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

Du, Yimeng

Takeuchi, Kenji

(Citation)
Journal of Environmental Economics and Management,95:178-197

(Issue Date)
2019-05

(Resource Type)
journal article

(Version)
Accepted Manuscript

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

Yimeng Du and Kenji Takeuchi*

Graduate School of Economics, Kobe University
Kobe 657-8501 Japan

January 16, 2019

Abstract

This study examines whether investment in climate change mitigation contributes to poverty alleviation. We investigate the impacts of the renewable energy-based clean development mechanism (RE-CDM) projects 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 biomass-based CDM projects significantly contribute to income improvement and employment generation in rural communities in China. Our estimation results also reveal that wind energy-based CDM projects have the potential to increase income and the share of labor force in the primary industry in rural areas. These results suggest different channels through which renewable energy sources affect income.

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

*E-mail: sissitoh@gmail.com (Du), takeuchi@econ.kobe-u.ac.jp (Takeuchi). Earlier versions of this paper were presented at the Seventh Congress of the East Asian Association of Environmental and Resource Economics, 2017 annual meeting of the Society for Environmental Economics and Policy Studies, and the Environmental Economics Seminar at Kyoto University. Authors acknowledge helpful comments from Yushi Kunugi, Daisuke Ichinose, Makoto Hasegawa, Emiko Inoue and seminar participants. This work was supported by JSPS KAKENHI Grant Numbers JP16H03006, JP26241033.

1 Introduction

More than 5.7% of Chinese population live below the poverty line in 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 the 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, demonstrates the government's aim to alleviate rural poverty through deploying distributed solar photovoltaic (PV) systems in poor areas. Another critical targets of the 13th FYP for Rural Bioenergy Development is to increase the income of rural residents and improve the living conditions of rural households by promoting the utilization of agricultural waste. Moreover, 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.[4]

Can renewable energy really play a key role in reducing the rural poverty? To explore the question, we investigate the previous Chinese experiences with clean development mechanism (CDM) projects and examine their impacts on poverty reduction. The CDM, which is a part of the flexible mechanisms defined in the Kyoto Protocol, has led to numerous possibilities to absorb foreign investment and enhance sustainable development (SD) in developing coun-

[1] The official national rural poverty line of China is 2,300 yuan per year at constant 2011 purchasing power parity. 1 Chinese Yuan $\approx$ 0.15 U.S. Dollar in 2011.

[2] The National Energy Administration and Poverty Alleviation Office of the State Council decided to implement a poverty alleviation program through the installation of solar PV panels in poor households to increase their incomes. The SEPAP is scheduled to run for six years, starting from 2014. Information on the SEPAP is available at <http://www.nea.gov.cn/2014-10/17/c_133723326.htm>, last accessed on July 17, 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 accessed on January 16, 2018.

[4] Information on the announcement is available at <http://zfxxgk.nea.gov.cn/auto82/201711/t201711083046.htm>, last accessed on January 16, 2018.

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

Many existing studies have examined the extent to which the CDM can achieve its SD goals. Studies with positive findings suggest that the CDM contributes to SD in host countries in different ways. In particular, small-scale rural renewable energy projects, seem to offer the best prospects for poverty alleviation under the CDM (Brunt and Knechtel, 2005; Newell et al., 2011). However, when considering SD benefits, Olsen and Fenhann (2008) conclude that on the basis of a text analysis of 744 project design documents (PDDs), the project type is more significant than the differences between small- and large-scale projects. Wood (2011) confirms that the CDM projects that involve energy efficient or renewable energy-based cook stoves create substantial benefits for the poor, mainly by significantly improving the air quality within their houses and reducing household expenditure on fuel. 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, whereas hydro projects induce job losses. By contrast, Mori-Clement (2019) examines impacts of CDM projects on SD in Brazilian municipalities, revealing that only hydro projects have contributed to long-term poverty reduction. Weitzel et al. (2015) maintain that larger CDM projects and more advanced technologies are more likely to involve technology transfer. The impact of CDM projects on technology transfer has been also studied by many researchers (Seres et al., 2009; Wang, 2010; Zhang and Yan, 2015; Tang and Popp, 2016;

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

Huenteler et al., 2018; and Hayashi et al., 2018). Particularly, Tang and Popp (2016) observe that a project developer's experience and the joint learning within partnerships lead to the largest cost reductions and capacity factor improvement in CDM projects in China.

However, some researchers have suggested neutral or even negative SD impacts. For example, Zhang and Wang (2011) employ an econometric approach to estimate the CDM effect on reducing local air pollution in China and conclude that the CDM does not have a statistically significant effect in lowering SO_2 emissions. On the other hand, by examining a sample of working CDM projects in South Africa, Pillay (2015) concludes that the contribution of CDM to sustainable development is heavily skewed toward greenhouse gas reduction, with little priority given to health, education, and employment generation. Results from other studies have also suggested that the CDM projects do not contribute to poverty reduction and employment generation. 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. Sutter and Parreno (2007), after assessing 16 officially registered CDM projects, conclude that less than 1% of the CDM projects are likely to contribute significantly to SD in the host country. Subbarao and Lloyd (2011) examine 500 registered small-scale CDM projects in the fields of employment, migration, access to electricity, health, the use of local resources, local environment and stakeholder perception. They reveal that CDM projects have generated a modest impact on employment generation for the local community. Crowe (2013) examines 114 CDM projects for pro-poor benefits and the results indicate that nearly 74% of projects are categorized as delivering no pro-poor benefits at the local community level. Dirix et al. (2016) review empirical studies on the pro-poor benefits of the CDM to host country communities, concluding that the CDM has failed to deliver poverty alleviation. By assessing the ex-post quantitative effect that CDM projects have had on SD in Peru, Pécastaing et al. (2018) suggest that CDM investments had a slight effect on household consumption expenditure and had no effect on employment or in poverty alleviation.

In summary, previous studies have shown inconclusive results on whether CDM activities truly contribute to the SD in host countries. In this study, we aim to evaluate the social benefits of the CDM on rural communities of the host country. We particularly focus on income growth, the creation of job opportunities, and changes in the industrial structure as indicators of social benefits. Based on the PDD evaluations submitted in the context of the CDM, the UNFCCC has concluded that the most prominent benefits claimed by project developers are the stimulation of the local economy through employment creation and poverty alleviation (Dirix et al., 2016). 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: Currently, there are two primary approaches to study the SD benefits of CDM: (1) input-output methods or computable general equilibrium model (Wang et al., 2013; Timilsina and Shrestha, 2006); and (2) analytical methods, which generally rely on extensive surveys or PDDs of the projects (Olsen and Fenhann, 2008; Subbarao and Lloyd, 2011; and Crowe, 2013). Although Pécastaing et al. (2018) and Mori-Clement (2019) have used difference-in-differences (DID) methodology to study SD benefits of CDM projects in Peru and Brazil, respectively, their studies are limited in terms of the type and number of projects involved, and length of study period investigated. To fill this research gap, we used a fixed effects DID model in conjunction with the propensity score matching (PSM), to investigate the social benefits of RE-CDM projects in rural communities of China. China has been the largest host country for CDM projects and offers the best environment to study the impact of various types of renewable energy-based projects.

We also contribute to the literature by performing a rigorous robustness check of estimation results. In our context, selection bias matters if the siting of CDM projects is based on the expected growth in the hosting counties. To confirm whether this is the case, we implement a balancing test on differences in the baseline characteristics between treatment and control before and after matching. We also estimate the main models with interactions between baseline characteristics and year dummy as a robustness check to account for growth trends. Furthermore, we check the robustness of our estimation results, obtained through the PSM-DID approach by adopting the Mahalanobis distance matching (MDM) method. In addition, we investigate the impact of conventional thermal power projects on income and employment to compare with our main results.

Another contribution of this study is that our findings provide policy implications on the possibility of simultaneously achieving the goal of climate change mitigation and poverty alleviation. It is imperative that countries achieve their targets of poverty reduction under the Sustainable Development Goals (SDGs),[6] while meeting their commitments to greenhouse gas emission reductions under the Paris Agreement.[7] Thus, our study relates to the literature on poverty reduction and the environmental protection. By using satellite-based estimates of forest cover, Sims (2010) finds that protected areas increased average consumption and lowered poverty rates in Thailand. On the other hand, Sims and Alix-Garcia (2017) estimate the impacts of protected areas and payment for ecosystem services and confirm that the former had neutral impacts on livelihoods, while the latter led to small poverty alleviation. Meek et al. (2017) estimate the environmental and socio-economic impacts of biogas adoption by households in Nepal. Their results suggest that biogas adoption reduces forest cover loss as well as the amount of fuelwood collected and purchased.[8] We complement these studies by focusing on the renewable energy projects that require substantial investment and labor force thereby leading to significant impact on rural development.

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

[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 accessed on January 17, 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 accessed on January 17, 2018.

[8]Köhlin et al. (2015) review studies investigating the co-benefits of forest conservation and household energy interventions in developing countries.

income growth and job creation in rural communities in China. For example, implementing the biomass-based CDM projects increases the annual income of rural residents by 5.75%. Moreover, we find that wind energy projects can help to increase incomes and the share of workers in the primary sector 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 the promotion of the renewable energy in China. Section 3 describes 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 discusses the policy implication of this research.

2 Background

2.1 Income inequality in China

China's economic reforms since 1978 have not only led to rapid economic growth but also to severe income inequality. Figure 1 shows the income trends of rural and urban residents in China from 1985 to 2015.[9] The rural population of China comprised 618 million in 2014, accounting for about 45.2% of the total populations (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. In the mid-1980s, the Gini coefficient, a measure of income inequality, has soared to 0.47 from 0.25 (China Digital Times, 2013). Xie and Zhou (2014) argue that China's current

[9] Individuals are categorized as either "rural" or "urban" residents by the *Hukou* system, a household registration system that serves as an internal 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 nonagricultural sources of income. Migration rules in China were gradually relaxed in the 1990s. As a result, the number of rural migrants to cities almost reached 145 million by 2009, quadrupled from that of 1990 (Meng, 2012). Unfortunately, it is unclear how much of these inter-county migrations are accurately captured in labor force numbers reported in the provincial statistical yearbooks.

income inequality is significantly driven by the rural-urban divide and the regional variation in economic well-being. The 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[10] has increased to around 43% of the total income of rural residents, while the proportion of rural residential income from the primary sector has decreased to about 29%.[11] This change reflects the fact that the source of income of rural residents has shifted from the primary to the secondary and tertiary sectors. Rural areas tend to have a relatively smaller range of job opportunities, lower wages, and thus higher unemployment. These difficulties induced a large number of rural laborers to migrate 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 286 million as of 2017, constitutes more than one-third of the entire working population of China (NBSC, 2018). The sizable rural-to-urban migration not only increases the burden on urban cities but also creates many social problems in rural areas, such as mental health and education of the left-behind children, aging of the rural population, and decline in agricultural productivity (China Labour Bulletin, 2016). To alleviate these issues of rural China, policymakers focus on improving the employment environment by providing high quality job opportunities to the rural community.

2.2 Rural poverty and renewable energy

Recently, the Chinese government promoted investment in renewable energy in rural areas. With the formulation of several national promotion policies for renewable energy, such as the SEPAP and the 13th FYP for Rural Bioenergy Development, new energy industries are

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

[11] Authors' calculations based on the *China Statistical Yearbook* in 1996 and 2016.

ready to exploit the vast development space in rural areas. The 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. Also, 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[12] had received vocational training related to renewable energy, and 15,308 of them had obtained national vocational qualifications through an examination system.[13]

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).

Meanwhile, with the aggravation of the energy crisis and the increasing importance of environmental problems, climate policies have been high on the agenda of the 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, the adoption of RE-CDM projects could bring additional foreign investment to the host community, ultimately driving the development of local renewable energy industries. 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% comprise wind power projects while other projects, including bioenergy and solar energy, make up about 5.2% and 1.6%, respectively.[14]

[12] Qingxiu county belongs to Nanning city, Guangxi Zhuang Autonomous Region.

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

[14] Authors calculations based on UNFCCC's Database for Project Activities and Programme of Activities.

Rural counties[15] manage to 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 the 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. RE-CDM projects are not evenly distributed among regions, but mainly concentrated in regions endowed with sizable renewable energy resources, i.e., 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 is the environmental dimension, including environmental quality, pollution emissions, and material consumption (IRENA, 2016). Although various existing studies have empirically analyzed the economic and environmental benefits of the CDM (Seres et al., 2009; Wang, 2010; Tang and Popp, 2016; Zhang and Wang, 2011; and Castro, 2012), as per the authors knowledge, the existing research on the causal effects of projects on local income and labor demand based on econometric approach is still limited. In order to estimate the social impacts of increased

[15]County-level administrative areas in China include 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 the rural area in our analysis.

renewable energy deployment 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. By adopting RE-CDM activities, rural communities can diversify, stabilize, or increase the income of their residents in several ways. For instance, RE-CDM projects can alleviate poverty by helping unskilled laborers in rural areas, such as farmers, unemployed persons, and women with low education level, to serve as assembly line workers, equipment installers, and maintenance or sales staff. Another channel might be lease and compensation payment to farmers and residents by developers of renewable energy projects.

Second, the share of employed persons in the total population is used as an indicator of job creation in a rural county. The working populace 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 the employment among residents. In 2013, the renewable energy sector provided about 6.5 million direct and indirect jobs worldwide. 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 renewable energy deployment will raise the overall number of jobs. However, others believe that the relatively higher monetary costs of deploying renewables will reduce purchasing power and, consequently, employment. These arguments underscore the need for more detailed analyses and rigorous strategies to estimate the potential social benefits, especially employment creation from renewable energy deployment.

Lastly, we employ the share of rural laborers in the primary sector to capture the impact of RE-CDM on industrial transformation. Renewable energy industries can create valuable job opportunities for people in regions with low employment rates. 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, the primary income sources of farm households could switch from agricultural activities to the construction industry.

3.2 Data sources

To examine the effect of the RE-CDM on rural development, we obtained information on the construction period and location of RE-CDM projects, rural residential income, share of employed persons in rural area, and other characteristics of each county.[16] The panel data used for analysis cover a total of 1,955 rural counties across China and comprise three types of variables, namely, social benefits, county characteristics, and characteristics of RE-CDM projects. The sample period for this study is between 2002 and 2011, whereas the period 2002−2004 serves as preceding years because the first CDM project is registered in 2005.[17] After matching was applied, 82% of the counties had complete panel data from 2002 to 2010, and 48% of the counties had complete panel data from 2002 to 2011.[18] We restricted our data till 2011 because we focused on the short-term effects of RE-CDM projects and avoided evaluation of the long-term effects on outcome indicators that might be influenced by many factors. For example, outcome variables can be affected by technological development, growth in human capital, and change in industrial structure in the long run. To investigate the long-term impacts of CDM, these factors must be taken into consideration.

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 4,455

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

[17] 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 accessed on December 21, 2017.

[18] The provincial statistical yearbooks do not include data on some counties for some years. The reason for this might be a change in county boundaries or a lack of data collection by the province. For example, the Hebei and Jilin provinces do not indicate the 2011 rural income of many counties. In such cases, the missing data occurs in particular provinces.

yuan in the treatment group and approximately 4,938 yuan in the control group. The average share of employed persons in a county is around 53.19% in the treatment group and about 53.36% in the control group. The average share of laborers in the primary sector is about 35.09% in the treatment group; the corresponding number in the control group is 33.65%. A two-tailed t-test shows statistically significant differences in the mean value of social benefits and county characteristics. This suggests the need to adopt matching techniques in order to avoid selection bias.

[Table 1]

Data related to social benefits are collected from the statistical yearbook of each province. Per capita net income of rural households, the share of employed persons in the total population, and the share of rural laborers in the primary sector are used as indicators of social benefits. Data in the provincial statistical yearbooks are generally based on two sources: (1) rural household survey data collected by the State Statistical Bureau (SSB) and (2) Ministry of Agriculture (MOA) data based on annual reports of village leaders aggregated at the township and county levels (Park and Wang, 2001). Particularly, the latter dataset has been criticized for the possibility of misreporting and biases. Meng (2013) compares the MOA data with the National Poverty Monitoring Survey, which is another data source for poor counties, and finds no systematic over-reporting in the MOA data.

The county characteristic variables, including the gross output of the primary sector, the area of agricultural land, total government revenue, the share of students in compulsory education, production of oil crop, and the total capacity of agricultural machinery, are based on the China Rural Statistical Yearbook. Wind potential is based on National Development and Reform Commission (NDRC, 2016), where higher wind power potential regions are those regions with on-grid tariffs for wind power less than or equal to 0.54 yuan 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 yuan per kWh, with the lower tariffs applying in regions with higher wind power potential. Both geographical and social characteristics are considered because 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. 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.[19] 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.

4 Empirical analysis

4.1 Model

To measure the social benefits of RE-CDM in rural communities, we employ a DID estimator combined with a mix of fixed effects by running an Least Squares Dummy Variable 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 effects 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 1,955 rural counties in China from 2002 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 share of employed persons in total population; and (c) the share of rural laborers in

[19] 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.

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. In addition, we interact the treatment indicator with different types of renewable energy sources, namely, biomass, wind, and solar energy, to capture their differences in social benefits.[20] X_{it} is a vector of time-varying county characteristics: primary industry output, agricultural land area, government revenue, the share of students in compulsory education, oil crop production, and total capacity of agricultural machinery. δ_i is the vector of the county dummy 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, $p(x) = Pr(D = 1|x)$.

[20] Most of the biomass-based CDM projects use agricultural residue as burning fuels for power generation.

The matching method assumes that within 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 with-in group sample covariance matrix S. The distance between covariate x_1 and x_2 is $M(x_1,x_2) = (x_1\text{-}x_2)^T \mathrm{S}^{-1}(x_1\text{-}x_2)$.

First, to estimate the propensity score, we use covariates in the baseline year 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, a dummy variable for regions that have relatively higher wind power potential, net income of rural residents, and the share of employed person in total population. These covariates are chosen on the basis that the CDM projects are scrutinized regarding project additionality before registration. We suppose that project additionality relates to various county characteristics, particularly on the potential for economic growth and natural resource endowments that can be used as inputs for renewable energy generation. We use 2004 as the baseline year, which is one year before the year that the first RE-CDM projects in China were registered.

Second, we use the estimated propensity score to match treatment and control groups in the baseline year. A one-to-one matching approach without replacement was adopted while using the nearest-neighbor PSM and MDM algorithm. In other words, we choose only one county from the counties without RE-CDM activities as a match for a treatment county regarding their closest propensity score and Mahalanobis distance. An untreated county cannot be used more than once as a match. The total number of county decrease from 1,955 to 426 after the PSM and to 448 after the MDM because the observations out of the common support have been dropped from the sample.

Finally, to ensure that the matching procedure successfully balances the two groups, we compare the treatment and control groups after matching. Table 2 present the balancing test results for the PSM in Panel A and that of the MDM in Panel B. The results indicate that the differences between the treatment and control groups become statistically insignificant after matching. For instance, in Panel A of Table 2, we find that the difference of primary industry output between the treatment and control groups is nearly 14.2%. The difference between these two groups drops to 7.60% when the sample is matched.

[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 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.

[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 Table 3. Columns (1)–(4) show the results estimated by the PSM-DID approach and columns (5)–(8) represents the results estimated by the MDM-DID approach. We find that a positive relationship exists between RE-CDM activities and rural residential income. The coefficients of the treatment indicator *re_cdm* are positive and statistically significant at the 1% level in all models as shown in the first row of Table 3. The estimated effects correspond to an increase of approximately 311 yuan in annual income, which is about 6.3% of the average rural income of residents.[21] To check whether the results are not driven by the expected growth trends, we estimate models with the interactions between two baseline characteristics, namely, the

[21] According to the summary statistics in Table 1, the annual average net income of rural residences for control group in the sample is 4,938 yuan.

primary industry output and oil crop production, and year dummy in columns (3)–(4) and (7)–(8). The significance of RE-CDM remains robust in these specifications.

[Table 3]

Table 3 also reports the impact of the RE-CDM by different energy sources. The *biomass* and *wind* dummy variables are also positive and statistically significant in all regressions. This result indicates that both biomass and wind power-based CDM projects stimulated income growth substantially for rural residents. Specifically, the adoption of biomass-CDM projects generated 284 yuan, about a 5.75% increase in annual income for the rural residents. The coefficient of *wind* in column (2) in Table 3 suggests that the adoption of wind power-based CDM projects raises the annual income of rural residents by approximately 223 yuan or approximately a 4.52% increase in annual income. On the other hand, we do not find a significant impact of solar energy-based CDM projects on income generation.

Our results regarding the impact of the RE-CDM on income improvement illustrates that biomass and wind energy-based CDM projects are significant in stimulating income generation. Gan and Smith (2007) estimate 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. Based on a survey conducted for users and non-users in three villages of China, Van Groenendaal and Gehua (2010) conclude that the main benefit in relation to household income incurred from a bio-digester is reduction of expenditure on fuels and fertilizer. Similarly, Garfí et al. (2012) evaluate household biogas digesters technical, environmental, and socio-economic impacts in rural communities of the Peruvian Andes, concluding that the family's annual income is increased by 35.5% due to fertilizer savings and potato sales. As for the income generation impact of wind power, it is said that rural communities involved in wind power generation activities benefit from payments farmers receive to host turbines on their property (Farm Bureau, 2017). In the case of an on-grid wind power project located in Longchuan county in Guangdong province, the land rent provided for local residents is 4,500 yuan per ha.[22]

To confirm that the identifying assumption of common pre-trends is satisfied, we estimate models with interaction between treatment dummy and year dummy. Treatment dummy takes value one if the county is in the treatment group and zero otherwise. The results are reported in Table A1 in Appendix. Coefficients of interactions between treatment group dummy and year dummy before CDM period, namely the *Treatment* × *2002* and *Treatment* × *2003*, are not statistically significant. On the other hand, interactions of the treatment dummy with post-CDM period are statistically significant in many cases. These results suggest that the outcome variable have statistically significant differences between control and treatment only after the RE-CDM projects were adopted. As an additional robustness check, we also include a regression specification using the full sample without applying matching techniques for comparison. The estimation results are reported in Table A2 in Appendix. We find that they are similar to our main results although the sizes of estimated coefficients in the full sample analysis are higher than those in matched sample analysis.

5.2 Impact on employment generation

In Table 4, we assess the impact of the RE-CDM projects on employment generation using the PSM- and MDM-DID method. The coefficients of *RE-CDM* in all models in Table 4 indicate that the existence of renewable energy CDM projects raises the working population share by roughly 1.13%. This finding confirms the employment generation benefit of the renewable energy projects adopted under the CDM.

[Table 4]

In addition, the results illustrate that the employment generation impact of RE-CDM activities in rural areas differ by different renewable energy sources. The coefficients of

[22] Available at <http://www.longchuan.gov.cn/sy/tzgg/4406064.html>, last accessed on 23 January 2018.

Biomass are positive and significant at the 5% level as shown in the second row in Table 4. This result suggests that the adoption of biomass-CDM projects increase the share of working population in a rural county by approximately 1.48% points compared with the average rural labor share (53.4%) for control group. 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) quantify 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 biomass projects. Openshaw (2010) find 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. Chen et al. (2017) mention that the employment rate can be increased during and after the construction of the biogas CDM project, and also afterwards as operation and maintenance workers are needed to keep the facilities functioning.

On the other hand, we did not find a statistically significant impact on employment rate in the rural communities for wind and solar energy projects. Compared with biomass energy, electricity generation by these energy sources require less labor input and, therefore results to an insignificant increase in labor demand. The insignificance of wind energy projects on employment generation also suggests that the increase of rural income by wind power projects are caused by channels other than employment generation. The coefficient of solar power-based CDM projects is negative and statistically significant. It suggests that solar power-based CDM projects have negative impact on employment generation.

5.3 Impact on employment in the primary sector

In Table 5, we report the estimated impact of the RE-CDM adoption on the share of employment in the primary sector in rural communities. The coefficients of *Wind* shown in columns (2) and (4) in Table 5 indicate that the implementation of wind power projects under the CDM is associated with an increased share of rural laborers in primary industry by 1.42% points compared to the average value for control group in the sample 33.7%. We confirm the robustness of above results by the MDM-DID approach in columns (6) and (8) in Table 5. One of the attractiveness of wind power for farmers is to allow developers to install large wind turbines on their land. Large wind turbines typically use less than half an acre of land, including access roads; thus, farmers are able to earn extra income and continue their agricultural production. As a result, there is a potential of wind power-based CDM projects for attracting more laborers in the primary sector. If this shift is promoted by an incentive payment from wind developers to local farmers and land holders, then the shift of the labor force will persist for a considerable period during operations of wind power. Further research is required to investigate whether CDM projects contribute to long-run industrial transformation.

[Table 5]

In contrast, we find that solar power-based CDM projects decrease the share of rural laborers in the primary sector in rural communities. In the second column in Table 5, the coefficient of *Solar* is negative and statistically significant; that is, due to the adoption of solar energy-based CDM projects, the share of rural laborers in the primary sector decrease by 4.97% points. The finding implies that the presence of solar power projects may reduce the share of labor force in primary sector which is consistent with the argument that there is a tradeoff between solar power installation and agricultural practice. For example, Hernandez et al. (2015) investigated the impact of solar energy development on land use change in California and found that 28% of utility scale solar power plants are located in croplands and pastures. Nonhebel (2005) also found that the land required for solar energy is about 25% of the area required for food production in the rich situation yields. Moreover, Sacchelli et al. (2016) estimated potential crop production losses in case of solar panels installation on arable lands.

5.4 Impact by different project scales

Table 6 reports the estimated impact of the RE-CDM adoption on income generation and employment creation by different project scales. Project scales are captured by three dummy variables (*1 project*, *2 projects*, and $\geq$ *3 projects*) that take on the value one according to the number of RE-CDM projects that the county has in the year. While the coefficient of *1 project* is positive and statistically significant, those of *2 projects* and $\geq$ *3 projects* are not statistically significant. These results indicate that impact of RE-CDM projects on net income of rural residents is not observed in counties with multiple numbers of projects.

[Table 6]

On the other hand, results for *Rural labor%* and *Rural labor_primary%* indicate that project scales might matter to the size of the effect on these outcomes, although statistical significance is marginal for *2 project* and $\geq$ *3 project* in *Rural labor%*. Comparing the coefficients of *1 project* and $\geq$ *3 project* in column (3) of Table 6, we find that adopting more than three RE-CDM projects has a 2.6 times greater impact on increase of the working population share in the rural county than adopting one projects. Besides, the coefficients of $\geq$ *3 project* in columns (5) and (6) of Table 6 are all positive and significantly correlated with the share of working population in primary sector. The result shows that adopting more than three RE-CDM projects increase the share of labor force in primary sector by 2.14% points.

In summary, we find that having a larger number of projects in a county leads to a higher impact on employment generation and the share of laborer in primary sector. On the other hand, we find such effect is not significant for rural income. Although we cannot speculate the mechanism behind this, a possible interpretation is that larger number of projects increase inflow of labor force but does not affect income of local residents.

5.5 Impact of thermal power projects

To compare the social benefits of RE-CDM projects with traditional energy sources, we also investigate the income generation and job creation impact of the addition of thermal power plants. Information on the annual addition of thermal power plants over 10,000 kW are obtained from the Compilation of Power Industry Statistics collected by the China Electricity Council. The sample period for the thermal power-related regression is from 2005 to 2010. Study area is the same with our main regression, which includes a total of 1,955 rural counties in China.

Similar with the main regression, we adopt both the PSM-DID and MDM-DID approach to reduce possible selection bias caused by the location decisions of thermal power plants and trends of economic growth. The baseline year is set at 2005 in this regression and we drop all the counties that have newly added thermal power plants in that year. Covariates used for matching the sample are: gross output of the primary sector, agricultural land area, amount of oil crop production, net income of rural residents, and the share of employed person to total population. The balancing test results show that no statistical difference emerges after matching the treatment and control groups.

The treatment indicator of additional thermal power plants is the *Thermal* dummy variable. Similar with the *RE-CDM* dummy in the main regression, it takes on the value one in and after the year a new thermal power plants have been constructed in the rural county, and zero otherwise. As shown in Table A3 in the Appendix, the coefficients of *Thermal* are negatively and significantly correlated with the rural residential income. This result indicates that the addition of thermal power plants reduce the net income of rural residents by approximately 2,585 yuan.

The negative impact of thermal power plants on rural net income is generally consistent with previous findings on the relationship between resource abundance and economic performance in Chinese provinces. Zhang et al. (2008) investigated the relationship and found that provinces with abundant resources perform worse than their resource-poor counterparts in terms of per capita consumption growth. The negative effect of coal dependence was also found by Dai et al. (2018) that exploit a drop of global coal price as an exogenous shock to identify the effect on entrepreneurial activities. On the other hand, Xu and Nakajima (2016) estimated positive impact of coal mine regulations on regional economic growth in China.

6 Conclusions

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

Our results indicate that the RE-CDM projects can contribute to income and employment of the host counties. The increase in annual income of rural residents is 5.75% by adopting biomass- and 4.52% by adopting wind power-based RE-CDM projects. Moreover, we find that not all renewable energy technologies contribute to the social benefits in the same manner. Biomass-based CDM projects had the greatest potential in increasing the employment opportunities in rural areas. This result indicates that bioenergy projects provide more job opportunities for unskilled laborers than other types of energy sources. In contrast, wind power-based CDM projects promote rural development by attracting the 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 the poverty of rural communities in China. We conclude that the adoption of renewable energy projects under the CDM can offer an effective method to both reduce poverty and address the global externality. By promoting the development of renewable energy, particularly biomass and wind power 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 types of social benefits by improving health, welfare, access to education and jobs, and driving economic growth while reducing pollution (Climate Advisers, 2014).

Although our study confirms the role of RE-CDM in assisting host countries to advance rural development, further investigation is necessary to understand the 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.

References

Asian Development Bank, 2017. Poverty in the People's Republic of China. Available at <https://www.adb.org/countries/prc/poverty>, last accessed on 23 January 2018.

Brunt, C., Knechtel, A., 2005. Delivering sustainable development benefits through the Clean Development Mechanism, The Pembina Institute. Available at <http://www.pembina.org/pub/207>, last accessed on 15 January 2019.

Castro, P., 2012. Does the CDM discourage emission reduction targets in advanced developing countries? Climate Policy 12(2), 198–218.

Chen, Y., Hu, W., Chen, P., Ruan, R., 2017. Household biogas CDM project development in rural China, Renewable and Sustainable Energy Reviews 67, 184–191.

China Digital Times, 2013. How to Fix China's Income Inequality. Available at <http://chinadigitaltimes.net/2013/02/how-to-fix-chinas-income-inequality/>, last accessed on 17 July 2017.

China Labour Bulletin, 2016. Migrant workers and their children. Available at <http://www.clb.org.hk/content/migrant-workers-and-their-children>, accessed on 6 December 2017.

Chinese Academy of Social Sciences (CASS), 2016. Annual Report on China's Economic Growth 2016.

Climate Advisers, 2014. Reducing Poverty Through Climate Action. Available at <http://www.climateadvisers.com/wp-content/uploads/2014/05/2014-05-Climate-Poverty.pdf>, last accessed on 19 July 2017.

Cochran, W. G., Rubin, D. B., 1973. Controlling bias in observational studies: A review, Sankhyā: The Indian Journal of Statistics 35(4), 417–446.

Crowe, T.L., 2013. The potential of the CDM to deliver pro-poor benefits, Climate Policy 13(1), 58–79.

Dai, R., Li, L., Xi, T., Xie, X., 2018. Natural resource shocks and entrepreneurship: Evidence from coal productions in China. National School of Development, Peking University. April 7, 2018.

Dirix, J., Peeters, W., Sterckx, S., 2016. Is the Clean Development Mechanism delivering benefits to the poorest communities in the developing world? A critical evaluation and proposals for reform, Environ Dev Sustain 18(3), 839-855.

Faaij, A., Meuleman, B.,Turkenburg, W., Wijk, A., Bauen, A., Rosillo-Calle, F., Hall, D., 1998. Externalities of biomass based electricity production compared with power generation from coal in the Netherlands, Biomass and Bioenergy 14(2), 125–147.

Farm Bureau, 2017. Wind generation benefits: farmers, rural communities, and the environment. Available at <https://www.fb.org/viewpoints/wind-generation-benefits-farmers-rural-communities-and-the-environment>, last accessed on 2 October 2018.

Gan, J., Smith, C.T., 2007. Co-benefits of utilizing logging residues for bioenergy production: The case for East Texas, USA, Biomass and Bioenergy 31(9), 623–630.

Garfí, M., Ferrer-Martí, L., Velo, E., Ferrer, I., 2012. Evaluating benefits of low-cost household digesters for rural Andean communities, Renewable and Sustainable Energy Reviews 16, 575–581.

Hayashi, D. Huenteler, J., Lewis, J.I., 2018. Gone with the wind: A learning curve analysis of China's wind power industry, Energy Policy 120, 38–51.

Hernandez, R.R., Hoffacker, M.K., Murphy-Mariscal, M.L., Wu, G.C., Allen, M.F., 2015. Solar energy development impacts on land cover change and protected areas. Proceedings of the National Academy of Sciences 112(44), 13579–13584.

Huenteler, J., Tang, T., Chan, G., Anadon, L.D., 2018. Why is China's wind power generation not living up to its potential? Environmental Research Letters 13, 044001. Available at <http://iopscience.iop.org/article/10.1088/1748-9326/aaadeb/pdf>, last accessed on 17 January 2019.

IRENA, 2014. The Socio-economic Benefits of Solar and Wind Energy. Available at <http://www.irena.org/DocumentDownloads/Publications/Socioeconomic_benefits_solar_wind.pdf>, last accessed on 19 July 2017.

IRENA, 2016. Renewable Energy Benefits: Measuring the Economics. Available at <http://www.irena.org/DocumentDownloads/Publications/IRENA_Measuring-the-Economics_2016.pdf>, last accessed on 17 July 2017.

Köhlin, G., Pattanayak, S., Sills, E., Mattsson, E., Ostwald, M., Salas, A., Ternald, D., 2015. In search of double dividends from climate change interventions evidence from forest conservation and household energy transitions, EBA Report 2015:09. <http://eba.se/wp-content/uploads/2016/03/Report201509climate.pdf>, last accessed on 3 October 2018.

Meeks, R., Sims, K.R.E., Thompson, H., 2017. Waste not: Can household biogas deliver sustainable development? Environmental and Resource Economics, 1–32.

Meng, X., 2012. Labor market outcomes and reforms in China, Journal of Economic Perspectives 26(4), 75–102.

Meng, L., 2013. Evaluating China's poverty alleviation program: A regression discontinuity approach, Journal of Public Economics 101, 1–11.

Mori-Clement, Y., 2019. Impacts of CDM projects on sustainable development: Improving living standards across Brazilian municipalities? World Development 113, 222–236.

National Bureau of Statistics of China (NBSC), 2014. China Statistics Yearbook 2015. Available at <http://www.stats.gov.cn/tjsj/ndsj/2015/indexch.htm>, last accessed on 17 July 2017.

National Bureau of Statistics of China (NBSC), 2018. The 2017 Report on the Surveillance of Chinas Rural-to-Urban Migrant Workers. Available at <http://www.stats.gov.cn/tjsj/zxfb/201804/t20180427_1596389.html>, last accessed on 3 October 2018.

National Development and Reform Commission (NDRC), 2016. The Notice on Tariff Price of On-shore Wind Power. Available at <www.spicxj.com/FileDownload.do?affixid=10624>, accessed on 24 July 2017, in Chinese.

National Energy Administration (NEA), 2015. Work program on implementation of photovoltaic poverty alleviation project. Available at <http://www.nea.gov.cn/2016-04/05/c_135250679.htm>, last accessed on 17 July 2017.

Newell, P., Phillips, J., Mulvaney, D., 2011. Pursuing clean energy equitably, Human Development Research paper, United Nations Development Programme. Available at <http://hdr.undp.org/en/content/pursuing-clean-energy-equitably>, accessed on 15 January 2019.

Nonhebel, S., 2005. Renewable energy and food supply: will there be enough land? Renewable and Sustainable Energy Reviews 9, 191–201.

Olsen, K.H., Fenhann, J., 2008. Sustainable development benefits of clean development mechanism projects: A new methodology for sustainability assessment based on text analysis of the project design documents submitted for validation, Energy Policy 36(8), 2819–2830.

Openshaw, K., 2010. Biomass energy: Employment generation and its contribution to poverty alleviation, Biomass and Bioenergy 34(3), 365–378.

Park, A., Wang, S., 2001. China's poverty statistics, China Economic Review 12(4), 384–398.

Pécastaing, N., Dávalos, J., Inga, A., 2018. The effect of Peru's CDM investments on households welfare: An econometric approach, Energy Policy 123, 198–207.

Pillay, S., 2015. The impact of Clean Development Mechanism projects on sustainable development in South Africa, International Business & Economics Research Journal 14(6), 777–790.

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects, Biometrika 70(1), 41–55.

Sacchelli, S., Garegnani, G., Geri, F., Grilli, G., Paletto, A., Zambelli, P., Ciolli, M., Vettorato, D., 2016. Trade-off between photovoltaic systems installation and agricultural practices on arable lands: An environmental and socio-economic impact analysis for Italy, Land Use Policy 56, 90–99.

Seres, S., Haites, E., Murphy, K., 2009. Analysis of technology transfer in CDM projects: An update, Energy Policy 37, 4919–4926.

Sims, K.R.E., 2010. Conservation and development: Evidence from Thai protected areas, Journal of Environmental Economics and Management 60(2), 94–114.

Sims, K.R.E., Alix-Garcia, J.M., 2017. Parks versus PES: Evaluating direct and incentive-based land conservation in Mexico, Journal of Environmental Economics and Management 86, 8–28.

Sirohi, S., 2007. CDM: Is it a 'win-win' strategy for rural poverty alleviation in India? Climatic Change 84, 91–110.

Subbarao, S., Lloyd, B., 2011. Can the Clean Development Mechanism (CDM) deliver? Energy Policy 39(3), 1600–1611.

Sutter, C., Parreno, J.C., 2007. Does the current Clean Development Mechanism (CDM) deliver its sustainable development claim? An analysis of officially registered CDM projects, Climatic Change 84, 75–90.

Tang, T., Popp, D., 2016. The learning process and technological change in wind power: Evidence from China's CDM wind projects. Journal of Policy Analysis and Management 35, 195–222.

Thornley, P., Rogers, J., Huang, Y., 2008. Quantification of employment from biomass power plants, Renewable and Sustainable Energy Reviews 33(8), 1922–1927.

Timilsina, G.R., Shrestha, R.M., 2006. General equilibrium effects of a supply side GHG mitigation option under the Clean Development Mechanism, Journal of Environmental Management 80(4), 327–341.

United Nations, 2012. The Future We Want. RIO+20 United Nations Conference on Sustainable Development. Available at <https://sustainabledevelopment.un.org/content/documents/733FutureWeWant.pdf>, last accessed on July 17, 2017.

UNFCCC, 2014. Small scale methodology: renewable electricity generation. Available at <https://cdm.unfccc.int/methodologies/DB/W3TINZ7KKWCK7L8WTXFQQOFQQH4SBK>, last accessed on July 19, 2017.

Van Groenendaal, W., Gehua, W., 2010. Microanalysis of the benefits of China's family-size bio-digesters, Energy 35, 4457–4466.

Wang, B., 2010. Can CDM bring technology transfer to China?–An empirical study of technology transfer in China's CDM projects, Energy Policy 38, 2572–2585.

Wang, C., Zhang, W., Cai, W., Xie, X., 2013. Employment impacts of CDM projects in China's power sector, Energy Policy 59, 481–491.

Weitzel, M., Liu, W.H., Vaona, A., 2015. Determinants of technology transfer through the CDM: a within-country analysis for China, Climate Policy 15(5), 626–646.

Wood, R.G., 2011. Carbon finance and pro-poor co-benefits: The Gold Standard and Climate, Community and Biodiversity Standards, Sustainable Markets Discussion Paper, International Institute for Environment and Development. Available at <http://www.environmentportal.in/files/Carbon%20finance%20and%20pro-poor.pdf>, last accessed on 13 January 2019.

World Bank, 2015. Climate Change Complicates Efforts to End Poverty, The World Bank. Available at <http://www.worldbank.org/en/news/feature/2015/02/06/climate-change-complicates-efforts-end-poverty>, last accessed on July 19, 2017.

Worldwatch Institute, 2011. Green Economy and Green Jobs in China. Available at <http://www.worldwatch.org/system/files/185%20Green%20China.pdf>, last accessed on July 19, 2017.

Xie, Y., Zhou, X., 2014. Income inequality in today's China, Proceedings of the National Academy of Sciences of the United States of America 111(19), 6928–6933.

Xu, H., Nakajima, K., 2016. Did China's coal mine regulation positively affect economic growth? Resources Policy 50, 160–168.

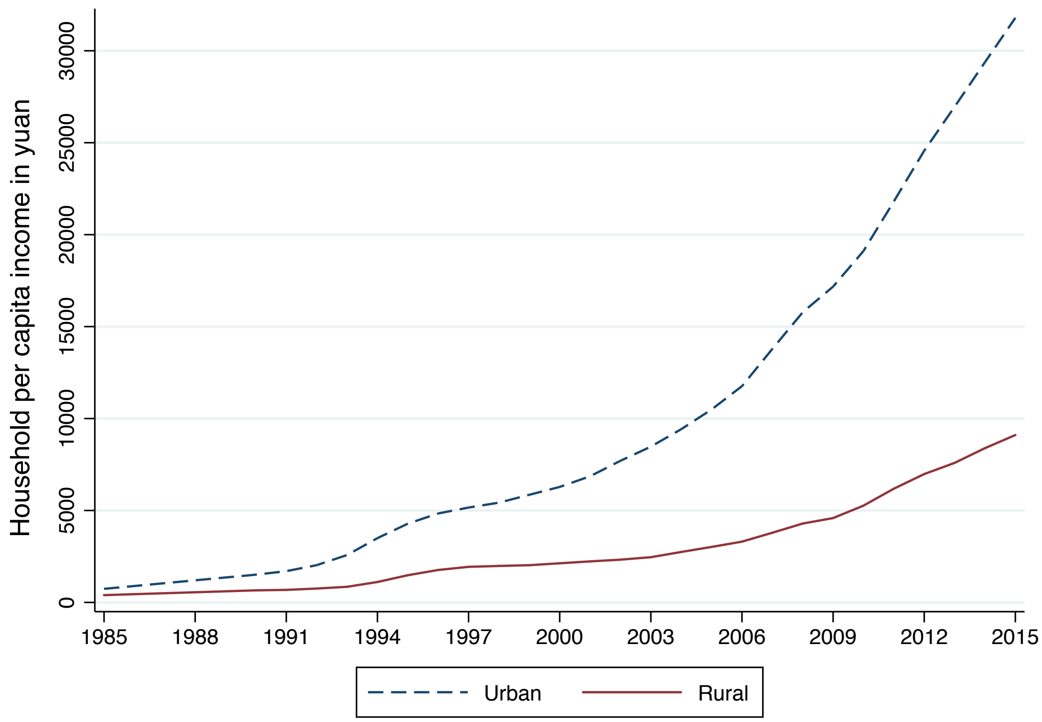
Xue, J., 2017. Photovoltaic agriculture - New opportunity for photovoltaic applications in China, Renewable and Sustainable Energy Reviews 73, 1–9.

Zhang, J., Wang, C., 2011. Co-benefits and additionality of the clean development mechanism: An empirical analysis, Journal of Environmental Economics and Management 62, 140–154.

Zhang, X., Xing, L., Fan, S., Luo, X., 2008. Resource abundance and regional development in China. Economics of Transition 16(1), 7–29.

Zhang, C., Yan, J., 2015. CDMs influence on technology transfers: A study of the implemented clean development mechanism projects in China, Applied Energy 158, 355–365.

Zhao, Z.Y., Li. Z.W., Xia, B., 2014. The impact of the CDM on the cost price of wind power electricity: a China study, Energy 69, 179–185.



Source: China Statistical Yearbook.

Figure 1: Per capita income of urban and rural households in China

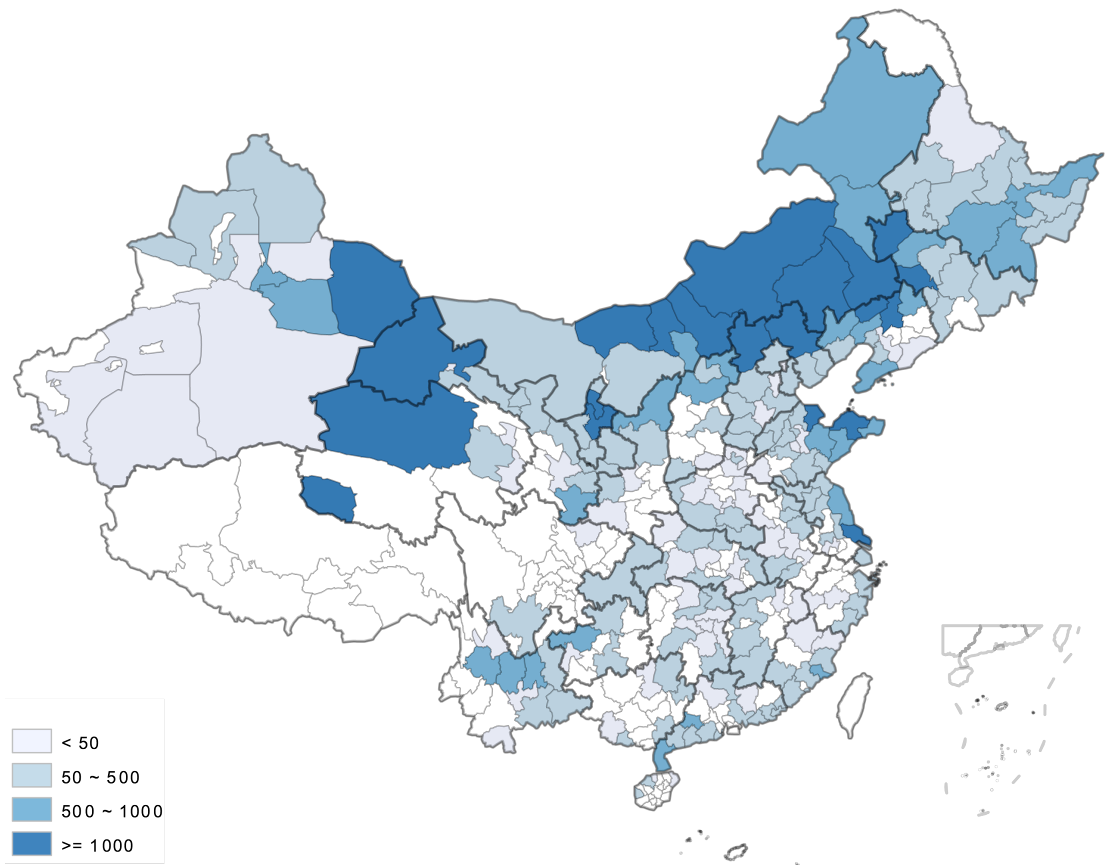


Figure 2: Locational distributions of RE-CDM projects by the cumulative installed capacity (MW) of power plants in 2012

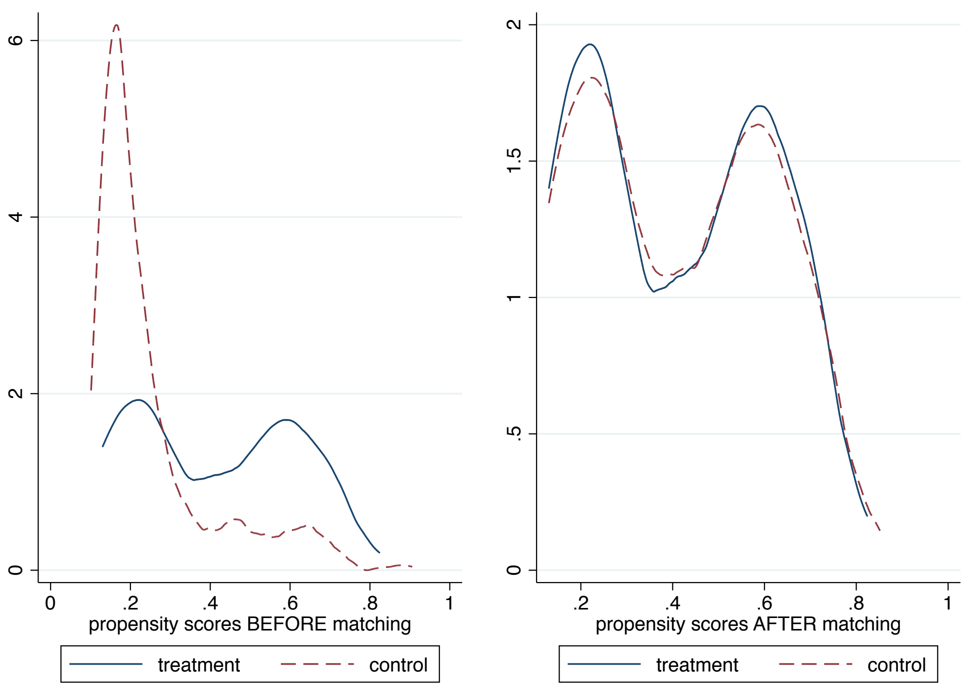


Figure 3: Distribution of propensity scores by treatment and control groups: before and after the nearest-neighbor PSM

Table 1: Descriptive statistics

		(1) Control groups			(2) Treatment groups		
	Unit	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Treatment Indicators							
RE-CDM	dummy	12,697	0.000	0.000	4,078	0.214	0.410
Biomass	dummy	12,697	0.000	0.000	4,078	0.041	0.199
Wind	dummy	12,697	0.000	0.000	4,078	0.172	0.377
Solar	dummy	12,697	0.000	0.000	4,078	0.014	0.115
Multi-projects	dummy	12,697	0.000	0.000	4,078	0.013	0.114
1 project	dummy	12,697	0.000	0.000	4,078	0.103	0.303
2 projects	dummy	12,697	0.000	0.000	4,078	0.024	0.154
$\geq$ 3 projects	dummy	12,697	0.000	0.000	4,078	0.016	0.124
Social Benefit Variables							
Income_rural	1,000 yuan	10,279	4.938***	7.932	3,683	4.455	2.710
Rural labor%	%	12,350	0.534	0.122	4,025	0.532	0.090
Rural labor_primary%	%	12,350	0.337***	0.118	4,025	0.351	0.120
County Characteristics							
Primary industry output	billion yuan	12,351	1.144***	1.074	4,024	1.546	1.392
Agricultural land area	1,000 km^2	10,371	0.376***	0.386	3,228	0.622	0.504
Government revenue	billion yuan	12,351	0.329	0.804	4,023	0.346	0.550
Student%	%	12,350	0.146***	0.038	4,023	0.141	0.049
Oil crop production	million ton	12,081	0.013***	0.021	3,922	0.019	0.033
Machinery power	1,000 kW	12,351	0.241***	0.330	4,024	0.323	0.449
Wind potential	dummy	12,697	0.153***	0.360	4,078	0.282	0.450

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) *Multi-projects* is a dummy variable that indicates if a county has more than two types of RE-CDM projects in the same year.

Table 2: Balancing test results

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

	Unmatched/	Mean				t-test	
Outcome: income_rural	Matched	Treatment	Control	%bias	%bias reduction	t-value	p-value
Primary industry output	U	1.287	1.087	14.2		1.84	0.065
	M	1.287	1.180	7.60	46.1	0.69	0.491
Agricultural land area	U	0.672	0.467	46.4		6.46	0.000
	M	0.672	0.606	15.0	67.8	1.72	0.087
Oil crop production	U	0.025	0.019	20.0		2.87	0.004
	M	0.025	0.025	2.30	88.3	0.23	0.816
Wind potential	U	0.313	0.146	40.2		5.71	0.000
	M	0.313	0.378	-15.7	61.0	-1.56	0.119
Income_rural	U	3.098	2.949	11.9		1.57	0.118
	M	3.098	2.927	13.7	-15.0	1.60	0.110
Rural labor%	U	0.527	0.551	-15.4		-1.83	0.067
	M	0.527	0.523	3.0	80.4	0.70	0.482

Panel B: Mahalanobis distance matching (MDM)

	Unmatched/	Mean				t-test	
Outcome: income_rural	Matched	Treatment	Control	%bias	%bias reduction	t-value	p-value
Primary industry output	U	1.287	1.087	14.2		1.84	0.065
	M	1.287	1.146	10.0	29.2	1.53	0.126
Agricultural land area	U	0.672	0.467	46.4		6.46	0.000
	M	0.672	0.638	7.80	83.1	0.86	0.392
Oil crop production	U	0.025	0.019	20.0		2.87	0.004
	M	0.025	0.023	8.5	57.4	0.90	0.370
Wind potential	U	0.313	0.146	40.2		5.71	0.000
	M	0.313	0.313	0.0	100.0	0.00	1.000
Income_rural	U	3.098	2.949	11.9		1.57	0.118
	M	3.098	3.039	4.8	60.1	0.59	0.557
Rural labor%	U	0.527	0.551	-15.4		-1.83	0.067
	M	0.527	0.532	-2.7	82.2	-0.66	0.510

Table 3: Effect of RE-CDM on rural residential income

	Explained variable: Income_rural							
	PSM-DID				MDM-DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RE-CDM	0.311***		0.343***		0.237***		0.255***	
	(0.060)		(0.060)		(0.060)		(0.060)	
Biomass		0.284***		0.218**		0.188**		0.162**
		(0.082)		(0.085)		(0.076)		(0.074)
Wind		0.223***		0.272***		0.161***		0.192***
		(0.060)		(0.059)		(0.059)		(0.059)
Solar		-0.458		-0.565		-0.426		-0.628*
		(0.337)		(0.349)		(0.325)		(0.334)
Multi-projects		-0.0303		0.102		-0.00250		0.105
		(0.298)		(0.310)		(0.285)		(0.293)
Primary industry output	0.109	0.109	0.0677	0.0709	0.314***	0.315**	0.321	0.331
	(0.070)	(0.071)	(0.047)	(0.050)	(0.121)	(0.122)	(0.200)	(0.206)
Agricultural land area	-1.006***	-0.998***	-1.157***	-1.164***	-1.005***	-0.999***	-1.022***	-1.010***
	(0.233)	(0.246)	(0.260)	(0.273)	(0.218)	(0.227)	(0.259)	(0.268)
Government revenue	1.252***	1.255***	1.162***	1.168***	1.271***	1.271***	1.281***	1.285***
	(0.131)	(0.132)	(0.132)	(0.134)	(0.115)	(0.116)	(0.113)	(0.115)
Student%	-3.903***	-3.989***	-3.429***	-3.572***	-2.782***	-2.824***	-2.802***	-2.859***
	(0.801)	(0.828)	(0.792)	(0.825)	(0.820)	(0.840)	(0.813)	(0.837)
Oil crop production	2.630***	2.873***	2.973**	3.133**	2.129**	2.324**	1.346	1.440
	(1.002)	(1.020)	(1.478)	(1.527)	(1.008)	(1.030)	(1.779)	(1.823)
Machinery power	0.167**	0.163*	0.101*	0.105*	0.081	0.080	0.097*	0.100*
	(0.085)	(0.085)	(0.057)	(0.060)	(0.060)	(0.060)	(0.051)	(0.053)
Constant	5.342***	5.350***	5.380***	5.395***	3.770***	3.770***	3.773***	3.766***
	(0.276)	(0.279)	(0.244)	(0.250)	(0.175)	(0.178)	(0.232)	(0.239)
Baseline characteristics × Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3384	3384	3384	3384	3566	3566	3566	3566
Adj. R^2	0.928	0.928	0.931	0.930	0.929	0.929	0.930	0.930

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4: Effect of RE-CDM on employment generation

	Explained variable: Rural labor%							
	PSM-DID				MDM-DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RE-CDM	1.128***		1.185***		1.222***		1.187***	
	(0.395)		(0.397)		(0.389)		(0.392)	
Biomass		1.484**		1.438**		1.472**		1.465**
		(0.659)		(0.641)		(0.651)		(0.638)
Wind		0.637		0.762*		0.796*		0.798*
		(0.454)		(0.460)		(0.450)		(0.453)
Solar		-4.016**		-4.504**		-3.685**		-3.823**
		(1.723)		(1.755)		(1.709)		(1.725)
Multi-projects		2.190		2.421*		2.070		2.113
		(1.349)		(1.325)		(1.337)		(1.327)
Primary industry output	0.212*	0.208*	0.267*	0.275*	0.634**	0.625**	1.004*	1.039*
	(0.115)	(0.113)	(0.160)	(0.167)	(0.265)	(0.263)	(0.586)	(0.606)
Agricultural land area	-1.350	-1.258	-1.129	-1.029	-1.100	-1.070	-0.525	-0.438
	(1.186)	(1.236)	(1.145)	(1.187)	(1.084)	(1.126)	(1.088)	(1.122)
Government revenue	-0.043	-0.032	0.011	0.049	0.210	0.222	0.272	0.312
	(0.311)	(0.313)	(0.341)	(0.345)	(0.338)	(0.340)	(0.353)	(0.357)
Student%	-0.013	-0.016	-0.008	-0.012	0.022	0.020	0.031	0.029
	(0.059)	(0.059)	(0.059)	(0.059)	(0.062)	(0.062)	(0.062)	(0.062)
Oil crop production	19.68**	21.11***	22.35***	23.35***	13.16*	14.43*	11.53	12.23
	(7.643)	(7.744)	(8.125)	(8.239)	(7.405)	(7.508)	(8.282)	(8.447)
Machinery power	-0.481*	-0.516*	-0.0192	-0.0354	-0.455	-0.481	0.004	-0.0145
	(0.279)	(0.294)	(0.234)	(0.240)	(0.285)	(0.297)	(0.207)	(0.213)
Constant	58.24***	58.26***	57.61***	57.63***	48.98***	49.00***	48.31***	48.28***
	(1.393)	(1.404)	(1.391)	(1.400)	(1.131)	(1.138)	(1.266)	(1.281)
Baseline characteristics × Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3397	3397	3397	3397	3579	3579	3579	3579
Adj. R^2	0.705	0.705	0.707	0.707	0.715	0.714	0.717	0.716

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 5: Effect of RE-CDM on employment in the primary sector

	Explained variable: Rural labor_primary%							
	PSM-DID				MDM-DID			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RE-CDM	0.548		0.579		0.809**		0.815**	
	(0.385)		(0.401)		(0.381)		(0.404)	
Biomass		-0.428		-0.447		-0.289		-0.259
		(0.438)		(0.438)		(0.425)		(0.416)
Wind		1.418***		1.500***		1.705***		1.714***
		(0.467)		(0.484)		(0.460)		(0.484)
Solar		-4.974**		-5.130**		-4.850**		-4.365**
		(1.979)		(2.057)		(1.963)		(2.040)
Multi-projects		-2.015		-2.020		-2.043		-2.276
		(1.438)		(1.506)		(1.411)		(1.505)
Primary industry output	-0.103	-0.102	-0.031	-0.023	-0.323	-0.311	-0.325	-0.286
	(0.103)	(0.102)	(0.080)	(0.06)	(0.210)	(0.205)	(0.343)	(0.326)
Agricultural land area	3.244***	3.230***	3.346***	3.328***	3.379***	3.326***	3.311***	3.273***
	(1.034)	(1.034)	(1.000)	(1.010)	(1.013)	(1.010)	(0.974)	(0.987)
Government revenue	-1.418**	-1.468**	-1.389**	-1.415**	-1.261*	-1.316**	-1.382**	-1.415**
	(0.572)	(0.573)	(0.624)	(0.624)	(0.648)	(0.649)	(0.699)	(0.700)
Student%	0.229***	0.231***	0.231***	0.231***	0.168**	0.168**	0.174***	0.174***
	(0.066)	(0.065)	(0.066)	(0.066)	(0.065)	(0.065)	(0.066)	(0.066)
Oil crop production	19.51**	19.09**	15.52	15.17	17.16**	16.51**	11.02	10.20
	(8.342)	(8.210)	(12.66)	(12.62)	(7.559)	(7.372)	(11.35)	(11.31)
Machinery power	-1.115***	-1.059***	-0.682**	-0.600**	-0.721**	-0.661**	-0.464**	-0.384**
	(0.407)	(0.388)	(0.288)	(0.263)	(0.295)	(0.283)	(0.199)	(0.192)
Constant	16.04***	16.02***	15.58***	15.55***	22.35***	22.40***	22.71***	22.72***
	(1.587)	(1.584)	(1.711)	(1.715)	(1.345)	(1.350)	(1.845)	(1.855)
Baseline characteristics × Year dummy	No	No	Yes	Yes	No	No	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3398	3398	3398	3398	3580	3580	3580	3580
Adj. R^2	0.607	0.608	0.607	0.607	0.603	0.604	0.603	0.604

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table 6: Number of RE-CDM projects

	Income_rural		Rural labor%		Rural labor_primary%	
	(1)	(2)	(3)	(4)	(5)	(6)
1 project	0.247***	0.187***	0.909**	1.031**	0.577	0.815*
	(0.0566)	(0.0542)	(0.442)	(0.438)	(0.430)	(0.424)
2 projects	0.229*	0.136	1.170*	1.256*	0.894	1.238**
	(0.119)	(0.120)	(0.693)	(0.694)	(0.628)	(0.624)
$\geq$ 3 projects	0.155	0.0696	2.404*	2.558*	2.138**	2.548**
	(0.160)	(0.158)	(1.347)	(1.341)	(1.052)	(1.043)
Primary industry output	0.111	0.318***	0.220*	0.656**	-0.101	-0.311
	(0.0714)	(0.123)	(0.119)	(0.271)	(0.102)	(0.206)
Agricultural land area	-1.015***	-1.006***	-1.532	-1.265	3.067***	3.195***
	(0.245)	(0.226)	(1.223)	(1.114)	(1.003)	(0.979)
Government revenue	1.256***	1.274***	-0.0553	0.192	-1.438**	-1.283**
	(0.117)	(0.132)	(0.310)	(0.336)	(0.573)	(0.648)
Student%	-4.047***	-2.853***	-0.0181	0.0170	0.228***	0.164**
	(0.832)	(0.843)	(0.0589)	(0.0616)	(0.0654)	(0.0654)
Oil crop production	2.774***	2.256**	19.63**	13.03*	19.12**	16.71**
	(1.023)	(1.024)	(7.673)	(7.440)	(8.338)	(7.549)
Machinery power	0.168*	0.0813	-0.472*	-0.450	-1.108***	-0.715**
	(0.0859)	(0.0599)	(0.275)	(0.284)	(0.405)	(0.295)
Constant	5.361***	3.774***	58.39***	49.10***	16.15***	22.48***
	(0.281)	(0.179)	(1.394)	(1.133)	(1.593)	(1.351)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	3384	3566	3397	3579	3398	3580
adj. R^2	0.928	0.929	0.705	0.715	0.607	0.603

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix

Table A1: Interaction between treatment and each year

	Income_rural		Rural labor%		Rural labor_primary%	
	PSM-DID	MDM-DID	PSM-DID	MDM-DID	PSM-DID	MDM-DID
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment × 2002	-0.033	0.001	0.304	0.275	-1.871	-2.505*
	(0.081)	(0.075)	(0.510)	(0.483)	(1.446)	(1.451)
Treatment × 2003	0.025	0.074	0.212	0.131	-1.781	-2.333
	(0.077)	(0.072)	(0.503)	(0.483)	(1.452)	(1.454)
Treatment × 2005	0.099	0.119**	0.043	0.098	-1.858	-2.384*
	(0.062)	(0.060)	(0.478)	(0.464)	(1.433)	(1.440)
Treatment × 2006	0.151**	0.138**	0.565	1.002**	-1.167	-1.514
	(0.068)	(0.063)	(0.550)	(0.487)	(1.498)	(1.500)
Treatment × 2007	0.213***	0.152**	1.054*	1.331**	-1.059	-1.206
	(0.065)	(0.062)	(0.567)	(0.557)	(1.446)	(1.456)
Treatment × 2008	0.271***	0.152**	1.125**	1.274**	-0.594	-0.780
	(0.071)	(0.067)	(0.554)	(0.512)	(1.459)	(1.464)
Treatment × 2009	0.298***	0.172**	0.800	1.204**	-1.414	-1.267
	(0.087)	(0.085)	(0.547)	(0.539)	(1.504)	(1.506)
Treatment × 2010	0.385***	0.208*	0.905	1.158	-1.713	-1.216
	(0.116)	(0.118)	(0.832)	(0.825)	(1.562)	(1.558)
Treatment × 2011	3.034***	2.700***	5.826***	4.977***	-4.042**	-4.258***
	(0.265)	(0.295)	(1.952)	(1.922)	(1.626)	(1.603)
Primary industry output	0.0799	0.257**	0.161*	0.542**	-0.0474	-0.231
	(0.054)	(0.102)	(0.093)	(0.236)	(0.0795)	(0.178)
Agricultural land area	-0.371**	-0.479**	-0.130	-0.208	2.424**	2.466**
	(0.173)	(0.197)	(1.167)	(1.085)	(1.039)	(0.981)
Government revenue	1.211***	1.246***	-0.114	0.174	-1.335**	-1.172*
	(0.109)	(0.126)	(0.306)	(0.335)	(0.567)	(0.645)
Student%	-2.591***	-1.676**	0.005	0.028	0.202***	0.135**
	(0.709)	(0.765)	(0.060)	(0.063)	(0.067)	(0.067)
Oil crop production	3.051***	2.675***	21.18***	14.69**	19.24**	17.10**
	(0.905)	(0.947)	(7.704)	(7.492)	(8.395)	(7.687)
Machinery power	0.128*	0.060	-0.556*	-0.510*	-1.072***	-0.706**
	(0.068)	(0.048)	(0.299)	(0.292)	(0.395)	(0.297)
Constant	4.831***	3.502***	57.24***	48.96***	17.21***	22.18***
	(0.219)	(0.178)	(1.459)	(1.167)	(1.935)	(1.126)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	3384	3566	3398	3580	3398	3580
adj. R^2	0.935	0.934	0.692	0.701	0.607	0.604

Note: The general form of the multi-period DID model can be written as: $y_{it} = \alpha + \sum_{t=-2}^{7} \beta_t Treatment_i \times \gamma_t + \lambda X_{it} + \delta_i + \gamma_t + \epsilon_{it}$. Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table A2: Full sample without matching

	Income_rural		Rural labor%		Rural labor_primary%	
	(1)	(2)	(3)	(4)	(5)	(6)
RE-CDM	0.475**		1.270***		0.801***	
	(0.196)		(0.353)		(0.299)	
Biomass		1.412***		1.060*		0.183
		(0.305)		(0.577)		(0.474)
Wind		0.270		1.140***		1.660***
		(0.225)		(0.415)		(0.348)
Solar		0.005		-3.920*		-2.830**
		(0.718)		(2.180)		(1.410)
Multi-projects		-0.258		2.510		-2.850**
		(0.670)		(1.750)		(1.110)
Primary industry output	-0.292	-0.300	0.230	0.232	-0.469*	-0.467*
	(0.218)	(0.221)	(0.192)	(0.193)	(0.243)	(0.241)
Agricultural land area	4.822***	4.857***	-3.340***	-3.340***	1.710**	1.850**
	(0.625)	(0.625)	(1.160)	(1.180)	(0.822)	(0.839)
Government revenue	11.34***	11.34***	-0.140	-1.350	-0.496***	-0.495***
	(1.059)	(1.059)	(0.148)	(0.147)	(0.139)	(0.139)
Student%	2.205	2.163	-0.083	-0.084	-0.006	-0.007
	(2.230)	(2.235)	(0.058)	(0.058)	(0.035)	(0.035)
Oil crop production	12.28**	12.93**	16.60	16.80	-1.040	-0.813
	(6.077)	(6.102)	(13.80)	(13.90)	(6.740)	(6.660)
Machinery power	-1.864***	-1.890***	-0.057	-0.053	-1.540***	-1.510***
	(0.686)	(0.698)	(0.260)	(0.261)	(0.463)	(0.005)
Constant	0.940	0.950	52.60***	52.60***	0.252***	0.252***
	(0.592)	(0.594)	(0.012)	(1.220)	(0.934)	(0.932)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	11105	11105	12938	12938	12938	12938
Adj. R^2	0.529	0.529	0.316	0.316	0.540	0.540

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

Table A3: Effect of additional thermal power

	Income_rural				Rural labor%				Rural labor_primary%			
	PSM-DID		MDM-DID		PSM-DID		MDM-DID		PSM-DID		MDM-DID	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Thermal power	-2.585***	-1.524**	-1.050**	-0.212	-0.305	-0.524	-0.150	-0.407	0.143	0.222	0.393	0.478
	(0.745)	(0.653)	(0.443)	(0.301)	(0.331)	(0.339)	(0.348)	(0.359)	(0.392)	(0.389)	(0.371)	(0.374)
Primary industry output	-2.186***	-3.721***	-1.213**	-1.935**	0.654**	0.912***	0.631**	0.834**	-0.062	0.350	-0.606**	-0.372
	(0.651)	(0.847)	(0.610)	(0.854)	(0.324)	(0.337)	(0.321)	(0.354)	(0.268)	(0.281)	(0.244)	(0.261)
Agricultural land area	6.947***	5.680***	4.231***	3.359***	-2.852**	-2.617*	-1.543	-1.399	-3.418**	-3.547**	-1.297	-1.413
	(1.192)	(1.158)	(0.801)	(0.737)	(1.436)	(1.438)	(1.445)	(1.448)	(1.507)	(1.489)	(1.365)	(1.363)
Government revenue	15.236***	16.693***	11.112***	11.558***	-0.249	-0.560***	-0.156	-0.273	-0.248*	-0.193	-0.056	-0.013
	(2.933)	(3.142)	(2.666)	(2.999)	(0.168)	(0.176)	(0.141)	(0.182)	(0.140)	(0.123)	(0.173)	(0.158)
Student%	0.054	0.080	0.148***	0.149***	-0.180***	-0.171***	-0.118*	-0.109	-0.078	-0.088	-0.166	-0.161
	(0.052)	(0.050)	(0.046)	(0.046)	(0.061)	(0.060)	(0.068)	(0.068)	(0.059)	(0.059)	(0.109)	(0.108)
Oil crop production	18.791	14.470	11.561	8.810	4.125	14.991	1.910	8.314	-4.140	21.460*	4.480	20.250**
	(11.630)	(12.235)	(10.719)	(10.833)	(11.974)	(12.720)	(10.462)	(10.974)	(11.367)	(12.384)	(9.349)	(10.227)
Machinery power	-1.001	-1.110	-1.162	-1.101	-0.029	0.068	0.041	0.140	-0.334	-0.053	-0.139	0.041
	(0.699)	(0.695)	(0.840)	(0.834)	(0.120)	(0.183)	(0.131)	(0.165)	(0.204)	(0.197)	(0.086)	(0.146)
Constant	4.073**	7.869***	-0.568	1.413	61.227***	59.875***	51.178***	50.142***	22.676***	21.423***	26.499***	26.012***
	(1.622)	(1.884)	(0.848)	(1.001)	(1.521)	(1.609)	(1.152)	(1.205)	(1.345)	(1.366)	(1.769)	(1.819)
Baseline characteristics × year dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3148	3148	3436	3436	3148	3148	3436	3436	3149	3149	3437	3437
adj. R^2	0.493	0.531	0.509	0.525	0.750	0.752	0.724	0.725	0.896	0.897	0.879	0.880

Note: Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.