



The role of OFDI in home-country pollution: insights from LMDI and 3SLS approaches

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Abstract

Under the global climate crisis, harnessing investment for sustainable development is a practical and effective measure for international society. Based on the logarithmic mean Divisia index (LMDI) decomposition and three-stage least squares (3SLS) structural approaches, this study explores the home-country pollution reduction effect of Chinese OFDI activities using the city-level panel data from 2007 to 2019. The findings of this study indicate that (1) China has made a remarkable achievement in PM_{2.5} pollution reduction and governance, especially from the year 2012. (2) The OFDI activities can significantly decrease the home-country PM_{2.5} pollution. With every 1% increase in OFDI flows, the overall pollution level will decrease by 0.76%. (3) Compared with the scale mechanism, the technology and composition mechanism effects of OFDI flows are more evident in addressing the home-country PM_{2.5} pollution. With several related policy implications, this study may fill the lacuna of how to play the role of OFDI activities in the home country, thus promoting sustainable development in the next stage.

Keywords OFDI · LMDI · 3SLS · Home-country effect · Sustainable development

JEL Classification F21 · F64 · Q56

Promoting investment in sustainable development and recovery.

–UNCTAD World Investment Report 2021

Introduction

Under the global climate crisis, how to achieve green recovery and sustainable development has become an emerging issue for international society (Khan et al. 2022; Watts et al. 2018). With the frequent occurrence of destructive and unpredictable weather, reducing and mitigating the actual and potential negative environmental effects caused

by economic activities is a practical measure for countries worldwide (Antweiler et al. 2001; Cunha-Zeri et al. 2022). In this regard, the social benefits of international investment activities have also changed in nature. Since the 1980s, outward foreign direct investment (OFDI) activities have mainly paid attention to economic benefits in the host country, such as market occupation and resource acquisition (Cicea and Marinescu 2020; Zameer and Yasmeen 2022). Nevertheless, as climate change intensifies, the environmental benefits of OFDI activities have aroused great concern in recent years, especially in the home country.

Based on the classical environmental Kuznets curve (EKC) theory, the relationship between OFDI activities and environmental pollution has come to the stage (Grossman and Krueger 1991; Hao et al. 2016). During the critical period of combating climate change, two opposing opinions have occupied a dominant position in practice (Cieślak and Goczek 2018; Huynh and Hoang 2019). The pollution shelter hypothesis holds that the home country can transfer environmental pollution to the host country through OFDI activities (Singhania and Saini 2021). In contrast, the pollution halo hypothesis argues that advanced technology and mature experience will finally improve the host-country

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environment (Duan and Jiang 2021). Although these two opinions are still in continuous development, they are actually interested in the host-country environmental benefits (Gyamfi et al. 2022). The international capital outflow from the home country will also induce environmental changes in its own ecosystem.

In this sense, an interesting and thought-provoking question is whether OFDI flows from the home country can affect their own environmental condition (Bhasin and Kapoor 2021; Luo and Wang 2012; Yin et al. 2020). With the occurrence and persistence of reverse spillover phenomena, such as reverse technology spillover and reverse structural transformation, the home-country environmental condition will also be affected by its own OFDI activities (Long et al. 2023; OECD 2012; Wang et al. 2022c). For example, both Xin and Zhang (2020), Zhou et al. (2019b), and Wang et al. (2019) have revealed the green reverse technology spillover effect of Chinese OFDI activities on the domestic environment at the province level. Therefore, exploring the home-country environmental effect of OFDI activities will be one of the emerging fields in international investment.

Under this background, this study focuses on the home-country effect of OFDI activities on environmental pollution. Currently, studies have mainly revealed the carbon emission reduction effect of OFDI activities on the home country. It has been found that OFDI activities can stimulate international technology spillovers, especially negative spillovers from developed to developing countries (Iqbal et al. 2022; Shahbaz et al. 2020; Sorrell et al. 2020). This negative carbon technology spillover strengthens the traditional technology spillover effect, making the home-country environmental governance possible (Nan et al. 2022; Verde 2020). Nevertheless, these are not enough to understand the role of OFDI in the home-country environment, especially in developing economies like China (Hao et al. 2020; Yang et al. 2021). On the one hand, except for the technology spillover effect in the home-country environmental governance, the scale growth and composition adjustment effects are also important, let alone the connection and linkages among them in the economic systems (Dogan and Inglesi-Lotz 2020; Yasmeen et al. 2019). On the other hand, achieving sustainable development also requires pollution reduction, such as PM_{2.5} emissions, as they are closely related to human health (Meo et al. 2021; Zameer et al. 2021b).

Based on the logarithmic mean Divisia index (LMDI) decomposition and three-stage least squares (3SLS) structural approaches, this study reveals the effect and mechanism of Chinese OFDI activities on PM_{2.5} pollution using city-level data from 2007 to 2019. We mainly find that Chinese OFDI activities can decrease PM_{2.5} pollution by an overall effect of 0.76% reduction, among which the technology and composition mechanisms are the main pathways. Regarding the factual implications of this study, (1) China has gradually

become an important participant in international investment activities after acceding to the World Trade Organization (WTO) in 2001. With OFDI activities of USD 136.9 billion in 2019, China ranks second in the world (UNCTAD 2022). (2) The unprecedented economic growth in the past decades has triggered social anxiety and environmental concerns. Although China has implemented diversified environmental policies to control and govern pollution, it has a long way to transfer from extensive development to sustainable development. Therefore, joining the hot debate about the home-country effect in China is necessary and meaningful.

Compared with previous studies, this study may have two possible contributions: (1) This study pays attention to the home-country effect of OFDI activities, which provides a novel insight into the current studies on international investment activities. To the best of our knowledge, most related studies are interested in the host-country environmental benefits. We change the research direction from the host country (the invested country) to the home country (the investing country), which largely enrich the current research perspective. (2) This study uses the LMDI decomposition and 3SLS structural approaches at the city level, which is relatively accurate and convictive. In comparison, the related studies are based on provincial-level data using single equation estimation, which cannot reveal the linkages among economic systems. However, the complexity of the ecosystem makes the decomposition and structure methods more advantageous. Consequently, in the post-COVID-19 pandemic era, finding extra measures outside environmental regulations, such as the home-country environmental effect of OFDI activities, is helpful to cope with the global climate crisis in the future.

The rest of this study proceeds as follows. Section 2 provides a literature review to build up the research foundation. Section 3 is the research design, including two identification strategies and sample data. Section 4 presents the LMDI decomposition results, the 3SLS overall effects, and the 3SLS mechanism effects. Section 5 then shows various robustness estimations, including the MCMC simulation, machine learning optimization, and single equation estimation. The main conclusions and policy implications are provided in the “[Conclusions and implications](#)” section.

Literature review

Background information

Chinese OFDI activities

From 1949 to 1978, China did not conduct many international activities for national security and political considerations (Cui et al. 2012; Keller et al. 2011). With the vision to

participate in the world economy in 1978, China first implemented the “reform and opening up” strategy to encourage “setting up companies abroad” activities. Due to the lack of capital and technology, the OFDI flows were less than USD 1 billion (Lai 2021; Luo et al. 2010). After that, the comparative advantage brought by economic globalization and international division has made Chinese international investment activities develop rapidly. The OFDI flows increased from USD 0.8 billion in 1990 to almost USD 10 billion in 2001. However, the Chinese government still had a direct and decisive right to OFDI activities at this time (Wang and Gao 2019).

With its accession to the WTO in 2001, China gradually implemented a diversified investment strategy combining the “bringing in” and “going out” aspects (Tang 2020). Since then, a package of supporting regulations has been proclaimed to reduce and simplify the approval processes of international investment activities, for example, the *Decision to Reform the Investment System* in 2004 and the *Administration of Approval and Filing of Overseas Investment Projects* in 2014 (Fan et al. 2004; Liu and Zhang 2020; Xia et al. 2022a). After that, companies can make independent investments and decisions with only ex-ante registering, filing, and reporting (Du and Zhang 2018; Pan and Al-Tabbaa 2021). As one of the leading participants in the world economy, China has achieved OFDI flows from about USD 10 billion in 2001 to USD 136.9 billion in 2019, ranking second only to the USA (UNCTAD 2022).

PM_{2.5} pollution in China

Since 1953, China has implemented a series of “the Outline of the Five-Year Plans for National Economic and Social Development (the Five-Year Plan)” to adjust the socio-economic speed, direction, attention, plan, and vision (Stern and Xie 2023; Zheng et al. 2022). In environmental stewardship, China has implemented dozens of policies and campaigns to control environmental pollution since 2000, including the green credit policy, energy saving and low carbon action, central environmental inspection, and national air quality monitoring program (Wang et al. 2022a; Zameer et al. 2020; Zhao et al. 2022).

In practice, it was around 2004 that China first became aware of the harm and dangers of PM_{2.5} pollution to humans and the environment. Long before that, it was generally believed that PM_{2.5} was a kind of harmless fog (Feng and Yuan 2022). And then, the US embassy monitored and released the air condition of Beijing with its own equipment in 2008, which attracted lots of public attention. Later, the Chinese government formally revised the *Ambient Air Quality Standards* in 2012, with PM_{2.5} added as a pollutant index (Barwick et al. 2019). Since then, China has gradually

increased the regulatory requirements for PM_{2.5} pollution (Cheng et al. 2020).

In the meantime, China set up a national air quality monitoring system in 2012 to strengthen public participation and supervision in environmental stewardship, especially the smog pollution caused by PM_{2.5}. As of now, more than 1400 monitoring stations have been set up in 337 cities, covering 98% of the population activity areas (Liu et al. 2021; Yu and Morotomi 2022). With regulatory requirements and public participation, China has effectively controlled PM_{2.5} pollution in recent years. For example, the average annual outdoor PM_{2.5} concentration in Beijing was reduced from 89.5 µg/m³ in 2013 to 33.2 µg/m³ in 2021 (Wang et al. 2022b; Wu et al. 2020).

OFDI and environment

The host-country environmental effect

To the best of our knowledge, the home-country environmental effect can be traced back to Grossman and Krueger (1991). As a pioneer, they first revealed the inverted U-shaped curve relationship between average income and environmental pollution, known as the environmental Kuznets curve (EKC). Since then, studies have begun to explore the relationship between economic growth and environmental pollution (Ansari 2022; Anwar et al. 2022). In the early stage of economic development, environmental pollution will worsen with the continuous negative impact of socio-economic activities. However, the environmental situation can get improved once the economy has stepped into a new development stage (Gyamfi et al. 2021; Isik et al. 2021). As they claimed, the three key influencing factors of economic growth on the environment are output value (scale factor), technology spillover (technology factor), and industrial structure (composition factor).

Following this framework, an important and interesting issue is the environmental benefits of international investments (An et al. 2021; Kiswani and Zaitouni 2021). First, in terms of the international investment direction, international investment will be FDI for the host country (the invested country) and OFDI for the home country (the investing country) (Gao 2023; Goh et al. 2013). Second, regarding the international investment opinion, the pollution shelter and halo hypotheses have dominated the major position (Singhania and Saini 2021). Last, considering the international investment economies, developed economies have been prominent investors in global investment activities since the 1980s. However, in recent decades, developing economies have gradually emerged in international society, especially after the COVID-19 pandemic (Bruhn et al. 2016; Zeng and Eastin 2012).

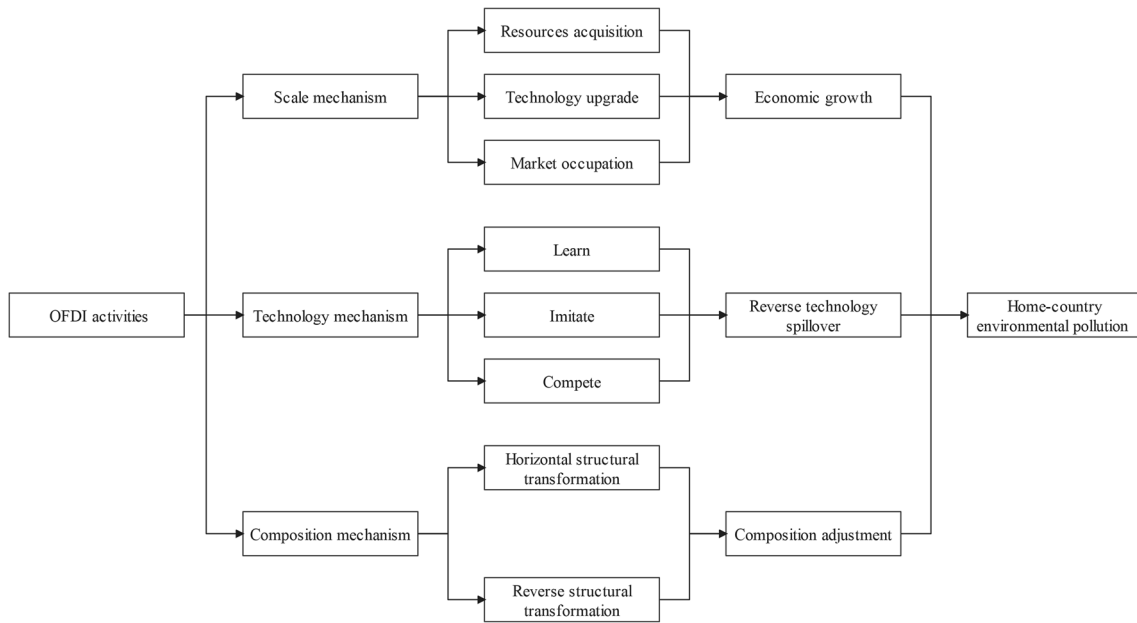


Fig. 1 The home-country OFDI activities and its own environmental pollution

Under these three aspects, most related studies on this issue have focused on the host-country environmental impacts of international investment flows from the home country, which usually is the developed economies (Voituriez et al. 2019; Yoon and Heshmati 2021). On the one hand, the pollution shelter hypothesis holds that, due to the relatively low environmental regulatory requirements, the home country can transfer the high-emission and high-pollution industries and factories to the host country through international investment activities (Li et al. 2021; Zhao et al. 2021). On the other hand, the pollution halo hypothesis argues that, although international investment activities can bring cross-boundary pollution into the host country in the short term, it will also introduce green technology and mature management systems (Li and Yu 2020). In the long term, the increase and reform in domestic technology and structure will finally lead to pollution reduction from the beginning (Mert and Caglar 2020).

According to different indicators, periods, and countries, the research conclusions will be various. However, whether it is the pollution shelter hypothesis or the pollution halo hypothesis, they both concern the environmental changes in the host country, with no difference in nature in this aspect (Wang and Li 2021). The pollution halo hypothesis is somewhat a positive extension of the pollution haven hypothesis, similar to the “race to the bottom” theory (Ardiyono and Patunru 2022; Messerschmidt and Janz 2023). In this sense, current studies have paid much and enough attention to the host-country environmental

consequences of international investments from developed economies.

The home-country environmental effect

In comparison, few studies have explored the home-country environmental impacts of international investment flows from the home country itself, especially the developing economies. That is, OFDI activities from the home country can also affect its own environment, besides the effect on the host country mentioned above (Kong et al. 2020; Long et al. 2023). On the one hand, the international capital outflow from the home country will induce environmental changes in its own ecosystem. As for developing economies, capital outflow will cause considerable systemic changes in the domestic economy (Canuto 2023; Zameer and Wang 2018). On the other hand, with the prominent emerging phenomenon of reverse spillover (such as negative carbon leakage), OFDI activities can affect the home-country environment through various pathways (De Beule et al. 2022; Dechezleprêtre et al. 2022).

Based on the related studies, as far as we are concerned, the home-country environmental effect of international investments can be achieved through three channels: scale growth mechanism, technology spillover mechanism, and composition adjustment mechanism (Ahmadova et al. 2022; Hao et al. 2020; Long et al. 2023). See details in Fig. 1.

(1) The scale growth mechanism refers to the home-country economic benefits of OFDI activities. First,

resource-seeking OFDI activities will directly acquire all kinds of materials in the host country, thus transferring and lighting the environmental pressure from the home country to the host country. Through property rights control, the home country can use these resources to develop its own environment-friendly economy (Chen and Zulkifli 2012; Jain and Thukral 2022). Second, technology-seeking OFDI activities can obtain clean and advanced technology from the host country, contributing to the home-country economic development by reverse technology spillover effect (Balsalobre-Lorente et al. 2019). Third, market-seeking OFDI activities can help international trade after occupying and dominating a significant position in a specific market in the host country. The promotion of bilateral trade will eventually enhance domestic economic development (Ahmad et al. 2016; Kaushal 2022; Zhou and Wang 2022).

(2) The technology spillover mechanism mainly refers to the reverse technology spillover effect during the OFDI activities. Through OFDI activities, it will become easier for the home-country parent company to get attached to advanced technologies across the boundary (Wang et al. 2021b; Zhou et al. 2019a). First, the branch offices and subsidiaries of the home-country parent companies can get in touch with the host-country domestic companies through geographical advantage, which will induce the technology diffusion effect (Duan and Jin 2022). Second, the parent company can use property rights control to transfer these advanced technologies to the home country, leading to the spatial technology effect (Pan et al. 2020). During this process, the branch offices and subsidiaries will also need to take the initiative to learn, imitate, and compete in the market (Demena and van Bergeijk 2019). Among the above two processes, the most typical one is the negative carbon technology spillover, which has been regarded as a practical way to improve domestic technical ability in carbon emission control (Mörsdorf 2022; Zameer et al. 2021a).

(3) The composition adjustment mechanism refers to the home-country industrial structure transformations of OFDI activities. Due to the various consumption and production attributes, the environmental impacts across industries are different. Generally speaking, the secondary industry contains more high-pollution and carbon-intensive companies than others, leading to a high demand for funds and resource support. On the one hand, the change from focusing on the secondary industry to developing the tertiary industry can play the role of horizontal structural transformation effect, thus effectively relieving environmental pressure (Wang et al. 2021a). On the other hand, making the tertiary industry become the main driving force for economic growth will induce the reverse structural transformation effect, contributing to sustainable development in the next stage (Baymul and Sen 2020; Bräutigam and Tang 2014; Gnidchenko 2021; OECD 2012).

Combining Chinese OFDI activities and the above analyses, this study put forward the following testable *hypotheses* in exploring the home-country environmental effect:

Hypothesis 1: The home-country OFDI activities can significantly decrease its own environmental pollution (home-country environmental effect).

Hypothesis 2: The home-country environmental effect of OFDI activities can be transferred by scale growth, technology spillover, and composition adjustment mechanisms.

Research design

Identification strategy

LMDI decomposition approach

The logarithmic mean Divisia index (LMDI) decomposition approach, which can reflect the energy consumption and its accompanying emissions of various dimensions, is a classical “KAYA identity equation” analysis process proposed by Ang and Choi (1997).¹ Through a series of mathematical formula transformations, the LMDI decomposition approach can decompose the interested variable into the multiplicative form of related influencing factors (Ang 2015; Ang and Zhang 2000). Compared with other index decomposition methods, such as the Laspeyres, Fisher, and Shapley, the LMDI decomposition approach thoroughly addresses the residual term problem by introducing a new weight function. With a symmetrical and concise mathematical form, the LMDI decomposition approach has become the mainstream perfect decomposition method (Kaltenegger 2020; Xia et al. 2022b; Yasmeeen et al. 2020).

According to the practical guide of the LMDI decomposition approach, we present its basic mathematical form (Ang 2005). In Eq. (1), i refers to the types of related influencing factors (such as industrial sectors, energy types). On the left-hand side, V refers to the interested variable (such as energy consumption, energy intensity, carbon emissions, pollution emissions). On the right-hand side, $(x_{1,i} * x_{2,i} * x_{3,i} * \dots * x_{n,i})$ refers to the n related influencing factors of the i type.

$$V = \sum_i V_i = \sum_i (x_{1,i} * x_{2,i} * x_{3,i} * \dots * x_{n,i}) \quad (1)$$

First, we can calculate and analyze the changes of the interested variable V for the period from 0 to T . The subscript tot refers to the overall changes. Specifically, Eq. (2) shows the multiplicative decomposition process, which implies

¹ The “KAYA identity equation” refers to the environmental-economic model that links economic growth, human activity, and carbon emissions (Kaya and Yokobori 1997; Tavakoli 2018).

the relative contributions of each related influencing factors (D_{x_1}, \dots, D_{x_n}). Correspondingly, Eq. (3) shows the additive decomposition process, measuring the absolute changes of each related influencing factors ($\Delta V_{x_1}, \dots, \Delta V_{x_n}$).

$$D_{tot} = V^T / V^0 = D_{x_1} * D_{x_2} * D_{x_3} * \dots * D_{x_n} \tag{2}$$

$$\Delta V_{tot} = V^T - V^0 = \Delta V_{x_1} + \Delta V_{x_2} + \Delta V_{x_3} + \dots + \Delta V_{x_n} \tag{3}$$

Second, a new weight function $L(a, b)$ is introduced to eliminate the residual term when conducting the exponential-logarithmic decomposition. With appropriate values to a and b , we can get perfect decomposition weights W_i^1 and W_i^2 .

$$L(a, b) = \begin{cases} (a - b) / (\ln a - \ln b), & a \neq b \\ a, & a = b \end{cases} \tag{4}$$

$$W_i^1 = L(V_i^T, V_i^0) / L(V^T, V^0) \tag{5}$$

$$W_i^2 = L(V_i^T, V_i^0) \tag{6}$$

Therefore, as for the k -th related influencing factor in Eqs. (2)–(3), we can calculate its contribution through the following Eqs. (7)–(8).

$$D_{x_k} = e \left(\sum_i \left(W_i^1 * \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \right) \right) \tag{7}$$

$$\Delta V_{x_k} = \sum_i \left(W_i^2 * \ln \left(\frac{x_{k,i}^T}{x_{k,i}^0} \right) \right) \tag{8}$$

3SLS structural approach

The three-stage least squares (3SLS) structural approach, proposed by Zellner and Theil (1992), is a complete information estimation process designed for simultaneous equations. As it can adopt all available information to estimate the structural changes of each variable simultaneously, the 3SLS structural approach is more effective in solving multi-process problems (Sargan 1964; Zaman 2018). For example, Liu and Chen (2020) forecasted the outdoor PM_{2.5} concentrations in four Chinese cities using a 3SLS hybrid neural network approach. Ren et al. (2021) analyzed the relationship between economic growth, carbon emissions, and foreign direct investment in China by applying the 3SLS-STIRPAT model.² Although the specific process is very complicated, the consistency of the estimated results has made the 3SLS structural approach widely used.

² The STIRPAT model refers to the Stochastic Impacts by Regression on Population, Affluence, and Technology model (Dietz and Rosa 1997; Ehrlich and Holdren 1971; Ehrlich and Pei 2021).

The steps of the 3SLS structural approach are as follows. In Eq. (9), i refers to the i th equation in the whole multi-process problems. On the left-hand side, Y_i refers to the dependent variable (the interested variable) with $(n * 1)$ observations. On the right-hand side, \tilde{Y}_i refers to the $(n * g_i)$ -order sample matrix of the endogenous variables, X_i refers to the $(n * k_i)$ -order observation matrix of the predetermined exogenous variables. g_i and k_i are the number of endogenous and predetermined exogenous variables. β_i, γ_i , and u_i refer to the $(g_i * 1)$ -order, $(k_i * 1)$ -order, and $(n * 1)$ -order dimensional parameter column vectors, respectively. Equation (10) is the matrix form of Eq. (9).

$$Y_i = \tilde{Y}_i * \beta_i + X_i * \gamma_i + u_i, \quad i = 1, 2, \dots, G. \tag{9}$$

First, we apply the traditional ordinary least squares (OLS) method only for the dependent variable Y_i and the predetermined exogenous variables X_i . By doing that, we will get the OLS estimated value \hat{Y}_i for Y_i . It should be noted that \hat{Y}_i is not \tilde{Y}_i .

Second, we continue to apply the OLS method by adding the OLS estimated value \hat{Y}_i to the right-hand side of Eq. (10). And then we will obtain the two-stage least squares (2SLS) estimated values \hat{u}_i for u_i . \hat{u}_i is a $(n * 1)$ -order dimensional parameter column vector and will play a role in the next step.

$$Y_i = Z_i * b_i + u_i, \quad i = 1, 2, \dots, G. \tag{10}$$

$$Z_i = [\tilde{Y}_i \ X_i], \quad b_i = \begin{bmatrix} \beta_i \\ \gamma_i \end{bmatrix} \tag{11}$$

Last, we use the transpose matrix X_i' to conduct the left multiplication with Eq. (10). By applying the generalized least square (GLS) method in Eq. (12), we finally get the 3SLS estimated values \hat{b} for b .

$$\begin{bmatrix} X'Y_1 \\ \vdots \\ X'Y_G \end{bmatrix} = \begin{bmatrix} X'Z_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & X'Z_G \end{bmatrix} * \begin{bmatrix} b_1 \\ \vdots \\ b_G \end{bmatrix} + \begin{bmatrix} X'u_1 \\ \vdots \\ X'u_G \end{bmatrix} \tag{12}$$

$$Z = \begin{bmatrix} X'Z_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & X'Z_G \end{bmatrix}, \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_G \end{bmatrix}, \quad u = \begin{bmatrix} u_1 \\ \vdots \\ u_G \end{bmatrix}, \quad U = \begin{bmatrix} X'u_1 \\ \vdots \\ X'u_G \end{bmatrix} \tag{13}$$

$$\hat{b} = (Z' * \hat{\Phi}^{-1} * Z)^{-1} * (Z' * \hat{\Phi}^{-1} * Z) \tag{14}$$

$$\hat{\Phi}^{-1} = COV(U) = E(U * U') = E(X' * u * u' * X) = X' * E(u * u' * X) \tag{15}$$

Sample data

This study constructs a panel dataset of 222 Chinese cities from 2007 to 2019 by manually collecting the environmental-economic data from the *China City Statistical Yearbook*,

Table 1 Descriptive statistics

| Var | Definition | Obs | Mean | SD | Min | Max | Unit | Source |
|----------------|---|------|-------|------|-------|-------|--------------------------|-----------|
| $PM_{i,t}$ | The average annual outdoor $PM_{2.5}$ level | 2886 | 3.80 | 0.33 | 2.63 | 4.69 | $\mu\text{g}/\text{m}^3$ | NOAA |
| $OFDI_{i,t}$ | The outward foreign direct investment | 2886 | 16.98 | 9.31 | 0.00 | 32.01 | USD | Author |
| $GDP_{i,t}$ | The gross domestic product | 2886 | 16.53 | 0.97 | 13.65 | 19.76 | 10 k CNY | Yearbooks |
| $STR1_{i,t}$ | The first industry proportion | 2886 | 11.11 | 6.98 | 0.03 | 46.95 | % | Yearbooks |
| $STR2_{i,t}$ | The secondary industry proportion | 2886 | 48.82 | 9.95 | 11.70 | 82.08 | % | Yearbooks |
| $STR3_{i,t}$ | The tertiary industry proportion | 2886 | 40.07 | 9.97 | 11.99 | 83.50 | % | Yearbooks |
| $POP_{i,t}$ | The average annual population | 2886 | 5.96 | 0.68 | 2.90 | 8.14 | 10 k | Yearbooks |
| $Cap_{i,t}$ | The physical capital stock | 2886 | 17.50 | 1.00 | 14.54 | 20.51 | 10 k CNY | Author |
| $FDI_{i,t}$ | Foreign direct investment | 2886 | 10.21 | 1.79 | 0.00 | 14.94 | 10 k USD | Yearbooks |
| $RD_{i,t}$ | The research and development investment | 2886 | 10.29 | 1.44 | 6.43 | 15.53 | 10 k CNY | Yearbooks |
| $Energy_{i,t}$ | Energy consumption | 2886 | 4.70 | 1.19 | 0.25 | 8.31 | kg-ec | Yearbooks |

This table reports the descriptive statistics and sources of each variable. The dataset contains city-year pair panel data of 222 Chinese cities from 2007 to 2019. All variables are in natural logarithm form so as to reduce the heteroscedasticity problems and unit errors (if applicable)

the Annual Financial Reports of Chinese Listed Companies, and the Statistical Bulletin of China's Outward Foreign Direct Investment. All variables are in natural logarithm form (if applicable) so as to reduce the heteroscedasticity problems and unit errors. The descriptive statistical results are shown in Table 1.

The reasons for selecting 222 Chinese cities are as follows: (1) Since the LMDI decomposition and 3SLS structural approaches are more effective for large sample research, we have to use the data with better granules. According to the Administrative Division Code of the People's Republic of China 2021, there are four administrative levels in China, including 34 provincial-level, 333 prefecture-level, 2844 county-level, and 38,774 township-level administrative regions (Wang and Yeh 2020). The provincial-level and prefecture-level data will be suitable when considering the existence and availability of the related data. (2) In terms of cities in China, they are under three different administrative management: 4 provincial-level cities (municipalities directly under the central government), 333 prefecture-level cities, and 393 county-level cities. Therefore, the 337 city-level data (4 provincial-level and 333 prefecture-level administrative regions) will be the most appropriate. (3) We exclude ethnic-related self-administrative cities from the sample data as they have different development characteristics (Jiang et al. 2020). For example, we exclude the Garzê Tibetan autonomous prefecture (a city in Sichuan province). (4) As for the changes in administrative levels of some cities, we adjust them according to the latest administrative division code. For example, we adjust Chaohu (a city in Anhui province) and Laiwu (a city in Shandong province) from prefecture-level to county-level cities. (5) We use the predictive mean matching (PMM) and the multiple imputations by chained equations (MICE) methods to deal with the missing values. These two methods can automatically handle the missing values according

to the characteristics of the existing data (Bartlett and Morris 2015; Sterne et al. 2009; Wood et al. 2008). We finally exclude those missing values that can not be fixed from the sample data.

The reasons for choosing the sample period from 2007 to 2019 are as follows: (1) Before 2006, the total amount of Chinese OFDI flows was no more than USD 100 billion. In 2007, China implemented the “going globally” strategy to embrace globalization development in deep, thus largely stimulating and promoting overseas investment (Xia et al. 2022a). Therefore, we choose the year 2007 as the beginning period. (2) Since there is no official available city-level OFDI data, we have to collect them manually from various statistical platforms and public portals. To the best of our efforts, we can only construct the balanced panel data set from 2007 to 2019. In other words, we can not obtain as much available data for the years 2020 to 2022. As a result, we choose the year 2019 as the ending period. (3) The sample period from 2007 to 2019 involves exactly the majority time of three “Five-Year Plans”: the 11th Five-Year Plan (2006–2010), the 12th Five-Year Plan (2011–2015), and the 13th Five-Year Plan (2016–2020). It can help us to observe the pollution control effect in three different periods.

Model settings

LMDI decomposition model

This study mainly applies the multiplicative decomposition process to break down the dependent variable ($PM_{i,t}$). As shown in the following, the theoretical Eq. (2) will be transferred into the following Eq. (16), i refers to the city, and t refers to the time. On the left-hand side, $D_{PM_{i,t}}^{tot}$ refers to the overall changes tot of the independent variable from the period from 0 to T . On the right-hand side, $D_{STR_{i,t}}$, $D_{GDP_{i,t}}$, and $D_{Energy_{i,t}}$ refer to the contributions

of the industry structure, gross domestic product, and energy consumption.

Additionally, (1) $D_{STR_{i,t}}$ includes the changes in all three industry structures ($D_{STR1_{i,t}} + D_{STR2_{i,t}} + D_{STR3_{i,t}}$). (3) As for the period from 0 to T , we will use four different settings. We first use the whole sample period from 2007 to 2019 to observe the year-to-year effect and then use the periods from 2007 to 2010, 2011 to 2015, and 2016 to 2019 to capture the cumulative effect, respectively. As mentioned above, the three periods involve exactly the majority time of three “Five-Year Plan” periods, which can reflect some policy heterogeneity.

$$D_{PM_{i,t}}^{tot} = D_{STR_{i,t}} * D_{GDP_{i,t}} * D_{Energy_{i,t}} \tag{16}$$

3SLS structural model

This study applies the 3SLS structural approach by following the classical EKC theory proposed by Grossman and Krueger (1991). That is, domestic pollution depends on three important factors: domestic output value (scale), technology spillover (technology), and industrial structure (composition). As shown in the following Eqs. (17)–(23), i refers to the city, and t refers to the time.

For details, (1) $PM_{i,t}$ is the dependent variable referring to the average annual outdoor $PM_{2.5}$ concentration of the city i in the year t . (2) $OFDI_{i,t}$ is the independent variable referring to the OFDI flows of the city i in the year t . (3) $Scale_{i,t}$, $Tech_{i,t}$, and $Comp_{i,t}$ are the mechanism variables that transfer the effect of the OFDI flows to domestic pollution. $Scale_{i,t}$ is the scale mechanism measured by the gross domestic product; $Tech_{i,t}$ is the technology mechanism measured by energy intensity; and $Comp_{i,t}$ is the composition mechanism measured by the secondary industry proportion. (4) $GDP_{i,t}$, $POP_{i,t}$, $Cap_{i,t}$, $FDI_{i,t}$, and $RD_{i,t}$ are the mutual control variables. As a multi-equation estimation method, the 3SLS structural approach can link each equation through the mutual variables when conducting the seemingly unrelated estimation process. (5) Since international investment flows can induce changes in domestic physical capital stock, we use Eq. (22) to reflect this phenomenon (Hao et al. 2020). $GDP_{i,t-1}$ and $GDP_{i,t-2}$ refer to the value of the gross domestic product in the last one and two periods. (6) $\mu_{i,t}^N$ includes the constant term α_0^N , the error term $\varepsilon_{i,t}^N$, and the city-fixed and the year-fixed effects $\delta_{i,t}^N$. Other symbols refer to the coefficient of the corresponding variable.

$$PM_{i,t} = Scale_{i,t} * Tech_{i,t} * Comp_{i,t} \tag{17}$$

$$\ln PM_{i,t} = \alpha_1 \ln Scale_{i,t} + \alpha_2 \ln Tech_{i,t} + \alpha_3 \ln Comp_{i,t} + \mu_{i,t}^0 \tag{18}$$

$$\ln Scale_{i,t} = \beta_1^1 \ln OFDI_{i,t} + \beta_2^1 \ln Cap_{i,t} + \beta_3^1 \ln FDI_{i,t} + \beta_4^1 \ln PM_{i,t} + \mu_{i,t}^1 \tag{19}$$

$$\ln Tech_{i,t} = \beta_1^2 \ln OFDI_{i,t} + \beta_2^2 \ln GDP_{i,t} + \beta_3^2 \ln FDI_{i,t} + \beta_4^2 \ln RD_{i,t} + \mu_{i,t}^2 \tag{20}$$

$$\ln Comp_{i,t} = \beta_1^3 \ln OFDI_{i,t} + \beta_2^3 \ln GDP_{i,t} + \beta_3^3 \ln POP_{i,t} + \beta_4^3 \ln FDI_{i,t} + \mu_{i,t}^3 \tag{21}$$

$$\ln Cap_{i,t} = \beta_1^4 \ln OFDI_{i,t} + \beta_2^4 \ln (GDP_{i,t-1} - GDP_{i,t-2}) + \beta_3^4 \ln FDI_{i,t} + \mu_{i,t}^4 \tag{22}$$

$$\mu_{i,t}^N = \alpha_0^N + \delta_{i,t}^N + \varepsilon_{i,t}^N, N = 0, 1, 2, 3, 4. \tag{23}$$

Consequently, we can obtain the home-country effect of OFDI flows on domestic pollution based on the theoretical Eq. (14). The actual estimated coefficient of OFDI flows (β_{OFDI}) is shown in Eq. (24).

$$\beta_{OFDI} = \frac{(\alpha_1 \beta_1^1 + \alpha_2 \beta_1^2 + \alpha_3 \beta_1^3 + \alpha_1 \beta_2^1 \beta_1^4)}{(1 - \alpha_1 \beta_4^1)} \tag{24}$$

Variables

Independent variable

This study uses the annual city-level OFDI flows ($OFDI_{i,t}$) as the independent variable. As of now, China only releases national-level and provincial-level OFDI data, leading to the situation that there is no official available city-level OFDI data. For example, we can get the information that the total amount of Chinese OFDI flow was USD 136.91 billion in 2019, and the Hubei province contributed USD 15.51 billion in non-financial investment. However, we can not directly obtain the exact OFDI data from public yearbooks and databases like Wuhan and Tianmen (cities in Hubei province).

Under such a background, this study manually collects the city-level OFDI data from various statistical platforms and public portals. (1) We first obtain the list of Chinese overseas investment enterprises (institutions) from the Ministry of Commerce of China. Under Chinese law, all overseas investment activities must be reported and registered. Therefore, we can use this list to obtain OFDI-related data. (2) As for the listed companies in this list, we will extract the OFDI-related data from *the Annual Financial Reports of Chinese Listed Companies*. As for the non-listed companies with public financial reports, we can still obtain OFDI-related data. As for the others, we can only search the OFDI-related information from public portals. (3) We then use the “real business location” as the unique identifier to sum up the OFDI-related data at the city level. (4) To ensure the

accuracy of the data, we also search the official government websites of 222 sample cities to obtain some OFDI-related information and conduct a double-check.

In the absence of officially available data, the reasons for using our constructed city-level OFDI data are as follows: (1) After the “going globally” strategy, the listed companies have become the major participants in Chinese overseas investment activities (Chen et al. 2016; Guo et al. 2022). Going with that, we mainly use overseas investments from the listed companies to construct city-level OFDI data and then apply some OFDI-related information from non-listed companies and the official government websites to assist. (2) Previous studies have also used this method to construct city-level OFDI data. For example, Su et al. (2021) figured out the preference and determinants of Chinese OFDI using city-level data; Wong et al. (2021) explained the economic effect of city-level OFDI flows in the China-European railway project. (3) The Pearson correlation between our constructed city-level OFDI data and the official public provincial-level OFDI data is 0.63 at the 1% level. In sum, it will be acceptable to use our constructed city-level OFDI when lacking the official version.

Dependent variable

This study uses the average annual outdoor $PM_{2.5}$ concentration ($PM_{i,t}$) as the dependent variable. We obtain raw data from the climate data record of the National Oceanic and Atmospheric Administration (NOAA), which provides public economic, environmental, and meteorological data in a grid format. Then we transfer the original data from the “day-grid” pair form into the continuous “year-city” pair form using the annual average method.

Control variables

On the one hand, since the LMDI decomposition approach is a mathematical-based “KAYA identity equation” analysis process, there is no need to control other non-related influencing factors according to the practical guide proposed by Ang (2005). Actually, we care more about the breakdown components and respective proportions (Moutinho et al. 2018; Wang et al. 2011).

On the other hand, the 3SLS structural approach can estimate the changes in the dependent variable through multi-equations. The control variables will play a role unless they can affect the multi-equations simultaneously. To make our identification more accurate, we still use some control variables in the 3SLS structural approach. Specifically, we use the following as the control variables: the gross domestic product ($GDP_{i,t}$), the first industry proportion ($STR1_{i,t}$), the secondary industry proportion ($STR2_{i,t}$), the tertiary industry proportion ($STR3_{i,t}$), the average annual population ($POP_{i,t}$),

Table 2 The LMDI decomposition result

| From | To | $D_{PM_{i,t}}^{tot}$ (value) | $D_{STR_{i,t}}$ | $D_{GDP_{i,t}}$ | $D_{Energy_{i,t}}$ |
|------|-------------|------------------------------|-----------------|-----------------|--------------------|
| 2007 | 2008 | -1.6577 | 0.53 | -0.56 | -0.12 |
| 2008 | 2009 | 4.0001 | 0.35 | 0.34 | 0.31 |
| 2009 | 2010 | 2.0709 | 0.37 | 0.37 | 0.26 |
| 2010 | 2011 | -0.9189 | -1.09 | 1.08 | -1.17 |
| 2011 | 2012 | -6.2220 | -0.42 | 0.42 | -0.15 |
| 2012 | 2013 | 5.5331 | 0.41 | 0.41 | -0.18 |
| 2013 | 2014 | -0.0027 | -0.60 | 0.58 | -0.18 |
| 2014 | 2015 | -7.8368 | -0.24 | 0.24 | -0.52 |
| 2015 | 2016 | -7.1766 | -0.32 | 0.31 | -0.37 |
| 2016 | 2017 | -8.2631 | -0.33 | 0.45 | -0.21 |
| 2017 | 2018 | -5.0411 | -0.36 | 0.31 | -0.32 |
| 2018 | 2019 | -4.8245 | -0.48 | 0.48 | -0.05 |
| 2007 | 2010 | 4.4133 | 0.42 | 0.41 | 0.17 |
| 2011 | 2015 | -8.5284 | -0.39 | 0.39 | -0.22 |
| 2016 | 2019 | -18.1287 | -0.39 | 0.38 | -0.43 |

This table reports the LMDI decomposition result of OFDI flows from 2007 to 2019

the physical capital stock ($Cap_{i,t}$), foreign direct investment ($FDI_{i,t}$), the research and development investment ($RD_{i,t}$), and energy consumption ($Energy_{i,t}$). Following Zhang et al. (2004; 2008), we calculate the physical capital stock ($Cap_{i,t}$) at the city level, using the perpetual inventory method with a depreciation rate of 9.6%. Other variables are derived from the *China City Statistical Yearbook*.

Empirical results

The LMDI decomposition result

In Table 2, we first use the whole sample period from 2007 to 2019 to observe the year-to-year effect of LMDI decomposition in outdoor $PM_{2.5}$ concentration ($PM_{i,t}$). As for the overall changes in $PM_{2.5}$ concentration ($D_{PM_{i,t}}^{tot}$), it shows a fluctuation situation before 2013 and a downward trend after that, reflecting the pollution reduction achievement of the government. On the one hand, the Chinese government has implemented economic stimulus and pollution governance plans to support the 2008 Beijing Olympic Games. This action successfully controlled the pollution that year, with the gross domestic product ($D_{GDP_{i,t}}$) and energy consumption ($D_{Energy_{i,t}}$) mainly contributing to $PM_{2.5}$ pollution reduction. However, it was not sustainable in the following 2 years. On the other hand, with the enhancement of environmental protection awareness and the formulation of targeted environmental regulations around 2012, the

industry structure adjustment ($D_{STR_{i,t}}$) and energy consumption control ($D_{Energy_{i,t}}$) became the major pathway to reducing $PM_{2.5}$ pollution.

Moreover, we then use the periods from 2007 to 2010, 2011 to 2015, and 2016 to 2019 to capture the cumulative effect. During the 11th Five-Year Plan period (2007 to 2010), $PM_{2.5}$ pollution was not effectively controlled and alleviated. At that time, China suffered from a large-scale acid rain event, leading to strict governance of SO_2 emissions (Karplus et al. 2018; Zhao et al. 2009). During the 12th Five-Year Plan period (2010 to 2015), the Chinese government gradually turned its attention to $PM_{2.5}$ pollution due to the unusual smog events. With the implementation of industrial structure regulations such as the green credit guideline 2012, China has transformed and upgraded its industrial structure in this period. The outdoor $PM_{2.5}$ concentration was reduced effectively. During the 13th Five-Year Plan period (2015 to 2019), the synergistic effect in $PM_{2.5}$ pollution and carbon emission has further improved the environmental quality. At this time, the reduction of energy consumption caused by technological progress is the main factor of pollution and emission reduction.

In comparison, the LMDI decomposition results are consistent with related studies. Under the framework of total factor productivity, some studies used the LMDI decomposition to reveal the relationship between national per capita $PM_{2.5}$ emission intensity and economic development level, especially energy-oriented consumption (Xu et al. 2021; Zhang et al. 2019). Considering the ecosystem synergies phenomenon, some studies highlighted the synergistic effect of CO_2 and $PM_{2.5}$ emissions in the coal consumption sector (Dong et al. 2019; Jia et al. 2023). In this study, the LMDI decomposition results go further by revealing the driving factors of $PM_{2.5}$ pollution in Chinese different economic stages. It points out that industrial transformation and technological upgrades are the main measures to govern and reduce $PM_{2.5}$ pollution, providing a factual fundament for the following 3SLS structural analysis.

The 3SLS structural result

Benchmark effect

In Table 3, columns (1)–(5) show the estimation results of Eqs. (18)–(23), respectively. In all estimations, we add both the city-fixed and the year-fixed effects, with the standard error clustered at the target city level. As we use the lag period form in Eq. (22), the actual data used in the 3SLS structural approach is 2442. The R square (R^2) and root mean square error (RMSE) show that each equation fits relatively well.

We first obtain the actual estimated coefficient of the OFDI flows (β_{OFDI}) according to Eq. (24), which is -0.76%

after calculating. This negative effect at the 1% significance level indicates an increase in environmental stewardship and pollution control. With every 1% increase in OFDI flows ($OFDI_{i,t}$), the overall domestic pollution emissions ($PM_{i,t}$) will decrease by 0.76%. Although 0.76% seems like a small value, it has great socio-economic significance. Studies have pointed out that there will be a 5.3% more death risk for every $5 \mu\text{g}/\text{m}^3$ increase in outdoor $PM_{2.5}$ concentrations (Apte et al. 2018; Bowe et al. 2019; Yue et al. 2020). In that sense, an overall 0.76% reduction is a considerable effect. This result supports our testable *Hypothesis 1*.

Considering the related studies and conclusions, it can be divided into two aspects. On the one hand, most studies focused on the home-country carbon emission reduction of Chinese OFDI flows. For example, Hao et al. (2020) and Tan et al. (2021) both revealed that Chinese OFDI activities can promote domestic carbon mitigation under sustainable development goals. On the other hand, some studies made a step in the carbon reduction effect by finding its accompanying economic benefits, including environment-economic performance and green total factor energy efficiency (Kong et al. 2020; Long et al. 2023; Ren et al. 2022). However, all these studies have paid attention to carbon emissions without considering environmental pollution (Tian et al. 2023). In this sense, our conclusion will be one of the few studies that point out the home-country pollution reduction effect of Chinese OFDI flows.

Mechanism effect

We then analyze how OFDI flows can affect domestic pollution based on the classical EKC theory. In column (1), we can observe three mechanisms between OFDI flows and domestic pollution: scale mechanism ($Scale_{i,t}$), technology mechanism ($Tech_{i,t}$), and composition mechanism ($Comp_{i,t}$). After decomposing Eq. (24), we can obtain their respective mechanism effect: 0.43%, -0.27% , and -0.91% . This result indicates that the technology and composition mechanism effects of OFDI flows are the main pathways to addressing domestic environmental pollution, especially for outdoor $PM_{2.5}$ situations.

- (1) The scale mechanism process. It is found that OFDI flows can significantly increase domestic output value by 4.78% after combining the results of columns (2) and (5).³ As an important economic activity, market-seeking OFDI activities can promote domestic economic growth by occupying market share and forming market barriers in the host country. Although this investment has played an essential role in past eco-

³ This value is calculated by $(\beta_1^1 + \beta_2^1 \beta_1^4)$ in Eq. (24).

Table 3 Effect of OFDI flows on domestic pollution, the 3SLS structural estimation

| | (1) $PM_{i,t}$ | (2) $Scale_{i,t}$ | (3) $Tech_{i,t}$ | (4) $Comp_{i,t}$ | (5) $Cap_{i,t}$ |
|-----------------------------|--------------------------------|--------------------------------|---------------------------------|---------------------------------|--------------------------------|
| $Scale_{i,t}$ | 0.0878 ^{***} (12.78) | | | | |
| $Tech_{i,t}$ | -0.0913 ^{***} (-9.55) | | | | |
| $Comp_{i,t}$ | 0.0164 ^{***} (23.59) | | | | |
| <i>cons</i> | 0.4402 ^{***} (2.66) | | | | |
| $OFDI_{i,t}$ | | -0.0036 ^{***} (-3.14) | | | |
| $Cap_{i,t}$ | | 0.8918 ^{***} (84.05) | | | |
| $FDI_{i,t}$ | | 0.0650 ^{***} (13.91) | | | |
| $PM_{i,t}$ | | 0.1419 ^{***} (7.15) | | | |
| <i>cons</i> | | -0.2361 (-1.49) | | | |
| $OFDI_{i,t}$ | | | 0.0297 ^{***} (11.40) | | |
| $GDP_{i,t}$ | | | -0.2164 ^{***} (-6.11) | | |
| $FDI_{i,t}$ | | | 0.0052 (0.42) | | |
| $RD_{i,t}$ | | | 0.0024 (1.02) | | |
| <i>cons</i> | | | -9.0805 ^{***} (-23.51) | | |
| $OFDI_{i,t}$ | | | | -0.5638 ^{***} (-16.63) | |
| $GDP_{i,t}$ | | | | 3.2897 ^{***} (8.01) | |
| $POP_{i,t}$ | | | | -4.2057 ^{***} (-11.14) | |
| $FDI_{i,t}$ | | | | 0.0588 (0.38) | |
| <i>cons</i> | | | | 28.1968 ^{***} (6.19) | |
| $OFDI_{i,t}$ | | | | | 0.0581 ^{***} (27.57) |
| $GDP_{i,t-1} - GDP_{i,t-2}$ | | | | | 0.0784 ^{***} (9.28) |
| $FDI_{i,t}$ | | | | | 0.2290 ^{***} (23.93) |
| <i>cons</i> | | | | | 13.2050 ^{***} (25.26) |
| City FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Cluster | Yes | Yes | Yes | Yes | Yes |
| N | 2442 | 2442 | 2442 | 2442 | 2442 |
| RMSE | 0.3126 | 0.3048 | 0.7357 | 0.7443 | 0.7126 |
| R ² | 0.1348 | 0.8922 | 0.2067 | 0.2861 | 0.4059 |

This table reports the 3SLS structural estimation results of OFDI flows on domestic pollution. All the regressions are clustered at the target city level with the city-fixed and the year-fixed effects (if applicable). The *t*-statistics are presented in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively

conomic development, it also contributed to environmental pollution in the current economic stage (Christofi et al. 2022; Wadhwa and Reddy 2011).

(2) The technology mechanism process. The result in column (3) shows an obvious reverse technology spillover phenomenon of an overall 2.97% effect in the current OFDI activities. Traditional technology innovation theory holds that international investments can promote technology development in the host country. Whereas, with the introduction of the reverse technology spillover phenomenon, international investments can also induce technology innovation in the home country. Studies have shown that this type of investment activity has gradually become the main direction in future development. One typical phenomenon is the increas-

ingly apparent negative and reverse technology spillover effect in carbon-related sectors (Chen et al. 2020; Hao et al. 2021).

(3) The composition mechanism process. The result in column (4) shows a 56.38% negative effect on the secondary industry proportion, indicating the optimization of the whole industrial structure. In contrast, the secondary industry is a relatively resource-dependent and pollution-emitting industry, which needs lots of support to achieve transformation and upgrading. Correspondingly, OFDI flows can improve the domestic industrial structure in several ways. For example, technology upgrades can reduce emissions from high-pollution sectors, and new market development can accelerate the transformation process.

Table 4 Effect of OFDI flows on domestic pollution, robustness estimations

| | (1) $PM_{i,t}$ | (2) $PM_{i,t}$ | (3) $PM_{i,t}$ | (4) $Scale_{i,t}$ | (5) $Tech_{i,t}$ | (6) $Comp_{i,t}$ | (7) $PM_{i,t}$ |
|----------------------------|------------------------|-----------------------|----------------------|-------------------|------------------|----------------------|-----------------------|
| $OFDI_{i,t}$ | -0.0077*** (-17.47) | -0.0067*** (-9.57) | -0.0005** (-2.01) | | | | |
| $OFDI_{i,t}$ | | | | -0.0008 (-1.43) | | | 0.0143*** (3.10) |
| $Scale_{i,t}$ | | | | | | | 0.0526*** (2.95) |
| $OFDI_{i,t} * Scale_{i,t}$ | | | | | | | -0.0091*** (-3.01) |
| $OFDI_{i,t}$ | | | | | 0.0062*** (3.44) | | 0.0025*** (2.68) |
| $Tech_{i,t}$ | | | | | | | -0.0003*** (-3.04) |
| $OFDI_{i,t} * Tech_{i,t}$ | | | | | | | -0.0002*** (-4.52) |
| $OFDI_{i,t}$ | | | | | | -0.023*** (-4.14) | 0.0013*** (3.86) |
| $Comp_{i,t}$ | | | | | | | 0.0008*** (2.60) |
| $OFDI_{i,t} * Comp_{i,t}$ | | | | | | | -0.0005*** (-7.52) |
| City FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Variables | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2886 | 2886 | 2886 | 2886 | 2886 | 2886 | 2886 |
| MAR | 0.33 | — | — | — | — | — | — |
| Adjusted R ² | — | — | 0.78 | 0.55 | 0.34 | 0.48 | 0.78 ^a |

This table reports the robustness estimation results of OFDI flows on domestic pollution. All the regressions are clustered at the target city level with the city-fixed and the year-fixed effects (if applicable). The t-statistics are presented in parentheses. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. To conserve space, this table only shows the results of the main variables

^aIn column (7) of Table 4, the value of adjusted R² for three mechanism estimations are both equal to 0.78 (if rounded up to 2 decimal points)

In sum, our findings are consistent with some related studies on Chinese OFDI activities. Generally speaking, it is found that Chinese OFDI activities still play a good role in overseas market acquisition. The home-country environmental effects are mainly reflected in technology feedback and structural improvement (Yang et al. 2021; Yang and Zheng 2021). Therefore, these three mechanism effects support our testable Hypothesis 2.

Robustness estimations

The MCMC simulation

This study adopts the Markov chain Monte Carlo (MCMC) simulation to enhance the 3SLS structural result. The MCMC simulation is a random sampling process that can approximate the posterior distribution of the target parameter in a given probability space (Blum et al. 2020; Roy 2020). With appropriate sampling distributions, we can use the sample value to estimate the overall expectation based on the law of large numbers. In the MCMC simulation, we set the number of the total draws to 1000, the number of

burn-in draws to 100, and the number of draws retained to 900. After 1000 times adaptive simulation, the mean acceptance rate (MAR) is 0.33 with 50% sampling distributions, which is relatively effective. Similar to R² and RMSE in the benchmark results, the MAR reflects the effectiveness of the MCMC simulation. As shown in column (1) of Table 4, the effect of OFDI flows on domestic pollution is -0.77% at the 1% significance level. This result is consistent with -0.76% in the 3SLS structural result, indicating no obvious bias in the above analysis and conclusions.

Machine learning optimization

We then apply the grid-search (GS) optimization procedure to re-estimate the 3SLS structural result. As a machine learning optimization, the GS optimization procedure is a cyclic ergodic search estimation process in a probability space (Chi et al. 2022; Lerman 1980). Compared with the MCMC simulation, it pays more attention to randomness and ergodicity. In the GS optimization, we will set a 50% sample probability space for the ergodic search. The result in column (2) of Table 4 shows a significant negative effect of -0.67%, illustrating the robustness of the 3SLS structural estimation. In

sum, since the MCMC simulation and GS optimization are non-linear OLS estimations, we can conclude that the 3SLS structural result is reasonable and acceptable.

Single equation estimation

We also use the fixed effect panel model to re-estimate the effect and mechanism of OFDI flows on domestic pollution. In Table 4, column (3) only shows the relationship between OFDI flows and domestic pollution, and columns (4)–(7) show the two-step mechanism process among them. Similarly, we add both the city-fixed and the year-fixed effects in all estimations, with the standard error clustered at the target city level. Since the fixed effect panel model is a single equation estimation method, we have to estimate each result one by one.

The result in column (3) shows that OFDI flows have a significant negative effect of -0.05% on domestic pollution, much smaller than -0.76% in the 3SLS structural result. Since the results of the 3SLS structural approach, the MCMC simulation, and GS optimization are consistent, we can hold that the single equation estimation has underestimated the home-country environmental effects of OFDI flows. Hao et al. (2020) also put forward this conclusion by comparing the carbon reduction effect of Chinese OFDI between the 3SLS structural approach and the single equation estimation.

Furthermore, we conduct the two-step mechanism process in columns (4)–(7). That is, we first regress mechanism variables ($Scale_{i,t}$, $Tech_{i,t}$, and $Comp_{i,t}$) on OFDI flows ($OFDI_{i,t}$), and then we regress domestic pollution ($PM_{i,t}$) on the interactive terms ($OFDI_{i,t} * Mechanism_{i,t}$). As for the scale mechanism process, we can not observe the significant effect of OFDI flows at the first step in column (4), which causes ineffective mechanism transmission. As for the technology mechanism process, OFDI flows can significantly promote the reverse technology spillover phenomenon in column (5), thus leading to a decreasing effect of 0.02% in domestic pollution. As for the composition mechanism process, OFDI flows have a noticeable structural effect in column (6), affecting domestic pollution with a 0.05% improvement effect.

Naturally, it is not difficult to find that the single-equation estimation does have some bias, especially for the multi-factor mutual process. For example, since column (4) does not consider the potential influence on domestic physical capital stock, we can not obtain the actual scale mechanism between OFDI flows and domestic pollution. However, the LMDI decomposition result shows the increased outdoor $PM_{2.5}$ concentration caused by economic scale growth. In comparison, the 3SLS structural approach can capture the changes in domestic physical capital stock through Eq. (22).

In sum, the single equation estimation results also enhance the robustness in Table 3.

Conclusions and implications

Main conclusions

In past decades, the rapid development of the global economy has caused severe and irreversible environmental problems. To deal with the global climate crisis, countries must find a way to balance economic development and environmental protection. Under this background, harnessing investment for sustainable development seems to be a practical and effective measure. Using the LMDI decomposition and the 3SLS structural approaches, this study reveals the home-country effect and mechanism of Chinese OFDI activities on $PM_{2.5}$ pollution at the city level from 2007 to 2019. Our results and conclusions remain stable after several estimations, including the MCMC simulation, machine learning optimization, and single equation estimation. The main conclusions are as follows:

(1) China has made a remarkable achievement in $PM_{2.5}$ pollution reduction and governance, especially from the year 2012. The LMDI decomposition results show that, during the critical period of tackling $PM_{2.5}$ pollution, industrial transformation and technological upgrades are the major pathways. (2) In the 3SLS structural results, the OFDI activities can significantly decrease the home-country $PM_{2.5}$ pollution. With every 1% increase in OFDI flows, the overall pollution level will decrease by 0.76% . This reduction effect is relatively considerable when considering the harmfulness of $PM_{2.5}$ pollution. (3) Compared with the scale mechanism, the technology and composition mechanism effects of OFDI flows are more evident and obvious in addressing the home-country $PM_{2.5}$ pollution. (4) Since the multi-factor mutual process, the LMDI decomposition and the 3SLS structural approaches are more reasonable and acceptable.

Policy recommendations

This study contributes to the literature by broadening the understanding of the role of OFDI activities in home-country environmental stewardship. To the best of our knowledge, few studies have examined the extent to which how OFDI activities from the home country will affect its own environment. We put forward the following policy recommendations based on the above conclusions.

- (1) Strengthen the home-country environmental effect of OFDI activities. Under the global climate change crisis, promoting international investment in sustainable development and recovery is an inevitable choice. In

the long term, OFDI activities can play the role of the pollution halo phenomenon. That is, OFDI activity can not only improve the host-country environment, but it can also decrease the home-country environmental pollution. Therefore, governments worldwide should enhance the role of OFDI activities in environmental stewardship. For example, making up targeted green economic stimulus policies to expand the covered countries and sectors of Chinese OFDI activities, especially those measurements that can improve investment facilitation. According to the World Economic Forum and World Investment Forum, China's overall business facilitation level is in the middle of the world. Improving investment efficiency and reducing the approval process are the current effective measures.

- (2) Expand technology-seeking OFDI activities gradually. One of the solutions to the climate crisis is to improve energy efficiency, thereby reducing pollution emissions. Without a technological breakthrough, achieving zero pollution in a short time will be difficult. Therefore, governments should vigorously promote and strengthen technology-seeking OFDI activities, thus creating a favorable research environment. In practice, the technology-seeking OFDI activities should focus on two aspects: one is a more advanced and cleaner production technology, and the other is the terminal pollution control method. As of now, China has put a lot of effort into the latter, such as a series of environmental regulations. In the near future, the government should use OFDI activities to promote and upgrade traditional production equipment.
- (3) Make full use of the reverse spillover phenomena and effects. Governments should pay enough attention to whether it is the reverse technology spillover or the reverse structural transformation. In addition to conventional economic measures, all these reverse spillover phenomena can bring pollution reduction effects other than environmental regulation. Take the negative carbon spillover phenomena as an example, which is currently very effective in emission reduction. Although it belongs to the technology mechanism, it will also drive the remaining two mechanisms through the connection of the economic system. Since reverse spillover phenomena can be achieved regarding carbon emissions, obtaining the same goal in PM_{2.5} pollution control is possible. What the government needs to do is to increase the possibility of reverse spillover phenomena through OFDI activities.

To a certain extent, some limitations prevent us from making further improvements in this study. First, since the LMDI decomposition and 3SLS structural approaches are more effective for ample and large data granules, we can not

directly conduct the sub-regional differences. Second, due to the short time range of the sample data, it is challenging to analyze the long-term dynamic effect and the spatial spillover effect. Better data will be collected to address these two issues in the next plan.

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Declarations

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References

- Ahmad F, Draz MU, Yang SC (2016) A novel study on OFDI and home country exports: implications for the ASEAN region. *J Chin Econ Foreign Trade Stud* 9(2):131–145. <https://doi.org/10.1108/JCEFTS-06-2016-0016>
- Ahmadova G, Delgado-Márquez BL, Pedauga LE, Leyva-de La Hiz DI (2022) Too good to be true: the inverted U-shaped relationship between home-country digitalization and environmental performance. *Ecol Econ* 196:107393. <https://doi.org/10.1016/j.ecolecon.2022.107393>
- An T, Xu C, Liao X (2021) The impact of FDI on environmental pollution in China: evidence from spatial panel data. *Environ Sci Pollut Res* 28(32):44085–44097. <https://doi.org/10.1007/s11356-021-13903-9>
- Ang BW (2005) The LMDI approach to decomposition analysis: a practical guide. *Energy Policy* 33(7):867–871. <https://doi.org/10.1016/j.enpol.2003.10.010>
- Ang BW (2015) LMDI decomposition approach: a guide for implementation. *Energy Policy* 86:233–238. <https://doi.org/10.1016/j.enpol.2015.07.007>
- Ang BW, Zhang FQ (2000) A survey of index decomposition analysis in energy and environmental studies. *Energy* 25(12):1149–1176. [https://doi.org/10.1016/S0360-5442\(00\)00039-6](https://doi.org/10.1016/S0360-5442(00)00039-6)
- Ang BW, Choi KH (1997) Decomposition of aggregate energy and gas emission intensities for industry: a refined Divisia index method. *Energy J* 18(3). <https://doi.org/10.5547/ISSN0195-6574-EJ-Vol18-No3-3>

- Ansari MA (2022) Re-visiting the Environmental Kuznets curve for ASEAN: a comparison between ecological footprint and carbon dioxide emissions. *Renew Sustain Energy Rev* 168:112867. <https://doi.org/10.1016/j.rser.2022.112867>
- Antweiler W, Copeland BR, Taylor MS (2001) Is free trade good for the environment? *Am Econ Rev* 91(4):877–908. <https://doi.org/10.1257/aer.91.4.877>
- Anwar MA, Zhang Q, Asmi F, Hussain N, Plantinga A, Zafar MW, Sinha A (2022) Global perspectives on environmental Kuznets curve: a bibliometric review. *Gondwana Res* 103:135–145. <https://doi.org/10.1016/j.gr.2021.11.010>
- Apte JS, Brauer M, Cohen AJ, Ezzati M, Pope CA (2018) Ambient PM_{2.5} reduces global and regional life expectancy. *Environ Sci Technol Lett* 5(9):546–551. <https://doi.org/10.1021/acs.estlett.8b00360>
- Ardiyono SK, Patunru AA (2022) The impact of employment protection on FDI at different stages of economic development. *World Econ* 45(12):3679–3714. <https://doi.org/10.1111/twec.13299>
- Balsalobre-Lorente D, Gokmenoglu KK, Taspinar N, Cantos-Cantos JM (2019) An approach to the pollution haven and pollution halo hypotheses in MINT countries. *Environ Sci Pollut Res* 26(22):23010–23026. <https://doi.org/10.1007/s11356-019-05446-x>
- Bartlett JW, Morris TP (2015) Multiple imputation of covariates by substantive-model compatible fully conditional specification. *Stand Genomic Sci* 15(2):437–456. <https://doi.org/10.1177/1536867X1501500206>
- Barwick PJ, Li S, Lin L, Zou E (2019) From fog to smog: the value of pollution information. *Natl Bur Econ Res* w26541. <https://doi.org/10.3386/w26541>
- Baymul C, Sen K (2020) Was Kuznets right? New evidence on the relationship between structural transformation and inequality. *J Dev Stud* 56(9):1643–1662. <https://doi.org/10.1080/00220388.2019.1702161>
- Bhasin N, Kapoor K (2021) Impact of outward FDI on home country exports. *Int J Emerg Mark* 16(6):1150–1175. <https://doi.org/10.1108/IJOEM-05-2017-0160>
- Blum A, Hopcroft J, Kannan R (2020) *Foundations of data science*. Cambridge University Press, Cambridge, UK. ISBN-13: 978-1-108-48506-7. <https://doi.org/10.1017/9781108755528>
- Bo S (2011) A literature survey on environmental Kuznets curve. *Energy Procedia* 5:1322–1325. <https://doi.org/10.1016/j.egypro.2011.03.229>
- Bowe B, Xie Y, Yan Y, Al-Aly Z (2019) Burden of cause-specific mortality associated with PM_{2.5} air pollution in the united states. *JAMA Netw Open* 2(11):e1915834. <https://doi.org/10.1001/jamanetworkopen.2019.15834>
- Bräutigam D, Tang X (2014) “Going global in groups”: structural transformation and China’s special economic zones overseas. *World Dev* 63:78–91. <https://doi.org/10.1016/j.worlddev.2013.10.010>
- Bruhn NCP, de Alcântara JN, Tonelli DF, Reis RP, Antonialli LM (2016) Why firms invest abroad? A bibliometric study on OFDI determinants from developing economies. *Glob Bus Rev* 17(2):271–302. <https://doi.org/10.1177/0972150915619802>
- Canuto O (2023) *Capital flows and emerging market economies since the global financial crisis*. Foreign Exch Constraint Dev Econ 208–222. Edward Elgar Publishing, Cheltenham, England, UK. ISBN-13: 978–1–800–88049–8, e-ISBN-13: 978–1–800–88050–4. <https://doi.org/10.4337/9781800880504.00019>
- Chen JE, Zulkifli SAM (2012) Malaysian outward FDI and economic growth. *Procedia Soc Behav Sci* 65:717–722. <https://doi.org/10.1016/j.sbspro.2012.11.189>
- Chen VZ, Li Y, Hambright S (2016) Regulatory institutions and Chinese outward FDI: an empirical review. *Multinat Bus Rev* 24(4):302–333. <https://doi.org/10.1108/MBR-09-2015-0044>
- Chen J, Liu Y, Liu W (2020) Investment facilitation and China’s outward foreign direct investment along the belt and road. *China Econ Rev* 61:101458. <https://doi.org/10.1016/j.chieco.2020.101458>
- Cheng Z, Li L, Liu J (2020) The impact of foreign direct investment on urban PM_{2.5} pollution in China. *J Environ Manag* 265:110532. <https://doi.org/10.1016/j.jenvman.2020.110532>
- Chi Y, Zhang Y, Li G, Yuan Y (2022) Prediction method of Beijing electric-energy substitution potential based on a grid-search support vector machine. *Energies* 15(11):3897. <https://doi.org/10.3390/en15113897>
- Christofi M, Vrontis D, Makrides A (2022) Exploring the role of institutions in Chinese OFDI: a systematic review and integrative framework. *Asia Pac Bus Rev* 28(2):187–213. <https://doi.org/10.1080/13602381.2022.2013607>
- Cicea C, Marinescu C (2020) Bibliometric analysis of foreign direct investment and economic growth relationship. A research agenda. *J Bus Econ Manag* 22(2):445–466. <https://doi.org/10.3846/jbem.2020.14018>
- Cieřlik A, Goczek Ł (2018) Control of corruption, international investment, and economic growth – evidence from panel data. *World Dev* 103:323–335. <https://doi.org/10.1016/j.worlddev.2017.10.028>
- Cui X, Tang J, Deng H (2012) New book proposal: Chinese foreign direct investment: does China have enough money? *Transl Corp Rev* 4(3):123–128. <https://doi.org/10.1080/19186444.2012.11658340>
- Cunha-Zeri G, Guidolini JF, Branco EA, Ometto JP (2022) How sustainable is the nitrogen management in Brazil? A sustainability assessment using the entropy weight method. *J Environ Manag* 316:115330. <https://doi.org/10.1016/j.jenvman.2022.115330>
- De Beule F, Schoubben F, Struyfs K (2022) The pollution haven effect and investment leakage: the case of the EU-ETS. *Econ Lett* 215:110536. <https://doi.org/10.1016/j.econlet.2022.110536>
- Dechezleprêtre A, Gennaioli C, Martin R, Muùls M, Stoerk T (2022) Searching for carbon leaks in multinational companies. *J Environ Econ Manag* 112:102601. <https://doi.org/10.1016/j.jeem.2021.102601>
- Demena BA, van Bergeijk PAG (2019) Observing FDI spillover transmission channels: evidence from firms in Uganda. *Third World Q* 40(9):1708–1729. <https://doi.org/10.1080/01436597.2019.1596022>
- Dietz T, Rosa EA (1997) Effects of population and affluence on CO₂ emissions. *Proc Natl Acad Sci* 94(1):175–179. <https://doi.org/10.1073/pnas.94.1.175>
- Dogan E, Inglesi-Lotz R (2020) The impact of economic structure to the environmental Kuznets curve (EKC) hypothesis: evidence from European countries. *Environ Sci Pollut Res* 27(11):12717–12724. <https://doi.org/10.1007/s11356-020-07878-2>
- Dong F, Yu B, Pan Y (2019) Examining the synergistic effect of CO₂ emissions on PM_{2.5} emissions reduction: evidence from China. *J Clean Prod* 223:759–771. <https://doi.org/10.1016/j.jclepro.2019.03.152>
- Du J, Zhang Y (2018) Does one belt one road initiative promote Chinese overseas direct investment? *China Econ Rev* 47:189–205. <https://doi.org/10.1016/j.chieco.2017.05.010>
- Duan Y, Jiang X (2021) Pollution haven or pollution halo? A re-evaluation on the role of multinational enterprises in global CO₂ emissions. *Energy Econ* 97:105181. <https://doi.org/10.1016/j.eneco.2021.105181>
- Duan D, Jin H (2022) Environmental regulation and green technology diffusion: a case study of Yangtze river delta. *China Land* 11(11):1923. <https://doi.org/10.3390/land11111923>
- Ehrlich PR, Holdren JP (1971) Impact of population growth: complacency concerning this component of man’s predicament is unjustified and counterproductive. *Science* 171(3977):1212–1217. <https://doi.org/10.1126/science.171.3977.1212>
- Ehrlich I, Pei Y (2021) Endogenous immigration, human and physical capital formation, and the immigration surplus. *J Hum Cap* 15(1):34–85. <https://doi.org/10.1086/714037>

- Fan S, Zhang L, Zhang X (2004) Reforms, investment, and poverty in rural china. *Econ Dev Cult Change* 52(2):395–421. <https://doi.org/10.1086/380593>
- Feng W, Yuan H (2022) The pain of breathing: how does haze pollution affect urban innovation? *Environ Sci Pollut Res* 29(28):42664–42677. <https://doi.org/10.1007/s11356-021-18279-4>
- Gao R (2023) Inward FDI spillovers and emerging multinationals' outward FDI in two directions. *Asia Pac J Manag* 40(1):265–293. <https://doi.org/10.1007/s10490-021-09788-4>
- Gnidchenko AA (2021) Structural transformation and quality ladders: evidence from the new Theil's decomposition. *Struct Chang Econ Dyn* 59:281–291. <https://doi.org/10.1016/j.strueco.2021.09.002>
- Goh SK, Wong KN, Tham SY (2013) Trade linkages of inward and outward FDI: evidence from Malaysia. *Econ Model* 35:224–230. <https://doi.org/10.1016/j.econmod.2013.06.035>
- Grossman G, Krueger A (1991) Environmental impacts of a north American free trade agreement. *Natl Bur Econ Res* w3914. <https://doi.org/10.3386/w3914>
- Guo G, Li J, Wang D, Zhang L (2022) Political connection, contract intensity, and OFDI: evidence from China. *J Econ Surv* 36(3):534–557. <https://doi.org/10.1111/joes.12448>
- Gyamfi BA, Adebayo TS, Bekun FV, Agyekum EB, Kumar NM, Alhelou HH, Al-Hinai A (2021) Beyond environmental Kuznets curve and policy implications to promote sustainable development in Mediterranean. *Energy Rep* 7:6119–6129. <https://doi.org/10.1016/j.egyrs.2021.09.056>
- Gyamfi BA, Bein MA, Udemba EN, Bekun FV (2022) Renewable energy, economic globalization and foreign direct investment linkage for sustainable development in the E7 economies: revisiting the pollution haven hypothesis. *Int Soc Sci J* 72(243):91–110. <https://doi.org/10.1111/issj.12301>
- Hao Y, Liu Y, Weng J-H, Gao Y (2016) Does the environmental Kuznets curve for coal consumption in China exist? New evidence from spatial econometric analysis. *Energy* 114:1214–1223. <https://doi.org/10.1016/j.energy.2016.08.075>
- Hao Y, Guo Y, Guo Y, Wu H, Ren S (2020) Does outward foreign direct investment (OFDI) affect the home country's environmental quality? The case of China. *Struct Chang Econ Dyn* 52:109–119. <https://doi.org/10.1016/j.strueco.2019.08.012>
- Hao Y, Ba N, Ren S, Wu H (2021) How does international technology spillover affect China's carbon emissions? A new perspective through intellectual property protection. *Sustain Prod Consum* 25:577–590. <https://doi.org/10.1016/j.spc.2020.12.008>
- Huynh CM, Hoang HH (2019) Foreign direct investment and air pollution in Asian countries: does institutional quality matter? *Appl Econ Lett* 26(17):1388–1392. <https://doi.org/10.1080/13504851.2018.1563668>
- Iqbal N, Naeem MA, Suleman MT (2022) Quantifying the asymmetric spillovers in sustainable investments. *J Int Financ Mark Inst Money* 77:101480. <https://doi.org/10.1016/j.intfin.2021.101480>
- Isik C, Ongan S, Ozdemir D, Ahmad M, Irfan M, Alvarado R, Ongan A (2021) The increases and decreases of the environment Kuznets curve (EKC) for 8 OECD countries. *Environ Sci Pollut Res* 28(22):28535–28543. <https://doi.org/10.1007/s11356-021-12637-y>
- Jain A, Thukral S (2022) What causes outward foreign direct investment (OFDI) from India into least developed countries (LDCS)? *J Asia Pac Econ* 1–30. <https://doi.org/10.1080/13547860.2022.2097619>
- Jia W, Li L, Lei Y, Wu S (2023) Synergistic effect of CO₂ and PM_{2.5} emissions from coal consumption and the impacts on health effects. *J Environ Manag* 325:116535. <https://doi.org/10.1016/j.jenvman.2022.116535>
- Jiang B, Wu T, Xia W, Liang J (2020) Hygrothermal performance of rammed earth wall in Tibetan autonomous prefecture in Sichuan province of China. *Build Environ* 181:107128. <https://doi.org/10.1016/j.buildenv.2020.107128>
- Kaltenegger O (2020) What drives total real unit energy costs globally? A novel LMDI decomposition approach. *Appl Energy* 261:114340. <https://doi.org/10.1016/j.apenergy.2019.114340>
- Karplus VJ, Zhang S, Almond D (2018) Quantifying coal power plant responses to tighter SO₂ emissions standards in China. *Proc Natl Acad Sci* 115(27):7004–7009. <https://doi.org/10.1073/pnas.1800605115>
- Kaushal LA (2022) Institutional and economic determinants of Indian OFDI. *Cogent Econ Finance* 10(1):2147648. <https://doi.org/10.1080/23322039.2022.2147648>
- Kaya Y, Yokobori K (1997) Environment, energy, and economy: strategies for sustainability. *United Nations University Press*, USA. ISBN-13: 978–9–280–80911–4. Retrieved from <https://unu.edu/publications/books/environment-energy-and-economy-strategies-for-sustainability.html>, last accessed 30 March 2023.
- Keller W, Li B, Shiue CH (2011) China's foreign trade: perspectives from the past 150 years: China's foreign trade. *World Econ* 34(6):853–892. <https://doi.org/10.1111/j.1467-9701.2011.01358.x>
- Khan I, Xue J, Zaman S, Mehmood Z (2022) Nexus between FDI, economic growth, industrialization, and employment opportunities: empirical evidence from Pakistan. *J Knowl Econ*. <https://doi.org/10.1007/s13132-022-01006-w>
- Kisswani KM, Zaitouni M (2021) Does FDI affect environmental degradation? Examining pollution haven and pollution halo hypotheses using ARDL modelling. *J Asia Pac Econ* 1–27. <https://doi.org/10.1080/13547860.2021.1949086>
- Kong Q, Guo R, Wang Y, Sui X, Zhou S (2020) Home-country environment and firms' outward foreign direct investment decision: evidence from Chinese firms. *Econ Model* 85:390–399. <https://doi.org/10.1016/j.econmod.2019.11.014>
- Lai K (2021) National security and FDI policy ambiguity: a commentary. *J Int Bus Policy* 4(4):496–505. <https://doi.org/10.1057/s42214-020-00087-1>
- Lerman PM (1980) Fitting segmented regression models by grid search. *Appl Stat* 29(1):77. <https://doi.org/10.2307/2346413>
- Li F, Yu C (2020) OFDI and home country structural upgrading: does spatial difference exist in China? *Emerg Mark Financ Trade* 56(7):1532–1546. <https://doi.org/10.1080/1540496X.2019.1602037>
- Li M, Du W, Tang S (2021) Assessing the impact of environmental regulation and environmental co-governance on pollution transfer: micro-evidence from China. *Environ Impact Assess Rev* 86:106467. <https://doi.org/10.1016/j.eiar.2020.106467>
- Liu H, Chen C (2020) Prediction of outdoor PM_{2.5} concentrations based on a three-stage hybrid neural network model. *Atmos Pollut Res* 11(3):469–481. <https://doi.org/10.1016/j.apr.2019.11.019>
- Liu G, Zhang C (2020) Economic policy uncertainty and firms' investment and financing decisions in China. *China Econ Rev* 63:101279. <https://doi.org/10.1016/j.chieco.2019.02.007>
- Liu G, Dong X, Kong Z, Dong K (2021) Does national air quality monitoring reduce local air pollution? The case of PM_{2.5} for China. *J Environ Manag* 296:113232. <https://doi.org/10.1016/j.jenvman.2021.113232>
- Long W, Luo L, Sun H, Zhong Q (2023) Does going abroad lead to going green? Firm outward foreign direct investment and domestic environmental performance. *Bus Strateg Environ* 32(1):484–498. <https://doi.org/10.1002/bse.3156>
- Luo Y, Wang SL (2012) Foreign direct investment strategies by developing country multinationals: a diagnostic model for home country effects. *Glob Strateg J* 2(3):244–261. <https://doi.org/10.1111/j.2042-5805.2012.01036.x>
- Luo Y, Xue Q, Han B (2010) How emerging market governments promote outward FDI: experience from China. *J World Bus* 45(1):68–79. <https://doi.org/10.1016/j.jwb.2009.04.003>

- Meo SA, Adnan Abukhalaf A, Sami W, Hoang TD (2021) Effect of environmental pollution PM_{2.5}, carbon monoxide, and ozone on the incidence and mortality due to SARS-CoV-2 infection in London, United Kingdom. *J King Saud Univ - Sci* 33(3):101373. <https://doi.org/10.1016/j.jksus.2021.101373>
- Mert M, Caglar AE (2020) Testing pollution haven and pollution halo hypotheses for Turkey: a new perspective. *Environ Sci Pollut Res* 27(26):32933–32943. <https://doi.org/10.1007/s11356-020-09469-7>
- Messerschmidt L, Janz N (2023) Unravelling the ‘race to the bottom’ argument: foreign direct investment and different types of labour rights. *World Dev* 161:106097. <https://doi.org/10.1016/j.worlddev.2022.106097>
- Mörsdorf G (2022) A simple fix for carbon leakage? Assessing the environmental effectiveness of the EU carbon border adjustment. *Energy Policy* 161:112596. <https://doi.org/10.1016/j.enpol.2021.112596>
- Moutinho V, Madaleno M, Inglesi-Lotz R, Dogan E (2018) Factors affecting CO₂ emissions in top countries on renewable energies: a LMDI decomposition application. *Renew Sustain Energy Rev* 90:605–622. <https://doi.org/10.1016/j.rser.2018.02.009>
- Nan S, Huo Y, You W, Guo Y (2022) Globalization spatial spillover effects and carbon emissions: what is the role of economic complexity? *Energy Econ* 112:106184. <https://doi.org/10.1016/j.eneco.2022.106184>
- OECD (2012) OECD environmental outlook to 2050: the consequences of inaction. *Organisation for Economic Co-operation and Development (OECD) Publishing*, Paris, France. ISBN-13: 978–9–264–12216–1, e-ISBN-13: 978–9–264–12224–6. <https://doi.org/10.1787/9789264122246-en>
- Pan P, Al-Tabbaa O (2021) The effect of the Chinese government policies on outward foreign direct investment by domestic enterprises: a policy analysis. *Strateg Chang* 30(6):561–572. <https://doi.org/10.1002/jsc.2469>
- Pan X, Li M, Wang M, Chu J, Bo H (2020) The effects of outward foreign direct investment and reverse technology spillover on China’s carbon productivity. *Energy Policy* 145:111730. <https://doi.org/10.1016/j.enpol.2020.111730>
- Ren YS, Apergis N, Ma C, Baltas K, Jiang Y, Liu JL (2021) FDI, economic growth, and carbon emissions of the Chinese steel industry: new evidence from a 3SLS model. *Environ Sci Pollut Res* 28(37):52547–52564. <https://doi.org/10.1007/s11356-021-14445-w>
- Ren S, Hao Y, Wu H (2022) The role of outward foreign direct investment (OFDI) on green total factor energy efficiency: does institutional quality matters? Evidence from China. *Resour Policy* 76:102587. <https://doi.org/10.1016/j.resourpol.2022.102587>
- Roy V (2020) Convergence diagnostics for Markov chain Monte Carlo. *Ann Rev Stat Appl* 7(1):387–412. <https://doi.org/10.1146/annur-ev-statistics-031219-041300>
- Sargan JD (1964) Three-stage least-squares and full maximum likelihood estimates. *Econometrica* 32(1/2):77. <https://doi.org/10.2307/1913735>
- Shahbaz M, Raghutla C, Song M, Zameer H, Jiao Z (2020) Public-private partnerships investment in energy as new determinant of CO₂ emissions: the role of technological innovations in China. *Energy Econ* 86:104664. <https://doi.org/10.1016/j.eneco.2020.104664>
- Singhania M, Saini N (2021) Demystifying pollution haven hypothesis: role of FDI. *J Bus Res* 123:516–528. <https://doi.org/10.1016/j.jbusres.2020.10.007>
- Sorrell S, Gatersleben B, Druckman A (2020) The limits of energy sufficiency: a review of the evidence for rebound effects and negative spillovers from behavioural change. *Energy Res Soc Sci* 64:101439. <https://doi.org/10.1016/j.erss.2020.101439>
- Stern N, Xie C (2023) China’s new growth story: linking the 14th Five-Year Plan with the 2060 carbon neutrality pledge. *J Chin Econ Bus Stud* 21(1):5–25. <https://doi.org/10.1080/14765284.2022.2073172>
- Sterne JAC, White IR, Carlin JB, Spratt M, Royston P, Kenward MG, ..., Carpenter JR (2009) Multiple imputation for missing data in epidemiological and clinical research: potential and pitfalls. *BMJ* 338(29):b2393–b2393. <https://doi.org/10.1136/bmj.b2393>
- Su Z, Taltavull de La Paz P, Haran M (2021) Investigating China’s outward FDI in the European real estate industry with a gravity-model-based benchmark. *Real Estate Financ* 38(2):105–119. Retrieved from <http://hdl.handle.net/10045/120012>, last accessed 30 March 2023.
- Tan F, Wan H, Jiang X, Niu Z (2021) The impact of outward foreign direct investment on carbon emission toward china’s sustainable development. *Sustainability* 13(21):11605. <https://doi.org/10.3390/su132111605>
- Tang M (2020) From “bringing-in” to “going-out”: transnationalizing China’s internet capital through state policies. *Chin J Commun* 13(1):27–46. <https://doi.org/10.1080/17544750.2019.1657474>
- Tavakoli A (2018) A journey among top ten emitter country, decomposition of “KAYA Identity.” *Sustain Cities Soc* 38:254–264. <https://doi.org/10.1016/j.scs.2017.12.040>
- Tian L, Zhai Y, Zhang Y, Tan Y, Feng S (2023) Pollution emission reduction effect of the coordinated development of inward and outward FDI in China. *J Clean Prod* 391:136233. <https://doi.org/10.1016/j.jclepro.2023.136233>
- UNCTAD (2021) World investment report 2021: investing in sustainable recovery. *The United Nations Conference on Trade and Development (UNCTAD) Publications*, New York, USA. ISBN-13: 978–9–211–13017–1, e-ISBN-13: 978–9–210–05463–8. Retrieved from <https://unctad.org/publication/world-investment-report-2021>, last accessed 30 March 2023.
- UNCTAD (2022) World investment report 2022: international tax reforms and sustainable investment. *The United Nations Conference on Trade and Development (UNCTAD) Publications*, New York, USA. ISBN-13: 978–9–211–13049–2, e-ISBN-13: 978–9–210–01543–1. Retrieved from <https://unctad.org/publication/world-investment-report-2022>, last accessed 30 March 2023.
- Verde SF (2020) The impact of the EU emissions trading system on competitiveness and carbon leakage: the econometric evidence. *J Econ Surv* 34(2):320–343. <https://doi.org/10.1111/joes.12356>
- Voituriez T, Yao W, Larsen ML (2019) Revising the ‘host country standard’ principle: a step for China to align its overseas investment with the Paris Agreement. *Climate Policy* 19(10):1205–1210. <https://doi.org/10.1080/14693062.2019.1650702>
- Wadhwa K, Reddy SS (2011) Foreign direct investment into developing Asian countries: the role of market seeking, resource seeking and efficiency seeking factors. *Int J Bus Manag* 6(11):p219. <https://doi.org/10.5539/ijbm.v6n11p219>
- Wang B, Gao K (2019) Forty years development of China’s outward foreign direct investment: retrospect and the challenges ahead. *Chin World Econ* 27(3):1–24. <https://doi.org/10.1111/cwe.12278>
- Wang H, Li J (2021) Dual effects of environmental regulation on PM_{2.5} pollution: evidence from 280 cities in China. *Environ Sci Pollut Res* 28(34):47213–47226. <https://doi.org/10.1007/s11356-021-14011-4>
- Wang J, Yeh AG (2020) Administrative restructuring and urban development in China: effects of urban administrative level upgrading. *Urban Stud* 57(6):1201–1223. <https://doi.org/10.1177/0042098019830898>
- Wang WW, Zhang M, Zhou M (2011) Using LMDI method to analyze transport sector CO₂ emissions in China. *Energy* 36(10):5909–5915. <https://doi.org/10.1016/j.energy.2011.08.031>
- Wang R, Zameer H, Feng Y, Jiao Z, Xu L, Gedikli A (2019) Revisiting Chinese resource curse hypothesis based on spatial spillover effect: a fresh evidence. *Resour Policy* 64:101521. <https://doi.org/10.1016/j.resourpol.2019.101521>

- Wang ML, Pang SL, Wang F, Guo X, He ZX (2021) Dynamic interaction between outward foreign direct investment and home country industrial upgrading: regional differences in China. *Growth Chang* 52(4):2293–2317. <https://doi.org/10.1111/grow.12548>
- Wang X, Wang L, Wang S, Fan F, Ye X (2021) Marketisation as a channel of international technology diffusion and green total factor productivity: research on the spillover effect from China's first-tier cities. *Technol Anal Strat Manag* 33(5):491–504. <https://doi.org/10.1080/09537325.2020.1821877>
- Wang J, Dong H, Xiao R (2022) Central environmental inspection and corporate environmental investment: evidence from Chinese listed companies. *Environ Sci Pollut Res* 29(37):56419–56429. <https://doi.org/10.1007/s11356-022-19538-8>
- Wang J, Gao J, Che F, Wang Y, Lin P, Zhang Y (2022) Decade-long trends in chemical component properties of PM_{2.5} in Beijing, China (2011–2020). *Sci Total Environ* 832:154664. <https://doi.org/10.1016/j.scitotenv.2022.154664>
- Wang Y, Mao X, Zameer H (2022) Designing benefit distribution driven innovation strategy for local enterprises under the global value chain system. *Manag Decis Econ* 43(6):2358–2373. <https://doi.org/10.1002/mde.3531>
- Watts N, Amann M, Ayeb-Karlsson S, Belesova K, Bouley T, Boykoff M, ..., Costello A (2018) The Lancet countdown on health and climate change: from 25 years of inaction to a global transformation for public health. *Lancet* 391(10120):581–630. [https://doi.org/10.1016/S0140-6736\(17\)32464-9](https://doi.org/10.1016/S0140-6736(17)32464-9)
- Wong Z, Li R, Peng D, Kong Q (2021) China-European railway, investment heterogeneity, and the quality of urban economic growth. *Int Rev Financ Anal* 78:101937. <https://doi.org/10.1016/j.irfa.2021.101937>
- Wood AM, White IR, Royston P (2008) How should variable selection be performed with multiply imputed data? *Stat Med* 27(17):3227–3246. <https://doi.org/10.1002/sim.3177>
- Wu W, Zhang M, Ding Y (2020) Exploring the effect of economic and environment factors on PM_{2.5} concentration: a case study of the Beijing-Tianjin-Hebei region. *J Environ Manag* 268:110703. <https://doi.org/10.1016/j.jenvman.2020.110703>
- Xia H, Dong F, Yang H (2022a) Stepping-stone or stumbling block: impact of the economic system on China's OFDI. *Econ Res-Ekonomska Istraživanja* 35(1):6901–6917. <https://doi.org/10.1080/1331677X.2022.2053866>
- Xia YS, Sun LX, Feng C (2022) What causes spatial inequalities of low-carbon development in China's transport sector? A newly proposed meta-frontier DEA-based decomposition approach. *Socio-Econ Plan Sci* 80:101151. <https://doi.org/10.1016/j.seps.2021.101151>
- Xin D, Zhang Y (2020) Threshold effect of OFDI on China's provincial environmental pollution. *J Clean Prod* 258:120608. <https://doi.org/10.1016/j.jclepro.2020.120608>
- Xu S, Zhou Y, Feng C, Zhang J (2021) The factors of regional PM_{2.5} emissions inequality in China. *Process Saf Environ Prot* 150:79–92. <https://doi.org/10.1016/j.psep.2021.04.005>
- Yang G, Zheng Q (2021) Impact of China's outward foreign direct investment on environmental pollution in the home country. *Chin J Popul Resour Environ* 19(3):221–229. <https://doi.org/10.1016/j.cjpre.2021.12.024>
- Yang T, Dong Q, Du Q, Du M, Dong R, Chen M (2021) Carbon dioxide emissions and Chinese OFDI: from the perspective of carbon neutrality targets and environmental management of home country. *J Environ Manag* 295:113120. <https://doi.org/10.1016/j.jenvman.2021.113120>
- Yasmeen H, Wang Y, Zameer H, Solangi YA (2019) Does oil price volatility influence real sector growth? Empirical evidence from Pakistan. *Energy Rep* 5:688–703. <https://doi.org/10.1016/j.egy.2019.06.006>
- Yasmeen H, Wang Y, Zameer H, Solangi YA (2020) Decomposing factors affecting CO₂ emissions in Pakistan: insights from LMDI decomposition approach. *Environ Sci Pollut Res* 27(3):3113–3123. <https://doi.org/10.1007/s11356-019-07187-3>
- Yin H, Yang J, Lu X (2020) Bank globalization and efficiency: host-and home-country effects. *Res Int Bus Finance* 54:101305. <https://doi.org/10.1016/j.rifab.2020.101305>
- Yoon H, Heshmati A (2021) Do environmental regulations affect FDI decisions? The pollution haven hypothesis revisited. *Sci Public Policy* 48(1):122–131. <https://doi.org/10.1093/scipol/scaa060>
- Yu C, Morotomi T (2022) The effect of the revision and implementation for environmental protection law on ambient air quality in China. *J Environ Manag* 306:114437. <https://doi.org/10.1016/j.jenvman.2022.114437>
- Yue H, He C, Huang Q, Yin D, Bryan BA (2020) Stronger policy required to substantially reduce deaths from PM_{2.5} pollution in China. *Nat Commun* 11(1):1462. <https://doi.org/10.1038/s41467-020-15319-4>
- Zaman K (2018) The impact of hydro-biofuel-wind energy consumption on environmental cost of doing business in a panel of BRICS countries: evidence from three-stage least squares estimator. *Environ Sci Pollut Res* 25(5):4479–4490. <https://doi.org/10.1007/s11356-017-0797-1>
- Zameer H, Wang Y (2018) Energy production system optimization: evidence from Pakistan. *Renew Sustain Energy Rev* 82:886–893. <https://doi.org/10.1016/j.rser.2017.09.089>
- Zameer H, Yasmeen H (2022) Green innovation and environmental awareness driven green purchase intentions. *Mark Intell Plan* 40(5):624–638. <https://doi.org/10.1108/MIP-12-2021-0457>
- Zameer H, Yasmeen H, Wang R, Tao J, Malik MN (2020) An empirical investigation of the coordinated development of natural resources, financial development and ecological efficiency in China. *Resour Policy* 65:101580. <https://doi.org/10.1016/j.resourpol.2020.101580>
- Zameer H, Wang Y, Saeed MR (2021) Net-zero emission targets and the role of managerial environmental awareness, customer pressure, and regulatory control toward environmental performance. *Bus Strateg Environ* 30(8):4223–4236. <https://doi.org/10.1002/bse.2866>
- Zameer H, Wang Y, Vasbieva DG, Abbas Q (2021) Exploring a pathway to carbon neutrality via reinforcing environmental performance through green process innovation, environmental orientation and green competitive advantage. *J Environ Manag* 296:113383. <https://doi.org/10.1016/j.jenvman.2021.113383>
- Zellner A, Theil H (1992) Three-stage least squares: simultaneous estimation of simultaneous equations. In Henri Theil's contributions to economics and econometrics. *Advanced studies in theoretical and applied econometrics*, 23:147–178. Springer Netherlands, Dordrecht, Netherlands. https://doi.org/10.1007/978-94-011-2546-8_10
- Zeng K, Eastin J (2012) Do developing countries invest up? The environmental effects of foreign direct investment from less-developed countries. *World Dev* 40(11):2221–2233. <https://doi.org/10.1016/j.worlddev.2012.03.008>
- Zhang J (2008) Estimation of China's provincial capital stock (1952–2004) with applications. *J Chin Econ Bus Stud* 6(2):177–196. <https://doi.org/10.1080/14765280802028302>
- Zhang Y, Shuai C, Bian J, Chen X, Wu Y, Shen L (2019) Socioeconomic factors of PM_{2.5} concentrations in 152 Chinese cities: decomposition analysis using LMDI. *J Clean Prod* 218:96–107. <https://doi.org/10.1016/j.jclepro.2019.01.322>
- Zhang J, Wu G, Zhang J (2004) The estimation of China's provincial capital stock: 1952–2000. *Econ Res J* 10:35–44. Retrieved from <http://www.cnki.com.cn/Article/CJFDTotal-JJYJ200410004.htm>, last accessed 30 March 2023.
- Zhao Y, Duan L, Xing J, Larssen T, Nielsen CP, Hao J (2009) Soil acidification in China: is controlling SO₂ emissions enough? *Environ Sci Technol* 43(21):8021–8026. <https://doi.org/10.1021/es901430n>
- Zhao Y, Liang C, Zhang X (2021) Positive or negative externalities? Exploring the spatial spillover and industrial agglomeration

- threshold effects of environmental regulation on haze pollution in China. *Environ Dev Sustain* 23(8):11335–11356. <https://doi.org/10.1007/s10668-020-01114-0>
- Zhao J, Wang J, Dong K (2022) The role of green finance in eradicating energy poverty: ways to realize green economic recovery in the post-COVID-19 era. *Econ Chang Restruct*. <https://doi.org/10.1007/s10644-022-09411-6>
- Zheng J, He J, Shao X, Liu W (2022) The employment effects of environmental regulation: evidence from eleventh five-year plan in China. *J Environ Manag* 316:115197. <https://doi.org/10.1016/j.jenvman.2022.115197>
- Zhou M, Wang X (2022) Research on the impact of host country environmental regulations on china's ofdi under different investment motivations——empirical research based on panel data of asian countries. *Adv Econ Manag Res* 1(1):184. <https://doi.org/10.56028/aemr.1.1.184>
- Zhou C, Hong J, Wu Y, Marinova D (2019a) Outward foreign direct investment and domestic innovation performance: evidence from China. *Technol Anal Strat Manag* 31(1):81–95. <https://doi.org/10.1080/09537325.2018.1485890>
- Zhou Y, Jiang J, Ye B, Hou B (2019) Green spillovers of outward foreign direct investment on home countries: evidence from China's province-level data. *J Clean Prod* 215:829–844. <https://doi.org/10.1016/j.jclepro.2019.01.042>

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