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Does FDI have energy-saving spillover effect in China? A perspective of energy-biased technical change

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ABSTRACT

Existing studies pay little attention to when or under which conditions foreign direct investment (FDI) can spill energy-saving technologies. From a perspective of energy-biased technical change and using a two-layer nested constant elasticity of substitution (CES) production function, this paper investigates the energy-saving spillover effect of FDI on technical change (i.e., energy-saving spillovers) in China between 2002 and 2015. In particular, we consider the conditions of marketization, industry, technology, and labor mobility to examine whether and when FDI has energy-saving spillovers. The results indicate no income inequality effect, i.e., there is no evidence supporting that FDI flowing into low- and middle-income regions increases energy consumption, while FDI flowing into high-income regions conserves energy. However, there is a condition effect: FDI can improve (support the halo effect) or deteriorate (contradict the halo effect) the environmental performance under different conditions. Moreover, there is a threshold effect: the direction of FDI spillovers varies with the different levels of the threshold variables. An increasing marketization motivates enterprises to select energy-biased technologies. It is more likely to generate energy-saving spillovers in the regions with a lower specialized agglomeration level. FDI will have energy-biased spillovers when domestic technological level is relatively high with an evident energy-biased technology. In addition, a moderate labor mobility is beneficial to the energy-saving spillovers of FDI.

1. Introduction

Excessive investment, numerous energy consumption and rapid growth are widely claimed to be the typical and primary characteristics of China's economy. China, yet, is now suffering from the dual pressures of energy resources deficiency and environmental pollution. Mounting concern about these issues has increased the urgency of understanding this phenomenon and finding solutions through the technology, especially the clean technology in China. With respect to the solutions for these issues, it must be pointed out that the foreign direct investment (FDI) has increasingly become an important way to diffuse energy-saving technologies and improve the environmental quality. However, when does FDI spill energy-saving technologies?

The correlations between investment in environmental governance and FDI and between energy consumption intensity and FDI are presented in Fig. 1 and Fig. 2, respectively. The two downward-sloping lines in the two figures show that both investment in environmental governance and energy consumption intensity declines with FDI in China, which seems to contradict the findings in Lin and Liu (2015). According to the halo effect hypothesis, advanced knowledge or technology and environmental-friendly practices brought by multinational companies would motivate domestic companies to adopt the energy-saving technologies, which would improve the environmental quality in the host countries. Moreover, some studies also find supporting evidence that FDI can exhibit important energy-saving technology spillover effects. For example, using the data of 20 emerging market economies over 1991–2012, Paramati et al. (2016) documented that FDI spillovers had a considerable positive impact on the clean energy consumption. Seker et al. (2015) examined the impact of FDI on CO_2 emissions and showed that the impact was positive but relatively small. Liu et al. (2017) selected the SO_2 and CO_2 emissions per capita as the proxy for environmental quality and employed a

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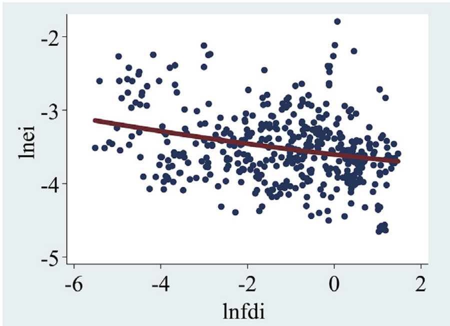

Fig. 1. Correlation between investment in environment governance and FDI.

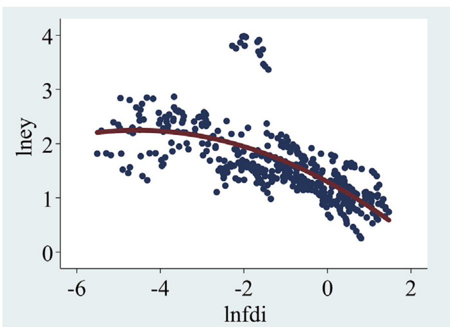

Fig. 2. Correlation between energy consumption intensity and FDI.

simultaneous equations model to investigate the environmental consequences of domestic and foreign investment by using China's provincial panel data over the period of 2002–2015. The results indicated that direct, indirect and total effects of FDI on pollutant emissions were all negative. Their findings echo Zhu et al. (2016), who adopted a panel quantile regression model to analyze the impact of FDI, economic growth and energy consumption on carbon emissions in five members in the Association of South East Asian Nations (ASEAN-5).

However, some studies find the negative energy-saving spillover effects of FDI in many countries. Adom and Amuakwa-Mensah (2016) studied the driven factors of the energy-saving role of FDI and industrialization in East Africa, and focused on the conditional impacts of FDI and industrialization on the energy productivity. They documented that FDI significantly decreased energy productivity only in low-income countries. Based on the data of 19 nations out of the G20 from 1971 to 2009, Lee (2013) investigated the effect of the net inflows of FDI on economic growth, clean energy use, and carbon emissions. The empirical results indicated that FDI had played an important role in economic growth for the G20 whereas no compelling evidence of FDI linked with clean energy use. The “pollution paradise” hypothesis holds that because of increasingly strict environmental rules and energy consumption regulations in developed countries, multinational companies incline to transfer energy-intensive industries to developing countries to avoid high environmental governance costs, thus negatively affecting the environmental equality in host countries.

Meanwhile, the hypothesis of “environmental Kuznets curve”, an inverse U-shape curve between pollution and income, illustrates that the levels of pollution are increasing with economic growth (often associated with globalization) in low-income economies until reaching a certain level of economic development. A number of empirical studies that have appeared recently do indeed find evidence on this hypothesis. Based on the industrial panel data, Ren et al. (2014) used the two-step generalized method of moments (GMM) to measure the impacts of FDI, trade openness, exports, imports and per capita income on CO_2 emissions. Their findings suggested that obvious FDI spillovers further increased China's CO_2 emissions. Rafindadi et al. (2018) examined the effects of FDI and energy consumption on environmental pollution in resource-based economies of the Gulf Cooperation Council (GCC) from 1990 to 2014, finding that FDI spillovers aggravated environmental pollution. Using rich firm-level data and national input-output tables in 17 transition economies, Gorodnichenko et al. (2014) investigated the effect of FDI on productivity. They found that backward linkages had a consistently positive effect on productivity of domestic firms, while horizontal and forward linkages showed no consistent effect in different countries.

Using the panel data consisting from 13 East African countries in the period of 1980–2011, Lovely and Popp (2011) adopted the general equilibrium model to analyze the impact of foreign trade on environmental regulation. They argued that the competition caused by foreign trade would inhibit the effect of environmental regulations, but it could also reduce the cost of pollution control, which meant that the positive and negative effects of foreign trade on environmental regulation coexisted. Doytch and Uctum (2016) investigated the environmental impact of capital inflows and the halo effect (FDI improves the environmental quality), and suggested that FDI had a differential industry effect on pollution: FDI flows into manufacturing to increase the pollution (negative halo effect), while FDI flows into services to decrease the pollution (support the halo effect hypothesis). In addition, their results also implied that FDI had an income inequality effect on pollution as well: FDI flowing into low- and middle-income countries degraded the environmental quality, while flowing to high-income countries benefited the environment (supported the halo effect). Zhao et al. (2019) empirically examined the FDI's spillovers and its impact on energy intensity of China's 30 provincial-level regions from 2005 to 2014 with the spatial econometric model which extended the traditional convergence model. They also revealed that advanced technologies along with the inflow of FDI improved energy efficiency, which conversely triggered energy rebound effect (i.e., higher energy efficiency finally leads more energy consumption).

Thus, we can conclude that the evidence on FDI's spillovers remains ambiguous. In this paper, we use the 2002–2015 panel data in 29 provincial-level regions in China, to investigate when or under which conditions FDI has energy-saving spillovers. First, previous studies focus on whether there are FDI's spillovers or not, while this paper investigates the conditions of energy-saving spillover and the change of spillover direction, and examines whether FDI has an income inequality effect on energy conservation in different regions. In addition, this study enriches existing literature by measuring multiregional spillover direction within a country rather than country-level data, which can eliminate or reduce data bias caused by the difference of multinational institution. More importantly, we offer the explanation for why FDI's spillover direction varies from different conditions. Second, to the best of our knowledge, this is the first study to shed light on the impacts of the market freedom degree, industry condition, technology conditon, and factor flows on FDI's spillover direction. Thus, we provide some evidence on more heterogeneous conditions about the changes in FDI's spillover direction. One the one hand, we find that FDI's spillover direction will transfer with different conditions and with various levels under the same condition. On the other hand, our estimation results show that whether FDI is directed to energy-saving spillovers depends on some specific conditions. Moreover, there is no income inequality effect on energy-saving spillovers. Namely, there is no supporting evidence that the energy-consuming spillovers of FDI exist in low- and middle-income regions, while the energy-saving spillovers of FDI exist in high-income regions.

The paper is organized as follows. Section 2 estimates the energy-biased technical change. In Section 3, we examine the energy-saving technology spillover effects of FDI. In addition, we identify the heterogeneous conditions of FDI's energy-saving spillovers in Section 4. Section 5 provides some concluding remarks.

2. Estimation of energy-biased technical change

Generally, there are two kinds of widely-used production functions, i.e., the Cobb-Douglas (C-D) function and the constant elasticity of substitution (CES) function, to estimate the energy-biased technical change. However, the C-D function is usually set as the neutral technological progress. In fact, the technological progress is often biased and has asymmetric effects on energy, labor or capital in the real economic circumstance (e.g., Karanfil and Yeddir-Tamsamani, 2010). Moreover, the non-neutral technical change has been intensively demonstrated by existing studies (e.g., Sanstad et al., 2006; Hassler et al., 2012; Hübler and Glas, 2014; Wang et al., 2014; Zha et al., 2017). Obviously, the specification of the neutral technological progress is difficult to mirror the real world. In contrast, the CES function has no such a limitation. Therefore, we select the CES function to estimate the energy-biased technical change.

Specifically, according to the indicator of the biased technical change proposed by Acemoglu (2002) and Wang et al. (2014), we set the production function as a form of the two-layer nested constant elasticity of substitution, including three factors i.e., energy, labor, and capital. The specification is as follows:

$$Y_t = \left\{ \alpha (A_{Lt}L_t)^{\rho} + (1-\alpha)\left[\beta (A_{Et}E_t)^{\theta} + (1-\beta)(A_{Kt}K_t)^{\theta}\right]^{\frac{\rho}{\theta}} \right\}^{\frac{1}{\rho}} \tag{1}$$

where t denotes the year; Y is the total output; Capital (K), labor (L), and energy (E) are inputs, which have corresponding factor augmenting technical efficiency, A_{it} ($i = K, L, E$); α and β are the output share of labor and energy, respectively; θ and ρ are the elasticity of substitution among energy, capital, and labor, respectively. Thus, we can calculate the energy bias index of technical change (tc) as follows:

$$tc = \frac{1}{TRS}\frac{\partial TRS}{\partial (A_{Et}/A_{Kt})} \times d\left(\frac{A_{Et}}{A_{Kt}}\right) \Big/ dt = \theta \left(\frac{A_{Et}}{A_{Kt}}\right)^{-1} d\left(\frac{A_{Et}}{A_{Kt}}\right) \Big/ dt \tag{2}$$

where $TRS = \frac{\partial Y_t/\partial E}{\partial Y_t/\partial K} = \frac{\beta}{1-\beta}\left(\frac{A_{Et}}{A_{Kt}}\right)^{\theta}\left(\frac{E_t}{K_t}\right)^{\theta-1}$.

Eq. (2) shows that the biased direction of technical change depends on the change in the relative marginal output of production factors. If $tc > 0$, technological progress increases more the marginal output of energy than that of capital. That is to say, there is energy-biased or energy-use technical change. If $tc < 0$, technological progress reduces the marginal output of energy relative to capital, and then it appears to be capital-biased or energy-saving technical change.

In previous studies, other indicators, such as energy consumption intensity and clean technology indicators, are frequently used. Compared with the energy bias index of technical change (tc), however, energy consumption intensity refers to energy consumption per unit output and is an indicator of energy efficiency, and cannot directly reflect the utilization of energy-saving technologies (Lin and Du, 2015; Huang and Yu, 2016; Huang et al., 2017). In addition, clean technology usually refers to new and clean energy technology or environmentally friendly technology. Clean technology level is often measured by clean technology patents in patent database (Johnstone et al., 2010; Noailly and Shestalova, 2017; Miyamoto and Takeuchi, 2019). In this sense, clean technology can reflect the energy-biased technical change to some extent. However, the energy bias index of technical change can further reflect the increased marginal output (or productivity) of energy caused by technological progress with the constant proportion of factor inputs. Therefore, the energy bias index of technical change used in this study is more reasonable to response to energy-saving technology than these two kinds of indicators.

According to the standardized procedure of CES production function proposed by Klump et al. (2007), we standardize Eq. (1) and obtain the equations as follows:

$$\frac{Y_t}{\xi \overline{Y}} = \left\{ \overline{\alpha}\left(\frac{L_t}{\overline{L}}\right)^{\rho} e^{\rho g_L(t,\overline{t})} + (1-\overline{\alpha})\left[\beta\left(\frac{E_t}{\overline{E}}\right)^{\theta} e^{\theta g_E(t,\overline{t})} + (1-\beta)\left(\frac{K_t}{\overline{K}}\right)^{\theta} e^{\theta g_K(t,\overline{t})}\right]^{\frac{\rho}{\theta}} \right\}^{\frac{1}{\rho}} \tag{3}$$

$$\frac{\tau_t L_t}{Y_t} = \overline{\alpha} e^{\rho g_L(t,\overline{t})} \xi^{\rho} \left(\frac{Y_t/\overline{Y}}{L_t/\overline{L}}\right)^{-\rho} \tag{4}$$

$$\frac{\omega_t E_t}{Y_t} = (1-\overline{\alpha})\beta e^{\theta g_E(t,\overline{t})} \left(\frac{Y_t}{\xi \overline{Y}}\right)^{-\rho} \left(\frac{E_t}{\overline{E}}\right)^{\theta} \left[\beta\left(\frac{E_t}{\overline{E}}\right)^{\theta} e^{\theta g_E(t,\overline{t})} + (1-\beta)\left(\frac{K_t}{\overline{K}}\right)^{\theta} e^{\theta g_K(t,\overline{t})}\right]^{\frac{\rho}{\theta}-1} \tag{5}$$

$$\frac{\psi_t K_t}{Y_t} = (1-\overline{\alpha})(1-\beta) e^{\theta g_K(t,\overline{t})} \left(\frac{Y_t}{\xi \overline{Y}}\right)^{-\rho} \left(\frac{K_t}{\overline{K}}\right)^{\theta} \left[\beta\left(\frac{E_t}{\overline{E}}\right)^{\theta} e^{\theta g_E(t,\overline{t})} + (1-\beta)\left(\frac{K_t}{\overline{K}}\right)^{\theta} e^{\theta g_K(t,\overline{t})}\right]^{\frac{\rho}{\theta}-1} \tag{6}$$

where $\overline{\alpha}$ is the average output share of labor; ξ is the scale factor, and $\overline{Y}$, $\overline{L}$, $\overline{K}$, $\overline{E}$, and $\overline{t}$ represent the average values of output, labor, capital, energy input, and year, respectively; τ_t, ω_t, and ψ_t are the marginal outputs of labor, energy, and capital, respectively; g_i ($i = K$, L, and E) is the growth rate of augmenting technology efficiency. We assume that technical change rates of capital, labor and energy are in line with BOX-COX transformation as follows:

$$A_{it} = A_{i\overline{t}} e^{g_i(t,\overline{t})}, g_i(t,\overline{t}) = \left\{ \overline{t} \frac{\gamma_i}{\lambda_i} \left[\left(\frac{t}{\overline{t}} \right)^{\lambda_i} - 1 \right] \right\} \tag{7}$$

where γ_i and λ_i ($i = K$, L) represent the parameters of augmenting technology efficiency growth and technical curvature, respectively. Next, we detail the indicators and data sources of related variables, including output, inputs and factor incomes.

(1) Output. Y_{it}, the output at region i and year t, is measured by gross regional domestic product, using data from the *China Statistical Yearbook*.
(2) Inputs. Labor input (L_{it}) is represented by the annual average number of employees. Capital input (K_{it}) is measured by capital stock by using the method of perpetual inventory and fixed asset investment data. Energy consumption (E_{it}) is measured by the coal consumption for power generation in China. The data of regional inputs are from the *China Statistical Yearbook* and *China Energy Statistical Yearbook*.
(3) Factor incomes. Labor income includes total wages and social insurance funds. Remuneration of capital is calculated by the total operating profits deducting the depreciation of fixed assets. The data source is from the *China Statistical Yearbook* and *China Labor Statistics Yearbook*. In addition, Hassler et al. (2012) claimed that the income share of energy factor was almost less than 5% compared with capital and labor factors. Referring to the method proposed by Liu et al. (2016), we figure out that the average income share of energy factor in national income is pegged by 5%.

The above indicators measured by monetary value are at constant prices. Figs. 3 and 4 depict the variation of regional energy-biased levels of technical change over 2002–2015. In particular, Fig. 3 shows the trend in regions where the energy-biased level of technical change is greater than zero, indicating that technical change in these regions is energy-biased or energy-consuming. Conversely, Fig. 4 illustrates the trend in regions where the energy-biased level is less than zero, implying that technical change in these regions is capital-biased or energy-saving.

According to the two figures, we can arrive at following conclusions. First, the energy-biased level of technical change differs in regions. Specifically, 11 regions in Fig. 3 where technical change are energy-consuming include Beijing, Hebei, Shanxi, Inner Mongolia, Liaoning, Jiangsu, Zhejiang, Anhui, Fujian, Ningxia, and Xinjiang. While other 18 regions in Fig. 4 where technical changes are energy-saving or capital-biased include Tianjin, Jilin, Heilongjiang, Shanghai, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, and Qinghai. We can find that the energy-biased level does not coincide with the level of a region's economic development, which means that not all technical changes in economically developed regions exhibit the direction to energy conservation.

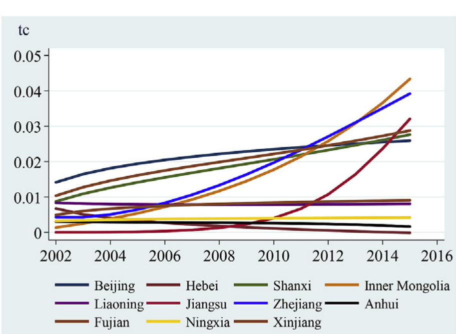

Fig. 3. Energy bias in regions with energy-biased technical change.

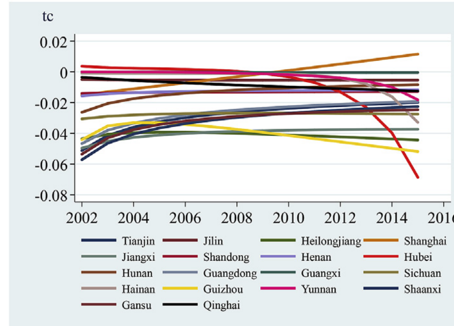

Fig. 4. Energy bias in regions with energy-saving technical change.

Second, directions of technical change are inconsistent during the same period and the developing trends diverge as well. On the one hand, for regions where technical changes are energy-biased, bias levels are almost above zero but there are divergent trends which can be divided into two categories. One category has a steady upward trend and exhibits gradually enhanced energy intensity. The other category presents a J-shape curve showing an increasing trend of energy use. On the other hand, for regions where technical change is energy-saving, there are also two trends of energy-biased levels: steadily descending and continuously ascending. Besides, for some regions like Shanghai, the energy-biased level is less than zero, and technical change is capital-biased in the initial period. However, since 2010 the bias index has become positive which implies the conversion of technical change to energy consumption.

Third, it should be emphasized that some well-developed provincial-level regions with higher income, such as Beijing, Jiangsu, and Zhejiang, have not totally exhibited the energy-saving characteristic of technical change. While there are some less-developed provincial-level regions with low- and middle-income showing the energy-saving technical change, such as Jiangxi, Guangxi, Yunnan, and Qinghai. Therefore, our findings suggest that there is no income inequality effect on the regional energy bias.

Furthermore, the Kernel distribution of regional energy bias change in 2002–2008 and 2009–2015 are presented in Figs. 5 and 6, respectively. In Fig. 5, we can see that the bimodal distribution is shown in 2002–2008 and moves from the left to right, indicating that there is a direction towards energy use. However, as shown in Fig. 6, the bimodal feature disappears from 2009 to 2015. The bottom and top width of the distribution are broadened, indicating that some regions move towards the energy-saving direction, while others move towards the energy-consuming direction. In addition, the variance increases and the polarization of energy bias among regions is intensified.

3. Investigation of FDI' s energy-saving spillovers

3.1. Baseline regression

Based on energy bias of technical change, we will investigate

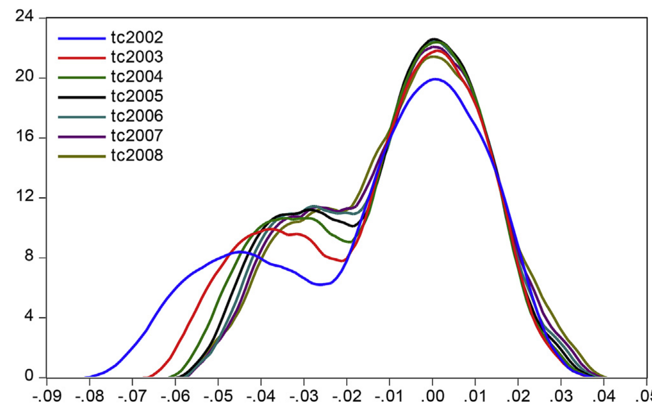

Fig. 5. Kernel distribution of regional energy bias change from 2002 to 2008.

energy-saving spillover effects of FDI. We firstly examine the determinants of energy bias in China, and then analyze the spillover effects of FDI. Controlling the price and market size effects and the factor abundance (Acemoglu, 2002), we get the following equation:

$$tc_{it} = \beta_0 + \beta_1 \ln e_{it} + \beta_2 \ln kl_{it} + \beta_3 \ln h_{it} + \beta_4 \ln rdpl_{it} + \beta_5 \ln eq_{it} + \beta_6 Cer_{it} + \varepsilon_{it} \tag{8}$$

where tc_{it} is the energy bias index at region i and year t. Variables *lne* and *lnkl* denote the logarithm of energy input and capital per labor, respectively. *lnh* is the logarithm of human capital expressed by average years of schooling. *lnrdpl* denotes regional R&D investment per labor measured by regional internal expenditure for research funding. *lneq* is the environmental carbon emission level measured by average carbon dioxide emissions per capita. The index of environmental regulation *Cer* is introduced, which represents the cumulative number of the legislation in each region, based on the data of the *China Environmental Yearbook*. The environmental regulations can effectively curb the emissions of firms and increase firms' willingness to innovate in technology, especially energy-saving technologies. The reason is that firms can reduce losses caused by the increasing production cost through innovative compensation effect. β_j ($j = 0, 1, 2, \ldots, 6$) are the coefficients of explanatory variables, and ε_{it} is the random error term.

The calculation of independent variables, *lnh* and *lneq* are specified as follows. With respect to variable *lnh*, we first divide the education level into seven grades, including illiterate and semi-literate, elementary, junior high, senior high, junior college, college and post graduate. Then, according to the general duration of education in China, we define the education years of these seven grades as 0, 6, 9, 12, 15, 16, and 20 years, respectively. Finally, the average years of schooling is the population multiplies the education years divided by the total employment. The related data are collected from the *China Population and Employment Statistics Yearbook*, *China Labor Statistics Yearbook*, and *China Statistical Yearbook*.

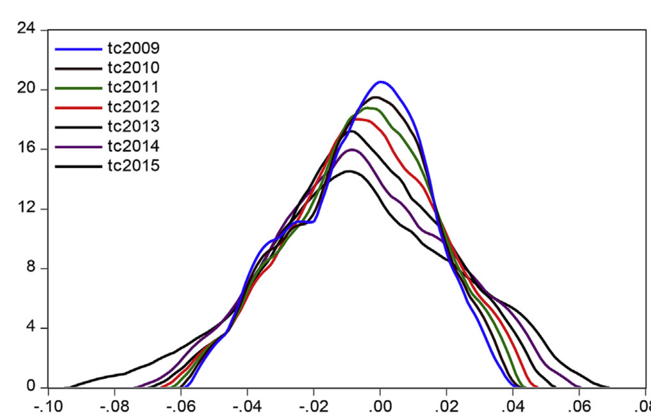

Fig. 6. Kernel distribution of regional energy bias change from 2009 to 2015.

Following our previous works (Shao et al., 2011; Yang et al., 2017; Yao et al., 2018), we calculate CO_2 emissions (*lneq*) according to $CO_{2it} = \sum_i E_{it} NCV_{it} CEF_{it} COF_{it} * 44/12$, where E is energy consumption; NCV_{it} denotes average low calorific value of each energy in China; *CEF* and *COF* are carbon content and carbon oxidation rate, respectively; numbers 44 and 12 refer to the molecular and atomic weights of CO_2 and C, respectively. The related data are collected from the *China Energy Statistical Yearbook*, IPCC (2006), and NDRC (2011). It is noteworthy that the IPCC's (2006) method for the estimation of CO_2 emissions has some uncertainties, which have been quantified and discussed in some studies (e.g., Liu et al., 2015; Mi et al., 2017). The uncertainties in energy-related CO_2 emissions derive from the individual uncertainties of energy use and emission factors. There are inconsistencies in China's energy statistics that energy consumption data at the national level are always lower than the sum of regional data (Guan et al., 2012). In addition, reliance on the global default values of CO_2 emission factors recommended by IPCC (2006) would cause some uncertainties (Liu et al., 2015). It is also believed that trade pattern and emission intensity are the main reasons for the difference of carbon emission types in different regions and cities (Mi et al., 2019; Song et al., 2019). In this study, we use China's specific CO_2 emission factors released by the Chinese government (NDRC, 2011), which largely reduces the uncertainties of estimation. To our knowledge, NDRC (2011) is currently a proper reference for the estimation of China's CO_2 emissions.

We make the empirical analysis based on the panel model of 29 provincial-level regions over 2002–2015. In particular, it should be noted that Tibet is not included and that Chongqing and Sichuan are merged into one region due to incomplete data. Table 1 reports the results of baseline regression. The regressions in the first two columns in Table 1 are estimated by the panel corrected standard errors (PCSE) method. The R-squared are 0.8938 and 0.9298, respectively, which indicate that the selection of control variables are as expected. The baseline regression can fully control the

Table 1
Baseline regression results.

	(1)	(2)	(3)
lne	0.0124***	0.0087***	0.0157***
	(0.0025)	(0.0012)	(0.0045)
lnkl	−0.0054***	−0.0045***	−0.0057***
	(0.0010)	(0.0009)	(0.0022)
lnh	0.0053	0.0004	0.0037
	(0.0082)	(0.0072)	(0.0127)
lnrdpl	0.0032***	0.0031***	0.0027
	(0.0012)	(0.0013)	(0.0021)
lneq	−0.0038	−0.0104*	−0.0053*
	(0.0028)	(0.0055)	(0.0031)
Cer		0.0006	
		(0.0001)	
Constant	−0.1015***	−0.0664***	−0.1548***
	(0.0192)	(0.0149)	(0.0386)
R-squared	0.8938	0.9298	
Wald chi2	997873.94	516285.46	527.38
Prob>chi2	0.0000	0.0000	0.0000
Obs.	406	377	406
Number of regions	29	29	29

Notes: Standard errors are in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

variation of energy bias, to a large extend.

The coefficient of energy input (*lne*) is significantly positive at 1% level and that of *lnkl* is significantly negative, which implies that the energy bias of technical change is affected by the factor endowment. Furthermore, if there is more energy input, technical change is more energy-biased. Otherwise, it is more capital-biased. In other words, the market size effect has greater impact on the direction of technical change than the price effect. The human capital level (*lnh*), characterized by average years of schooling, has a positive effect on the energy bias, but the coefficient is not significant. That suggests it depends on the capital and energy rather than human capital whether technological progress is energy-biased or not.

The coefficient of R&D investment (*lnrdpl*) is positive and significant at 1% level, which indicates that technological innovation contributes more to the direction of technical change towards energy use. The main reasons are from two aspects. First, the rebound effect of energy efficiency induced by technological progress usually leads to additional energy consumption (Shao et al., 2014; Liu et al., 2016; Li et al., 2019). The potential energy savings resulting from technical change are offset by the rebound effect, especially in the context of low energy prices in China (Zha et al., 2018; Shao et al., 2019; Liu et al., 2019). In other words, low energy costs make it less profitable to supply energy-saving technologies (André and Smulders, 2014). Second, it usually takes a long term from R&D investment to commercial application or industrialization for energy-saving technologies. Conversely, energy-biased technologies have more advantages than energy-saving technologies in terms of the initial investment and market share (Zha et al., 2017). Therefore, without the stimulation measures from governments, enterprises prefer to invest energy-biased technologies.

The CO_2 emissions (*lneq*) have a significantly negative effect on the energy bias in Column (2), indicating that if regional carbon emissions are higher, the environmental quality is worse and technical change is more directed to energy saving. In other words, the deterioration of environmental quality is helpful to induce the direction of technical change towards energy use. The insignificant coefficient of *Cer* shows that environmental regulations fail to effectively increase firms' willingness to innovate in energy-saving technologies. Column (3) shows that after controlling for the endogeneity between the energy input and energy bias by selecting the first-order lag term of *lne* as the instrumental variable, the result is basically consistent with Column (1).

As we discussed above, the human capital has no significant impact on the energy bias. R&D investment doesn't reflect the tendency of firms to actively choose the energy-saving technology. Similarly, the environmental regulation doesn't have effective energy-saving performance, which implies that it is difficult to encourage firms to research and develop the technology of energy saving through the enforcement of environmental regulation. As a result, we further examine the technology spillover effects of FDI in the following part.

3.2. Test for spillover direction of FDI

The direction of technical change is not only affected by the factor endowment and policy, but also by FDI in the host country. FDI is the principal access to import advanced technologies. Compared to domestic companies, multinational companies usually have higher labor productivity, more advanced technology and management experience. Therefore, domestic companies can acquire the improvement of productivity and the upgrade of technology with the inflow of FDI. Meanwhile, foreign-invested enterprises can alter the direction of technical change in the host country through industrial linkage, technology demonstration and imitation, and labor mobility. Therefore, we introduce foreign direct investment (*fdip*) into Eq. (8) to examine the technology spillover direction of FDI. Variable *fdip* is measured by actual use amount of FDI. The exchange rate conversion and price adjustment for this indicator are performed with a unit of one billion yuan and the data source is the *China Statistical yearbook*. Table 2 presents the results based on the estimation of Eq. (8).

We adopt the method of Feasible Generalized Least Squares (FGLS), which could deal with the heteroscedasticity of model, to investigate the impact of FDI's technology spillovers on the energy bias in China. Table 2, Column (1) shows that the coefficients of *lne* and *lnkl* are significantly positive and negative, respectively, which are consistent with the results of Eq. (1) in Table 1. This means that abundant factor will contribute more to the direction of technical change towards itself. Besides, it suggests that the human capital (*lnh*) makes technical change be directed to energy conservation, but its significance is less than that of capital (*lnkl*). Meanwhile, the carbon emissions or environmental quality (*lneq*) have a significant effect on the energy bias, reflecting that the deterioration of environmental quality may contribute to the endeavor of curbing the

Table 2
Test results of the spillover direction of FDI.

	(1)	(2)	(3)	(4)
	(2002–2015)	(2002–2006)	(2011–2015)	(2013–2015)
lne	0.0138***	0.0003*	−0.0033	0.0161
	(0.0012)	(0.0035)	(0.0094)	(0.0192)
lnkl	−0.0040***	0.0003	−0.0075	−0.0057
	(0.0005)	(0.0042)	(0.0049)	(0.0084)
lnh	−0.0065*	0.0219**	0.0082	0.0256
	(0.0037)	(0.0114)	(0.0219)	(0.0274)
lnrdpl	0.0041***	0.0055***	0.0066	−0.0042
	(0.0006)	(0.0024)	(0.0064)	(0.0093)
lneq	−0.0083***	0.0020	0.0194**	−0.0099
	(0.0010)	(0.0030)	(0.0093)	(0.0144)
fdip	−0.0006**	−0.0041***	−0.0028*	−0.0019
	(0.0003)	(0.0016)	(0.0017)	(0.0018)
Constant	−0.0858***	−0.0759***	−0.0269	−0.1132
	(0.0104)	(0.0299)	(0.0986)	(0.1891)
Wald chi2	28591.29	7256.29	2495.68	2596.38
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Obs.	406	145	145	87
Number of regions	29	29	29	29

Notes: Standard errors are in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Technology spillover coefficient of FDI.

Panel A: energy-biased spillover effects (11 provincial-level regions)					
Province	Coefficient	Province	Coefficient	Province	Coefficient
Beijing	0.000517	Heilongjiang	0.010500	Shandong	0.000060
Yunnan	0.067085	Shanghai	0.009976	Liaoning	0.000059
Shaanxi	0.026757	Fujian	0.001190	Anhui	0.000017
Hunan	0.015829	Jilin	0.000374		
Panel B: energy-saving spillover effects (18 provincial-level regions)					
Province	Coefficient	Province	Coefficient	Province	Coefficient
Hebei	−0.000230	Shanxi	−0.001780	Tianjin	−0.017079
Henan	−0.000260	Jiangxi	−0.002230	Xinjiang	−0.025150
Guangxi	−0.000290	Jiangsu	−0.002753	Inner Mongolia	−0.029780
Guangdong	−0.000710	Ningxia	−0.003850	Guizhou	−0.032380
Sichuan	−0.000760	Qinghai	−0.011880	Gansu	−0.050308
Zhejiang	−0.001690	Hainan	−0.015580	Hubei	−0.065470

pollution emissions and influencing R&D activities. R&D investment (*lnrdpl*) remains significantly positive directed to energy consumption, which means that the environmental regulations couldn't affect in R&D activities. To a certain extent, it confirms that energy-saving technologies lack of some advantages in the free market economy. Therefore, it is the key to promote the energy-saving innovation that formulating accurately and implementing timely the environmental regulations, and reorienting the investment in fiscal capital as well as human capital. In Column (1) of Table 2, it is obvious that FDI spills energy-saving technologies. This indicates that if the inflow of FDI is higher, technical change is more biased to the energy saving.

We further investigate the time variation of FDI's spillovers through selecting two periods of sample: 2002–2006 and 2011–2015. The results based on two periods are presented in Columns (2) and (3) in Table 2, respectively. Although the change of sample size would alter the significance of coefficient of some indicators, we can still observe that the energy-saving spillovers caused by FDI varies with time. The characteristics are mainly reflected from two aspects. On the one hand, FDI shows obvious energy-saving spillover effects in all types of the sample period. On the other hand, there is a decline in the energy-saving spillover effects of FDI by time. At the earlier period (2002–2006), FDI has significant energy-saving spillover effects. In the last five years (2011–2015), FDI still exhibits the energy-saving characteristics, but the significance of the coefficient declines (only at a 10% level). Furthermore, in order to investigate whether the energy-saving spillover effects are descending with time, we select the sample with the period of 2013–2015 again. The estimation is presented in Column (4). However, the energy-saving spillover effects have become completely insignificant. Compared with the results in Columns (2)–(4), we can infer two questions according to the variation of the coefficient and the statistical significance of *fdip*: Are there any other factors affect the direction of FDI's technology spillovers? Are there heterogeneous features for FDI's technology spillovers in different regions?

Table 3 summarizes the coefficients of FDI's technology spillover in 29 regions. As depicted in the table, on the one hand, the coefficients are positive in 11 regions showing energy-biased spillover effects (see as Panel A), while they are negative in other 18 regions showing energy-saving spillover effects (see as Panel B). On the other hand, the coefficients are very small and even close to zero in some regions. It suggests that FDI's spillovers in these regions are directed to energy saving but the spillovers effects are weak. In consequence, there are two questions: whether there are some other factors affecting the direction of FDI's spillover and whether the spillovers are different in different regions. Why does FDI have energy-saving technology spillovers in some regions, and energy-biased technology spillovers in other regions? This can be attributed to the differences of regional conditions, such as market-oriented condition, industrial condition, technological level, and factor mobility condition. Such differences cause FDI to choose heterogeneous technologies resulting in the difference of technology spillover direction. Additionally, local governments have different policies for foreign-funded enterprises to attract different types of FDI from heterogeneous industries with different technologies. Therefore, it is not surprised that there is the difference of FDI's technology spillover direction in different regions.

Table 4 summarizes the coefficients of FDI's energy-saving spillovers and the levels of energy bias in all regions. We find that there are 11 regions, including Tianjin, Jiangxi, Henan, Hubei, Guangdong, Guangxi, Hainan, Sichuan, Guizhou, Gansu, Qinghai, where both FDI's spillovers and technical changes are energy-saving. Meanwhile, 4 regions exhibit energy-biased spillovers and technical changes, including Beijing, Liaoning, Anhui, Fujian. Because the spillovers' directions are consistent with the energy bias levels in above-mentioned regions, FDI's spillovers can explain the directions of technical change. However, in the remaining 14 regions, the spillovers' directions are opposite to the energy-biased levels of technical change. Therefore, we explore whether the directions of technical change in these regions are determined by regional factor endowment.

Referring to the analytical framework proposed by Li and Xu (2018), the abundance of mineral resources like coal is measured by the ratio of the employment in the mining industry to the total employment. We use this indicator of resources abundance to

Table 4
Regional difference of FDI's spillovers.

	Energy-saving spillovers of FDI	Energy-biased spillovers of FDI
Energy-biased technical change	Hebei, Shanxi, Inner Mongolia, Jiangsu, Zhejiang, Ningxia, Xinjiang	Beijing, Liaoning, Anhui, Fujian
Energy-saving technical change	Tianjin, Jiangxi, Henan, Hubei, Guangdong, Guangxi, Hainan, Sichuan, Guizhou, Gansu, Qinghai	Jilin, Heilongjiang, Shanghai, Shandong, Hunan, Yunnan, Shaanxi

Table 5
Ratio of urban employment in the mining industry to the total employment.

Province	Ratio	Rank	Province	Ratio	Rank	Province	Ratio	Rank
Shanxi	20.75	1	Guizhou	5.63	11	Hubei	1.69	21
Ningxia	9.21	2	Jilin	5.47	12	Jiangsu	1.36	22
Heilongjiang	8.65	3	Qinghai	4.97	13	Guangxi	1.29	23
Anhui	7.42	4	Hebei	4.80	14	Hainan	0.98	24
Inner Mongolia	7.17	5	Yunnan	4.66	15	Beijing	0.83	25
Shaanxi	6.99	6	Gansu	4.57	16	Fujian	0.78	26
Xinjiang	6.64	7	Sichuan	3.24	17	Guangdong	0.24	27
Henan	6.44	8	Tianjin	3.21	18	Zhejiang	0.14	28
Shandong	6.43	9	Hunan	2.62	19	Shanghai	0.01	29
Liaoning	5.72	10	Jiangxi	2.46	20			

explain the inconsistent directions between FDI's spillovers and technical change. Table 5 calculates and ranks the ratio of employment in the mining industry from 2008 to 2015 by regions. We also display the correlation between FDI's spillovers and the energy-biased technical changes in Fig. 7. The large (small) circles in figure present these provincial-level regions with median-above (median-below) ratio of urban employment in the mining industry. The resources abundance in 7 regions out of these 11 energy-biased provincial-level regions (see in the Table 4), Hebei, Shanxi, Inner Mongolia, Ningxia, and Xinjiang, are above the median, indicating that the resource abundance can explain the inconsistent directions between FDI's spillovers and technical change in these regions. While the resources abundance is below the median in those regions, Shanghai, Hunan, and Yunnan, where FDI's spillovers are energy-biased but technical changes are energy-saving. Therefore, we can conclude that the energy-saving technical change is mainly determined by the resource abundance in these 3 regions. In brief, there are 23 regions where the directions of technical change can be explained by FDI's spillovers and factor endowment.

4. Conditions of FDI's spillovers

The above results have revealed that the energy-saving spillover effects of FDI have gradually abated. Meanwhile, the direction and intensity of the spillovers differ greatly among regions. Therefore, we investigate the determinants and conditions of FDI's spillovers from four perspectives: marketization, industry, technology and labor mobility.

4.1. Marketization condition

Generally, if the degree of regional marketization is higher, there will be fiercer competition among local enterprises. Obviously, the market competition may play an important role in changing the direction and intensity of FDI's spillovers. Therefore, we use the marketization index to examine how it affects the changes of FDI's spillovers. The data on the marketization come from “*China Marketization Index Report*” compiled by Wang et al. (2017).

Based on the average marketization level, 29 provincial-level regions are divided into two groups. The first group is consisted of 9 provincial-level regions, including Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong, where the marketization level is above 8.8. The remaining provincial-level regions are regarded as the second group. The marketization is denoted by a dummy variable, *md*, marking the first group as 1 and the second as 0. We also control the interaction between the dummy variable and FDI in the model with the aim of examining the different FDI's spillovers in two groups.

Table 6 reports the regression results including the interaction. It is obvious that the influences of control variables on the energy bias remain the same as that of Tables 1 and 2 The significantly negative coefficient of *fdip* shows that FDI has energy-saving spillovers. However, the coefficient of *fdip***md* is significantly positive at the 1% level, suggesting that the market competition and market-oriented reforms divert FDI to spill energy-biased technologies. It also means that with the increasing marketization level, the market competition has been intensified gradually. To sum up, the marketization level plays an important role in determining the types of technology spillover effects. When the level is low, FDI will exhibit the energy-saving spillovers. When the marketization is higher, FDI will spill more energy-consuming technologies.

The findings above could be explained as follows. In fact, the marketization level has changed constantly, which may not be reflected only by the dummy variable. Therefore, we use the panel threshold model to examine the boundary conditions of marketization of the energy-saving spillovers. The model is estimated as follows:

$$tc_{it} = \beta_0 + \beta_1 \ln e_{it} + \beta_2 \ln kl_{it} + \beta_3 \ln h_{it} + \beta_4 \ln rdpl_{it} + \beta_5 \ln eq_{it} + \gamma_1 fdip_{it} \bullet I(mak < m) + \gamma_2 fdip_{it} \bullet I(mak \geq m) + \varepsilon_{it} \quad (9)$$

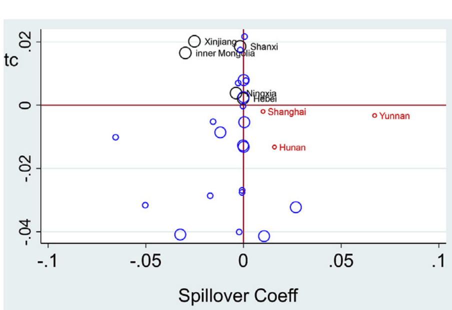

Fig. 7. Energy-biased technical changes (*tc*) and FDI's spillovers.

Table 6
Differential effects of various marketization levels on FDI's energy-saving spillovers.

Variable	Coef.	Std. Err.	Z statistic
lne	0.0090***	0.0027	3.40
lnkl	−0.0046***	0.0010	−4.45
lnh	0.0061	0.0086	0.71
lnrdpl	0.0037***	0.0012	3.05
lneq	−0.0020	0.0027	−0.77
fdip	−0.0037***	0.0006	−6.09
*fdip***md*	0.0057***	0.0013	4.45
Constant	−0.0850***	0.0227	−3.75
R-squared	0.8962	Obs.	406
Wald chi2	386421.20	Pro>chi2	0.0000

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Threshold test results of market condition for FDI's energy-saving spillovers.

Model	Threshold estimate	95% confidence interval	F test	P value	Bootstrap times
Single threshold model	13.19	(12.71,13.89)	53.079***	0.010	300
Double threshold model	11.45	(3.86,14.21)	8.592*	0.070	300
	13.71	(13.17,14.21)			
Triple threshold model	4.64	(3.86,13.05)	6.012	0.180	300

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

where *mak*, the marketization level, denotes the threshold variable, m is the threshold parameter that divide the equation into two regimes with coefficients γ_1 and γ_2. $I(\cdot)$ is the indication function. If the expression in the parentheses is true, $I(\cdot)$ equals to one, otherwise, it equals to zero. Other variables are the same as before.

We firstly determine the number of thresholds in Eq. (9) through the Bootstrap method proposed by Hansen (2000). As shown in Table 7, the single-threshold model's estimator is 13.19 with 95% confidence interval [12.71, 13.89]. The F statistic is highly significant. Therefore, we reject the null hypothesis that there is no single threshold. For the double threshold test, the null hypothesis is rejected at the 10% level of significance as well. For the triple threshold test, however, the null hypothesis is accepted, indicating that there is no triple threshold effect.

In addition, we can view the threshold confidence interval by plotting the LR statistic, seen as Figs. 8–11. In these figures, the horizontal axis represents the marketization level, the vertical axis is the value of the LR statistic. The dashed line denotes the critical value (7.35) of LR statistic at the 95% confidence level. It is obvious that the threshold effect of variable *mak* does exist in Figs. 8–10, while it does not exist in Fig. 11. Obviously, the double-threshold model is accepted in this paper according to the testing results analyzed above.

Table 8 presents the regression results for the single and double threshold models. First, for the single-threshold model, the spillover direction of FDI changes in the opposite direction above and below the threshold estimate. Specifically, when the marketization level is relatively low, FDI has a negative effect on the energy bias of technical change, but the effect is not significant. However, when the marketization level is relatively high and exceeds the threshold

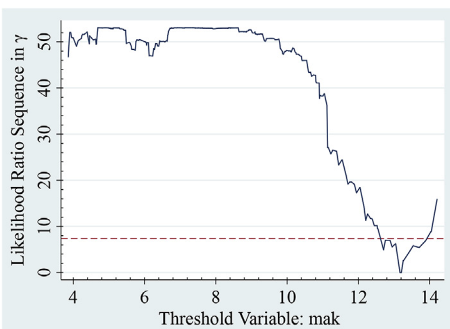

Fig. 8. Single threshold effect test.

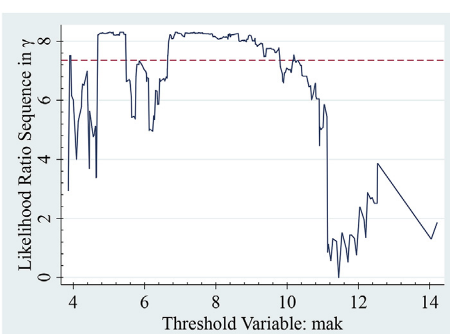

Fig. 9. Double threshold effect test 1.

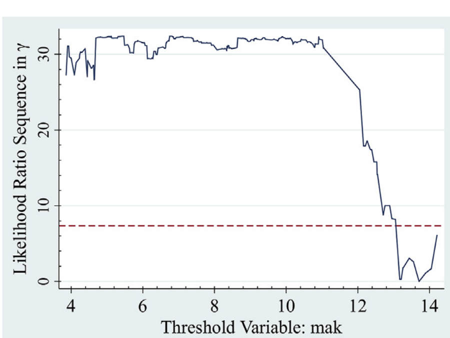

Fig. 10. Double threshold effect test 2.

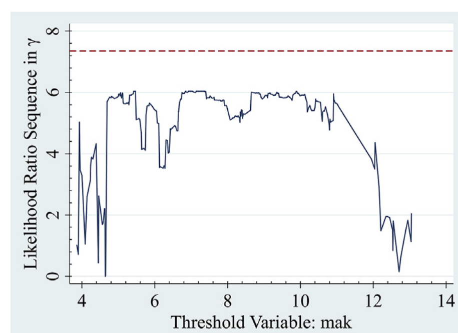

Fig. 11. Triple threshold effect test.

Table 8
Market condition for FDI's energy-saving spillovers.

Variable	Single threshold	Double threshold
lne	0.0078***(0.0037)	0.0074**(0.0037)
lnkl	−0.0044***(0.0021)	−0.0035*(0.0021)
lnh	0.0065(0.0120)	0.0008(0.0119)
lnrdpl	0.0002(0.0021)	−0.0007(0.0020)
lneq	0.0031***(0.0030)	0.0037(0.0030)
fdip1	−0.0001(0.0011)	−0.0004(0.0011)
fdip2	0.0053***(0.0013)	0.0019*(0.0011)
fdip3		0.0069***(0.0014)
Cons	−0.0963***(0.0343)	−0.0791**(0.0346)
F test	14.62	14.01
Prob>F	0.0000	0.0000
Obs.	406	406
Number of regions	29	29

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(13.19), the intensified market competition will induce the inflow of FDI, which causes a positive effect on the technological change. Finally, FDI could have energy-consuming spillovers and technical change is also biased to energy. This finding is similar to that of Albornoz et al. (2009). Albornoz et al. (2009) confirmed that when the regional marketization level became higher, both domestic and foreign enterprises would be confronted with greater competition. Most enterprises, therefore, present the preference to energy-biased technologies due to less cost and more profit compared with energy-saving technologies. In other words, it will be more difficult for enterprises to get profit because of a large amount of R&D investment in energy-saving technologies. Consequently, on a free market, the supply of energy-saving technologies is often insufficient. In order to raise the level of energy-saving technologies, environmental policies, such as R&D subsidies and carbon taxes, are important to stimulate R&D investment.

Second, the estimated result of double-threshold model is basically similar to that of single-threshold model. When the marketization level is lower, FDI exhibits energy-saving spillover effects but not significant. While the marketization level exceeds the first threshold (11.45), FDI spills energy-biased technologies. Moreover, when exceeding the second threshold (13.71), the energy-biased spillover effects of FDI are stronger.

In addition, we give more details on the regional disparity of marketization. Taking the sample in 2010 and 2015 as an example, Table 9 shows the distribution of regional marketization. In 2010, there are 4 regions where the marketization levels exceed the threshold (11.45), showing that FDI has energy-biased spillover effects in these provincial-level regions. In 2015, there are 9 regions where the marketization levels are above the threshold (11.45). The increasing number of regions exceeding the threshold shows that there is an upward trend with respect to FDI's energy-biased spillovers in China. However, the other regions exhibit weak energy-saving spillover effects. It should be concerned that the developed provincial-level regions have exceeded the threshold estimate earlier. For example, Shanghai first surpassed the threshold estimate in 2007, and Zhejiang in 2008. To sum up, along with the increasing marketization level in developed regions, more fiercer market competition discourages the innovative activities in energy-saving technologies, which leads to a phenomenon that multinational firms incline to use energy-biased technologies.

4.2. Industry condition

Along with the intense market competition, the degree of the industrial agglomeration has increased, affecting FDI's spillovers. First, the industrial agglomeration will strengthen the linkages among firms through shortening the distance. The closer connections among firms will further intensify FDI's spillover effects by exchanging and collaborating with neighboring firms. Second, the technology spillovers not only exist among similar industries, but also among the industries with forward and backward linkages, which is called as Jacobian externality. When diversified industries with forward and backward linkages cluster in one place, it is easier for knowledge and technology to be exchanged and assimilated mutually through the related economic activities, such as purchasing raw materials, selling intermediate products. This means that the industrial agglomeration has an innovative effect. However, it also appears the monopolistic competition among firms along with the industrial agglomeration, thereby restraining the willingness of entrepreneurs to pour money into R&D sector. Namely, the monopolistic competition caused by the industrial agglomeration may inhibit technology spillovers. Overall, the FDI's spillovers are ambiguous under the condition of industrial agglomeration.

We now identify the threshold effect of the industrial condition on FDI's spillovers. The industrial agglomerations are measured as two indicators in the empirical analysis, namely the industrial specialization (*IS*) and industrial diversification (*ID*). We calculate the two indicators by expressions as follows:

$$IS = \max(P_{m,it}/P_{m,t}) \tag{10}$$

$$ID = \sum_{m=1}^{M} P_{m,it}\Big(\sum_{k\in Um}(P_{k,it}/P_{m,it})\ln(P_{m,it}/P_{k,it})\Big) \tag{11}$$

where $\max(\cdot)$ is the maximum function; $P_{m,it}$ and $P_{k,it}$ measure the share of labor in two-digit industries $m(=1, 2, \ldots, M)$ and three-digit industries k ($k=1, 2, \ldots, K$) at region i in year t, respectively; U_m represents the set of three-digit industries contained in the industry m with two-digit codes.

We also use the panel threshold model to estimate the threshold effect of industrial condition on FDI's spillovers. The bottom panel of Table 10 reports the threshold effect test, which suggests that the double-threshold model is accepted with the indicator of industrial specialization (*IS*) and the single-threshold model is accepted with the indicator of industrial diversification (*ID*). First, it is consistent with above regression results in Table 2 that the abundance of energy has a positive effect on the energy bias of technical change, which suggests that if a certain factor is more abundant, technical change is more directed to it. More specifically, the influence directions of the energy and capital per labor on technical change are opposite, which implies that the more energy contributes to the energy-biased technical change and the more capital encourages the technical change to direct to saving energy. Besides, the effect of the human capital and R&D investment is almost positive but not significant.

Column (3), where the indicator of industrial condition is measured as industrial specialization, shows that the coefficients of *fdi*1 and *fdi*2 are both significantly negative, while the coefficient of *fdi*3 is significantly positive. In particular, when the level of industrial specialization (*IS*) is lower than the first threshold (1.336), FDI will exhibit significant energy-saving spillover effects. When *IS*

Table 9
Regional distribution of marketization level.

Year	Marketization level	Region	Marketization level	Region
2010	$mak<11.45$	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	$mak\geq 11.45$	Shanghai, Jiangsu, Zhejiang, Guangdong
2015	$mak<11.45$	Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Hainan, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	$mak\geq 11.45$	Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong

Table 10
Threshold test and regression results of industry condition for FDI's energy-saving spillovers.

Threshold variable	Industrial specialization		Industrial diversification
	Single threshold	Double threshold	Single threshold
lne	0.0112***	0.0056	0.0093***
	(0.0037)	(0.0038)	(0.0039)
lnkl	−0.0042**	−0.0042**	−0.0043*
	(0.0022)	(0.0021)	(0.0022)
lnh	0.0074	0.0157	0.0030
	(0.0123)	(0.0120)	(0.0126)
lnrdpl	0.0033	0.0025	0.0031
	(0.0021)	(0.0020)	(0.0021)
lneq	−0.0049**	0.0009	−0.0023
	(0.0029)	(0.0030)	(0.0030)
fdip1	−0.0135***	−0.0148***	0.0028**
	(0.0027)	(0.0026)	(0.0014)
fdip2	−0.0007 (0.0011)	−0.0019* (0.0011)	−0.0009 (0.0011)
fdip3		0.0062***	
		(0.0017)	
Constant	−0.1261***	−0.0998***	−0.1043***
	(0.0346)	(0.0339)	(0.0365)
Threshold estimate (τ_1)	1.336		1.560
Threshold estimate (τ_2)	2.713		1.688
	1.336		1.560
Threshold estimate (τ_3)	1.547		1.604
Single threshold effect test (P)	32.943**		12.677* (0.070)
	(0.030)		
Double threshold effect test (P)	28.8553*		11.992 (0.187)
	(0.057)		
Triple threshold effect test (P)	12.169		6.995 (0.257)
	(0.137)		
F test	11.66	14.18	8.68
Prob>F	0.0000	0.0000	0.0000
Obs.	406	406	406
Number of regions	29	29	29

Notes: Standard errors are in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

is higher than the first threshold (1.336) and lower than the second threshold (2.713), FDI will continue to spill relatively weaker energy-saving effect. However, when *IS* exceeds the second threshold (2.173), FDI turns to spill energy-biased technologies.

Column (4) reports the results of FDI's spillovers under the condition of industrial diversification (*ID*). The coefficient of *fdi*1 is significant positive, but that of *fdi*2 is not significant. Therefore, we can conclude that when the level of *ID* is lower, FDI will spill energy-biased effect. When the level of *ID* increases, FDI begins to spill energy-saving effect, but the spillover effect is not significant.

It is generally believed that the higher agglomeration is more beneficial for domestic enterprises to imitate and learn more advanced technologies. In this case, the technology spillovers of FDI will be stimulated to some extend. However, our findings fail to support this view. Conversely, FDI has the energy-saving spillovers in regions with medium and low level of industrial specialization according to the above results in this paper. We believe that the most likely explanation is that the differences in the two types of technology, energy-saving and energy-biased, cause some trade-off. If the energy-biased technology is applied in almost regions, it is difficult for the energy-saving technology to come out and survive. As the level of specialized agglomeration gradually increases, fierce competition in the market further depresses the yields obtained by each firm. To survive in the fierce competition, firms tend to pour more capital and other resources into product sales or market development rather than the innovation of energy-saving technologies. In this sense, the industrial agglomeration has relatively strong competitive effect and weak innovation effect.

In addition, the lower level of industrial diversification is more beneficial to the energy-biased spillovers of FDI, according to the results in Table 10, Column (4). In other words, the energy-biased spillovers of FDI are more obvious in regions with the low level of industrial diversification. It means that R&D activities on the energy-biased technology not only transfer costs to consumers by improving the quality of products and charging higher prices, but also realize the internalization of externality by saving factor inputs and increasing the production efficiency. Therefore, if there are more types of firms with forward and backward linkages, it is easier to generate the Jacobian externality and stimulate the energy-biased spillovers. Nooteboom (1999) argued that technology spillovers existed among firms with complementary knowledge but closer cognitive distances generally. Because firms could absorb and digest new advanced knowledge with moderate cognitive distances, making it possible for companies to learn from each other.

We exhibit the regional distribution of FDI's spillovers under the condition of specialized agglomeration in Table 11. When the agglomeration level is lower than the first threshold (1.336), FDI exhibits strong energy-saving spillover effects in some regions, including Hebei (2001, 2002, 2004), Jiangsu (2001, 2002), Anhui (2005), Jiangxi (2011, 2013), Henan (2001, 2005), Hubei (2013, 2013, 2015) and Yunnan (2009). It can be found that there are few regions with strong energy-saving technology spillovers. When the agglomeration level is higher than the first threshold (1.336) and lower than the second threshold (2.713), there are 23 provincial-level regions where FDI presents the weak energy-saving spillovers, including Tianjin, Hebei, and Inner Mongolia. Moreover, 15 provincial-level regions exhibit weak energy-saving spillovers during the entire sample period, including Liaoning, Jilin, Shanghai, Zhejiang, Fujian, Shandong, Hunan, Guangdong, Guangxi, Sichuan, Guizhou, Shaanxi, Gansu, Qinghai, and Ningxia.

Table 11
Regional distribution of industrial specialization condition.

Specialization	Regions with strong energy-saving spillovers	Specialization	Regions with weak energy-saving spillovers
$IS < 1.336$	Hebei (2002, 2004)	$1.336 \le IS < 2.713$	Tianjin (2002, 2003, 2005)
	Jiangsu (2002)		Hebei (2003, 2005–2015)
	Anhui (2005)		Inner Mongolia (2002)
	Jiangxi (2011, 2013)		Liaoning (2002–2015)
	Henan (2005)		Jilin (2002–2015)
	Hubei (2013, 2014, 2015)		Shanghai (2002–2012)
	Yunnan (2009)		Jiangsu (2003–2015)
			Zhejiang (2002–2015)
			Anhui (2002–2004, 2006–2015)
			Fujian (2002–2015)
			Jiangxi (2002–2010, 2012, 2014–2015)
			Shandong (2002–2015)
			Henan (2002–2004, 2006–2015)
			Hubei (2002–2012)
			Hunan (2002–2015)
			Guangdong (2002–2015)
			Guangxi (2002–2015)
			Sichuan (2002–2015)
			Guizhou (2002–2015)
			Yunnan (2002–2008, 2010–2015)
			Shaanxi (2002–2015)
			Gansu (2002–2015)
			Qinghai (2002–2015)
			Ningxia (2002–2015)

Note: The number in parentheses denotes the year when the strong or weak energy-saving spillovers appeared.

4.3. Technology condition

Besides the market and industry condition, the technology condition also plays an important role in affecting FDI's spillovers. The technology spillovers will cause a demonstration effect through the forward and backward relationship between multinational and domestic firms. This is because multinational firms buy raw materials, intermediate goods and other related services from domestic firms, and domestic firms provide reprocessing of intermediates for multinational firms. Moreover, considering the quality of products, multinational enterprises will provide technical guidance, consultation and training in order to meet the standards of raw materials or intermediates provided by suppliers. And then, FDI will form technology spillovers to domestic enterprises. It should be noted that FDI's spillovers are determined by the matching degree of the factor endowment, especially the technological level, between multinational and domestic firms. Some studies have suggested that the FDI's spillover effects will be weakened when the technological level is too high or too low (e.g., Li et al., 2001). In the host country, if the technological level is too high or the distance to the frontier technology is shorter, the scope of demonstration effect provided by multinational companies will be smaller. If the technological level is lower and the distance to the frontier technology is further, the mismatching of production factors caused by technological gaps between multinational and domestic companies will affect adversely the digestion and absorption of advanced technology.

Therefore, we examine the threshold effect of domestic technology condition on FDI's spillovers in this paper. The technology condition is measured as the number of patent applications of industrial enterprises. Besides, we also take into account the clean technology, measured as the number of patents granted of the clean technology. The data are from the *Chinese Patent Full-text Database*.

Table 12 presents the results of the threshold effect of domestic technology condition. The threshold effect test in the bottom panel of the table shows that the single-threshold model is accepted. Table 12, Columns (1) shows that FDI has energy-saving technology spillovers but not significant if the technological level is lower than the threshold (1.992). However, if the technological level exceeds the threshold (1.992), FDI exhibits significant energy-biased spillovers. Column (2) shows the same result with the threshold variable of clean technology. The potential explanation is that both multinational and local companies mainly adopt the energy-biased technology, causing higher energy-biased spillovers. In order to control for the endogeneity between FDI and local technological level, we further use the first-order lag term of the threshold variable to estimate the threshold model. The results are presented in Columns (3) and (4) of Table 12. Compared with Columns (1) and (2), the results of Columns (3) and (4) remain consistent. Therefore, it can be drawn from Table 12 that the higher technology level will strengthen the energy-biased spillovers of FDI.

4.4. Labor mobility condition

Labor mobility is an important way of FDI's spillovers. Domestic companies can acquire advanced technologies, operating skills, organizational forms, and management experience by sending technicians to study in multinational enterprises and cooperating with them. Meanwhile, domestic companies also can absorb advanced management experience, technologies and skills by employing multinational companies' staff. All these approaches contribute to FDI's spillovers.

Based on the data availability, using the data on regional employee mobility measures the labor mobility between local and foreign enterprises. More specifically, we can characterize the labor mobility by subtracting the natural population growth rate from regional labor growth rate, and then multiplying by regional total employees.

Table 13 presents the results of threshold test, indicating that the double-threshold model is accepted. Table 14 reports the threshold effect of labor mobility on the energy-saving spillovers of FDI. First, the coefficient of $fdip1$ is positive but insignificant before reaching the first threshold ($labl<206.889$). That suggests the energy-saving spillovers of FDI does not exist, conditioning of lower labor mobility. The most likely explanation is that lower labor

Table 12
Threshold test and regression results of industry condition for FDI's energy-saving spillovers.

	(1)	(2)	(3)	(4)
Threshold variable	*Patai*	*Cpatae*	*Lpatai*	*Lcpatae*
	industrial enterprise patent applications	patents granted for cleaning technology	industrial enterprise patent applications	patents granted for cleaning technology
	(ten thousand piece)	(ten thousand piece)	(ten thousand piece)	(ten thousand piece)
Lne	0.0124***	0.0128***	0.0133***	0.0134***
	(0.0037)	(0.0039)	(0.0037)	(0.0038)
Lnkl	−0.0033	−0.0049**	−0.0033	−0.0055***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Lnh	−0.0035	0.0003	−0.0054	0.0004
	(0.0124)	(0.0125)	(0.0124)	(0.0125)
Lnrdpl	0.0002	0.0112	0.0001	0.0019
	(0.0022)	(0.0021)	(0.0022)	(0.0021)
Lneq	−0.0019	−0.0013	−0.0023	−0.0018
	(0.0030)	(0.0030)	(0.0029)	(0.0030)
fdip1	−0.0006	−0.0001	−0.0003	−0.0002
	(0.0011)	(0.0001)	(0.0011)	(0.0011)
fdip2	0.0030***	0.0028**	0.0036***	0.0024**
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Constant	−0.1071***	−0.1223***	−0.1099***	−0.1330***
	(0.0352)	(0.0352)	(0.0348)	(0.0353)
Threshold estimate (τ_1)	1.992	0.155	2.286	0.144
Threshold estimate (τ_2)	0.013	0.936	0.005	0.782
	1.949	0.155	1.992	0.144
Threshold estimate (τ_3)	7.276	0.001	5.221	0.001
Single threshold effect test (P)	28.566**(0.040)	20.143**(0.053)	33.854***(0.037)	16.387**(0.050)
Double threshold effect test (P)	10.582(0.123)	11.093(0.130)	8.827(0.107)	5.611(0.273)
Triple threshold effect test (P)	7.886(0.213)	6.903(0.133)	6.008(0.340)	4.676(0.147)
F test	11.02	9.78	11.80	9.23
Prob>F	0.0000	0.0000	0.0000	0.0000
Obs.	406	406	406	406
Number of regions	29	29	29	29

Notes: Standard errors are in parentheses; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 13
Threshold test results of labor mobility condition for FDI's energy-saving spillovers.

	Threshold estimate	95% confidence interval	F test	P value	Bootstrap times
Single threshold model	137.144	(0.547, 207.938)	11.061	0.110	300
Double threshold model	206.889	(201.898, 207.938)	26.230***	0.017	300
	230.676	(0.547, 260.431)			
Triple threshold model	113.790	(0.547, 184.700)	9.330	0.113	300

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 14
Labor mobility condition for FDI's energy-saving spillovers.

Variable	Coefficient	Std. Err.	T value
lne	0.0106***	0.0038	2.82
lnkl	−0.0052***	0.0022	−2.40
lnh	0.0028	0.0122	0.23
lnrdpl	0.0044***	0.0021	2.13
lneq	−0.0040	0.0029	−1.37
fdip1	0.0006	0.0012	−0.01
fdip2	−0.0192***	0.0035	−5.49
fdip3	−0.0008	0.0014	−0.61
Cons	−0.1171***	0.0347	−3.37
F test	10.83	Pro>chi2	0.0000
Obs.	406	Number of regions	29

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

mobility is not beneficial to the exchange of advanced technology, thus weakening the energy-saving spillovers of FDI. Second, the coefficient of *fdip*2 is significantly negative. Specifically, when the labor mobility level is between the first threshold value and the second threshold value (i.e., $206.889 \leq labl < 230.676$), FDI exhibits the energy-saving spillover effects in the environment where the labor mobility is moderate. However, when the labor mobility level exceeds the second threshold ($labl \geq 230.676$), the effect of FDI on the energy bias is negative but not significant. One potential explanation for this result is that it is difficult for labors in domestic enterprises to successfully imitate, digest and absorb advanced technologies brought by FDI in a short term, especially under the condition of a high labor mobility, not to mention the innovation. Therefore, a moderate labor mobility is more beneficial to the energy-saving spillovers of FDI.

In conclusion, in the case of moderate labor mobility, the effect

Table 15
Regional distribution of moderate labor mobility.

Labor mobility	Regions with moderate mobility
$206.889 \leq labl < 230.676$	Hebei (2015), Anhui (2001, 2010, 2013), Henan (2005, 2008), Hubei (2015), Hunan (2009), Guangxi (2007, 2008), Yunnan (2001, 2002, 2003, 2005)

Note: The number in parentheses denotes the year when there was a moderate mobility level in the corresponding regions.

of FDI on the energy-saving spillovers is significant. Table 15 presents the regions and corresponding years that labor mobility is moderate, including Hebei (2015), Anhui (2001, 2010, 2013), Henan (2005, 2008), Hubei (2015), Hunan (2009), Guangxi (2007, 2008), Yunnan (2001, 2002, 2003, 2005).

5. Concluding remarks

Many empirical studies have analyzed the spillovers of FDI. In contrast, relatively little attention has been paid to the energy-saving spillovers of FDI. Moreover, there has been little empirical testing of the threshold effects of determinants on FDI's spillovers. Therefore, starting from the perspective of the energy bias, we investigate when FDI spills energy-saving technologies by establishing a two-layer nested CES production function and adopting the standard system methods to estimate the energy bias of technical change. Specifically, we focus on analyzing the threshold effects of the marketization, industrial agglomeration, technology and labor mobility on energy-saving spillovers of FDI.

There are three primary findings. First, there is no income inequality effect on the energy-saving technology in China, i.e., there is no evidence supporting that FDI flowing into low- and middle-income regions increases energy consumption, while FDI flowing into high-income regions conserves energy. Second, there is a regional difference of FDI's spillovers. Results suggest that the direction of FDI's spillovers varies in different regions in China. Specifically, FDI promotes energy-biased technologies in some provincial-level regions like Yunnan, while it promotes energy-saving technologies in other provincial-level regions like Hubei. There are four mechanisms, including the marketization, industrial agglomeration, technology, and labor mobility, affecting FDI's spillovers. Third, this paper presents evidence of the threshold effect on the FDI's energy-saving spillovers. The direction of spillovers will be changed between energy consumption and conservation depending on the level of the threshold variables. For the threshold variable of market condition, it contributes to energy-saving spillovers of FDI when the marketization level is lower. However, when the level of marketization exceeds the threshold, the pressure from market competition often forces companies to prefer energy-biased technologies. For the industry condition, it is more likely to achieve the energy-saving spillovers of FDI in regions with lower specialized agglomeration. If there are different types and the higher industrial diversification is, it is easier to generate the Jacobian externality and spill more energy-biased technologies. For the technology condition, FDI is more likely to spill energy-biased technologies with higher technology level. For the labor mobility condition, it can effectively stimulate FDI to exhibit energy-saving spillover effects when the labor mobility is moderate.

According to the threshold effects of the marketization, industrial agglomeration, technology, and labor mobility on energy-saving spillovers of FDI, some policy implications can be put forward as follows. First, it is imperative for China's local governments to attract the investment or entry of multinational enterprises with advanced technology and efficient management skills, based on the comparative advantages in resources or factors in different regions. Second, local governments should make use of the positive effect of marketization and labor mobility on the energy-saving spillovers of FDI to develop the energy-saving technologies and to promote the green innovative activities and technical efficiency of local enterprises. Third, it is essential for local governments to implement R&D subsidies and environmental (carbon) taxes to stimulate enterprises to develop or adopt energy-saving technologies, especially new energy technologies or clean technologies. Fourth, local governments should further strengthen market competition mechanism to improve the green innovative conditions faced by enterprises. Finally, since moderate labor mobility helps FDI spill over energy-saving technology, local governments should lessen market interference and strengthen labor mobility through market competition mechanism, to promote the exchange and cooperation between domestic and foreign enterprises.

Actually, there are still some issues to be further explored. On the one hand, the impacts of marketization, industry, and technology on FDI spillovers and the conditions under which these factors are beneficial to developing energy-saving technologies in some special and important regions in China, such as the Yangtze River Delta region and the Pearl River Delta region, should be investigated carefully. On the other hand, the comparison of the impacts of R&D subsidies and carbon taxes on energy-biased or energy-saving technological progress is also an important issue. The optimal portfolio of these conditions or policies should be examined.

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References

Acemoglu, D., 2002. Directed technical change. Rev. Econ. Stud. 69 (4), 781–809.
Adom, P.K., Amuakwa-Mensah, F., 2016. What drives the energy saving role of FDI and industrialization in East Africa. Renew. Sustain. Energy Rev. 65, 925–942.
Albornoz, F., Cole, M.A., Elliott, R.J.R., Ercolani, M.G., 2009. In search of environmental spillovers. World Econ. 32 (1), 136–163.
André, F.J., Smulders, S., 2014. Fueling growth when oil peaks: directed technological change and the limits to efficiency. Eur. Econ. Rev. 69, 18–39.
Doytch, N., Uctum, M., 2016. Globalization and the environmental impact of sectoral FDI. Econ. Syst. 40, 582–594.
Gorodnichenko, Y., Svejnar, J., Terrell, K., 2014. When does FDI have positive spillovers? Evidence from 17 transition market economies. J. Comp. Econ. 42, 954–969.
Guan, D., Liu, Z., Geng, Y., Lindner, S., Hubacek, K., 2012. The gigatonne gap in China's carbon dioxide inventories. Nat. Clim. Change 2 (9), 672–675.
Hansen, B.E., 2000. Sample splitting and threshold estimation. Econometrica 68 (3), 575–603.

Hassler, J., Krusell, P., Olovsson, C., 2012. Energy-saving Technical Change. National Bureau of Economic Research (NBER) Working Paper No. 18456.
Huang, J.B., Yu, S.W., 2016. Effects of investment on energy intensity: evidence from China. Chin. J. Population Res. Environ. 14 (3), 197–207.
Huang, J.B., Du, D., Tao, Q.Z., 2017. An analysis of technological factors and energy intensity in China. Energy Policy 109, 1–9.
Hübler, M., Glas, A., 2014. The energy-bias of North-South technology spillovers: a global, bilateral, bisectoral trade analysis. Environ. Resour. Econ. 58 (1), 59–89.
The Intergovernmental Panel on Climate Change (IPCC), 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Institute for Global Environmental Strategies (IGES), Hayama, Kanagawa, Japan.
Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45 (1), 133–155.
Karanfil, F., Yeddir-Tamsamani, Y., 2010. Is technological change biased toward energy? A multi-sectoral analysis for the French economy. Energy Policy 38 (4), 1842–1850.
Klump, R., McAdam, P., Willman, A., 2007. Factor substitution and factor-augmenting technical progress in the United States: a normalized supply-side system approach. Rev. Econ. Stat. 89 (1), 183–192.
Lee, J.W., 2013. The contribution of foreign direct investment to clean energy use, carbon emissions and economic growth. Energy Policy 55, 483–489.
Li, J.L., Xu, B., 2018. Curse or blessing: how does natural resource abundance affect green economic growth in China. Econ. Res. J. (9), 151–167.
Li, X., Liu, X., Parker, D., 2001. Foreign direct investment and productivity spillovers in the Chinese manufacturing sector. Econ. Syst. 25 (4), 305–321.
Li, J.L., Liu, H.X., Du, K.R., 2019. Does market-oriented reform increase energy rebound effect? Evidence from China's regional development. China Econ. Rev. 56, 101–304.
Lin, B.Q., Du, K.R., 2015. Measuring energy rebound effect in the Chinese economy: an economic accounting approach. Energy Econ. 50, 96–104.
Lin, B.Q., Liu, H.X., 2015. Does energy and environment efficiency benefit from foreign trade? The case of China's industrial sectors. Econ. Res. J. (9), 127–141.
Liu, Z., Guan, D., Wei, W., Davis, S.J., Ciais, P., Bai, J., Peng, S., et al., 2015. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature 524 (7565), 335–338.
Liu, Y., Zhou, M.F., Feng, S.H., Wang, Y., 2016. Rebound effect and its decomposition – an analysis based on energy types in China. Chin. J. Population Res. Environ. 14 (4), 245–252.
Liu, Y., Yu, H., Gao, Y., 2017. The environmental consequences of domestic and foreign investment: evidence from China. Energy Policy 108, 271–280.
Liu, H.X., Du, K.R., Li, J.L., 2019. An improved approach to estimate direct rebound effect by incorporating energy efficiency: a revisit of China's industrial energy demand. Energy Econ. 80, 720–730.
Lovely, M., Popp, D., 2011. Trade, technology and the environment: does Access to technology promote environmental regulation. J. Environ. Econ. Manag. 61 (1), 16–35.
Mi, Z.F., Meng, J., Guan, D., Shan, Y.L., Song, M.L., Wei, Y.M., Liu, Z., Hubacek, K., 2017. Chinese CO_2 emission flows have reversed since the global financial crisis. Nat. Commun. 8, 1712.
Mi, Z.F., Zheng, J.L., Meng, J., Zheng, H.A., Li, X., Coffman, D.M., Woltjer, J., Wang, S.Y., Guan, D., 2019. Carbon emissions of cities from a consumption-based perspective. Appl. Energy 235, 509–518.
Miyamoto, M., Takeuchi, K., 2019. Climate agreement and technology diffusion: impact of the Kyoto Protocol on international patent applications for renewable energy technologies. Energy Policy 129, 1331–1338.
National Development and Reform Commission (NDRC) of P. R. China, 2011. Guidelines for Provincial Greenhouse Gas Inventories [Chinese Document] (Beijing, China).
Noailly, J., Shestalova, V., 2017. Knowledge spillovers from renewable energy technologies: lessons from patent citations. Environ. Innovation Soc. Trans. 22, 1–14.
Nooteboom, B., 1999. Innovation and inter-firm linkages: new implications for policy. Res. Pol. 28 (8), 793–805.
Paramati, S.R., Ummalla, M., Apergis, N., 2016. The effect of foreign direct investment and stock market growth on clean energy use across a panel of emerging market economies. Energy Econ. 56, 29–41.
Rafindadi, A.A., Muye, I.M., Kaita, R.A., 2018. The effects of FDI and energy consumption on environmental pollution in predominantly resource-based economies of the GCC. Sustain. Energy. Technol. Asses. 25, 126–137.
Ren, S., Yuan, B., Ma, X., Chen, X., 2014. International trade, FDI and embodied CO_2 emissions: a case study of China's industrial sectors. China Econ. Rev. 28, 123–134.
Sanstad, A.H., Roy, J., Sathaye, J.A., 2006. Estimating energy-augmenting technological change in developing country industries. Energy Econ. 28 (5–6), 720–729.
Seker, F., Ertugrul, H.M., Cetin, M., 2015. The impact of foreign direct investment on environmental quality: a bounds testing and causality analysis for Turkey. Renew. Sustain. Energy Rev. 52, 347–356.
Shao, S., Yang, L., Yu, M.B., Yu, M.L., 2011. Estimation, characteristics, and determinants of energy-related industrial CO_2 emissions in Shanghai (China), 1994–2009. Energy Policy 39, 6476–6494.
Shao, S., Huang, T., Yang, L., 2014. Using latent variable approach to estimate China's economy–wide energy rebound effect over 1954–2010. Energy Policy 72, 235–248.
Shao, S., Guo, L., Yu, M., Yang, L., Guan, D., 2019. Does the rebound effect matter in energy import-dependent mega-cities? Evidence from Shanghai (China). Appl. Energy 241, 212–228.
Song, M.L., Cao, S.P., Wang, S.H., 2019. The impact of knowledge trade on sustainable development and environment-biased technical progress. Technol. Forecast. Soc. Change 144, 512–523.
Wang, C., Liao, H., Pan, S.Y., Zhao, L.T., Wei, Y.M., 2014. The fluctuations of China's energy intensity: biased technical change. Appl. Energy 135, 407–414.
Wang, L., Cai, X., Gao, Q., 2014. Skill Bias Level of Technical Change in China: 1979-2010. Economic Perspectives, pp. 56–65, 4.
Wang, X., Fan, G., Yu, J., 2017. Marketization Index for China's Provinces 2016. Social Sciences Academic Press.
Yang, Z., Fan, M., Shao, S., Yang, L., 2017. Does carbon intensity constraint policy improve industrial green production performance in China? A quasi-DID analysis. Energy Econ. 68, 271–282.
Yao, X., Kou, D., Shao, S., Li, X., Wang, W., Zhang, C., 2018. Can urbanization process and carbon emission abatement be harmonious? New evidence from China. Environ. Impact Assess. Rev. 71, 70–83.
Zha, D., Kavuri, A.S., Si, S., 2017. Energy biased technology change: focused on Chinese energy-intensive industries. Appl. Energy 190, 1081–1089.
Zha, D., Kavuri, A.S., Si, S., 2018. Energy-biased technical change in the Chinese industrial sector with CES production functions. Energy 148, 896–903.
Zhao, X., Zhang, Y., Li, Y., 2019. The spillovers of foreign direct investment and the convergence of energy intensity. J. Clean. Prod. 206, 611–621.
Zhu, H., Duan, L., Guo, Y., Yu, K., 2016. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: evidence from panel quantile regression. Econ. Modell. 58, 237–248.