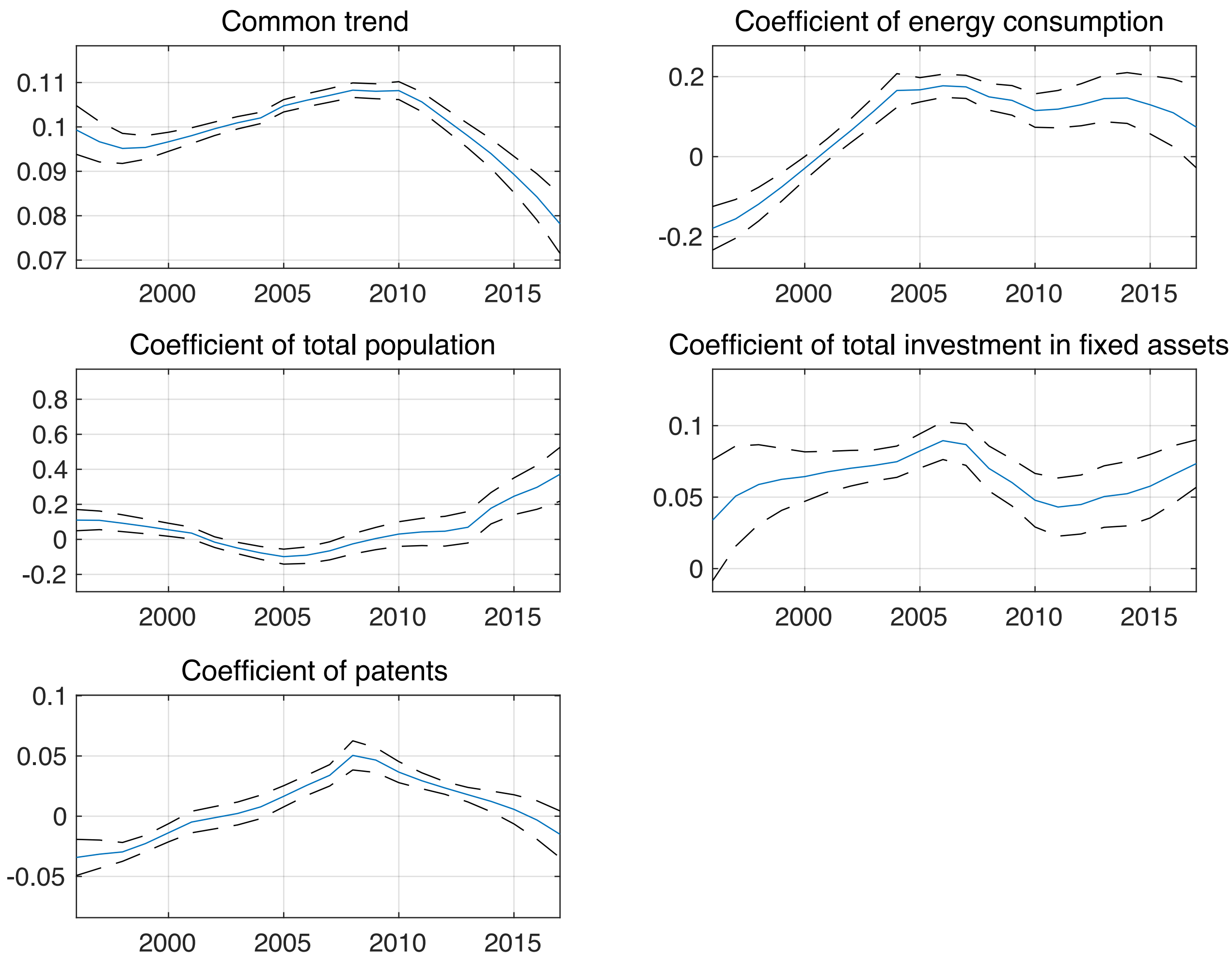

Figure 3: *LLDVE panel estimates of common trend and coefficients (solid blue lines), and their confidence intervals (dashed black lines) over the low-carbon sample.*

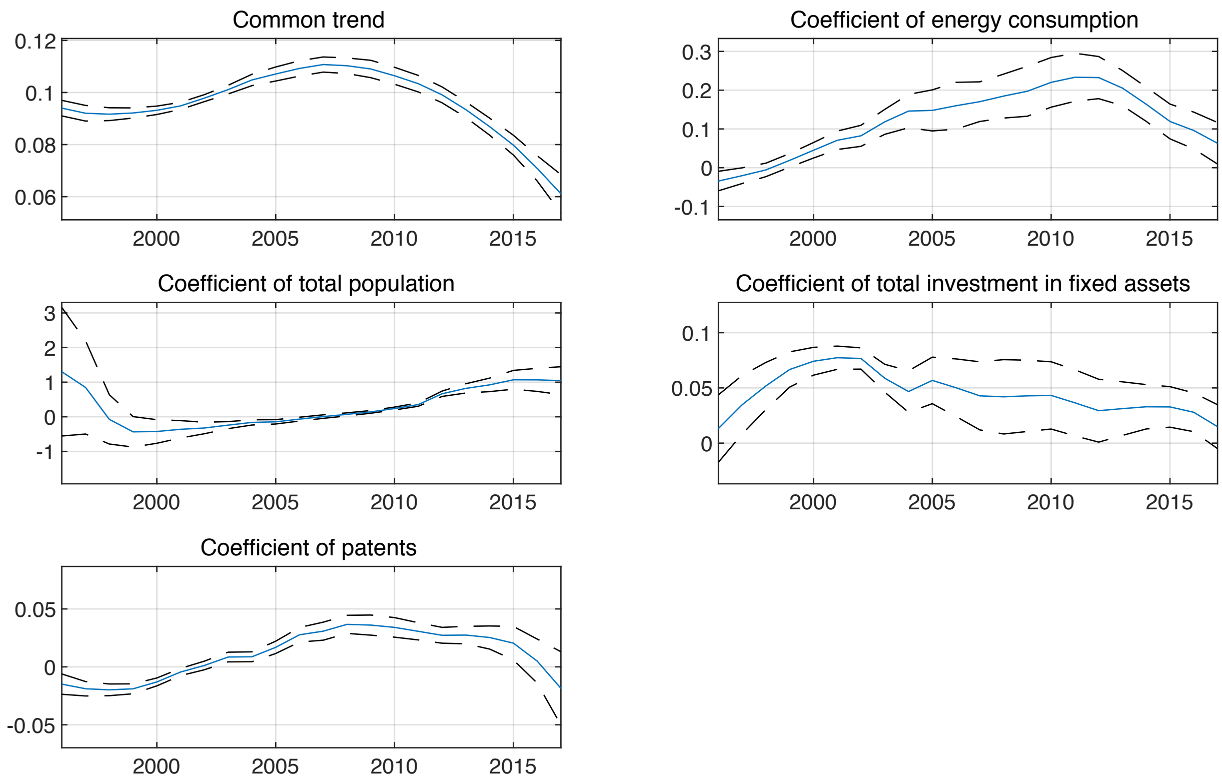

Figure 4: *LLDVE panel estimates of common trend and coefficients (solid blue lines), and their confidence intervals (dashed black lines) over the high-carbon sample.*

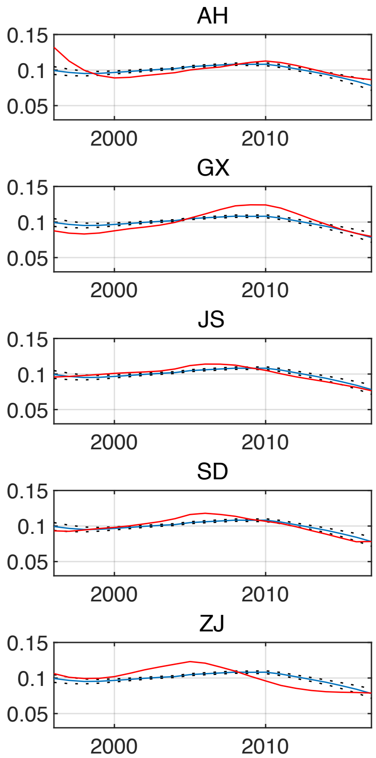

Figure 5: *Common trend (solid blue lines) and province-specific trends (solid red lines) over the low-carbon sample.*

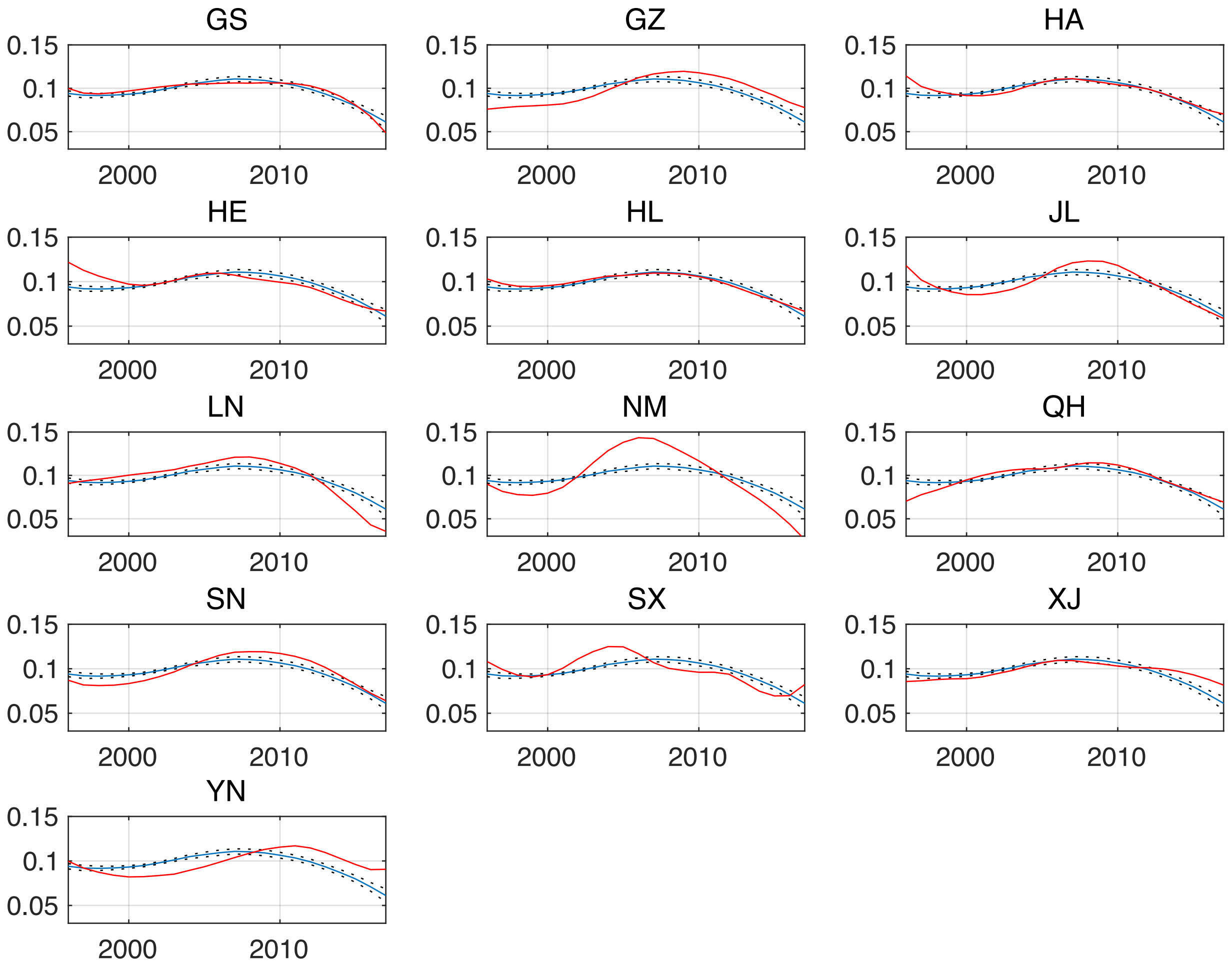

Figure 6: *Common trend (solid blue lines) and province-specific trends (solid red lines) over the high-carbon sample.*

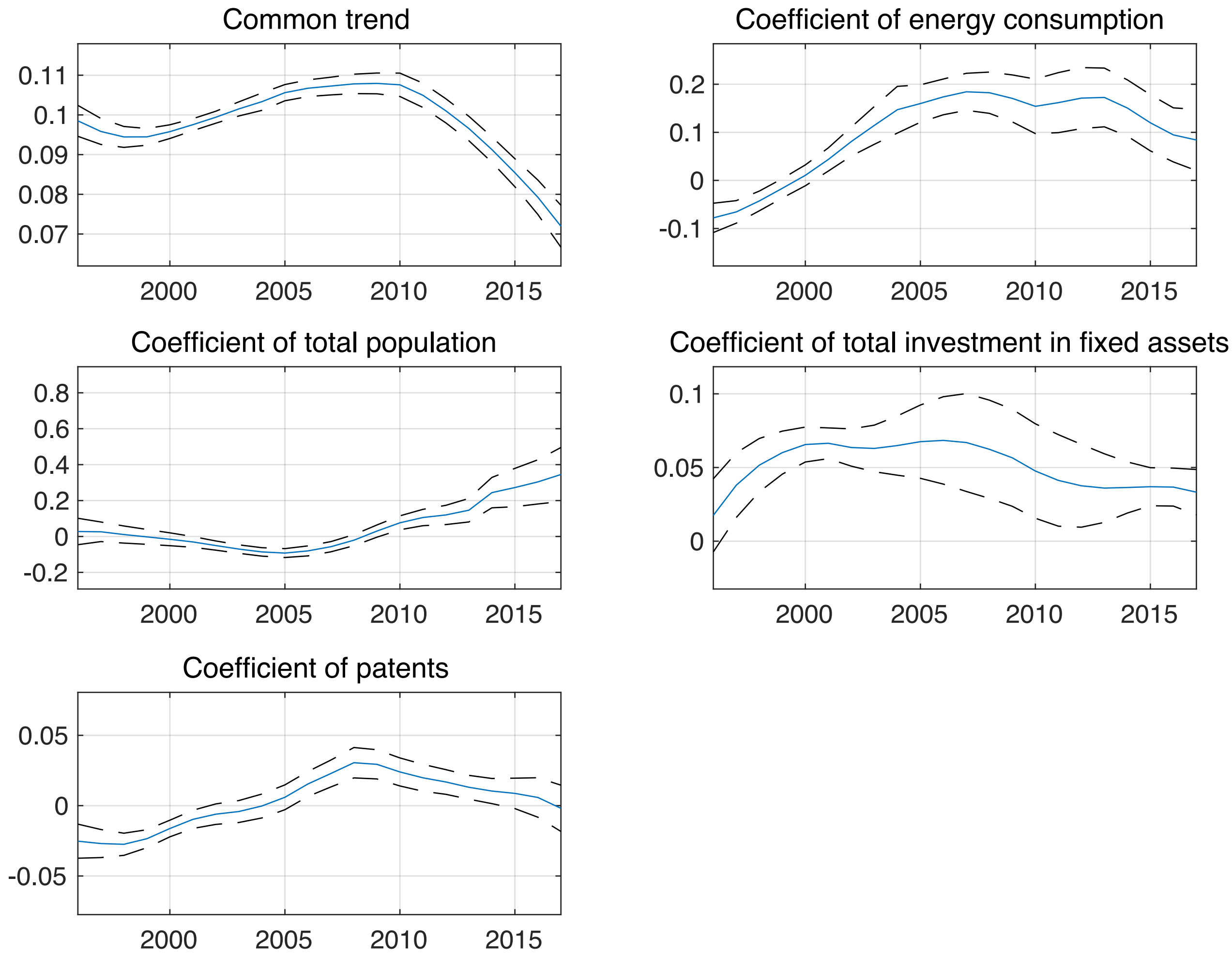

Figure 7: *LLDVE panel estimates of common trend and coefficients (solid blue lines), and their confidence intervals (dashed black lines) over the full sample.*

Table 1: *Descriptive statistics*

Variable	n	Mean	Std.Dev.	Min	Max
LnGDP	598	8.5063	1.0516	5.1078	10.9214
LnEC	598	8.9631	0.7255	6.5338	10.6001
LnINV	598	7.7988	1.2811	3.9724	10.5003
LnPOP	598	8.2246	0.6647	6.1759	9.3440
LnPAT	598	8.3198	1.6665	3.7842	12.4437
LnPAT2	598	7.8230	1.6073	3.3322	11.7486

Table 2: *Cross-sectional dependence test*

Variables	LnGDP	LnEC	LnINV	LnPOP	LnPAT	LnPAT2
CSD-test	86.270 (0.000)	84.229 (0.000)	84.716 (0.000)	42.743 (0.000)	84.693 (0.000)	84.579 (0.000)

Note: (i) CSD test of Pesaran (2021) is applied, whose null hypothesis are cross-sectional independence. (ii) The p-values are shown in parenthesis.

Table 3: *Unit root tests*

Variables		LLC	HT	Fisher-pperron	IPS	CIPS
LnGDP	Level	−3.6718***	1.0004	115.5972***	−0.6117	−1.910
	First difference	−9.4815***	0.7247***	102.0367***	−4.3796***	−3.132***
LnEC	Level	−3.8790***	0.9889	149.7304***	−1.6047*	−2.399***
	First difference	−18.9649***	0.0106***	663.9057***	−16.3189***	−4.509***
LnINV	Level	−2.6176***	0.9847	33.6618	1.1973	−1.545
	First difference	−11.8923***	0.4249***	193.1269***	−7.6781***	−2.585***
LnPOP	Level	−3.7658***	0.6164**	104.7123***	−3.1264***	−2.280
	First difference	−16.6910***	0.1293***	674.0179***	−14.8656***	−3.856***
LnPAT	Level	−1.4201*	1.0018	115.2886***	−0.4050	−2.357
	First difference	−18.6081***	0.0862***	699.1543***	−15.4330***	−4.254***
LnPAT2	Level	−1.9211**	1.0008	62.9650	0.2936	−2.092
	First difference	−18.0759***	0.1581***	742.6190***	−14.1334***	−4.151***

Note: (i) The null hypothesis of above unit root tests is that panels contain unit roots. (ii) ***, **, and* denotes statistical significance at the 1%, 5%, and10% level respectively.

Table 4: *Parametric estimates*

	Full sample	Low-carbon subsample	High-carbon subsample
dlnec	0.130***	0.109***	0.150***
	(0.015)	(0.019)	(0.022)
dlnpop	−0.098	−0.090	−0.070
	(0.076)	(0.075)	(0.090)
dlninv	0.092***	0.092***	0.092***
	(0.012)	(0.014)	(0.016)
dlnpat2	0.018***	0.022***	0.015***
	(0.004)	(0.005)	(0.006)
constant	0.079***	0.079***	0.073***
	(0.004)	(0.004)	(0.006)
F	12.130***	11.870***	2.940***
R^2	0.482	0.420	0.524
Observations	572	286	286

Note: (i) ***, **, and* denotes statistical significance at the 1%, 5%, and 10% level respectively. (ii) The standard errors are shown in parenthesis.