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Can climate mitigation help the poor? Measuring impacts of the CDM in rural China

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Abstract

This study aims to examine whether investment in climate change mitigation plays a role in poverty alleviation. We investigate impacts of the renewable energy-based clean development mechanism (RE-CDM) on rural communities in China. The impacts of RE-CDM projects are estimated by combining propensity score matching with the difference-in-differences approach. We found that the promotion of biomass-based CDM projects significantly contribute to income improvement, employment generation, and industrial transformation in rural communities in China. On the other hand, our estimation results reveal that large-scale wind and solar energy-based CDM projects have the potential to increase the labor force in the primary industry in rural areas.

Keywords: CDM; renewable energy; poverty alleviation; rural development; propensity score matching; difference-in-differences

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1 Introduction

More than 5.7% of Chinese population live below the poverty line as of 2015, mainly in remote rural areas with limited energy access and job opportunities (Asian Development Bank, 2017).[1] As one of the policy packages to alleviate poverty in rural area, the Chinese Government has adopted programs that promote renewable energy in remote areas, including the Solar Energy for Poverty Alleviation Programme (SEPAP)[2] and the 13th Five-year Plan (FYP) for Rural Bioenergy Development.[3] Implementation of the SEPAP, which commenced in 2014, reveals the government's aim to alleviate rural poverty through deploying distributed solar photovoltaic (PV) systems in poor areas. On the other hand, one of ultimate targets of the 13th FYP for Rural Bioenergy Development is to increase the income of rural residents and improve living conditions of rural households by promoting utilization of agricultural wastes. In addition, the Announcement on Accelerating Construction of Energy Projects in Impoverished Areas for Promoting Poverty Alleviation, published by the National Energy Administration (NEA) in 2017, emphasizes the contribution of renewable energy to poverty reduction as well.[4]

In reality, can renewable energy play a key role in reducing the rural poverty? To explore the answer to this question, we investigate the past Chinese experiences with clean development mechanism (CDM) projects and examine their impacts on poverty reduction. The CDM, as a part of the flexible mechanisms defined in the Kyoto Protocol, has opened a host of possibilities to absorb foreign investment and enhance sustainable development (SD) in

[1]The official national rural poverty line of China is 2,300 yuan per year at constant 2011 purchasing power parity.

[2]The National Energy Administration and Poverty Alleviation Office of the State Council decided to implement a poverty alleviation program through installation of solar PV panels in poor households to increase their incomes. The SEPAP is scheduled to run for a period of six years, starting from 2014. Information on the SEPAP is available at <http://www.nea.gov.cn/2014-10/17/c_133723326.htm>, last viewed 17 July 2017.

[3]Released by the National Development and Reform Commission (NDRC) on 25 January 2017. More information is available at <http://www.gov.cn/xinwen/2017-02/16/content_5168559.htm#1>, last viewed 16 January 2018.

[4]Informations on the announcement is available at <http://zfxxgk.nea.gov.cn/auto82/201711/t2017 1108 3046.htm>, last viewed 16 January 2018.

developing countries. According to the definition by the United Nations Framework Convention on Climate Change (UNFCCC), the SD co-benefits of CDM projects can be divided into three categories: social benefits, economic benefits, and environmental benefits. Examples of these benefits include poverty alleviation, employment generation and enhanced education services (social benefits); new industrial activities, productivity growth, and technology innovation (economic benefits); and improvement of air, water and land quality (environmental benefits).[5]

There are many studies that examine how far the CDM will achieve its SD goals. Studies with positive findings suggest that the CDM could contributes to SD in host countries in different ways. Olsen and Fenhann (2008) conclude, through a text analysis of 744 project design documents, that small-scale renewable energy projects have comparatively higher social benefits than large-scale projects. Wang et al. (2013) evaluate the employment impacts through an input-output approach. Their results show that solar projects have the greatest potential for indirect job creation, while hydro projects induce job losses. Weitzel et al. (2015) indicate that larger CDM projects and more advanced technologies are more likely to involve technology transfer.

However, several researchers provide contrasting results. Sirohi (2007) indicates that the socio-economic development potential of CDM projects in India is ambiguous, and suggests that for CDM to emerge as a "win-win" poverty alleviation strategy, its projects should be implemented at the rural community level. By assessing 16 officially registered CDM projects, Sutter and Parreno (2007) conclude that fewer than 1% of the CDM projects are likely to contribute significantly to SD in the host country. Zhang and Wang (2011) use an econometric approach to estimate the CDM effect on reducing local air pollution and conclude that the CDM does not have a statistically significant effect in lowering SO_2 emissions.

[5] The SD tool provided by the UNFCCC enables the project owners to show the value behind the certified emission reductions their CDM projects offer, by describing the SD co-benefits of projects. Available at: http://cdmcobenefits.unfccc.int/Pages/SD-Tool.aspx.

Previous studies show inconclusive results on whether or not CDM activities actually contribute to the SD in host countries. Thus, the primary concern of our study is to evaluate the SD benefits of the CDM on rural communities of the host country. As for the SD benefits, our main focus is on social benefits, which include income generation, creation of job opportunities, and changes in the industrial structure. Poverty alleviation through income and employment generation is considered as one of the most important indicators in CDM project evaluation. Moreover, the eradication of poverty is also regarded as an indispensable requirement for SD (United Nations, 2012).

The contributions of this study can be summarized as follows. Most of above-mentioned studies on the local impacts of the CDM adopt descriptive or the input-output analysis, and are not based on rigorous econometric approach. In order to fill this research gap, we use a fixed effect difference-in-differences (DID) model to investigate the social benefits of the RE-CDM projects at the rural community level. In addition, this research applies the propensity score matching (PSM) in conjunction with the DID model to adequately deal with several issues of the simple DID approach, such as selection bias and omitted variable bias. Besides, we check the robustness of our estimation results, obtained through the PSM-DID approach by adopting the Mahalanobis distance matching (MDM) method. Finally, our findings provide policy implications on the possibility of simultaneously achieving the goal of climate change mitigation and poverty alleviation. It is of critical importance that countries achieve their targets of poverty reduction under the Sustainable Development Goals (SDGs)[6], while meeting their commitments of greenhouse gas emission reductions under the Paris Agreement.[7] With this respect, our study relates to the literature on poverty and the environment (Sims, 2010; Sims and Alix-Garcia, 2017), but differs from these studies in that we examine the effect of projects that require substantial investment and technology.

[6] On 1 January 2016, the United Nations SDGs officially came into force. The first of the seventeen proposed SDGs is “End poverty in all its forms everywhere.” More information on the SDGs is available at: <http://www.un.org/sustainabledevelopment/>, last viewed 17 January 2018.

[7] The Paris Agreement on climate change came into force in 2016 to limit the rise in global temperatures. More information on the agreement is available at: <http://unfccc.int/paris_agreement/items/9485.php>, last viewed 17 January 2018.

The main result of this study is that the RE-CDM contributes significantly to rural development in China. Our findings suggest that biomass-based CDM projects can bring about income growth, job creation, and industrial transition in rural communities in China. For example, annual income of rural residents can be increased approximately 15.5% by adopting the biomass CDM projects. In addition, we find that large-scale wind and solar energy projects can help to increase the labor force in the primary industry in rural communities. These findings imply that investment in climate change mitigation can play a simultaneous role in poverty alleviation.

This paper is organized as follows: Section 2 provides the current status of income inequality and promotion of the renewable energy in China. In Section 3 we introduce the data for estimation and the measures of social benefits. Section 4 follows with an analysis framework, including a description of the empirical model and matching techniques. Estimation results and discussions are provided in Section 5. Finally, Section 6 presents our conclusions and discuss the policy implication of this research.

2 Background

2.1 Income inequality in China

Beginning in 1978, China's economic reform has led not only to rapid economic growth but also to serious income inequality. Figure 1 shows the income trends of rural and urban residents in China from 1985 to 2015.[8] The rural population of China comprised 618 million in 2014, accounting for about 45.2% of the total populations in 2014 (NBSC, 2014). At the end of 2015, the net income of urban residents was nearly 3.5 times as much as that of rural residents. The Gini coefficient, a measure of income inequality, has soared to 0.47

[8]Individuals are categorized as either "rural" or "urban" residents by the hukou system, a household registration system that serves as a domestic passport regime in China. Residents are required to stay and work within their designated geographic areas. Individuals living in rural areas depend on agriculture to make a living and are commonly known as rural residents. On the contrary, urban residents usually dependent on non-agricultural sources of income.

from 0.25 in the middle 1980s (China Digital Times, 2013). Xie and Zhou (2014) argue that China's current high income inequality is significantly driven by the rural-urban divide and the regional variation in economic well-being. Differences in economic structure play a critical role in creating the overall income inequality between rural and urban residents.

[Figure 1]

Simultaneously, the income structure of the rural population has transformed over the past two decades. As of 2015, the wage income[9] has increased to around 43% of total income of rural residents, while the proportion of rural residential income from the primary sector has decreased to about 29%.[10] The change reflects the fact that the source of income of rural residents has been shifted from the primary sector to the secondary and tertiary sectors. Rural areas tend to have a relatively smaller range of job opportunities, lower payment, and thus higher unemployment. This has caused a large number of rural laborers to move out from their registered places of residence and migrate to urban cities in search of job opportunities. The total stock of rural migrant labor, estimated to be around 282 million as of 2016, constitutes more than one-third of the entire working population of China (Walsh, 2017). The large rural-to-urban migration not only increases the burden on urban cities but also creates many social problems in rural areas, such as the mental health and education of the left-behind children, aging of the rural population, and decline in agricultural productivity (China Labour Bulletin, 2016). In order to alleviate these issues of rural China, policy makers focus on the way to improve the employment environment by providing high quality and sustainable job opportunities to the rural community.

2.2 Rural poverty and renewable energy

Recently, the Chinese government has promoted investment in renewable energy in rural areas. With the formulation of several national promotion policies for renewable energy,

[9]The income earned by an individual working as an employee.

[10]Authors' own calculations. Data collected from the China Statistical Yearbook in 1996 and 2016.

such as the SEPAP and the 13th FYP for Rural Bioenergy Development, new energy industries are ready to exploit the wide development space in rural areas. Development of the renewable energy industry is expected to attract both domestic and foreign investment, as well as the working-age population, into rural areas. In addition, access to cleaner and affordable energy options can improve the livelihood of rural households by raising their living conditions and transforming the production structure of local firms. Moreover, renewable energy industries can focus on retraining the low-skill and low-income workers. For instance, by the end of December 2014, a total of 16,542 rural residents in Qingxiu County[11] had received vocational training related to renewable energy, and 15,308 of them obtained national vocational qualifications through an examination system.[12]

By 2020, China's renewable energy industries are expected to provide employment opportunities for nearly a million people, including research and development, design, production, construction, operation, service, transportation, management, education, training, consulting, and other related jobs (Worldwatch Institute, 2011).

At the same time, with the aggravation of the energy crisis and increasing importance of environmental problems, climate policies have been high on the agenda of Chinese government for about a decade. The necessity and urgency of promoting the renewable energy sector in China have been providing entry points for the RE-CDM. Moreover, because adoption of RE-CDM projects could bring additional foreign investment to the host community, and ultimately drive the development of local renewable energy industries, local governments encourage local firms to develop renewable energy resources with CDM. Consequently, China has become the world's largest host country for CDM projects. Between 2005 and 2012, a total of 2,983 CDM projects were formally registered in China. Among the registered CDM projects, renewable energy projects make up the largest share, at about 82.7%. Of these, 40.6% is wind power project while other projects, including bioenergy and solar energy, make

[11] A county belonging to Nanning city, Guangxi Zhuang Autonomous Region, China.

[12] The Office of Rural Energy, Guangxi Province. <http://www.gxncny.cn/gxnycms/pxjn/3175.jhtml>, last viewed 15 February 2018.

up about 5.2% and 1.6%, respectively.[13]

Rural counties[14] attract a large part of investment related to RE-CDM deployment because they tend to be sparsely populated, amply endowed with renewable sources of energy, and spacious enough for land-intensive developments like wind farms. As of 2012, a total of 461 rural counties had adopted RE-CDM activities in China, which installed capacity accounts for about 86.8% of total installed capacity of the RE-CDM. Figure 2 depicts the locational distribution of RE-CDM projects by the cumulative installed capacity at the prefecture level. The RE-CDM projects are not evenly distributed among regions, but mainly concentrated in regions endowed with large renewable energy resources, the northern, northeastern, and northwestern regions.

[Figure 2]

3 Data

3.1 Measures of the social benefits

There are three dimensions that compose SD in the local community. The first is the social dimension, which includes welfare indicators such as household income, employment, and spending on health and education. The second is the economic dimension, which is often related to consumption and investment in productive capital. The last one is the environmental dimension, including environmental quality, pollution emissions, and material consumption (IRENA, 2016). Many previous studies focus on investigating both the economic and environmental benefits of the CDM while its social benefits have received less attention. In order to estimate the social impacts of increased renewable energy deployment

[13] Authors' own calculations. Data collected from UNFCCC's Database for Project Activities and Programme of Activities.

[14] County-level administrative areas in China consist of the county and county-level city and municipal districts, where the county is usually considered as the backward region in each prefecture. Considering that the objective of this study is to evaluate the impact of the CDM on rural development, we only adopt those CDM projects located in the county, also known as rural area in our analysis.

under the CDM, this study employs three indicators: income generation, job creation, and the transformation of industrial structure.

First, we adopt the per capita net income of rural households to measure the impact of the RE-CDM activities on rural income. Rural communities can diversify, stabilize, or increase the income of their residents in several ways by adopting RE-CDM activities. For instance, the income level of rural residents can be increased through subsides from local governments. In 2009, the Chinese central government's subsidy standard for rural household biogas was improved to 1,500 yuan for each rural household in the northeastern and western areas, 1,200 yuan in the central region, and 1,000 yuan in the eastern region (Qiu et al., 2013). Besides, RE-CDM projects can reduce the poverty that characterizes rural regions by helping unskilled laborers in rural areas, such as farmers, unemployed persons, and women with low education level in rural area, to serve as assembly line workers, equipment installers, and maintenance or sales staff.

Second, the number of rural laborers is used to capture the working population in a rural county. The working population of rural communities increases with more job opportunities for rural residents. Development and promotion of the renewable energy industry is an important way to increase employment of local residents. Worldwide, the renewable energy sector provided about 6.5 million direct and indirect jobs in 2013. Fuel supply from bioenergy feedstock, installations, and equipment manufacturing will generate most jobs in the renewable energy value chain (IRENA, 2014). Some argue that the decentralized nature of renewables deployment will raise the overall number of jobs. However, others hold that the relatively higher monetary costs of deploying renewables will reduce purchasing power and consequently employment. These arguments underscore the need for more country-specific empirical analysis and reliable approaches to estimate the potential social benefits, especially employment creation from renewable energy deployment.

Lastly, we employ the number of rural laborers in the primary sector to capture the impact of RE-CDM on industrial transformation. Renewable energy related industries can create valuable job opportunities for people in regions with low employment. It provides both direct jobs, such as operating and maintaining equipment, and indirect jobs along the supply chain, such as fuel supply, manufacturing, construction, and other related specialized services. For example, if the presence of renewable energy installations can revive construction activities related to renewable energy power plants, then the main income sources of farm households could switch from agricultural activities to the construction industry. According to the Construction Plan of the National Rural Biogas Project (2006-2010) released by the Ministry of Agriculture of China in 2007, construction and maintenance of every 10,000 biogas pools can absorb about 800 rural laborers; thus, the whole country can provide about 368,000 jobs per year for the rural labor (MOA, 2007).

3.2 Data sources

To assess the effect of the RE-CDM on rural development, we collect information on the construction period and location of RE-CDM projects, rural residential income, number of laborers in rural area, and other characteristics of each county.[15] The panel data used for analysis cover a total of 1,939 rural counties across China and consist of three types of variables, namely, social benefits, county characteristics, and characteristics of RE-CDM projects. The sample period for this study is between 2005 and 2011.

Table 1 contains descriptive statistics on the variables used in our analysis. Counties that adopted RE-CDM projects between 2005 and 2011 are included in the treatment group in this study. On the other hand, counties with no RE-CDM activities during the research period are included in the control group. The average rural household income is about 5,027 yuan in the treatment group, and approximately 5,486 yuan in the control group. The mean number of rural laborers in a county is around 0.231 million in the treatment group and about 0.217 million in the control group. The average number of rural laborers in the primary sector is about 0.122 million in the control group; the corresponding number in the

[15] A county is an administrative unit ranking below a prefecture and above a township.

treatment group is 0.011 million lower. A two-tailed t-test shows that there is a statistically significant differences in the mean value of social benefits and county characteristics. It suggests the need to adopt matching techniques in order to avoid selection bias.

[Table 1]

Data related to social benefits are collected from the China Statistical Yearbook for Regional Economy. Per capita net income of rural households, number of rural laborers, and number of rural laborers in the primary sector are used as indicators of social benefits.

The county characteristic variables, including share of gross output of the primary sector, area of agricultural land, rural population, total government revenue, share of students accepting compulsory education, production of oil crop, and total capacity of agricultural machinery, are based on the China Rural Statistical Yearbook. Both geographical and social characteristics are considered since these factors may affect the existing energy infrastructure and influence the promotion of renewable energy industries.

CDM data are obtained from the UNFCCC's Database for Project Activities and Programme of Activities, which includes basic information on every registered project. Only RE-CDM projects registered between 2005 and 2011 are considered in our study because of the limitations of the county-level economic data. Hydroelectric projects are excluded from the sample because of their potential to generate social benefits and social problems for rural communities at the same time.[16] The geographic location of each project is collected from the CDM location map provided by the NDRC. ArcGIS 10.1 is used to generate the location data of RE-CDM projects.

[16]The construction of reservoirs can improve water supply, increase farmland irrigation, produce electricity, and produce other social and economic benefits. However, it also has its disadvantages. For example, the resettlement of residents will lead to changes in the economic structure.

4 Empirical analysis

4.1 Model

In order to measure social benefits of RE-CDM in rural communities, we employ a DID estimator combined with a mix of fixed effects by running a LSDV model. The DID estimator compares the change in social benefits connected to RE-CDM projects in counties that adopted the project to the change in social benefits in counties that did not. The fixed effect estimation allows us to control for time invariant and time varying unobservable county characteristics that may be correlated with a county's RE-CDM project adoption decision.

This study uses unbalanced panel data on the social benefit indicators for 1,939 rural counties in China from 2005 to 2011. The general form of the model adopted can be written as follows:

$$y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 X_{it} + \delta_i + \gamma_t + \varepsilon_{it},$$

where y_{it} indicates the social benefits variables, which includes: (a) rural residential income; (b) the number of rural laborers; and (c) the number of rural laborers in the primary sector in the county i in year t.

D_{it} is the treatment indicator that takes on the value one in and after the year the CDM renewable energy power plants have been constructed in county i, and zero otherwise. We also interact the treatment indicator with different scales and types of renewable energy sources to capture their differences in social benefits. There are two major classes of renewable energy-based project scales defined by the CDM Executive Board[17]: large utility-scale (>15MW) projects that sell wholesale electricity to energy providers, and small-scale ($\leq$15MW) projects that often include biomass fuel switches, small wind generators for civilian use, farm or rooftop solar implementation, and solar cooker projects (UNFCCC, 2014). X_{it} is a set of time-varying county characteristics. δ_i is the vector of the county dummy

[17]The CDM Executive Board supervises the Kyoto Protocol's clean development mechanism under the authority and guidance of the Conference of the Parties serving as the Meeting of the Parties to the Kyoto Protocol.

variable, which is used to control for unobserved county characteristics that shape the level of development across counties. Year dummy γ_t is included to control for trends that shape rural development over time such as changes in policies and regulations at the national level. ε_{it} is the error term.

4.2 Matching techniques

There is a concern that the DID estimator may suffer from two sources of bias. The first may arise if the levels and trends in social benefit indicators in treatment and control counties differ before the CDM project adoption. Another bias could arise if the CDM project sites are not randomly assigned but determined by various geographical, political, and socio-economic factors. Therefore, in this study, we adopt two matching approaches to mitigate potential bias by pairing treatment counties with counties that have similar observed attributes from the control pool.

We adopt the PSM approach developed by Rosenbaum and Rubin (1983). The objective of the PSM is to construct a control group by finding controls that have observed x similar to those of the treatment group. To match treatment and control units on the basis of x is equivalent to matching them using a propensity score $p(x)$, which gives the probability of receiving treatment given the pretreatment value of x, that is, $p(x) = Pr(D = 1|x)$. The matching method assumes that, in a set of subjects all with the same propensity score, the observed outcome distribution will be the same between the treatment and control groups. To check the robustness of the PSM, we also use the simple MDM, which was first discussed by Cochran and Rubin (1973). For the MDM, the variance-covariance matrix of x is estimated by the pooled within group sample covariance matrix S. The distance between covariate x_1 and x_2 is $M(x_1,x_2) = (x_1\text{-}x_2)^T \mathrm{S}^{-1}(x_1\text{-}x_2)$.

In the first step, in order to estimate the propensity score, we use covariates to identify the probability of a county adopting a RE-CDM project, which include: gross regional product of the primary sector, agricultural land area, amount of oil crop production, and a dummy variable for regions that have relatively higher wind power potential.[18] We assume each covariate affects the county's decision on RE-CDM adoption and the social benefit outcomes of the treatment and control groups in the pre-treatment period.

In the second step, we use the estimated propensity score to match treatment and control groups in the baseline year. Here, we use 2005 as the baseline year since most of the RE-CDM projects were implemented after this year.[19] In order to ensure that all the rural counties did not have RE-CDM activities in the baseline year, counties that adopted RE-CDM activities in 2005 were dropped from the sample. A one-to-one matching approach without replacement was adopted while using the nearest-neighbor PSM and MDM algorithm. It means that we choose only one county from the counties without RE-CDM activities as a match for a treatment county in terms of their closest propensity score and Mahalanobis distance. An untreated county cannot be used more than once as a match. The observations decrease from 11,537 to 2,078 after the PSM, and to 2,031 after the MDM, since the observations out of the common support have been dropped from the sample.

In the final step, in order to ensure that the matching procedure successfully balances the two groups, we compare the treatment and control groups after matching. We present the balancing test results for the PSM in Table 2, Panel A and that of the MDM in Panel B. The results illustrate that there are statistically significant differences between the mean values of the estimated propensity scores of the treatment and control groups before matching. For instance, in the first row of Table 2, Panel A, we find that the difference of primary industry output between the treatment and control groups is nearly 29.0%. Whereas, the second row shows that the difference between these two groups drops to 7.10% when the sample is matched. In addition, results of the t-test indicate that matched groups do not have

[18] High wind potential regions are those regions with on-grid tariffs for wind power less than or equal to 0.54 CNY per kWh including tax. According to The Notice on Tariff Price of On-shore Wind Power, on-grid tariffs for wind power generators are 0.47–0.60 CNY per kWh, with the lower tariffs applying in regions with higher wind power potential (NDRC, 2016).

[19] The first CDM project in China was the Huitengxile wind farm project, which was successfully registered in 2005. <https://cdm.unfccc.int/Projects/DB/TUEV-SUED1113481234.64/view>, last viewed: 21 December 2017.

statistically significant differences in the mean value of covariates. These results illustrate that no statistical difference emerges after matching the treatment and the control groups.

[Table 2]

The balancing test results are also shown in Figure 3, which depicts the differences in the distribution of the propensity scores by treatment and control groups. The figure shows that selected observations of the control groups have extremely similar kernel density of propensity score with observations in the treatment groups. It suggests that differences in the distribution of the two groups have been significantly reduced after the PSM is applied as well.

[Figure 3]

5 Results and discussion

5.1 Impact on rural residential income

The estimation results of the RE-CDM's effect on rural residential income are reported in Tables 3 (PSM-DID) and 4 (MDM-DID). The results in Table 3 suggest that a positive relationship exists between RE-CDM activities and rural residential income. The coefficient of the treatment indicator *re_cdm* is positive and statistically significant at the 10% level, as shown in column 1. The estimated effects correspond to an increase of approximately 276 yuan in annual income, which is about 5.03% of the average rural income of residents.[20]

[Table 3]

[Table 4]

[20] This calculation is based on the assumption that annual average income of rural residents is 5,486 yuan.

Table 3 also reports the impact of the RE-CDM by different energy sources. The *largebio* dummy is positive and significant at the 5% level, as shown in column 2. This result indicates that the biomass based CDM projects stimulated income growth substantially for rural residents. Specifically, the adoption of large-scale biomass-CDM projects generated 851 yuan, about a 15.5% increase in annual income for the rural residents. In addition, we find a similar result when utilizing the MDM-DID approach. Our result regarding the impact of the RE-CDM on income improvement illustrates that only the utility-scale biomass energy-based CDM projects were significant in stimulating income generation. According to Faaij et al. (1998), bioenergy-based electricity production tends to have a greater impact on local income than power generation using coal because of the use of locally produced feedstocks. Moreover, Gan and Smith (2007) estimated the co-benefits associated with the utilization of logging residues for bioenergy production in East Texas, USA. The input-output modeling revealed that the most noticeable socio-benefits of bioenergy production were income and job creation.

5.2 Impact on employment generation

In Tables 5 and 6, we assess the impact of the RE-CDM projects on employment generation using the PSM- and MDM-DID method, respectively. The results indicate that the employment generation impact of the RE-CDM activities in rural areas differ by different renewable energy sources. The coefficients of *largebio* are positive and significant at the 5% level, as shown in columns 2 in Tables 5 and 6, respectively. These results suggest that the number of labor in a rural county can be increased by approximately 13,000 workers, 5.99% of the average number of rural laborers, through the adoption of large-scale biomass-CDM projects.[21]

[Table 5]

[21] The calculation is based on the assumption that the average number of labor is 0.217 million workers in a rural community.

[Table 6]

In line with the arguments of Thornley et al. (2008) and Openshaw (2010), our results illustrate that biomass energy based projects show remarkable contributions to employment generation in rural communities. Thornley et al. (2008) quantified the expected employment impacts of individual bioenergy development and suggested that the larger bioenergy power plants had a larger employment impact, which confirms our results on the employment creation impact of large-scale biomass projects. Additionally, Openshaw (2010) highlighted the importance of bioenergy systems as a means to poverty alleviation. Openshaw found that in Malawi, Africa, the equivalent to 93,500 and 133,000 full-time workers were employed in the biomass supply chain in 1996 and 2008, respectively. In contrast, about 3,400 and 4,600 people were employed in the supply chain of other conventional fuels, such as coal and petroleum, in those years.

5.3 Impact on industrial transformation

In Tables 7 and 8, we report the estimated impact of the RE-CDM adoption on industrial transformation in rural communities. The coefficient of *smallbio*, shown in column 3 of Table 7, indicates that the implementation of small-scale bioenergy projects under the CDM is associated negatively with 20,000 workers annually in primary industry, which is about a 16.39% decrease in the number of rural laborers in the primary sector.[22] The results estimated by the MDM-DID approach in Table 8 confirm the robustness of our PSM-DID estimation. These results on *smallbio* suggest that the transformation of the economic structure from primary industry to other industries is likely to be achieved by introducing small-scale biomass based CDM projects into the rural communities. The finding implies that the presence of individual biomass-CDM projects may promote production activities beyond agricultural production in those rural areas with large numbers of unskilled laborers. This is based on the thought

[22] This calculation is based on the assumption that the average number in primary industry rural labor force is approximately 0.122 million workers.

that small-scale projects are often community based, and therefore, it is easier for unskilled rural laborers to be involved in the production process after skill training. According to the report released by the Ministry of Agriculture of China, the industrial scale of bioenergy production has been growing continually, with over 20,000 small-scale biogas projects and more than 4,700 large and medium-sized biogas projects approved for production as of the end of 2010. More than 300,000 farmers can be transferred to such local jobs each year in the stages of biogas power plant construction and service providing alone (MOA, 2010).

[Table 7]

[Table 8]

Interestingly, we found that both large-scale wind and solar energy-based CDM projects have the potential to induce the reintegration of migrant rural labor. The coefficients of *largewind*, shown in column 4 and *largesolar* in column 5 of Table 7, indicate positive and statistically significant impacts of large-scale wind- and solar-CDM power plants on the number of rural labor in the primary industry sector at the 1% level. Our results illustrate that large-scale wind projects attract approximately 4,000 rural laborers into the primary sector each year, which is about 1.01% of the total population of a county.[23] Moreover, due to the adoption of large-scale solar energy projects, the number of rural work force in the primary industry can be increased by 19,000 annually, which is about 4.80% of the total rural population.[24] The promotion of photovoltaic agriculture[25] is said to have improved the efficiency of agricultural production, encouraged small villages to form an agricultural town, and promoted the return of migrant rural workers (China Energy Net, 2011). For example, this effect is observed in the case of a 20 MW agriculture-photovoltaic power station

[23]In this study, mean value of the total population of a rural county is about 0.396 million people in control groups, and 0.430 million people in treatment groups.

[24]The calculation is based on the assumption that the mean value of the rural population is 0.396 million people.

[25]Photovoltaic agriculture is the combination of photovoltaic power generation and agricultural activities. There are several main application modes of photovoltaic agriculture such as a photovoltaic agricultural greenhouse, photovoltaic breeding, and a new type rural solar power station, among others (Xue, 2017).

located in Zhengyang county.[26] The expected power generation of the Zhengyang ecological agricultural farm is 20 GWh per year, with the power generated by solar panels used for agricultural production inside the farm and the rest of the generated electricity transmitted to the national grid. More than 120 migrant workers who returned to the county are said to be employed by this photovoltaic agriculture farm (Farmer Daily, 2017).

6 Conclusions

By focusing on the social benefits brought by the renewable energy projects, we examine whether the RE-CDM improved Chinese rural communities in terms of rural residential income, job opportunities, and transforming the industrial structure. In addition, our study investigates the impact generated by various renewable energy sources in order to understand which energy source provides higher social benefits.

Our results indicate that the bioenergy-based CDM projects significantly contribute to local sustainability of the host counties. The increase in annual income of rural residents by adopting bioenergy CDM projects was calculated at about 851 yuan per year. The growth in rural residential income caused by biomass-CDM projects was likely due to increased job opportunities and the transformation of the labor structure. As described in 2009 annual report by the China Association of Rural Energy Industry, the biogas projects provide a large number of employment opportunities for the rural surplus labor force and migrant workers, significantly increasing the income of the farmers, and promoting the social stability in the project areas (CAAE, 2010). Moreover, we find that not all renewable energy technologies contribute to the social benefits in the same manner. Small-scale biomass-CDM projects had the largest potential in improving the labor structure in rural areas since their impact on transferring primary sector rural labor to other sectors was around 13,000 workers per year. This result indicates that small-scale bioenergy provides more job opportunities for unskilled laborers than other types of energy sources. In contrast, large-scale wind and solar

[26] Zhengyang county is a rural county belonging to Zhumadian city, Henan province, China.

energy-based CDM projects promote rural development by encouraging agricultural reform and attracting labor force into the primary sector.

Climate change represents a direct and immediate threat to poverty alleviation (World Bank, 2015). In this study, we assess whether activities for climate change mitigation can alleviate poverty of rural communities in China. We conclude that the adoption of renewable energy projects under the CDM can offer an effective way to both reducing poverty and addressing the global externality. By promoting the development of renewable energy, particularly bioenergy in local communities, it might be possible to reduce poverty in ways that support low-carbon growth. Providing clean electricity and access to modern energy services may also contribute to other type of social benefits, by improving health and welfare, access to education and jobs, and drive economic growth while reducing pollution (Climate Advisers, 2014).

Although our study confirms the role of the RE-CDM in assisting host countries in achieving SD, a further investigation is necessary to understand links between climate change mitigation and poverty reduction strategies. For example, it is important to compare the social benefits of domestic renewable energy projects and RE-CDM projects in order to evaluate the effectiveness of different investment channels. Another limitation of our study is that the long-run effect of the RE-CDM has not been considered. Future research should be designed to capture the dynamics of the relationship between the RE-CDM and rural development in the long-run.

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Table 1: Descriptive statistics

	Unit	(1) Control groups			(2) Treatment groups		
		Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Treatment Indicators							
re_cdm	dummy	8,719	0.000	0.000	2,818	0.310	0.463
largebio	dummy	8,719	0.000	0.000	2,818	0.057	0.232
smallbio	dummy	8,719	0.000	0.000	2,818	0.004	0.059
largewind	dummy	8,719	0.000	0.000	2,818	0.241	0.428
smallwind	dummy	8,719	0.000	0.000	2,818	0.008	0.086
largesolar	dummy	8,719	0.000	0.000	2,818	0.011	0.104
smallsolar	dummy	8,719	0.000	0.000	2,818	0.011	0.106
Social Benefit Variables							
income_rural	1,000 yuan	8,247	5.486*	8.748	2,756	5.027	2.837
rural labor	million person	8,719	0.217*	0.169	2,818	0.231	0.176
rural labor_primary	million person	8,719	0.122*	0.094	2,818	0.133	0.095
County Characteristics							
grp_primary%	%	8,719	0.247	0.130	2,818	0.249	0.135
land area_ agriculture	1,000 km^2	6,876	0.387*	0.409	2,178	0.633	0.520
rural population	million person	8,719	0.396*	0.299	2,818	0.430	0.327
government income	billion yuan	8,719	0.416	0.930	2,817	0.434	0.627
student%	%	8,719	0.139*	0.035	2,817	0.133	0.039
oil production	million ton	8,450	0.014*	0.022	2,716	0.020	0.034
machinery power	1,000 kw	8,719	0.033*	0.036	2,818	0.045	0.049

Note: 1) * indicates that the means differ with statistical significance in a two-tailed t-test at the 1% level between the treatment and control groups; 2) *re_cdm* is a dummy variable used to indicate if county i contains RE-CDM projects in year t: 0 = no,1 = yes; *income_rural* is the annual per capita net income of rural households; *rural labor* is amount of working population in rural area; *rural labor_primary* is the number of rural laborers in the primary sector; *grp_primary%* is the share of primary industry product in the gross regional product; *government income* is the total value of the government budget revenue; *student%* is the share of students accepting compulsory education out of total residents; *oil production* is the amount of oil crop production; *machinery power* is the total capacity of agriculture machinery.

Table 2: Balancing test results

Panel A: Nearest-neighbor propensity score matching (PSM)

	Unmatched/	Mean				t-test	
Outcome var: income_rural	Matched	Treatment	Control	%bias	%bias reduction	t-value	p-value
grp_primary	U	1.232	0.977	29.0		4.40	0.000
	M	1.232	0.170	7.10	75.6	0.82	0.412
land area_agriculture	U	0.610	0.412	43.6		6.34	0.000
	M	0.610	0.578	7.00	83.9	0.75	0.451
wind potential	U	0.272	0.166	25.8		3.84	0.000
	M	0.272	0.331	-14.3	44.5	-1.50	0.135
oil production	U	0.021	0.014	23.7		3.75	0.000
	M	0.021	0.018	9.70	59.1	1.05	0.294

Panel B: Mahalanobis distance matching (MDM)

	Unmatched/	Mean				t-test	
Outcome var: income_rural	Matched	Treatment	Control	%bias	%bias reduction	t-value	p-value
grp_primary	U	1.232	0.977	29.0		4.40	0.000
	M	1.232	1.189	5.00	82.8	0.54	0.586
land area_agriculture	U	0.610	0.412	43.6		6.34	0.000
	M	0.610	0.581	6.50	85.0	0.75	0.453
wind potential	U	0.272	0.166	25.8		3.84	0.000
	M	0.272	0.272	0.00	100	0.00	1.000
oil production	U	0.021	0.014	23.7		3.75	0.000
	M	0.021	0.019	7.60	67.8	0.80	0.422

Table 3: Regression results (Explained variable: income_rural)

	Estimation method: PSM-DID						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
re_cdm	0.276*						
	(0.151)						
largebio		0.851**					
		(0.315)					
smallbio			1.916				
			(1.279)				
largewind				0.085			
				(0.147)			
smallwind					-0.440		
					(0.719)		
largesolar						-1.164	
						(0.879)	
smallsolar							-0.299
							(0.817)
grp_primary%	9.328***	9.274***	9.091***	9.286***	9.260***	9.191***	9.258***
	(3.126)	(3.122)	(3.128)	(3.132)	(3.123)	(3.091)	(3.125)
land area_agri	2.709***	2.793***	2.843***	2.742***	2.775***	2.896***	2.776***
	(0.672)	(0.671)	(0.676)	(0.676)	(0.677)	(0.717)	(0.682)
rural population	-0.243	-0.201	-0.172	-0.211	-0.190	-0.180	-0.186
	(1.210)	(1.203)	(1.209)	(1.215)	(1.207)	(1.207)	(1.208)
income_gov	4.763***	4.769***	4.768***	4.765***	4.767***	4.767***	4.766***
	(1.485)	(1.483)	(1.484)	(1.486)	(1.486)	(1.486)	(1.485)
student%	6.920*	6.755*	6.560*	6.650*	6.559*	6.567*	6.533*
	(3.966)	(3.958)	(3.955)	(3.969)	(3.970)	(3.945)	(3.968)
oil production	15.01**	14.72**	14.67**	15.28**	15.58***	15.10**	15.42***
	(5.865)	(5.791)	(5.787)	(5.934)	(5.884)	(5.965)	(5.876)
machinery power	0.626	0.599	0.581	0.634	0.615	0.604	0.624
	(0.830)	(0.812)	(0.797)	(0.842)	(0.831)	(0.815)	(0.834)
constant	-2.629	-2.646	1.574	1.563	1.583	1.571	1.593
	(2.169)	(2.179)	(1.046)	(1.042)	(1.043)	(1.042)	(1.040)
Year dummy	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES
N	2,078	2,078	2,078	2,078	2,078	2,078	2,078
adj. R^2	0.758	0.758	0.758	0.758	0.758	0.758	0.758

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression results (explained variable: income_rural)

	Estimation method: MDM-DID						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
re_cdm	0.423						
	(0.312)						
largebio		1.646***					
		(0.488)					
smallbio			3.720				
			(2.279)				
largewind				-0.013			
				(0.308)			
smallwind					0.479		
					(1.355)		
largesolar						-0.890	
						(1.413)	
smallsolar							0.414
							(1.627)
grp_primary%	8.477**	8.390**	8.077**	8.391**	8.422**	8.337**	8.398**
	(3.817)	(3.809)	(3.842)	(3.828)	(3.817)	(3.802)	(3.821)
land area_agri	4.119***	4.250***	4.349***	4.196***	4.190***	4.283***	4.182***
	(0.935)	(0.931)	(0.931)	(0.945)	(0.936)	(0.976)	(0.937)
rural population	3.063	3.131	3.183	3.154	3.133	3.166	3.143
	(3.186)	(3.155)	(3.173)	(3.182)	(3.173)	(3.178)	(3.172)
income_gov	11.33***	11.34***	11.34***	11.33***	11.33***	11.33***	11.33***
	(2.925)	(2.920)	(2.923)	(2.927)	(2.925)	(2.926)	(2.926)
student%	13.97**	13.88**	13.59**	13.56**	13.58**	13.62**	13.58**
	(5.950)	(5.945)	(5.926)	(5.909)	(5.937)	(5.917)	(5.938)
oil production	30.19***	29.61***	29.56***	30.93***	30.98***	30.81***	30.80***
	(11.38)	(11.21)	(11.17)	(11.49)	(11.45)	(11.46)	(11.41)
machinery power	-0.410	-0.464	-0.495	-0.404	-0.424	-0.423	-0.394
	(0.919)	(0.907)	(0.902)	(0.929)	(0.921)	(0.916)	(0.923)
constant	-6.005***	-2.613	-2.587	-6.085***	-2.597	-2.621	-2.593
	(2.307)	(1.957)	(1.956)	(2.331)	(1.959)	(1.959)	(1.959)
Year dummy	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES
N	2,031	2,031	2,031	2,031	2,031	2,031	2,031
adj. R^2	0.741	0.742	0.741	0.741	0.741	0.741	0.741

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regression results (explained variable: rural labor)

	Estimation method: PSM-DID						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
re_cdm	-0.004						
	(0.002)						
largebio		0.013**					
		(0.007)					
smallbio			0.050				
			(0.036)				
largewind				-0.007***			
				(0.002)			
smallwind					-0.005		
					(0.023)		
largesolar						-0.005	
						(0.007)	
smallsolar							-0.009
							(0.014)
grp_primary%	-0.054***	-0.053***	-0.057***	-0.055***	-0.053***	-0.053***	-0.053***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
landarea_agri	-0.019***	-0.020***	-0.018***	-0.018***	-0.020***	-0.020***	-0.020***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
rural population	0.066	0.065	0.065	0.067	0.065	0.065	0.065
	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)	(0.045)	(0.045)
income_gov	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
student%	-0.038	-0.030	-0.033	-0.042	-0.033	-0.033	-0.034
	(0.036)	(0.035)	(0.035)	(0.036)	(0.036)	(0.036)	(0.036)
oil production	0.015	0.000	-0.001	0.017	0.011	0.009	0.012
	(0.098)	(0.097)	(0.095)	(0.098)	(0.098)	(0.098)	(0.097)
machinery power	0.035	0.035	0.034	0.035	0.035	0.035	0.035
	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)	(0.027)
constant	0.122***	0.148***	0.149***	0.121***	0.149***	0.148***	0.149***
	(0.013)	(0.015)	(0.015)	(0.013)	(0.015)	(0.015)	(0.015)
Year dummy	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES
N	2,078	2,078	2,078	2,078	2,078	2,078	2,078
adj. R^2	0.988	0.988	0.988	0.988	0.988	0.988	0.988

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The values of adjusted R-square are approximately 0.99 since the LSDV estimation including a dummy variable for each county, namely the county dummy, perfectly explains the between variance.

Table 6: Regression results (explained variable: rural labor)

	Estimation method: MDM-DID						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
[1em] re_cdm	-0.003						
	(0.002)						
largebio		0.013**					
		(0.007)					
smallbio			0.050				
			(0.037)				
largewind				-0.007***			
				(0.002)			
smallwind					-0.003		
					(0.023)		
largesolar						-0.004	
						(0.007)	
smallsolar							-0.009
							(0.014)
grp_primary	-0.054***	-0.053***	-0.057***	-0.055***	-0.053***	-0.053***	-0.053***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
land area_agri	-0.021***	-0.021***	-0.019***	-0.020***	-0.021***	-0.021***	-0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ruralpopulation	0.063	0.062	0.063	0.064	0.063	0.063	0.063
	(0.043)	(0.044)	(0.044)	(0.043)	(0.044)	(0.044)	(0.044)
income_gov	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
student	-0.031	-0.030	-0.030	-0.034	-0.028	-0.028	-0.028
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
oilproduction	-0.012	-0.027	-0.035	-0.009	-0.015	-0.017	-0.014
	(0.097)	(0.096)	(0.094)	(0.097)	(0.094)	(0.097)	(0.095)
machinerypower	0.032	0.032	0.031	0.032	0.032	0.032	0.032
	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)
constant	0.123***	0.148***	0.149***	0.122***	0.149***	0.149***	0.149***
	(0.013)	(0.015)	(0.015)	(0.013)	(0.015)	(0.015)	(0.015)
Year dummy	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES
N	2,031	2,031	2,031	2,031	2,031	2,031	2,031
adj. R^2	0.989	0.989	0.989	0.989	0.989	0.989	0.989

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: The values of adjusted R-square are approximately 0.99 since the LSDV estimation including a dummy variable for each county, namely the county dummy, perfectly explains the between variance.

Table 7: Regression results (explained variable: rural labor_primary)

	Estimation method: PSM-DID						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
re_cdm	0.002						
	(0.002)						
largebio		-0.005					
		(0.003)					
smallbio			-0.020**				
			(0.009)				
largewind				0.004***			
				(0.002)			
smallwind					0.002		
					(0.011)		
largesolar						0.019***	
						(0.005)	
smallsolar							0.012
							(0.009)
grp_primary%	-0.056***	-0.056***	-0.054***	-0.055***	-0.056***	-0.055***	-0.056***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
landarea_agri	0.000	0.000	-0.000	-0.001	0.000	-0.002	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
rural population	0.037**	0.037**	0.037**	0.036**	0.037**	0.037**	0.037**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
income_gov	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
student%	-0.008	-0.010	-0.010	-0.004	-0.010	-0.010	-0.010
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)	(0.030)
oil production	0.101	0.106	0.110	0.0989	0.102	0.107	0.100
	(0.080)	(0.080)	(0.081)	(0.080)	(0.081)	(0.081)	(0.081)
machinery power	-0.032**	-0.032**	-0.031**	-0.032**	-0.032**	-0.031**	-0.031**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
constant	0.100***	0.078***	0.078***	0.100***	0.078***	0.079***	0.078***
	(0.014)	(0.007)	(0.007)	(0.014)	(0.007)	(0.007)	(0.007)
Year dummy	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES
N	2,078	2,078	2,078	2,078	2,078	2,078	2,078
adj. R^2	0.981	0.981	0.981	0.981	0.981	0.981	0.981

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The values of adjusted R-square are approximately 0.98 since the LSDV estimation including a dummy variable for each county, namely the county dummy, perfectly explains the between variance.

Table 8: Regression results (explained variable: rural labor_primary)

	Estimation method: MDM-DID						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
re_cdm	0.001						
	(0.002)						
largebio		-0.005					
		(0.003)					
smallbio			-0.019**				
			(0.009)				
largewind				0.004***			
				(0.002)			
smallwind					-0.000		
					(0.011)		
largesolar						0.020***	
						(0.005)	
smallsolar							0.013
							(0.009)
grp_primary%	-0.071***	-0.071***	-0.070***	-0.070***	-0.071***	-0.070***	-0.070***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)
land area_agri	0.000	0.000	-0.000	-0.001	0.001	-0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ruralpopulation	0.038**	0.039**	0.039**	0.038**	0.039**	0.038**	0.038**
	(0.017)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)
income_gov	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
student	-0.002	-0.004	-0.003	0.001	-0.003	-0.004	-0.003
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
oilproduction	0.071	0.076	0.080	0.070	0.073	0.075	0.069
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
machinerypower	-0.034**	-0.033**	-0.033**	-0.033**	-0.033**	-0.033**	-0.033**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
constant	0.105***	0.079***	0.079***	0.106***	0.079***	0.079***	0.079***
	(0.012)	(0.007)	(0.007)	(0.012)	(0.007)	(0.007)	(0.007)
Year dummy	YES	YES	YES	YES	YES	YES	YES
County dummy	YES	YES	YES	YES	YES	YES	YES
N	2,031	2,031	2,031	2,031	2,031	2,031	2,031
adj. R^2	0.981	0.981	0.981	0.982	0.981	0.982	0.981

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: The values of adjusted R-square are approximately 0.98 since the LSDV estimation including a dummy variable for each county, namely the county dummy, explains the between variance perfectly.

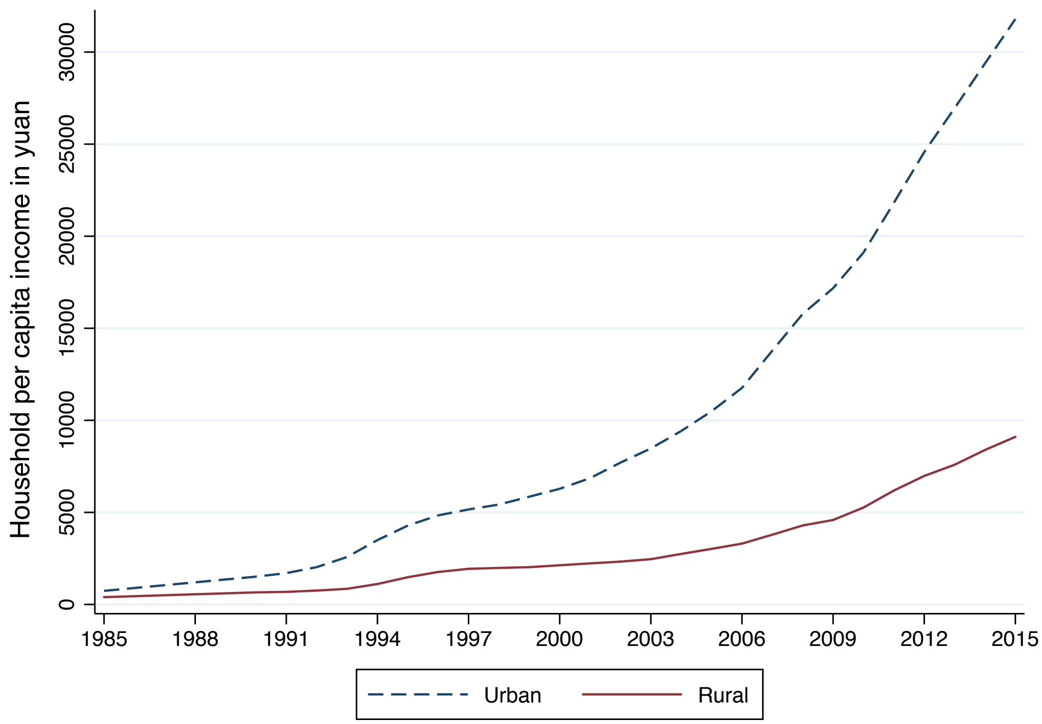

Figure 1: Trends in growth of per capita income of urban and rural households in China. Source: China Statistical Yearbook.

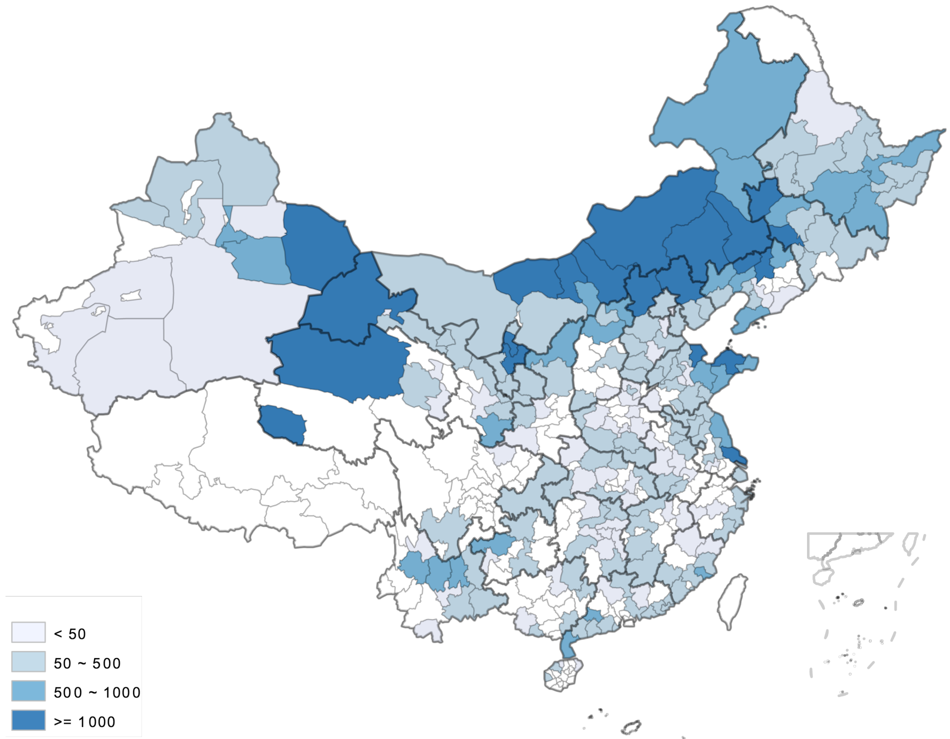

Figure 2: Locational distributions of RE-CDM projects by the cumulative installed capacity (MW) of power plants in 2012

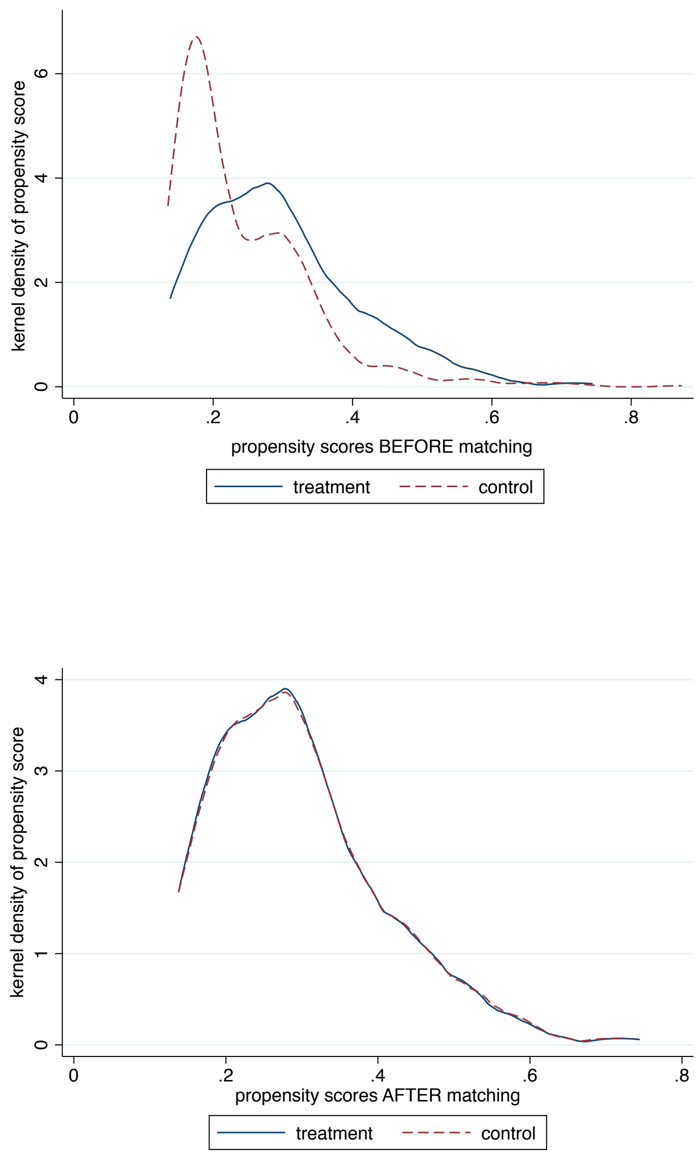

Figure 3: Distribution of propensity scores by treatment and control groups: before and after the nearest-neighbor PSM