RESEARCH ARTICLE

Effect of market fragmentation on ecological efficiency: evidence from environmental pollution in China

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Abstract

Local governments restrict cross-regional flows of factors and products for achieving the purpose of profit, which lead to market fragmentation. China's domestic market is fragmented, leading to the situation that market boundaries are demarcated. We use the relative price method to measure market fragmentation and find that market fragmentation is indeed a serious problem in China. This study evaluates the ecological efficiency using the bootstrap DEA method that takes air and water pollution into account and investigates the effect of market fragmentation on ecological efficiency based on the system GMM approach by employing data from a panel of 29 provinces in China during the period 2000–2015. The results indicate that there are differences in ecological efficiency among provinces. The market fragmentation has negative impact on ecological efficiency, which shows market fragmentation significantly inhibits the improvement of ecological efficiency. The similar findings are confirmed by a series of robustness tests, which include the alternative indicator and sub-sample regression. Based on the above findings, the central government should reduce market fragmentation, promote market integration, increase the efficiency of resource allocation, and improve environmental quality.

Keyword Market fragmentation · Ecological efficiency · Bootstrap DEA · Relative price method · Air and water pollution

Introduction

Market-oriented reform and economic globalization are important factors for China to make great achievements and become the second largest economy in the world (Fan et al. 2003). The relationship between government and market, as well as government and society, has gradually improved in the process of market-oriented reform. However, market-oriented reform fails to effectively improve the integrity of the domestic market (Young 2000). China's domestic market is far less integrated. Because of the imbalance of resources endowment and economic development in space, there are great differences in the ecological efficiency among provinces. If the country can further optimize the utilization of resources among provinces, it will greatly improve the ecological efficiency. Unfortunately, China's domestic market is a segmented market rather than an integrated one, which will inevitably affect the flow and allocation of resources among provinces. The allocation efficiency of resources among provinces has an important impact on environmental efficiency (Lin and Chen 2018; Dai and Cheng 2016). Under the parallel system of fiscal decentralization and administrative centralization, local protectionism driven by local government competition leads to market fragmentation. Market fragmentation means that local governments restrict the access of resources in other regions to local markets or restrict the flow of local resources to other regions to form intangible barriers and protect local industries for their own interests. Market fragmentation delays research and development (R&D) investment, induces slow technological progress, and results in increasing environmental uncertainty and pollution emission (Wei and Zheng 2017; Yang et al. 2018; Bian et al. 2019). Ecological efficiency is an indicator for evaluating the impact of environment on economic development. The improvement of ecological efficiency is simplified to achieve more economic output with less

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environmental cost (Ma et al. 2018). This leads to a natural question whether market fragmentation among regions inhibits the improvement of ecological efficiency? This study tries to respond to this question.

The average shipping distance of goods indicates the China's domestic market fragmentation. This distance of goods by railway increased by only 7.4%, far less than the average travel distance of railway passengers which increased by 94.8% and the total length of operating railway which increased by 34.7% (Ding and Niu 2019). Market fragmentation is also reflected directly or indirectly from the following aspects. First, provincial boundaries hinder the development of domestic trade (Poncet 2003). Local protectionism involves barriers to the transport of domestic imports and price of domestic imports, higher requirements for product quality and technical standards from other provinces, subsidy to local corporations, and protection of local enterprises from kinds of risk. China's political isolation and the insufficient interprovincial transport infrastructure have led it to adopt an inward development strategy, which has resulted in local protectionism (Poncet 2005). Local protectionism leads to the market fragmentation and breaks the production mode based on comparative advantage (Young 2000). Second, the industrial structure is similar across provinces, and the degrees of industrial agglomeration and regional specialization are relatively low (Young 2000; Bai et al. 2004). The decentralization of fiscal power has increased the pressure on provincial government revenue, while the provincial governments receive few additional resources, which are allocated by the central government (Ding et al. 2014). Third, prices vary greatly among provinces (Young 2000). The government has realized the harm of market fragmentation to economic development. Despite the government's policy incentives, market fragmentation is still a serious problem. Many empirical results show that developed markets are fully integrated while emerging markets are partially fragmented (Adler and Qi 2003). Gradual market-oriented reform has been carried out in China. The central government achieves the goal of high-speed economic growth by expanding the market-oriented allocation of resources and encouraging local governments to develop their economy in the form of fiscal decentralization. However, these policies also lead to the local protection and market fragmentation. Since the reform of fiscal decentralization, the dynamic preferences between central and local governments have been inconsistent. Fiscal revenue and promotion incentive drive local governments to adopt market fragmentation to compete for interests, which leads to the non-integration of domestic market. China's market fragmentation has become a typical representative of developing countries. Therefore, as an emerging market country, China is a good case for studying market fragmentation.

The accelerated depletion of resource and the increasing air pollution are becoming more and more serious (Lin and Chen 2018), which have plunged developing countries into the double oppression of resource and environment (Wang et al. 2013). While remarkable achievements have been made in economic development in China, high investment and high consumption have also brought about serious problems of unsustainable growth (Yuan et al. 2008). Energy is overused in China's industrial subsectors (Ouyang and Sun 2015). In order to solve the balance between economic development and environmental protection, the government has taken many measures to reduce environmental pollution and improve ecological efficiency (Narayan et al. 2007). Ecological efficiency is used to evaluate the balance between environmental pollution and economic growth, which takes air and water pollution into account to analyze the ecological sustainability (González et al. 2014).

"A new development strategy for China through to 2030" was proposed, including strengthening structural reform such as restructuring state-owned enterprises (SOEs), reforming capital, land, labor, and energy markets in order to become a market-based economy in the *China 2030* report of the World Bank (2012). This report clearly points out that market-oriented reform plays an important role in solving China's environmental problems. Many studies have assessed the efficiency losses caused by local protection and confirmed that the misallocation of resources caused by local protection (Young 2000; Poncet 2003; Li et al. 2003). Market fragmentation has indeed reduced the quality of regional development (Yang et al. 2018). However, the majority of the studies on ecological efficiency ignore the role of market fragmentation in particular. Governments influence corporate behaviors, such as energy consumption and pollution emissions. The markets are not freely competitive in the developing countries (Nie et al. 2017).

In view of the theoretical basis of the benefits of market integration, the situation of serious market fragmentation in China raises important discussions on the economic effects. Consequently, our study emphasizes the ecological effects of market fragmentation. Our study contributes to the existing literature in several aspects. First, few studies have been made on the relationship between market fragmentation and ecological efficiency. Only recently, some studies came to realize the environmental effect of market fragmentation. Bian et al. (2019) analyze the impact of market segmentation on pollution, such as sulfur dioxide and suspended particles. Que et al. (2018) consider the effect of factor market fragmentation in the relationship between fiscal decentralization and pollution emissions. These studies either take pollution emissions as dependent variables or indirectly analyze a part of market fragmentation. To fill in this gap, we take the ecological efficiency as dependent variable and directly investigate the impact of market fragmentation on ecological efficiency using the environmental pollution data. The lagging effect is analyzed in the dynamic panel. Second, the bootstrap data envelopment analysis (DEA) model is used to generate a large number of numerical simulation samples to estimate the ecological efficiency considering air and water pollution as undesirable outputs, which makes up for the shortcomings of the traditional DEA model in small samples. The ecological efficiency calculated by the bootstrap DEA method reflects the regional distribution and difference of ecological efficiency in China, which is conducive to improving the accuracy of the results.

The rest of the study is organized as follows: the "Literature review" section reviews the literature. The "Empirical methodology" section introduces the empirical methods, variable measurement, and data. The "Empirical analysis" section discusses and summarizes the empirical results and robustness test. The "Discussion" section puts forward research conclusions and policy recommendations.

Literature review

Previous studies have shown that spillover effect of market integration is significant (Johansson and Ljungwall 2009). Moreover, various studies find that there is a positive relationship between market integration and per capita GDP growth in emerging market (Harrison 1996; Edwards 1993; Edwards 1998), and wage inequality (Bigsten and Durevall 2006; Mcnabb and Said 2013; Ke 2015; Jensen and Miller 2018). Although there is a lot of evidence on the positive effects of market integration, many empirical studies find that regional markets in China are highly fragmented (Li et al. 2003; Young 2000; Poncet 2005; Yang and He 2014). Market fragmentation restricts free flow of factors and distorts allocation of resource, resulting in loss of efficiency.

Since the fiscal decentralization reform in 1994, the dynamic preferences between central government and local governments have been inconsistent. The fiscal revenue and promotion incentive mechanism have driven local governments to compete for benefits, which lead to market fragmentation and the non-integration of the domestic market (Poncet 2003). Poncet (2005) suggests that domestic trade protection promotes socioeconomic stability and maximizes fiscal revenues. China is not an integrated market, but a collection of separate regional economies protected by barriers. Compared with the developed market economies, China's fragmented market is controlled by local officials (Young 2000). China's economy is divided into many fragmented regional economies, which leads to the failure of improving the efficiency of the national economy (Liu and Ye 2019). Serious fragmentation exists in the labor market (Hertel and Zhai 2006; Knight and Li 2005), capital market (Fan et al. 2003), and energy market (Ju et al. 2017; Shi and Sun 2017) in China. Production taking advantage of scale economies is hindered in fragmented markets (Li et al. 2003). Regional energy market fragmentation may become an obstacle to economic growth (Horii 2011). Trade barriers affect competition (Epifani and Gancia 2011). Local protectionism hinders the geographical concentration of industry in China (He et al. 2008). Bai et al. (2004) find that compared with the scale economy and external economy, market fragmentation caused by local protection is not conducive to the industrial specialization.

Faced with increasing pressure on excessive consumption of resource and energy, the central government emphasizes that green development is a fundamental path of sustainable development of the country. Ecological efficiency is an important indicator reflecting sustainable development, which aims to improve the utilization efficiency of resources to solve the sustainability of economic growth. Therefore, the study of ecological efficiency has attracted the attention of the researchers. The concept of ecological efficiency, first proposed by Schaltegger and Sturm (1990), emphasizes the impact of economic activities on the environment damage. The improvement of ecological efficiency is simplified to achieve more economic output with less environmental cost (Wang et al. 2011; Beltrán-Esteve et al. 2014). Subsequently, ecological efficiency implies environmental performance in terms of sustainability of production systems (Korol et al. 2016). At present, the research on ecological efficiency mainly discusses the measurement of ecological efficiency (Charnes et al. 1979; Zhang et al. 2008; Camarero et al. 2013; Chu et al. 2016; Rashidi and Saen 2015) , and application of ecological efficiency (Hu et al. 2019; Lamas et al. 2013). Environmental planning, business strategy, technology progress, industrial structure, urbanization, and energy use are considered to be important factors affecting ecological efficiency (Passetti and Tenucci 2016; Charfeddine and Mrabet 2017; Bai et al. 2018). Yu et al. (2018) indicate that the ownership structure has an important impact on industrial ecological efficiency. Government transparency enhances eco-efficiency performance (Li et al. 2017). Non-democratic governments using social resources to gain benefits have an important impact on air quality (Bernauer and Koubi 2009).

From the perspective of the impact of market fragmentation on environmental efficiency, Sun and Lin (2014) suggest that energy subsidies distort price signals, further leading to excessive energy consumption. Lin and Chen (2018) find that factor market distortion affected by government intervention hinders the promotion of green total factor productivity. The protection of local government reduces the motive force of R&D investment, leads to the stagnation of green energy-saving technology, and hinders technological progress (Yang et al. 2018). Dai and Cheng (2016) argue that market distortion is an obstacle to improving productivity in China's energy industries. Drabo (2017) suggests that primary commodity export has positive impact on the increase in greenhouse gas emissions. Compared with capital prices, energy prices are relatively low. Energy price reform has a positive impact on improving energy allocation efficiency (Ouyang and Sun 2015). Chang et al. (2018) indicate that political power plays an important role for efficient environmental protection, and government efficiency affects energy efficiency. Bian et al. (2019) analyze the impact of market segmentation on pollution, such as sulfur dioxide and suspended particles. Que et al. (2018) consider the effect of factor market fragmentation in the relationship between fiscal decentralization and pollution emissions.

To summarize, the existing literature most focuses on the measurement, influencing factors and economic effects of market fragmentation. In addition, some studies take pollution emissions as dependent variables to discuss the relationship between market fragmentation or factor market fragmentation and pollution emissions. Unlike these studies, we take ecological efficiency as dependent variable and consider the impact of market fragmentation on ecological efficiency.

Empirical methodology

Estimation of market fragmentation

Market fragmentation derived from local government competition seriously restricts the effective and rational flow of labor, capital, and energy in the national market. For the measurement of market fragmentation, there are five main methods: production method (Young 2000), trade law method, economic cycle method (Xu 2002), market survey method, and price method. The price method is widely used to measure market fragmentation because it contains more information and has advantages in data collection, while other methods are difficult to form panel data and carry out empirical tests. The core connotation of the price method comes from the Glacier Cost Model and One Price Law. It holds that the prices in regions i and j are not equal. We follow the price method proposed by Parsley and Wei (2001) and use price indexes of 9 commodities[1] to measure market fragmentation index in China from 2000 to 2015. The detailed calculation steps are as follows.

First, we construct a three-dimensional ($t \times i \times k$) panel data covering year (t), region (i), and commodities (k). Next, we calculate the absolute value ($\left|\Delta Q_{ijt}^k\right|$) of region i and region j in year t of commodity k based on first-order difference form. The formula used is as follows.

$$\Delta Q_{ijt}^k = \ln\left(p_{it}^k / p_{it-1}^k\right) - \ln\left(p_{jt}^k / p_{jt-1}^k\right) \tag{1}$$

where p is the actual price, i and j indicate two provinces, t presents time periods, k indicates 9 categories of commodities in our study, and ΔQ_{ijt}^k is the fluctuation of the relative price of product k at time t between two provinces. Transportation costs are closely related to the difference in the price of the same goods between the two regions in an integrated market. Considering the relative stability of transport costs, the smaller the fluctuation of ΔQ_{ijt}^k, the more integrated the market between two provinces.

Due to the market fragmentation, the price ratio of the two provinces shows the characteristics of fluctuating up and down. If the difference is greater than the transportation cost, the two regional markets will be more or less fragmented. The band of arbitrage is measured by the absolute value.

$$\left|\Delta Q_{ijt}^k\right| = \left|\ln\left(p_{it}^k / p_{it-1}^k\right) - \ln\left(p_{jt}^k / p_{jt-1}^k\right)\right| \tag{2}$$

The removing mean method is used to eliminate system errors caused by fixed effects associated with commodity heterogeneity.

We assume that:

$$\left|\Delta Q_{ijt}^k\right| = a^k + \varepsilon^{ijk} \tag{3}$$

where a^k is the price change caused by the characteristics of the product k, and ε^{ijk} is the market environment of i and j province. Parsley and Wei (2001) propose that elimination of a^k by subtracting $\left|\Delta Q_{ijt}^k\right|$ from the mean of $\left|\Delta Q_{ijt}^k\right|$, which can be shown in the following formula:

$$q_{ijt}^k = \left|\Delta Q_{ijt}^k\right| - \left|\Delta \overline{Q}_{ijt}^k\right| = \left(a^k - \overline{a}^k\right) + \left(\varepsilon^{ijk} - \overline{\varepsilon}^{ijk}\right) \tag{4}$$

where $\left|\Delta \overline{Q}_{ijt}^k\right|$ is the mean of absolute value for commodity k of i and $j$province in t year.

$$\operatorname{var}\left(q_{nt}^k\right) = \left(\sum_{i \neq j} \operatorname{var}\left(q_{ijt}^k\right)\right) / N \tag{5}$$

where the variance $\operatorname{var}\left(q_{nt}^k\right)$ reflects the all commodities price fluctuations, which is caused by market fragmentation between provinces i and j at time t, and connotes the market fragmentation between two regional markets. In order to ensure that the estimated coefficients in subsequent estimates are not too small, we multiply the estimated original market fragmentation index by 100.

Calculation of ecological efficiency

Considering several statistical limitations of traditional DEA (Dyson et al. 2001), the bootstrap method, which uses

[1] These commodities are food, tobacco and alcohol, clothing, shoes and hats, cultural office supplies, daily necessities, Chinese and Western medicines and medical and health care supplies, books, magazines and electronic publications, and fuel, which are consistent with Zhang and Lu (2017).

empirical data and repeats sampling to improve confidence interval estimation and critical value accuracy statistics (Efron 1979), is selected. The bootstrap DEA method corrects the error of DEA efficiency estimation and obtains the confidence interval corresponding to the efficiency value by using a large number of simulated sample values generated by the numerical simulation self-help method (Simar and Wilson 1999). In the bootstrap DEA model, the sample distribution obtained by the bootstrap method simulates the original sample distribution, thus correcting the error correction of efficiency estimation (Song et al. 2013). Following Wijesiri et al. (2015) and Song et al. (2013), the bootstrap DEA proposed by Wilson (2008) is used to measure the ecological efficiency in China.

First, we calculate the efficiency score ($\hat{\theta}_k$) using the traditional DEA model for each decision-making unit (DMU) noted DMU_k, $k = 1, \ldots, n$, that have input X_k and output Y_k. Second, for the efficiency score $\hat{\theta}_k$, random efficiency values $\theta^*_{kb} = \{\theta^*_{1b}, \ldots, \theta^*_{nb}\}$ (b is the bootstrap iteration of the order b) of size n were produced by the bootstrap method. We calculate the pseudo-data set$\{(X^*_{kb}, Y_k), k = 1, \ldots, n\}$, where $X^*_{kb} = (\hat{\theta}_k / \theta^*_{kb}) \times X'_k$ is used to construct reference bootstrap technology. Third, we calculate bootstrap estimate $\widehat{\theta^*_{kb}}$ for each efficiency scores $\hat{\theta}_k$. Fourth, we repeat the above steps to obtain a set of efficiency values $\widehat{\theta^*_{kb}}(b = 1, \ldots, B)$ for $k = 1, \ldots, n$. B indicates the total number of iteration.

In the absence of samples, the efficiency value using the DEA method is easy to lead to estimation bias. However, the sample distribution obtained by the bootstrapping method can simulate the distribution of the original sample estimator and correct the deviation estimation of the efficiency value obtained by the traditional DEA method.

The biased of the corrected efficiency values is calculated as follows:

$$\mathrm{Bias}(\hat{\theta}_k) = E(\hat{\theta}_k) - \hat{\theta}_k \tag{6}$$

$$\mathrm{Bias}\left(\hat{\theta}_k\right) = B^{-1} \sum_{b=1}^{B} \left(\hat{\theta}^*{}_{kb}\right) - \hat{\theta}_k \tag{7}$$

The biased corrected efficiency values are as follows:

$$\hat{\theta}_k = \hat{\theta}_k - \mathrm{Bias}\left(\hat{\theta}_k\right) = 2\hat{\theta}_k - B^{-1} \sum_{b=1}^{B} \left(\hat{\theta}^*{}_{kb}\right) \tag{8}$$

The confidence interval is calculated as follows. Our study constructs $1-\alpha$ percent confidence interval for DMU_k to compute the values of $\widehat{b_\alpha}$ and $\widehat{\alpha_\alpha}$ according to the $\widehat{\theta^*_{kb}} - \widehat{\theta_k}$.

$$P_r\left(-\widehat{b_\alpha} \le \widehat{\theta^*_{kb}} - \widehat{\theta_k} \le -\widehat{\alpha_\alpha}\right) = 1-\alpha \tag{9}$$

$$P_r\left(-\widehat{b_\alpha} \le \widehat{\theta_k} - \theta_k \le -\widehat{\alpha_\alpha}\right) \approx 1-\alpha \tag{10}$$

We set the $-\widehat{b_\alpha}$ and $-\widehat{\alpha_\alpha}$ equal to the endpoints to the sorted array ($\widehat{\alpha_\alpha} \le \widehat{b_\alpha}$); the efficiency value θ_k is calculated as follows:

$$\widehat{\theta_k} + \widehat{\alpha_\alpha} \le \theta_k \le \widehat{\theta_k} + \widehat{b_\alpha} \tag{11}$$

The core of ecological efficiency is to increase economic value by minimizing resource input and environmental costs (Hu et al. 2019). The bootstrap DEA is used to measure ecological efficiency in our research framework. The selection of input and output indicators from basic economic and environmental pollution is used to accurately reflect ecological efficiency. The output indicators include desirable outputs and undesirable outputs. Regional GDP of province is chosen to represent the added value of products and services. Sulfur dioxide emissions, solid waste emissions, waste water emissions, smoke and dust emissions are selected as undesirable outputs. Labor input is expressed by the total number of urban employees; capital stock is estimated by the fixed asset investment; the total energy consumption, cultivated area, and total water consumption of province are considered as resource inputs. Table 1 shows the input-output indicators of ecological efficiency based on the bootstrap DEA method.

Empirical method

This section covers the empirical method to address the impact of market fragmentation on ecological efficiency. First, regional ecological efficiency is dynamic in time evolution; many factors which are difficult to observe can be separated by controlling the time lag of dependent variables. Second, pollutant emissions are continuous indicators. The environmental pollution in the previous period will affect the current emission of pollution. Consequently, we consider it necessary to add the first-lagged ecological efficiency to the model and construct a dynamic model to control the difference of the initial states of each province. We follow the method used by Lin and Chen (2018) and estimate the model as follows:

$$\mathrm{eco}_{i,t} = \lambda_0 + \lambda_1 \mathrm{eco}_{i,t-1} + \lambda_2 \mathrm{segment}_{i,t} + X_{it}T + \alpha_i + \varepsilon_{it} \tag{12}$$

where i indexes province and t indexes year; $\mathrm{eco}_{i,\ t}$ is a dependent variable measuring ecological efficiency; $\mathrm{segment}_{i,\ t}$ is the indicator of the intensity of market fragmentation; X are vectors of province-specific control variables that also determine ecological efficiency according to previous studies. Moreover, region fixed effects α_i and an error term ε_{it} are included. We focus on coefficient λ_2, which determines the impact of market fragmentation on ecological efficiency.

Table 1 Input-output indicators of ecological efficiency

	Category	Specific indicators	Unit
Input indicators	Labor input	The total number of urban employees	10,000 people
	Capital input	The fixed asset investment	Billion RMB
	Resource inputs	Total energy consumption	10,000 tons
		Cultivated area	1000 hectare
		Total water consumption	100 million m^3
Output indicators	Desirable output	Regional GDP	Billion RMB
	Undesirable outputs	Sulfur dioxide emissions	10,000 tons
		Solid waste emissions	10,000 tons
		Waste water emissions	10,000 tons
		Smoke and dust emissions	10,000 tons

Estimation system

This study uses the system generalized method of moments (GMM) estimator proposed by Blundell and Bond (1998), which helps to control for the simultaneous and endogeneity problems that may arise in the model. The estimator combines in a system the equation in first differences with an equation in levels (Chen and Guariglia 2013). Blundell and Bond (1998) find that adding the original equation to the system and using the additional moment condition significantly improve the efficiency and reduce the finite sample bias compared with the simple first-differenced GMM. We regard all regression variables as endogenous regression variables in the model and test them by using their lag levels in differential equations and their lag differences in horizontal equations. We include year dummies and province dummies in all our regressions and instrument sets. We also use the Sargan statistics to examine the validity of the instruments.

Ecological efficiency is evaluated by using the bootstrap DEA method. Accordingly, we select input and output indicators to calculate ecological efficiency. Market fragmentation is calculated based on Eqs. (1)–(5). Other factors may also affect ecological efficiency. Based on the environmental Kuznets curve (EKC), economic development, industrial structure, urbanization, human capital, and infrastructure are selected as control variables to explain ecological efficiency (Yu et al. 2013; Dinda 2004). The relationship between economic growth and environment and pollution has been extensively studied (Lee and Oh 2015). Economic development reflects technological innovation and productivity, which affect energy consumption and pollution emissions. Therefore, it must be included in the regression model. Per capita GDP is used as a proxy for regional economic growth. Industrial structure affects the allocation of labor, capital, technology, energy, and other resources, and has an important impact on pollution emission (Chebbi 2010). Therefore, the impact of industrial structure must be taken into account. The ratio of the output value of the tertiary industry to that of the secondary industry is used to measure industrial structure, which captures the industrial development. Human capital plays an important role in sustainable development, which promotes the application of energy-saving technology and enhances environmental protection awareness (Li and Lin 2016). Therefore, human capital also affects ecological efficiency. Per capita average years of education is a proxy for human capital, which captures the quality of labor force. In the process of urbanization, agricultural economic activities have been replaced by new urban activities. Urbanization means the increase of urban construction activities, which affect pollution emission (Ji et al. 2018). The ratio of urban population to total populations is selected to estimate urbanization. Road mileage represents the infrastructure. Transportation infrastructure is not only an important source of material wealth accumulation but also an important source of environmental degradation. Existing studies have discussed the impact of transport infrastructure on air pollution (Sun et al. 2019). Therefore, this study also considers the impact of transport infrastructure. The length of roadway is used to measure the transport infrastructure.

Data and descriptive statistics

Due to the availability of data, the objects of this study are 29 provinces in China (excluding Hainan and Tibet), and the study period is from 2000 to 2015. All data are collected from China Compendium of Statistics (1949–2008), China Statistical Yearbook, China Environmental Statistics Yearbook, China Labor Statistics Yearbook, China Environmental Yearbook, China Population and Employment Statistics Yearbook, and China Energy Statistics Yearbook. Table 2 presents the summary statistics of key variables that are used in this study during the period 2000–2015.

According to the market fragmentation index obtained above, Fig. 1 lists the plots of market fragmentation for 29 provinces in China during the period of 2000–2015. From the results of our estimates, market fragmentation in China is indeed a serious problem. Generally speaking, the serious market

Table 2 Statistical descriptions of main variables

	Variable	*N*	Mean	Std. Dev	Min	Max
eco	Ecological efficiency	464	0.8156	0.0909	0.5204	0.9682
segment	Market fragmentation	464	0.0480	0.0437	0.0082	0.3893
pgdp	Economic development	464	9.9218	0.8128	7.9226	11.5895
industry	Industrial structure	464	1.1793	0.2951	0.2478	2.0119
edu	Human capital	464	8.3568	1.0619	5.4383	12.2813
urban	Urbanization	464	0.4873	0.1524	0.2000	0.9000
infra	Infrastructure	464	1.0706	0.6907	0.0430	3.1560

fragmentation is mainly concentrated in Shanghai, Beijing, and Tianjin. It can be seen that the province with highest market fragmentation index is Beijing in 2000 (0.2312), while Fujian is the province with lowest market fragmentation index in 2000 (0.0142). Shanghai is the area with highest market fragmentation in 2015 (0.0461). Figure 2 shows the average market fragmentation index of 29 provinces in China from 2000 to 2015. The results indicate that the market fragmentation indexes of Beijing, Tianjin, and Shanghai are relatively high. The market fragmentation indexes of Shandong and Henan are relatively low. Fortunately, according to our estimates, the degree of market fragmentation is tending to improve in recent years, and an integrated domestic market is emerging. However, we find that market fragmentation still has great room for improvement.

Figure 3 illustrates the average of ecological efficiency for 29 provinces during the period of 2000–2015. The results indicate that the highest average ecological efficiency is 0.8681 in east region, and the lowest average ecological efficiency is 0.7460 in west region. More specifically, the top five provinces in average ecological efficiency are mainly concentrated in the eastern region; the lowest ecological efficiency provinces are located in the western region. The result of *t* test (p values < 0.01) indicates that the average of ecological efficiency is significantly different. Therefore, it can be concluded that there is significant regional disparities of ecological efficiency, which is attributable to economic and market differences among various regions. In addition, the estimated ecological efficiency provides valuable information for policy-making. Similar targets may not be appropriate for different regions because there are significant regional disparities in ecological efficiency. Therefore, a new policy implication can be designed by assigning higher goals to provinces with lower ecological efficiency and lower goals to provinces with higher ecological efficiency.

Empirical analysis

Preliminary analysis based on the static panel

On the basis of the static panel, we make a preliminary analysis, observe the influence of explanatory factors, and provide effective comparison. Based on Song et al.'s (2019) and Bian et al.'s (2019) studies, linear regression model is used to analyze the relationship between market fragmentation and ecological efficiency. We choose OLS, RE, and FE models to carry out preliminary analysis. Moreover, Table 3 presents the results of using different methods based on the static panel. According to Table 3, the coefficient of market fragmentation is − 0.1363 at the 5% level, which indicates that market fragmentation has significantly negative impact on ecological efficiency based on the ordinary least square (OLS) model. The Hausman test results indicate that the fixed effect model is more suitable for analysis compared with the random effect model. Therefore, the fixed effect method is applied in further discussions. In column 3, we observe that the coefficient of market fragmentation is − 0.0923 at the level of 5%, which suggests that market fragmentation has significantly negative impact on ecological efficiency. The findings demonstrate that market fragmentation significantly inhibits the improvement of ecological efficiency based on the fixed effect model, which is consistent with our expectation.

GMM method of dynamic panel

The first-lagged-dependent variable is added to construct the dynamic model in Eq. (12). However, the dynamic panels have weaknesses in endogenous problems. Dynamic panel endogeneity and excessive recognition of tool variables are effectively solved by using the GMM method. Two tests are carried out before using the GMM model. First, the first- and second-order autocorrelations AR (1) and AR (2) of the perturbation term need to be confirmed. We also make sure that the null hypothesis has no residual correlation. Second, we continue to test whether the GMM model is over-recognition. Sargan test is used to test the validity of variable estimation.

According to Table 4, the Wald test of all models is significant, which demonstrates that the regression results are significant. AR (1) and AR (2) suggest that the first-order correlation is significant and the second-order correlation is not significant, which is consistent with the requirement of the GMM method. The Sargan test shows that all regression models do not reject the null hypothesis that the selected instrumental variables are valid, which indicates that the instrumental variables used in the estimation are reasonable and valid.

The method of adding one control variable at a time is used to discuss the results in order to enhance the robustness of the

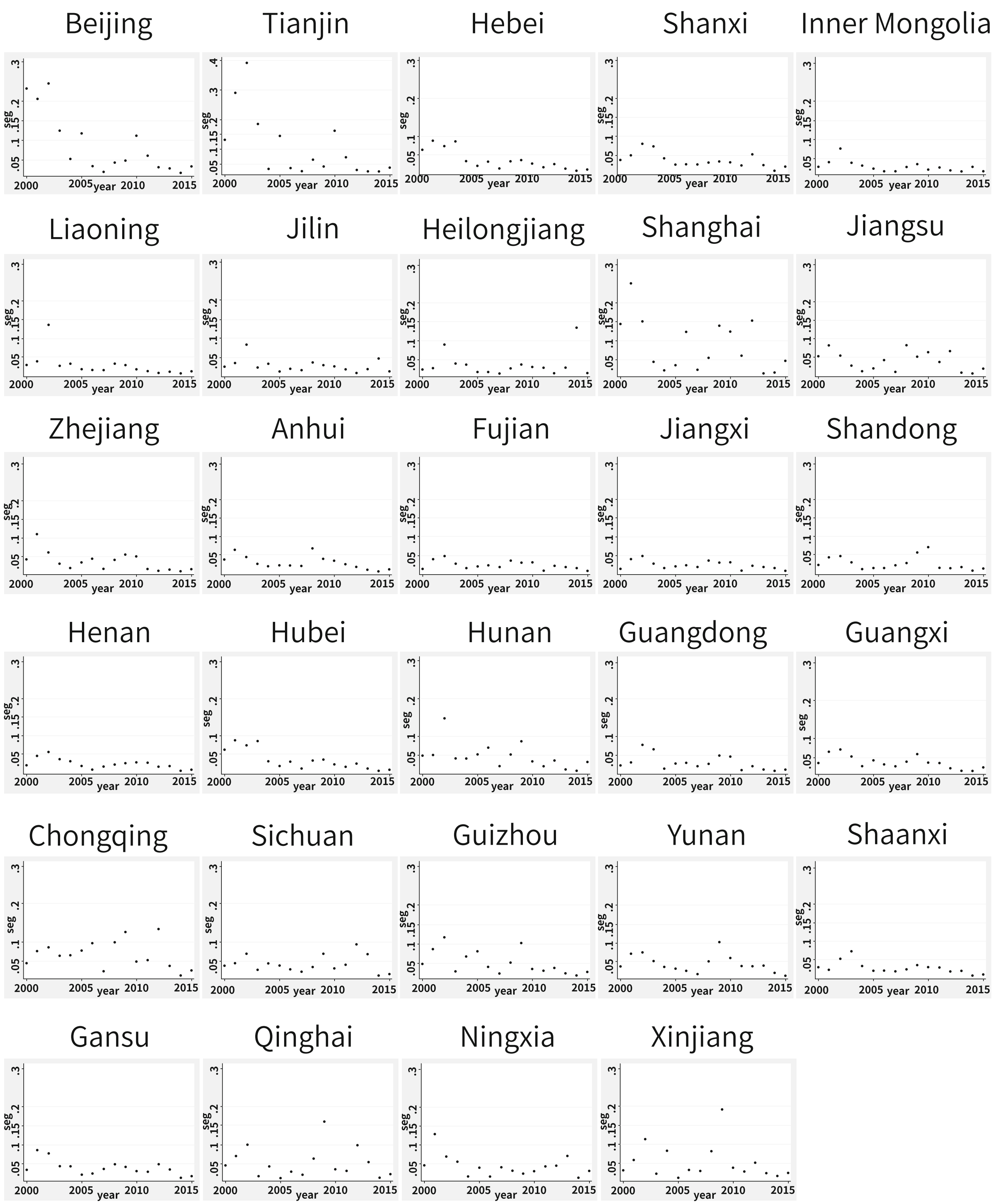

Fig. 1 Plots of market fragmentation for 29 provinces in China during the period of 2000–2015

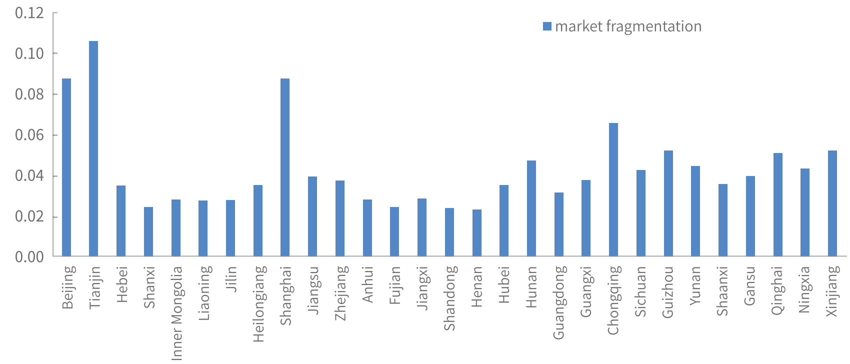

Fig. 2 Average of market fragmentation for 29 provinces from 2000–2015

results. The empirical results using the system GMM method are showed in Table 4. According to Table 4, the regression coefficient of market fragmentation is significantly negative and statistically significant at the 1% level, which is in line with our expectation. With the gradual adding of control variables, the coefficients of market fragmentation are all statistically significant negative, and eventually, the coefficient of market fragmentation stabilizes at about −0.1386 at the 1% level. The results of the dynamic panel indicate that market fragmentation hinders the improvement of ecological efficiency.

Discussion

The government plays a crucial role for the ecological efficiency and renewable energy policy (Kocaoglu et al. 2016; Sovacool 2015). Many studies have confirmed the impact of government intervention on the development of energy supply technology (Kiss and Neij 2011). Political power affects the pollution (Chang et al. 2018). Previous studies actually confirm the concern of many economists that market fragmentation is indeed a serious problem in China (Ding and Niu 2019). China's domestic market is fragmented, leading to the existence that market boundaries are demarcated (Ding and Niu 2019). Local governments obtain their own short-term interests through market fragmentation. Market fragmentation breaks the production mode of productive activities based on comparative advantage in different regions (Young 2000). Market fragmentation also restricts the free flow of productive factors among regions, distorts allocation structure, results in lower productivity and marginal output, and ultimately hinders the improvement of industrial competitiveness. Market fragmentation affects ecological environment by changing the competitive behavior of enterprises. Enterprises use excessive resources for rent-seeking to maintain their monopoly behavior, resulting in distortion and waste of resources allocation. Therefore, market fragmentation inhibits the ecological efficiency.

As mentioned earlier, local governments adopt market fragmentation strategy for economic rent (Young 2000). Cai et al. (2008) propose that local government behaviors affected by decentralization and extensive economic growth affect environmental problems. He et al. (2012) also claim decentralization has a negative impact on air pollution. The distortion caused by market fragmentation prevents essential productive factors from flowing sufficiently among regions according to price signals (Zhang and Lu 2017). This misallocation of resources makes it impossible for backward energy-consuming industries to be eliminated. It is noted that these industries are important sources of pollution emissions. Bian et al. (2019) obtain similar findings that market fragmentation affects pollution emissions through resource allocation. Lin and Du (2013) show that market distortion has a positive impact on total energy loss. In addition, traditional

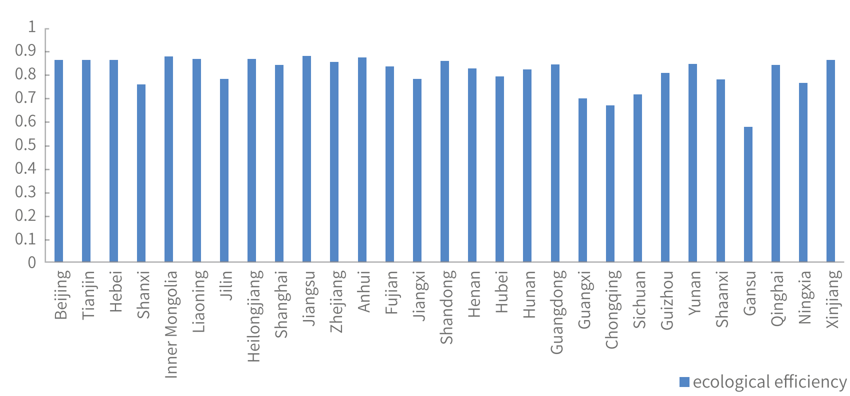

Fig. 3 Average of ecological efficiency for 29 provinces from 2000–2015

Table 3 Regression of market fragmentation on ecological efficiency by OLS, RE, and FE models

	OLS model (1)	RE model (2)	FE model (3)
segment	− 0.1363** (− 1.97)	− 0.0961** (− 2.28)	− 0.0923** (− 2.09)
pgdp	0.0543*** (5.04)	0.0700*** (3.63)	0.0705*** (3.39)
industry	0.0230* (1.80)	− 0.0205 (− 1.11)	− 0.0222 (− 1.18)
edu	− 0.0063 (− 1.21)	− 0.0100 (− 1.44)	− 0.0105 (− 1.40)
urban	0.1247** (2.06)	0.0396 (0.28)	0.0467 (0.22)
infra	0.0244*** (3.97)	0.0121 (0.93)	0.0108 (0.73)
constant	0.2212*** (3.18)	0.2012* (1.68)	0.1991 (1.63)
sample size	464	464	464
R^2	0.4542	0.6900	0.6900

*Indicates significance at the 10% level

**Indicates significance at the 5% level

***Indicates significance at the 1% level

manufacturing enterprises are protected by local governments through administrative policy, which lose the motivation for clean technology innovation (Lin and Chen 2018). While these enterprises bring high-profit tax, they also consume a lot of resources and produce pollution. In general, we find that previous studies have focused on the results of pollution emissions, which are consistent with those of our study.

We further explore the relationship between market fragmentation and ecological efficiency based on the economic situation in China. The formation of market fragmentation in China is closely related to the gradual reform. It appears in the process of China's transition from centralized planned economy to market economy. Under the parallel system of fiscal decentralization and administrative centralization, local protectionism driven by local government competition leads to market fragmentation. First, one of the main motivations for local governments to adopt market fragmentation is to protect some local state-owned enterprises. Some state-owned enterprises may have closer political ties with local governments to obtain more factor rents and product price protection, which leads to high-energy consumption, low economic output, and inefficient management. Second, in order to attract investment, expand production, and promote local economic growth, local governments distort the prices of factors of production such as energy, capital, and labor. These distorted

Table 4 Regression of market fragmentation on ecological efficiency based on GMM

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
segment	− 0.1459*** (− 3.69)	− 0.1407*** (− 3.58)	− 0.1379** (− 2.19)	− 0.1279*** (− 3.28)	− 0.1334*** (− 3.29)	− 0.1386*** (− 3.27)
pgdp		0.0041 (1.03)	0.0042 (1.05)	− 0.0027 (0.59)	− 0.0123** (− 2.12)	− 0.0203*** (− 2.67)
industry			0.0081 (1.21)	0.0137** (2.02)	0.0151** (2.37)	0.0142** (2.21)
edu				0.0083* (1.89)	0.0012 (0.28)	0.0022 (0.48)
urban					0.1768*** (2.76)	0.2104*** (3.23)
infra						0.0088* (1.77)
eco_{t-1}	0.9551*** (4.62)	0.9126*** (9.05)	0.9096*** (9.24)	0.9142*** (10.30)	0.9043*** (9.99)	0.8920*** (8.40)
constant	0.5231*** (2.65)	0.0450** (2.09)	0.0370* (1.66)	0.0257 (1.14)	0.1001*** (2.60)	0.1566*** (2.86)
sample size	435	435	435	435	435	435
AR (1)	0.0407	0.0434	0.0355	0.0319	0.0394	0.0271
AR (2)	0.6064	0.5829	0.5146	0.4299	0.4128	0.3364
Sargan value	29.698	28.376	27.775	26.158	24.097	22.982

*Indicates significance at the 10% level

**Indicates significance at the 5% level

***Indicates significance at the 1% level

Table 5 Robustness test for alternative measurement

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
segment	− 0.0519*** (− 2.91)	− 0.0763*** (− 4.17)	− 0.0734*** (− 3.92)	− 0.0733*** (− 3.85)	− 0.0703*** (− 3.74)	− 0.0693*** (− 3.70)
pgdp		0.0103*** (3.60)	0.0102*** (3.54)	0.0010 (0.25)	− 0.0079* (− 1.66)	− 0.0123* (− 1.80)
industry			0.0049 (0.83)	0.0119* (1.81)	0.0136** (2.11)	0.0134** (2.07)
edu				0.0107*** (2.95)	0.0042 (1.09)	0.0048 (1.23)
urban					0.1633*** (4.03)	0.1816*** (4.02)
infra						0.0049 (0.90)
eco_{t-1}	1.0292*** (3.82)	0.9358 (9.61)	0.9335*** (9.46)	0.9376*** (9.08)	0.9290*** (9.15)	0.9223*** (8.50)
constant	− 0.0056 (− 0.41)	− 0.0297** (2.00)	− 0.0328** (− 2.15)	− 0.0435*** (− 2.73)	0.0246 (1.07)	0.0551 (1.35)
sample size	435	435	435	435	435	435
AR (1)	0.0314	0.0311	0.0227	0.0274	0.0269	0.0202
AR (2)	0.7712	0.6315	0.5986	0.5246	0.4156	0.5127
Sargan value	27.883	27.109	26.489	25.676	24.731	22.572

*Indicates significance at the 10% level

**Indicates significance at the 5% level

***Indicates significance at the 1% level

price signals affect factor production allocation. Enterprises use inexpensive elements to replace high-tech machinery and equipment, thus indirectly inhibiting the improvement of clean technology. Third, market fragmentation is not conducive to industrial agglomeration, the sharing of cleaner production technology, and the development of knowledge spillover and technology externality. Meanwhile, market fragmentation hinders the upgrading of industrial structure and aggravates environmental pollution. In conclusion, the above analysis supports the negative impact of market fragmentation on ecological efficiency.

Robustness test

In order to check the robustness, we conduct several tests of the results. First, following the prior studies, the proportion of employees in state-owned enterprises is adopted as an indicator for market fragmentation (Zhang and Lu 2017). We repeat the estimation in Eq. (12) by using the proportion of employees in state-owned enterprises as a proxy. The results of the effect of alternative proxy on ecological efficiency are presented in Table 5 as a comparison. The control variables are gradually added to the model. We find that the coefficients

Table 6 Robustness test for splitting the samples

	East	Central	West
segment	− 0.7975*** (− 2.92)	− 2.4416** (− 3.03)	− 1.1243** (− 2.18)
pgdp	− 0.0014 (− 0.16)	− 0.0283*** (− 2.87)	− 0.0022 (− 0.21)
industry	0.0011 (0.14)	0.0129 (1.60)	0.0107 (1.02)
edu	0.0078 (1.49)	− 0.0044 (− 0.65)	0.0027 (0.41)
urban	0.0360 (0.80)	0.3047*** (4.17)	0.0940 (1.01)
infra	0.0098* (1.73)	0.0237*** (3.44)	0.0164* (1.94)
eco_{t-1}	0.7873*** (6.01)	0.7631*** (7.99)	1.0147*** (8.76)
constant	0.1066** (2.30)	0.3406*** (5.52)	− 0.0259 (− 0.40)
Sample number	150	150	135
AR(1)	0.0432	0.0549	0.0335
AR(2)	0.7009	0.7821	0.6123
Sargan value	21.216	20.048	20.785

*Indicates significance at the 10% level

**Indicates significance at the 5% level

***Indicates significance at the 1% level of the key explanatory variable are significantly negative, and eventually, the coefficient of alternative proxy statistically stabilizes at about −0.0693. With the gradual adding of control variables, the coefficients of proxy of market fragmentation are all statistically significant, indicating that the estimation results are similar to the earlier findings. The result of market fragmentation hindering the improvement of ecological efficiency is robust.

The next robustness test is concerned with the unbalanced regional development of the province sample. The heterogeneity of social and economic development could be controlled by dividing the whole samples into sub-samples with different characteristics (Wen et al. 2016). Existing studies show that there are great differences in environmental performance among provinces (Ma et al. 2018). Total factor productivity and environmental performance are the highest in eastern area; the opposites are true in western area in China (Brandt et al. 2013). The eastern region has highly developed economies and high levels of the tertiary industry, while the economic development in the western region is low. Xiong et al. (2019) indicate that the industry structure and government intervention are closely related to energy efficiency. For a deeper investigation, the whole samples are divided into three sub-samples according to different levels of economic development and geographical location: east, central, and west. We further estimate Eq. (12) using the sub-samples. Table 6 displays the regression of market fragmentation on ecological efficiency in the sub-groups. The regression results demonstrate that the regression coefficients of market fragmentation are as expected, which are statistically significantly negative whether in the east or in the central and west. The findings indicate that market fragmentation has a significant and robustly negative impact on ecological efficiency, which is consistent with the results of baseline estimations.

Conclusion

Local governments restrict cross-regional flows of factors and products for profit, which lead to market fragmentation to some extent. China's domestic market is fragmented, leading to the situation that market boundaries are demarcated. Market fragmentation not only distorts resource allocation but also has an important impact on ecological efficiency. We use the relative price method to measure market fragmentation and find that market fragmentation is indeed a serious problem in China. This study evaluates the ecological efficiency using the bootstrap DEA method that takes air and water pollution into account and investigates the effect of market fragmentation on ecological efficiency based on the system GMM approach by employing data from a panel of 29 provinces in China during the period 2000–2015. The results indicate that the market fragmentation has negative impact on ecological efficiency, which shows market fragmentation significantly inhibits the improvement of ecological efficiency. The similar findings are confirmed by a series of robustness tests, which include the alternative indicator and sub-sample regression.

Based on the above discussion, the government should positively improve ecological efficiency through eliminating market fragmentation. This study puts forward the following policy recommendation:

First, eliminating institutional barrier and market fragmentation, breaking local protectionism and industrial monopoly, and building an integrated market should be the key emphases for expanding regional market scale and enhancing regional economic cooperation. These are also helpful to promote the upgrading of industrial structure and reduce pollution emissions. The government actively transforms its functions and promotes the transformation of government functions from production-oriented government to service-oriented government. In addition, we should reduce government intervention in the market, play the basic role of the market in resource allocation, and promote the free flow of factors and products among regions according to price signals.

Second, the central government can promote the integration of backward areas into the domestic market by means of transfer payments and other measures. Meanwhile, the government should strengthen the punishment of market fragmentation and increase the cost of market fragmentation by local governments, so as to speed up the integration of local markets into domestic markets. Local governments can integrate resources, share information, collaborate and innovate, and jointly control pollution emissions through economic cooperation, so as to improve ecological efficiency.

Third, market fragmentation affects environmental efficiency through resource allocation. Improving the efficiency of resource allocation, increasing the research and development of clean technologies, and promoting the application of energy-saving technologies are important factors for elevating environmental quality and sustainable development. Therefore, local governments should implement the reform of factor price including labor, capita, and energy, improve the efficiency of resource allocation, promote the flow of resources to efficient sectors, and optimize the industrial structure and energy consumption structure.

Finally, the government should improve the mechanisms for assessing performance of local government, strengthen laws and regulations to promote ecological progress, and make effective use of public oversight. The central government establishes a national dynamic monitoring system, promotes information disclosure, and strengthens environmental supervision.

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