Received: 2 June 2022 | Accepted: 12 March 2023

DOI: 10.1111/1467-8489.12515

ORIGINAL ARTICLE

The Australian Journal of Agricultural and Resource Economics · AARES

Has Chinese Certified Emission Reduction trading reduced rural poverty in China?

Yue-Jun Zhang[1,2] | Jing-Yue Liu[1,2] | Richard T. Woodward[3]

[1]Business School, Hunan University, Changsha, 410082, China

[2]Center for Resource and Environmental Management, Hunan University, Changsha, 410082, China

[3]Department of Agricultural Economics, Texas A&M University, TAMU2124, College Station, Texas 77843-2124, USA

Correspondence
Jing-Yue Liu, Business School, Hunan University, Changsha 410082, China.
Email: kerryla@foxmail.com

Funding information
National Natural Science Foundation of China, Grant/Award Number: 72204081, 71774051 and 72243003; National Social Science Fund of China, Grant/Award Number: 22AZD128

Abstract

Consolidating and expanding poverty alleviation while simultaneously reducing carbon emissions has become one of the main issues facing China. The Chinese Certified Emission Reduction (CCER) trading programme is an important supplementary mechanism to China's carbon trading market. Based on the data of 1782 counties in China from 2006 to 2017 and a difference-in-differences model, this study investigates the rural poverty reduction effect of CCER trading. We find that: (1) during the sample period, CCER trading has increased the per capita net income of rural residents by at least 2.5% or 187.5 RMB (about 27.8 USD or 39.3 AUD) per year. (2) The poverty reduction effect of CCER trading in poor counties is greater than that in nonpoor counties. (3) Some relevant heterogeneous effects are also measured. We find that CCER trading of hydropower projects has played a significant poverty reduction effect; the poverty reduction effect is further enhanced when the county has additional CCER projects; we also identify regional differences with CCER trading having a greater poverty reduction effect in the western and central regions. (4) Compared with the implementation of the CCER project, trading the emission reductions generated by the CCER project has brought more significant poverty reduction effects.

KEYWORDS

carbon trading, CCER, Certified Emission Reduction, difference-in-differences, poverty reduction

1 | INTRODUCTION

Since the implementation of reform and opening up in 1978, China has experienced rapid economic and social development and has made remarkable achievements in poverty reduction (Huang et al., 2020; Liu et al., 2020). *Poverty Alleviation: China's Experience and Contribution*, released by China's State Council, states that by the end of 2020, 98.99 million people in rural areas who were living below the current poverty threshold had been moved out of absolute poverty.[1] However, not only has economic development reduced poverty in China, but it has also brought serious environmental problems. As per its history of high-carbon fossil energy consumption and its sloppy development pattern (Adams, 2004; Shan et al., 2016), China has become the world's largest emitter of carbon dioxide (BP, 2022; Zhang & Cheng, 2021). In the context of global advocacy for low-carbon development, China is seeking a green development path that can further reduce poverty while simultaneously yielding ecological benefits.

Carbon trading is a market-based approach to reducing greenhouse gas emissions cost-effectively and has become China's national strategy for controlling greenhouse gas emissions (Jiang et al., 2018; Liu & Zhang, 2021). In January 2018, the National Development and Reform Commission of China (NDRC) issued the *Ecological Poverty Alleviation Work Plan*. This plan seeks to reform the voluntary greenhouse gas emission reduction trading programme (i.e. the Chinese Certified Emission Reduction [CCER] trading) to increase the support the programme provides for poor areas. Hence, an important but unanswered question is, 'does CCER trading in the carbon market help reduce rural poverty in China?' Exploring this question can provide insights for developing countries and newly industrialised countries to practice low-carbon poverty reduction. Particularly in the context of the *Paris Agreement*, ninety six countries have adopted carbon trading as an important policy tool to achieve their emission reduction commitments (World Bank, 2019), and these countries must simultaneously pursue economic development.

China's carbon trading programmes can be divided into two categories, allowance trading and Chinese Certified Emission Reduction (i.e. CCER) trading. In allowance trading, enterprises trade carbon allowances that are set and allocated following a 'Cap and Trade' type structure (Ross Lambie, 2010; Yan et al., 2022). The CCER programme is supplementary to the allowance market; enterprises can offset their carbon dioxide emissions by purchasing CCERs, which are generated from emission reduction projects (Galinato et al., 2011; Ye et al., 2021). The background of the CCER programme is shown in Note A1 in Appendix S1.

Most studies on carbon trading have focussed on the emission reduction effect (Cui et al., 2021; Liu, Woodward, & Zhang, 2021), but few studies have focussed on carbon trading's effect on poverty. Zhang and Zhang (2020) explore the poverty reduction effects of allowance trading in China's carbon trading market using a sample of 30 provinces. However, existing studies only examined the poverty reduction effect of allowance trading; the effect of CCER project trading remains to be examined. Moreover, existing studies only use provincial data (Zhang & Zhang, 2020), which makes it difficult to capture possibly important county-level variation. Few studies focus on the CCER mechanism in the carbon market (Cong et al., 2021; Ye et al., 2021), probably because CCER trading is a supplementary

[1]Poverty can be divided into absolute and relative poverty (Decerf, 2017). Absolute poverty is poverty on the material level, which means that income cannot meet the needs of survival (Allen, 2017), and relative poverty is based on comparing the living standard of the poor with that of the less poor members of society (Peng & Mao, 2022). Compared with absolute poverty, which focusses on the basic needs of low-income groups, relative poverty focusses more on the inequalities in the distribution of wealth, income and power (Wan et al., 2021). China's poverty reduction achievements and official poverty alleviation standards refer to absolute poverty. This paper takes China as the background, and to be consistent with the official standards of the Chinese government, rural poverty in this paper also refers to absolute poverty measured by per capita net income of rural residents.

mechanism to the carbon market. Also, the CCER programme originated late, and considering the small trading volume and the lack of standardisation of several projects in the CCER programme, the NDRC has suspended new CCER project applications since 2017, which results in a lack of continuity of data (Li, Ye, et al., 2019). Given the problems with the CCER programme, it is necessary to determine whether CCER trading can achieve the desired poverty reduction effect. Numerous authors have explored the poverty reduction effects of implementing carbon reduction projects, such as Clean Development Mechanism (CDM) projects (Du & Takeuchi, 2019; Mori-Clement, 2019) and Photovoltaic (PV) projects (Li, 2019; Li et al., 2020). Focussing solely on the implementation of carbon reduction projects fails to recognise the effect of the market mechanism. By studying CCER projects, we are able to look at the effects of carbon reduction projects on poverty and the trading that is behind those projects.

Using panel data of 1782 county-level administrative regions in China from 2006 to 2017, this paper empirically investigates the poverty reduction effect of CCER trading using a difference-in-differences (DID) model. We answer the following questions: Has CCER trading reduced rural poverty in China? Has this effect differed between poor and nonpoor counties? Has the effect of CCER trading on rural poverty varied with the type, number, emission reduction scale and distribution region of the CCER project? Finally, is there a difference between the poverty reduction effect of implementing the CCER project and the poverty reduction effect of CCER trading?

Compared with existing studies, the contributions of this paper are as follows. First, this paper looks specifically at the poverty reduction effect of carbon trading, which can provide empirical evidence for China and other developing countries to realise the 'win-win' of carbon reduction and poverty alleviation by market means. Second, unlike the existing literature that focusses mainly on allowance trading, this paper focusses on CCER trading. It is important to examine the poverty reduction effect of the CCER programme because compared with allowance trading, it has a broader poverty reduction coverage and a clearer poverty reduction mechanism.[2] Third, poverty levels vary significantly between counties within a single province's poor area; the existing studies are mainly at the provincial and city level, making it difficult to reveal the real poverty reduction effects of carbon trading at the county level. By using Chinese county-level data, this paper adresses the variation in poverty levels among counties.

2 | DATA AND METHODS

2.1 | Data

Considering that new CCER applications have been suspended since 2017, our sample interval is considered only until 2017. Using panel data of 1782 county-level administrative regions in China from 2006 to 2017, this paper explores the poverty reduction effect of CCER trading in China's carbon trading market, and the data are described below.

[2]Regarding poverty reduction coverage, allowance trading is limited to the seven pilot areas with relatively developed economies and does not cover poor areas outside the pilot. CCER projects, on the contrary, are widely distributed throughout China and are more representative of poor areas. In fact, China's poor areas are so widely distributed that most of them are not located in the seven pilots. These poor areas are the focus of China's poverty eradication efforts. In terms of poverty reduction mechanism, in allowance trading, the trading parties are the emission control enterprises in the pilot; thus, the capital flow only exists between the emission control enterprises in the same pilot. In CCER trading, its trading parties are the emission control enterprises and the CCER project suppliers from all over China; thus, through CCER trading, funds can flow from the emission control enterprises to the project suppliers to achieve poverty reduction.

TABLE 1 Categories of CCER projects.

CCER project type	Overall CCER	Sample CCER in this paper	Proportion of samples	Counties in sample with projects
Wind power	90	61	67.8%	42
PV	48	23	47.9%	16
Biogas	41	41	100.0%	47
Hydropower	32	27	84.4%	28
Biomass	17	14	82.4%	14
Waste disposal	9	2	22.2%	2
Gas power generation	9	5	55.6%	3
Waste heat and geothermal utilisation	3	2	66.7%	2
Others	5	2	40.0%	7
Total	254	177	70.0%	154[a]

County type	County with CCER projects (Treatment group)	County without CCER projects (Control group)	Total
Poor county	74	605	679
Nonpoor county	80	1023	1103
Total	154	1628	1782

[a]Since some counties have multiple types of projects, the sum does not equal to 154.

2.1.1 | CCER projects

The related information and data of CCER projects are from the Chinese Certified Emission Reduction Exchange Info-Platform.[3] The 254 CCER projects published in this platform cover 213 counties. There are missing data in the *China County Statistical Yearbook* and statistical yearbooks of various provinces; for example, the per capita net income of rural residents at the county level is not disclosed in Qinghai, Tibet, Guangdong and Sichuan.[4] Hence, after excluding the counties with missing data, our sample finally contains 177 CCER projects covering 154 counties, and the categories of CCER projects are shown in Table 1. Table 1 and Figure A1 in the Appendix S1 show that these 177 sample CCER projects account for 70% of all CCER projects, and the economic and geographical distribution of the sample CCER projects is similar to that of the overall CCER. That is, CCER projects in our sample are representative of the overall CCER programme in terms of type, economic distribution and geographic distribution.

As noted above, before a project can be traded in the CCER programme, it must be established (i.e. built or implemented) and certified by the programme. The projects in our dataset were developed between 2006 and 2015, with an average date of 2011. Trading, however, did not start until 2014 and has occurred in only 154 counties, 151 with an initial trade in 2014 and the remaining three counties with the first trade in 2015. We consider two different treatment dates: the year when trading occurred (Sections 3 and 4.1) and the year when the project was implemented (Section 4.2).

[3]http://cdm. ccchina.org.cn/ccer.aspx

[4]The provinces with missing values are not concentrated in economically developed or economically backward range (Figure A1), and thus, we believe that these sample misses are less likely to bias our results.

TABLE 2 Definition of variables and descriptive statistics.

Variable	Symbol	Definition	Obs	Mean	Std. dev	Min	Max
Poverty	*RuralIncome*	the per capita net income of rural residents (RMB) (log)	18,737	8.742	0.608	3.258	11.505
	PerGDP	per capita GDP (RMB) (log)	18,737	9.849	0.812	7.394	13.038
	PerRevenue	per capita local government revenue (RMB) (log)	18,737	6.807	1.108	2.692	10.771
CCER trading	*CCER*	Whether there is a CCER transaction in the county	18,737	0.028	0.165	0.000	1.000
Fiscal structure	*Finance*	Local government expenditures/local government revenue	18,737	5.294	5.619	0.000	152.266
Production of oil crops	*OilCrop*	Output of oil-bearing crops (tonne) (log)	18,737	8.510	1.791	0.000	13.009
Industrial structure	*Industry*	The share of the added value of the secondary industries in GDP	18,737	0.440	0.154	0.000	0.989
Total capacity of agricultural machinery	*AgPower*	Power of agricultural machinery (10,000 kw) (log)	18,737	3.378	0.935	0.000	7.321
Education level	*EduLevel*	Number of students in regular secondary schools/Total population	18,737	0.051	0.016	0.002	0.467

Note: All data are annual data at county level. Data of *RuralIncome* are derived from statistical yearbooks of various provinces, whereas other data are taken from *China County Statistical Yearbook*.

2.1.2 | Nationally designated poor counties

In 2012, China's State Council Leading Group Office of Poverty Alleviation and Development released the *List of 832 Poverty-stricken Counties in China* based on county-level indicators that are highly correlated with poverty, such as per capita net income of rural residents, per capita GDP and per capita local government revenue. There are 679 poor counties in our sample, of which 74 poor counties contain CCER projects, and the sample distribution is shown in Table 1. It can be seen that among the 1782 counties considered in this paper, the 154 counties containing CCER projects are the treatment group, and the remaining 1628 counties are the control group, which contain 74 and 605 poor counties, respectively.

2.1.3 | Poverty indicators and control variables

China's current official poverty alleviation standard is the annual per capita net income of rural residents of 2300 RMB (about 341 USD or 483 AUD), which was decided by the Chinese government at the *Central Work Conference on Poverty Alleviation and Development* on 29 November 2011. Meanwhile, the most important indicator for China's State Council Leading Group Office of Poverty Alleviation and Development to identify poor counties is the per capita net income of rural residents, which was even the only indicator before 2011.[6] Hence, the per capita net income of rural residents is the most important indicator for determining China's poverty alleviation standards and identifying poor counties. Combining with existing studies (Du & Takeuchi, 2019; Zhang, Wu, et al., 2020), this paper selects the per capita net income of rural residents as the dependent variable and the following five county characteristics as control variables: fiscal structure, production of oil crops, industrial structure, the total capacity of agricultural machinery and education level. In the robustness test, this paper uses per capita county GDP and per capita county local government revenue as the substitute variables of poverty indicators, which are newly added by the Chinese government after 2011 to identify poor counties. Data on per capita net income of rural residents are obtained from each province's statistical yearbooks from 2007 to 2018, and data on control variables are from the *China County Statistical Yearbook* from 2007 to 2018. The definition of variables and descriptive statistics are shown in Table 2.

2.2 | Methods

This paper uses a DID model to assess the poverty reduction effects of CCER trading. This model, which is widely used in research on policy evaluation, controls for the ex ante differences of research subjects and effectively identifies policy effects (Drysdale & Hendricks, 2018; Greenstone & Hanna, 2014). The DID estimator contains two time periods, ‘pre’ and ‘post’, and two groups, ‘treatment’ and ‘control’. A DID estimate is the difference between the change in outcomes before and after treatment (difference one) in the treatment versus control groups (difference two; Goodman-Bacon, 2021). That is, by comparing the per capita net income of rural residents in the treatment group (counties with CCER projects) and the control group (counties without CCER projects) before and

[5]For details, please see *List of 832 Poverty Counties in the Country*, http://www.gov.cn/gzdt/2012-03/19/content_2094524.htm

[6]For detailed criteria for setting national poor counties, please refer to the following website, http://www.gov.cn/gzdt/2013-03/04/content_2344631.htm

TABLE 3 Poverty reduction effects of CCER trading.

	Dependent variable: ***RuralIncome***					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
CCER	0.036***	0.029***	0.025**			
	(0.012)	(0.011)	(0.010)			
*Poor*CCER*				0.096***	0.080***	0.062***
				(0.017)	(0.016)	(0.016)
Nonpoor CCER*				−0.027**	−0.024**	−0.013
				(0.013)	(0.011)	(0.011)
Finance		−0.001***	−0.001***		−0.001***	−0.001***
		(0.000)	(0.000)		(0.000)	(0.000)
OilCrop		0.008**	0.001		0.008**	0.001
		(0.004)	(0.003)		(0.004)	(0.003)
Industry		0.275***	0.208***		0.275***	0.208***
		(0.031)	(0.030)		(0.031)	(0.030)
AgPower		0.071***	0.039***		0.069***	0.038***
		(0.007)	(0.007)		(0.007)	(0.007)
EduLevel		0.739***	0.573***		0.713***	0.553***
		(0.203)	(0.184)		(0.201)	(0.183)
Constant	8.741***	8.281***	8.488***	8.742***	8.291***	8.491***
	(0.000)	(0.037)	(0.037)	(0.000)	(0.037)	(0.037)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
*Year FE*Region FE*			Y			Y
Observations	18,737	18,737	18,737	18,737	18,737	18,737
Adjusted R-squared	0.955	0.957	0.959	0.955	0.957	0.959

Note: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$; Robust standard errors that are clustered at county level are in parentheses; *Poor* and *Nonpoor* are dummy variables of national poor counties and nonpoor counties, respectively.

after the CCER transaction time, the causal effects of CCER trading on poverty alleviation can be effectively identified. Hence, this paper contains not only the sample after the CCER transaction but also the sample before the CCER transaction, and the DID model is as follows.

$$RuralIncome_{it} = \alpha_0 + \beta CCER_{it} + \sum_{k=1}^{5} \gamma_k x_{kit} + \eta_i + \mu_t + \varepsilon_{it} \quad (1)$$

where $CCER_{it}$ is the dummy variable, representing whether there is a CCER transaction in county i in year t. Since the first CCER transaction occurred in November 2013, we do not expect policy effects until 2014. We set the time of policy intervention to 2014, with $CCER_{it} = 1$ if county i contains CCER projects and year $t \geq 2014$, and $CCER_{it} = 0$ otherwise. Since three counties established CCER projects in 2015 and these projects participate in trading since 2015, $CCER_{it} = 1$ for these three counties when $t \geq 2015$. The model also includes five control variables $x_{kit}(k = 1, 2, \cdots, 5)$: *Finance*, *OilCrop*, *Industry*, *AgPower* and *EduLevel*. County and time fixed effects, that is η_i and μ_t, are also included in the model, controlling unobservable confounders that vary with the county but not with time, and unobservable confounders that vary with time but not with the county, respectively. In addition, to control unobservable confounders that vary both over time and over the region, this paper also controls interactive fixed effects of time and region (East, Central and West regions).[7] Finally, ε_{it} is the error term.

3 | RESULTS

3.1 | The poverty reduction effect of CCER trading

The impact of CCER trading on rural residents' per capita net income is shown in Table 3. Column 1 controls for county fixed effects and year fixed effects, Column 2 further controls the control variables, and Column 3 further controls the interactive fixed effects of year and region based on Column 2.

The DID results suggest that CCER trading significantly alleviates the rural poverty level in the counties where CCER projects are located. The estimates of Column 3 indicate that the poverty reduction effect of CCER trading is about 0.025; that is, on average, CCER trading increases the per capita net income of rural residents by 2.5% during the sample period. Since the average value of per capita net income of rural residents in counties without CCER projects during the sample period is 7499.86 RMB (about 1112.98 USD or 1571.87 AUD), this indicates that CCER trading increases the average per capita net income of rural residents by 187.5 RMB (about 27.8 USD or 39.3 AUD) per year. This result, along with Zhang and Zhang (2020), reflects the positive poverty reduction effect of China's carbon trading market. However, compared with Zhang and Zhang (2020), who examine the impact of allowance trading using provincial-level data, this paper has a broader coverage of poverty alleviation and a clearer poverty alleviation mechanism because it examines CCER trading and uses county-level data.

In Columns 4–6, we decompose the poverty reduction effect of CCER trading between poor counties and nonpoor counties. Column 6, which includes the full suite of control variables

[7]Region refers to the eastern, central and western regions of China. The eastern region includes 12 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi and Hainan; the central region includes nine provinces: Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan; the western region includes nine provinces: Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai and Xinjiang.

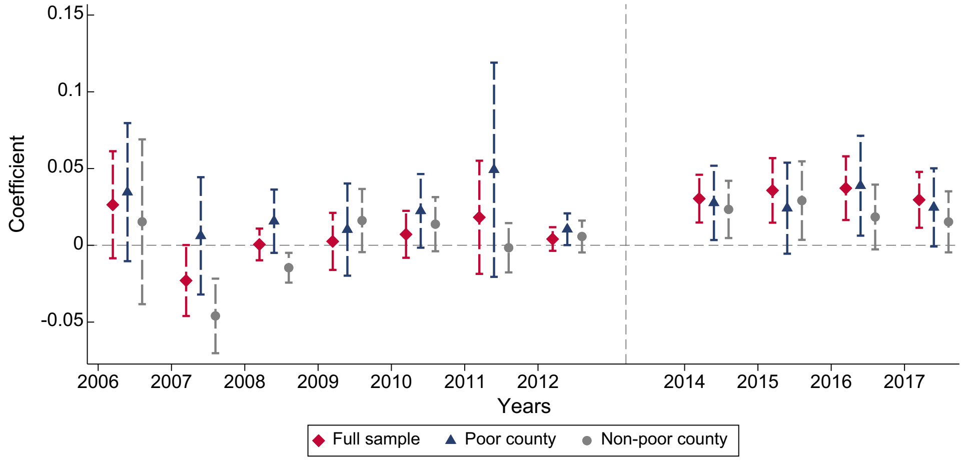

FIGURE 1 Parallel trend test: Estimated coefficients for the event study model with 95% confidence intervals. [Colour figure can be viewed at wileyonlinelibrary.com]

and fixed effects, is our most conservative specification. We estimate that during the sample period, CCER trading increases the per capita net income of rural residents in poor counties by 6.2% on average but has a slight negative, though statistically insignificant, impact on non-poor counties. One possible reason may be related to the fact that if CCER projects affect per capita income that is relatively constant across poor and nonpoor counties, this will result in a larger effect in percentage terms in the poor counties. The average per capita net income of rural residents in poor and nonpoor counties in the sample is 4872 RMB (about 723 USD or 1021 AUD) and 9040 RMB (about 1341.54 USD or 1894.66 AUD), respectively. A 6.2% increase in per capita income in the poor counties would equal to 300 RMB (44.52 USD or 62.88 AUD) income; a 300 RMB increase in nonpoor counties is only an increase of 3.3%. Hence, the marginal poverty reduction effect of CCER trading on poor counties may be greater than that of nonpoor counties. CCER trading can increase rural incomes, provide seed capital for rural residents and be an overall multiplier for rural economies in that 'money begets money' (Huang, 2018). In contrast, the income of rural residents in nonpoor counties is relatively high, and their production and business activities mostly rely on the accumulation of their funds (Wang et al., 2014); the funds brought by CCER trading are likely to be used for nonproductive projects. Thus, the effect of CCER trading on poverty reduction or income increase in non-poor counties is significantly lower than that in poor counties.

3.2 | Parallel trend test

The important condition for DID estimates to be unbiased is that the treatment and control groups meet the parallel trend assumption (Bose & Das, 2017). Without implementing CCER trading, the trend of the per capita net income of rural residents in the treatment group and the control group should be parallel, and there should be no systematic differences in pretrends across the treatment and control groups. Hence, referring to existing research (Greenstone & Hanna, 2014; Li, Liu, et al., 2019), this paper builds Model 2 based on the event study method to test the parallel trend assumption empirically.

$$RuralIncome_{it} = \alpha_0 + \sum_{j=-7}^{4} \beta_j Treated_{it}^{j} + \sum_{k=1}^{5} \gamma_k x_{kit} + \eta_i + \mu_t + \varepsilon_{it} \tag{2}$$

where $Treated_{it}^{j}$ is the dummy variable for the treatment group in the j^{th} year before and after the CCER trading.[8] The variable β_j represents the difference in poverty between the treatment group and the control group in the j^{th} year before and after the CCER trading.

Figure 1 plots the estimation results at 95% confidence intervals and shows that the treatment and control groups meet the parallel trend assumption. Specifically, from the results of the full sample (the red legend in Figure 1), when $j < 0$ (2006–2012), β_j is insignificant and approaches 0 (the mean value of β_j's is 0.0004), with no discernible trend over time. A significant difference in the pretreatment period was detected only in 2007; this indicates no significant difference in the poverty level between the treatment group and the control group before the CCER trading, supporting the parallel trend assumption. The values for β_j in the post-treatment period are strikingly different. After the CCER trading (2014–2017), the β_j values are significantly positive, indicating that since the CCER trading, the per capita net income of rural residents in the treatment group is significantly higher than that in the control group. In addition, the β_j values also show an increasing trend when $j > 0$; this suggests both that CCER trading has a sensitive and significant poverty reduction effect and that the poverty reduction effect of CCER trading has been increasing over time.

We also test parallel trends in the sample of poor and nonpoor counties, and the results are shown in the blue and grey legends in Figure 1, respectively. It can be seen that when $j < 0$ (2006–2012), 85.71% and 71.42% of the β_j values are insignificant in poor and nonpoor counties, respectively, and 75% of them are significantly positive in poor and nonpoor counties when $j > 0$. This indicates that samples for poor and nonpoor counties also satisfy the parallel trend assumption.

3.3 | Robustness test

To verify the validity of the results, we also conducted a series of robustness tests. First, our estimates may suffer from self-selection bias. To control for self-selection, referring to Wen et al. (2022), Zhang, Guo, et al. (2021) and Zhu et al. (2019), we re-estimate the DID model with a balanced sample of cities obtained using two matching methods: Propensity score matching (PSM) and Mahalanobis distance matching (MDM). After creating a balanced sample using both PSM-weighted DID and MDM-DID, we still find that CCER trading significantly alleviates poverty (Note A2 in Appendix S1). The second concern is whether the estimated effect results from spurious correlation driven by accidental factors, so we also use two placebo tests to investigate this issue (Note A3 in Appendix S1). Third, we are concerned about whether per capita net income of rural residents truly represents poverty. According to the *Identification of National Key Counties for Poverty Alleviation and Development and Counties in Contiguous Special Hardship Areas*, two additional statistics are strong indicators of poor counties: per capita county GDP (*PerGDP*) and per capita county local government revenue (*PerRevenue*). Here we test whether CCER trading also leads to improvements in these alternative two poverty-related indicators (Note A4 in Appendix S1). In addition, we replace the control group in this paper to further refine the poverty reduction effect. The control group was replaced from 1628 counties that do not participate in CCER trading to 328 counties with CCER projects but do not participate in CCER trading (Note A4 in Appendix S1). Finally, our estimates might capture the effects of other clean and low-carbon projects implemented during the same period. CDM and PV projects are typically clean and low-carbon projects in China (Liu, Huang, et al., 2021; Xie

[8] The first CCER trading occurred in November 2013, so we consider 2013 as the base year (i.e. $Treated_{it}^{0}$ is excluded).

[9] http://www.gov.cn:8080/gzdt/2013-03/01/content_2343058.htm

et al., 2014). Hence, to exclude the interference of CDM projects and PV projects in the results of this paper, we further control CDM projects and PV projects in our model (Note A5 in Appendix S1). All these results are consistent with the magnitudes in Table 3, supporting the conclusion that our results are robust.

4 | ADDITIONAL IMPACTS

4.1 | Heterogeneous effects of CCER projects

4.1.1 | Effects of different types of CCER projects

We use 177 CCER projects in our analysis, which can be divided into nine categories according to the types of project emission reduction activities, as shown in Table 1. Our analysis above finds that CCER trading significantly reduces poverty. We now evaluate whether that effect varies by project type. We evaluate that interacting the *CCER* variable with dummy variables for the following project types: *Wind*, *PV*, *Biogas*, *Hydropower and Biomass*, which together represent 95% of all projects in our data (Table 1) and a composite category, *Others*, which combines all other types including waste disposal, gas power generation, waste heat and geothermal utilisation.

Column 1 in Table 4 shows that CCER trading for hydropower significantly alleviates rural poverty in the counties where the projects are located. Specifically, *CCER*Hydropower* is significantly positive at the 5% level, which suggests that CCER trading for hydropower projects raises the per capita net income of rural residents in the counties where the projects are located by 8.5%. Considering that hydropower projects have a certain negative impact on the ecological environment (Auestad et al., 2018), most emissions exchanges restrict CCER trading from hydropower projects. Only the three exchanges in Shanghai, Hubei and Sichuan did not completely restrict hydropower projects (Table A1). There are several possible explanations for the significant hydropower results in the context of the unpopularity of hydropower projects in most exchanges. First, this may be related to the fact that hydropower projects are mainly located in Sichuan and Yunnan. These provinces not only have the highest installed hydropower capacity and generation capacity in China (Li, Chen, et al., 2018)[10] but also have more poor counties; this could lead to a relatively large marginal poverty reduction effect from hydropower CCER trading. Second, the hydropower CCER trading volume is large in the three exchanges that do not place restrictions on hydropower projects. In particular, the Sichuan emissions exchange, which ranks fifth in CCER's cumulative trading volume, not only does not place any restrictions on hydropower projects but also allows individual trading. This result is also in line with existing studies. For example, Mori-Clement (2019) estimates the poverty reduction effect of Brazil's CDM projects and finds that of the four types of projects, hydropower, biomass, landfill gas and methane avoidance, only the hydropower type of CDM projects achieved poverty reduction. Table 4, Column 1, shows our most conservative specification.[11]

4.1.2 | Effects of different numbers of CCER projects

Since our analysis covers 177 projects in 154 counties, several counties have more than one project. In our sample, 21 counties have more than one project; on average, there are 1.15

[10]https://news.bjx.com.cn/html/20170911/849086.shtml ; https://news.bjx.com.cn/html/20131016/465612.shtml

[11]Table A7 presents the full specification results, and in that case, CCER trading for wind power is also likely to have a 3.7% poverty reduction effect.

TABLE 4 Impact of different types, numbers and scales of CCER projects.

	Dependent variable: *RuralIncome*			
	(1)	**(2)**	**(3)**	**(4)**
*CCER*Wind*	0.026			
	(0.021)			
*CCER*PV*	0.030			
	(0.030)			
*CCER*Biogas*	−0.003			
	(0.012)			
*CCER*Hydropower*	0.085**			
	(0.035)			
*CCER*Biomass*	0.033			
	(0.024)			
*CCER*Others*	0.007			
	(0.026)			
*CCER*One-project*		0.021*		
		(0.011)		
*CCER*Multi-project*		0.046*		
		(0.024)		
CCER			0.025**	0.025**
			(0.010)	(0.010)
$CCER*ExpectedCO_2$			0.002	
			(0.010)	
$CCER*RealCO_2$				−0.013
				(0.010)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y
*Year FE*Region FE*	Y	Y	Y	Y
Observations	18,737	18,737	18,737	18,737
Adjusted R-squared	0.959	0.959	0.959	0.959

Note: (a) Robust standard errors that are clustered at county level are in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$. (b) This table includes the full suite of control variables and fixed effects and is our most conservative specification. For complete results, please refer to Tables A7–A9. (c) Variables *Wind*, *PV*, *Biogas*, *Hydropower* and *Biomass* are dummy variables for wind power, PV, biogas, hydropower and biomass, respectively; variable *Others* is a dummy variable that contains four project types: waste disposal, gas power generation, waste heat and geothermal utilisation, and others. (d) Variables *One-project* and *Multi-project* are dummy variables, which respectively indicate whether the number of projects is 1 and greater than 1. (e) Variables $ExpectedCO_2$ and $RealCO_2$ represent projects' expected CO_2 emission reductions and projects' actual emission reductions, respectively.

CCER projects per county in the treatment group. It is possible that the more projects a county has, the greater the poverty reduction effect of CCER trading in that county will be. Using the interaction terms between the variable *CCER* and the dummy variables (*One-project* and *multi-project*), this section will test whether additional projects have a positive effect. Variable *One-project* represents whether the number of projects in a county is 1, whereas Variable *multi-project* represents whether the number of projects in a county is greater than 1.

Column 2 in Table 4 shows that regardless of the number of CCER projects in a county, CCER trading has a significant rural poverty reduction effect on the county. This effect is further enhanced when the county has additional projects. As shown in Column 2, when the county has one CCER project and multiple CCER projects, the coefficients are 0.021 and 0.046, respectively; this may be because the more CCER projects owned by a county, the more projects and CCERs are involved in the transaction, and the greater the poverty reduction effect achieved through the transaction.

4.1.3 | Effects of different scales of CCER projects

CCER projects require a project design document (PDD) that reports the project's expected annual CO_2 emission reductions. Furthermore, the CCER project monitoring report estimates and reports the actual CO_2 emission reductions. Since different CCER projects have different CO_2 emission reduction scales, projects with larger emission reduction scales may have a larger poverty reduction effect. To investigate this issue, we add the interaction term between the variable *CCER* and dummy variables representing projects' CO_2 emission reductions, which can be divided into expected and actual emission reductions to Model 1, that is $CCER^{*}ExpectedCO_2$ and $CCER^{*}RealCO_2$. We examine whether the poverty reduction effect of CCER trading varies with a project's scale, in terms of either expected or monitored reductions. The results are shown in Columns 3 and 4 in Table 4.

We find that neither the projects' expected emission reductions nor the actual emission reductions significantly affect the poverty reduction effect of CCER trading. Specifically, Column 3 shows that projects' expected emission reductions do not significantly affect the poverty reduction effect of CCER trading. This result is consistent with Chen and Wan (2019), who find that CDM projects with a large scale of expected emission reduction do not have strong emission reduction effects. They believe this may be due to the exaggeration of the projects' expected emission reduction scale in the declaration to increase the pass rate of CDM projects.

In Column 4, we include the interaction term, $CCER^{*}RealCO_2$, and find that it is also insignificant. This suggests that the insignificance of the coefficient on $CCER^{*}ExpectedCO_2$ is unlikely to be due to exaggerating projects' expected emission reduction scale; neither the expected nor the actual emission estimates significantly change the poverty-reducing effect of CCER trading. We believe that the insignificant results of the projects' emission reduction scale may be related to the CCER trading rule of emissions exchange. The exchanges require that the CCERs available for trading only account for 5%–10% of the carbon allowances. This may result in the emissions reductions (i.e. CCERs) generated by the large-scale project that may not be sold in full, leaving CCERs in an oversupplied state in the market. In other words, there is a cap on how many CCERs can be sold regardless of the scale of the project, diminishing if not eliminating the impact of project scale in the generating county.

4.1.4 | Effects of different regions of CCER projects

Due to China's vast territory, the economic development level and natural geographical conditions of the eastern, central and western regions are quite different (Cheng et al., 2020; Zhang, Liu, & Su, 2020). In particular, the types of CCER projects that each region is good at developing are different due to natural constraints, and thus, the poverty reduction effects of CCER trading may vary in different regions. Hence, this section investigates whether the poverty reduction effect of CCER trading is heterogeneous by region using the interaction terms of the *CCER* and the dummy variables for three major regions: *East*, *Central* and *West*, representing 21.5%, 30.5% and 48% of all projects, respectively. Furthermore, we

TABLE 5 Impact of different regions of CCER projects.

	Dependent variable: *RuralIncome*			
		***Treated* = eastern region**	***Treated* = central region**	***Treated* = western region**
	(1)	**(2)**	**(3)**	**(4)**
*CCER*East*	−0.062***			
	(0.017)			
*CCER*Central*	0.051***			
	(0.015)			
*CCER*West*	0.061***			
	(0.016)			
CCER Poor*		−0.015	0.082***	0.092***
		(0.032)	(0.025)	(0.020)
*CCER*Nonpoor*		−0.074***	0.030**	−0.018
		(0.018)	(0.015)	(0.014)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Control variables	Y	Y	Y	Y
Observations	18,737	17,510	17,539	17,968
Adjusted R-squared	0.957	0.956	0.956	0.956

Note: (a) Robust standard errors that are clustered at county level are in parentheses; ***$p<0.01$, **$p<0.05$, *$p<0.1$. (b) This table includes the full suite of control variables and fixed effects and is our most conservative specification. (c) Variables *East*, *Central* and *West* are dummy variables for eastern, central and western regions, respectively. (d) Since this table is based on three major regions, there is no need to control Year FE*Region FE.

divide the treatment group into eastern, central and western regions and use the interaction terms between *CCER* and the dummy variables for county types (i.e. poor county and nonpoor county) to investigate the heterogeneous poverty reduction effects across regions and county types. It can be seen from Column 1 in Table 5 that the poverty reduction effect of CCER trading mainly occurs in the central and western regions. The CCER trading increases the per capita net income of rural residents in the central and western regions by 5.1% and 6.1%, respectively, while it reduces the per capita net income of rural residents in the eastern region by 6.2%.

Columns 2–4 show that the poverty reduction effects of CCER trading in poor and nonpoor counties are heterogeneous across regions. CCER trading produces a significant poverty reduction effect in the central and western regions and is mainly concentrated in poor counties. CCER trading significantly reduces rural poverty in poor and nonpoor counties in the central region. For the western region, CCER trading in nonpoor counties exerts significant poverty reduction effects. As shown in Column 4, the coefficient of *CCER*Poor* is significantly positive at the 1% level.

This spatial heterogeneity may be related to the different levels of economic development, project concentration and poverty reduction policies in the three major regions. During the sample period, the per capita net incomes of rural residents in the eastern, central and western regions are 9698, 7341 and 6131 RMB, respectively; the regions contain 51, 208 and 420 poor counties and have received 38, 54 and 85 CCER projects, respectively. Compared with the eastern region, the central and western regions have lower incomes and more poor counties. As a

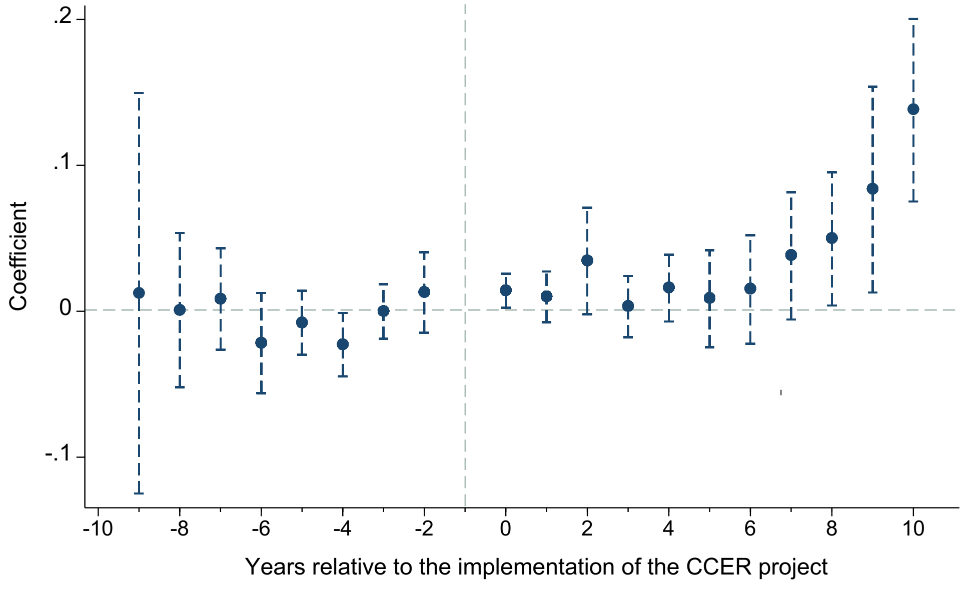

FIGURE 2 Parallel trend test of implementing the CCER project. [Colour figure can be viewed at wileyonlinelibrary.com]

result, the poorer regions have more emphasis on poverty reduction and a higher potential for poverty reduction (Choi et al., 2012; Cong et al., 2021). Hence, CCER trading is more likely to achieve positive and significant poverty reduction effects in the central and western regions. In addition, thanks to the natural geographical advantages, the central and western regions provide suitable conditions for renewable energy development, leading to more CCER projects in those regions (Lo & Cong, 2017). Overall, therefore, it is not surprising that we find significantly positive effects on poverty reduction in the western and central regions but negative effects in the eastern region.

4.2 | Effects of implementing CCER project

Numerous studies have analysed the poverty reduction effect of implementing carbon reduction projects (Liao & Fei, 2019; Mori-Clement, 2019; Pécastaing et al., 2018). They focus on the implementation or construction of projects rather than the transaction of emission reductions generated by projects studied in our paper. Generally, CCER projects include solar and wind energy projects, and solar and wind power generation from CCER projects will also generate revenue. Hence, could the change in poverty reduction effect be caused by implementing these CCER projects rather than by CCER transactions? It should be noted that there are differences between implementing the CCER project and CCER trading in terms of on whom they focus, when they occur, and their mechanisms for reducing poverty. The implementation of CCER projects focusses on establishing or constructing CCER projects, which are distributed from 2005 to 2015 in our sample, while trading refers to the trade date, either 2014 or 2015. The poverty reduction mechanism of implementing the CCER project may come from the sale of renewable energy power generation, the promotion of industrial development, the provision of employment opportunities and government subsidies for the construction and operation of projects. When CCER trading occurs,

TABLE 6 Poverty reduction effect of implementing CCER projects.

	Dependent variable: *RuralIncome*		
	(1)	**(2)**	**(3)**
Project	0.025*	0.019	0.015
	(0.013)	(0.012)	(0.011)
Finance		−0.001***	−0.001***
		(0.000)	(0.000)
OilCrop		0.008**	0.001
		(0.004)	(0.003)
Industry		0.276***	0.209***
		(0.031)	(0.030)
AgPower		0.071***	0.039***
		(0.007)	(0.007)
EduLevel		0.744***	0.579***
		(0.204)	(0.185)
Constant	8.741***	8.279***	8.486***
	(0.001)	(0.037)	(0.037)
County FE	Y	Y	Y
Year FE	Y	Y	Y
*Year FE*Region FE*			Y
Observations	18,737	18,737	18,737
Adjusted R-squared	0.955	0.957	0.959

Note: Robust standard errors that are clustered at county level are in parentheses; $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

project suppliers can profit from the sale of CCERs in the carbon market, thus creating an additional poverty reduction effect.[12]

In this section, we analyse whether the implementation or construction of CCER carbon reduction projects also has a poverty reduction effect. First, we test the parallel trend between the treatment and control groups. As shown in Figure 2, before the implementation of the CCER project, there was no significant difference between the poverty level in the treatment group and the control group. This indicates that the treatment and control groups meet the parallel trend assumption. However, after the implementation of the CCER project, the coefficients show an overall upward trend; that is, the per capita net income of rural residents in the treatment group shows an increasing trend relative to the control group.

Model 3 is built to test the poverty reduction effect of implementing CCER projects:

$$RuralIncome_{it} = \alpha_0 + \beta Project_{it} + \sum_{k=1}^{5} \gamma_k x_{kit} + \eta_i + \mu_t + \varepsilon_{it} \tag{3}$$

[12]For example, in the process of generating emission reductions and exerting carbon emission reduction effects for a CCER project built in 2010, the emission reductions generated from implementing CCER project were not assigned a commodity value, and its poverty reduction effect relied mainly on the government subsidies for the project; the project provided employment opportunities and promoted industrial development, among other ways. When CCER trading was started in November 2013, the emission reductions generated by the project were given a commodity value and could be sold to enterprises through the carbon market, and the poverty reduction effect of CCER trading relied mainly on selling the emission reductions to enterprises, thus making profits.

where $Project_{it}$ is a dummy variable, and $Project_{it} = 1$ if county i implements or establishes the CCER project in year t, otherwise $Project_{it} = 0$.

The estimates of Model 3 are shown in Table 6. It can be seen that the poverty reduction effect produced by implementing a CCER project is relatively weak. The coefficient on *Project* is positive in Columns 1–3, but only statistically significant (at the 10% level) in Column 1. Although we do not find the strong poverty reduction effects of carbon reduction projects that have been found in earlier studies (Du & Takeuchi, 2019; Grover & Rao, 2020; Mori-Clement, 2019), we do find that the implementation of CCER projects contributes to poverty reduction. However, our analysis suggests that the trading of CCERs brings greater poverty reduction effects than their implementation.

Existing relevant studies (Li, Zhang, et al., 2018; Zhang, Xu, et al., 2021) show that the implementation and operation of carbon reduction projects mainly rely on financial subsidies and support policies provided by the central and local governments and face problems such as large funding gaps and ineffective implementation of subsidies. This makes it difficult for the current profit distribution mechanism of low-carbon projects to attract local residents to participate in low-carbon poverty reduction projects such as PV power generation. In contrast, there is a strong incentive for enterprises to participate in CCER trading due to the demand for compliance in the pilot allowance market. CCER trading can improve the efficiency of poverty reduction and motivate project suppliers and enterprises to participate in the project, thus improving sustainability in reducing poverty. Some regions have reported economic benefits from CCER trading. For example, the Hubei provincial government discloses that agricultural and forestry CCERs in poor areas of Hubei province have sold a total of 713,000 tonnes, bringing more than 7 million RMB (1.038 million USD or 1.47 million AUD) to poor areas.[13]

Hence, compared with the effect when a CCER is traded, the poverty reduction effect of implementing a carbon reduction project appears to be relatively weak. The key to generating sustainable poverty reduction appears to be more associated with selling the emission reductions generated by projects than with implementing or establishing projects.

5 | CONCLUSIONS

Based on our panel data of 1782 county-level administrative regions in China from 2006 to 2017, this paper investigates the rural poverty reduction effect of Chinese Certified Emission Reduction (CCER) trading in the carbon trading market using a difference-in-differences model. The robustness of our results is verified using PSM-weighted DID and MDM-DID, two placebo tests, alternative dependent variables and control group, and controlling for other clean and low-carbon projects. We also explore the heterogeneity of the poverty reduction effects of CCER trading in terms of four aspects: type, number, emission reduction scale and distribution area of CCER projects. Finally, the differences between CCER trading and implementing CCER projects in terms of poverty reduction effects are examined.

The main conclusions are as follows. First, CCER trading in China's carbon trading market has achieved strong rural poverty reduction results. During the sample period, CCER trading increased the per capita annual net income of rural residents in counties where CCER projects are located by at least 2.5% or 187.5 RMB (about 27.8 USD or 39.3 AUD) on average; this result is still valid after a series of robustness tests. Second, the rural poverty reduction effect of CCER trading in poor counties is greater than that in nonpoor counties, increasing the per capita net income of rural residents in poor counties by 6.2% on average. Third, there is statistically significant heterogeneity in the effects: CCER trading of hydropower and wind

[13]http://www.hubei.gov.cn/zwgk/hbyw/hbywqb/201909/t20190917_1412219.shtml

power has a significant poverty reduction effect; the more CCER projects a county has, the better the poverty reduction effect of CCER trading for the county; and the poverty reduction effect of CCER trading is strongest in the western and central regions. However, the scale of carbon emission reduction of the CCER project does not affect the poverty reduction effect of CCER trading. Fourth, although both implementing CCER projects and CCER trading are project-based, they produce different effects on rural poverty reduction. We find that the effect of trading is stronger than the simple implementation of a CCER project.

Based on the above conclusions, this paper motivates three policy recommendations. First, our analysis suggests that there is a great potential benefit to restarting the application of the CCER project, which was suspended in March 2017. In fact, national carbon market documents released in China since 2021 indicate that CCER trading has been officially included in the national carbon market,[14] and CCER trading is expected to restart in 2023. We have found that CCER trading can alleviate poverty. Hence, as the programme restarts, China should focus on maximising its contributions to both carbon neutrality and poverty reduction.

Second, based on our heterogeneous analysis results, we believe local governments can focus on CCER trading to maximise rural poverty reduction. For example, when constructing CCER projects, counties should pay more attention to the number of projects than to the scale of projects' emission reduction.

Third, we believe that China should not only focus on implementing and constructing projects but also promote the active participation of emission reductions generated by the projects in carbon market trading. It is unclear why the moment of trading has a stronger effect than the moment of implementation, that is a question that merits future research. It is worth noting that after 2020, the focus of the Chinese government shifted from solving absolute poverty to alleviating relative poverty, and work remains to expand poverty eradication and rural revitalisation. Our results suggest that CCER trading in the national carbon market can help China reduce rural poverty.

There is, however, substantial work to be done in the future on this topic. This paper only considers absolute poverty measured by the per capita net income of rural residents. However, it does not consider relative poverty that reflects inequality, such as the urban–rural gap. Addressing relative poverty is essential for China to promote common prosperity for everyone in long-range objectives. In particular, China's carbon pricing system may also impact the urban–rural gap (Jia et al., 2022); thus, investigating the impact of CCER trading on the urban–rural gap is an important issue we need to explore in future. Due to the limited availability of CCER transaction data and variables related to rural households on the county level, it is difficult to obtain detailed transaction data for a specific CCER project and rich control variables. As for future research, we can use more project-level transaction data to identify the specific features of projects that lead to the greatest benefits and use richer indicators that are more relevant to rural residents' income as control variables. Finally, understanding why CCER trading has a stronger effect than implementing CCER projects could help find ways for carbon reduction policies to make even stronger contributions to reducing poverty.

ACKNOWLEDGEMENTS

We are grateful for financial support from the National Natural Science Foundation of China (nos. 72204081, 71774051 and 72243003) and the National Social Science Fund of China (no. 22AZD128).

[14]Article 29 of the *Measures for the Administration of Carbon Emission Trading* issued in January 2021 stipulated that key emitters can use CCERs to offset the carbon emission allowances each year, with the offset ratio not exceeding 5% of the carbon emission allowances. In October 2021, the Ministry of Ecology and Environment issued the *Notice on the Settlement and Payment of Emission Allowance of National Carbon Emissions Trading Market in the First Implementation Phase*, which clearly states that emission control enterprises can purchase CCERs in accordance with the relevant procedures to offset the carbon allowance.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Jing-Yue Liu https://orcid.org/0000-0002-0705-0129

REFERENCES

Adams, R.H. (2004) Economic growth, inequality and poverty: estimating the growth elasticity of poverty. *World Development*, 32(12), 1989–2014.

Allen, R.C. (2017) Absolute poverty: when necessity displaces desire. *American Economic Review*, 107, 3690–3721.

Auestad, I., Nilsen, Y. & Rydgren, K. (2018) Environmental restoration in hydropower development—lessons from Norway. *Sustainability*, 10(9), 3358.

Bose, N. & Das, S. (2017) Women's inheritance rights, household allocation, and gender bias. *American Economic Review*, 107(5), 150–153.

BP. (2022) *BP statistical review of world energy*. Available at: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html [Accessed 22nd March 2023].

Chen, L. & Wan, P. (2019) The Kyoto protocol and its clean development Mechanism's emission reduction effects: micro-project data on China's participation in global environmental governance. *Economic Research Journal*, 3, 55–71 (In Chinese).

Cheng, Z., Liu, J., Li, L. & Gu, X. (2020) Research on meta-frontier total-factor energy efficiency and its spatial convergence in Chinese provinces. *Energy Economics*, 86, 104702.

Choi, Y., Zhang, N. & Zhou, P. (2012) Efficiency and abatement costs of energy-related CO_2 emissions in China: a slacks-based efficiency measure. *Applied Energy*, 98, 198–208.

Cong, R., Lo, A.Y. & Yu, W. (2021) The distribution and regional determinants of nationally financed emissions-reduction projects in China. *Energy Policy*, 152, 112215.

Cui, J., Wang, C., Zhang, J. & Zheng, Y. (2021) The effectiveness of China's regional carbon market pilots in reducing firm emissions. *Proceedings of the National Academy of Sciences of the United States of America*, 118(52), e2109912118.

Decerf, B. (2017) Why not consider that being absolutely poor is worse than being only relatively poor? *Journal of Public Economics*, 152, 79–92.

Drysdale, K.M. & Hendricks, N.P. (2018) Adaptation to an irrigation water restriction imposed through local governance. *Journal of Environmental Economics and Management*, 91, 150–165.

Du, Y. & Takeuchi, K. (2019) Can climate mitigation help the poor? Measuring impacts of the CDM in rural China. *Journal of Environmental Economics and Management*, 95, 178–197.

Galinato, G.I., Olanie, A., Uchida, S. & Yoder, J.K. (2011) Long-term versus temporary certified emission reductions in forest carbon sequestration programs. *Australian Journal of Agricultural and Resource Economics*, 55(4), 537–559.

Goodman-Bacon, A. (2021) Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277.

Greenstone, M. & Hanna, R. (2014) Environmental regulations, air and water pollution, and infant mortality in India. *American Economic Review*, 104(10), 3038–3072.

Grover, D. & Rao, S. (2020) In, unemployment, and poverty impacts of mitigation investment: evidence from the CDM in Brazil and implications for a post-2020 mechanism. *Climate Policy*, 20(5), 609–625.

Huang, J., Rozelle, S., Zhu, X., Zhao, S. & Sheng, Y. (2020) Agricultural and rural development in China during the past four decades: an introduction. *Australian Journal of Agricultural and Resource Economics*, 64(1), 1–13.

Huang, Z. (2018) Does the establishment of national poverty-stricken counties promote local economic development? An empirical analysis based on PSM-DID methods. *Chinese Rural Economy*, 5, 98–111 (In Chinese).

Jia, Z., Wen, S. & Liu, Y. (2022) China's urban-rural inequality caused by carbon neutrality: a perspective from carbon footprint and decomposed social welfare. *Energy Economics*, 113, 106193.

Jiang, M., Zhu, B., Chevallier, J. & Xie, R. (2018) Allocating provincial CO_2 quotas for the Chinese national carbon program. *Australian Journal of Agricultural and Resource Economics*, 62(3), 457–479.

Li, J., Wang, Z., Cheng, X., Shuai, J., Shuai, C. & Liu, J. (2020) Has solar PV achieved the national poverty alleviation goals? Empirical evidence from the performances of 52 villages in rural China. *Energy*, 201, 117631.

Li, L., Ye, F., Li, Y. & Chang, C. (2019) How will the Chinese certified emission reduction scheme save cost for the national carbon trading system? *Journal of Environmental Management*, 244, 99–109.

Li, S., Liu, Y., Purevjav, A.O. & Yang, L. (2019) Does subway expansion improve air quality? *Journal of Environmental Economics and Management*, 96, 213–235.

Li, X., Chen, Z., Fan, X. & Cheng, Z. (2018) Hydropower development situation and prospects in China. *Renewable and Sustainable Energy Reviews*, 82, 232–239.

Li, Y. (2019) A photovoltaic ecosystem: improving atmospheric environment and fighting regional poverty. *Technological Forecasting and Social Change*, 140, 69–79.

Li, Y., Zhang, Q., Wang, G., McLellan, B., Liu, X.F. & Wang, L. (2018) A review of photovoltaic poverty alleviation projects in China: current status, challenge and policy recommendations. *Renewable and Sustainable Energy Reviews*, 94, 214–223.

Liao, C. & Fei, D. (2019) Poverty reduction through photovoltaic-based development intervention in China: potentials and constraints. *World Development*, 122, 1–10.

Liu, J., Huang, F., Wang, Z. & Shuai, C. (2021) What is the anti-poverty effect of solar PV poverty alleviation projects? *Evidence from Rural China. Energy*, 218, 119498.

Liu, J.Y., Woodward, R.T. & Zhang, Y.J. (2021) Has carbon emissions trading reduced $PM_{2.5}$ in China? *Environmental Science & Technology*, 55(10), 6631–6643.

Liu, J.Y. & Zhang, Y.J. (2021) Has carbon emissions trading system promoted non-fossil energy development in China? *Applied Energy*, 302, 117613.

Liu, M., Feng, X., Wang, S. & Qiu, H. (2020) China's poverty alleviation over the last 40 years: successes and challenges. *Australian Journal of Agricultural and Resource Economics*, 64(1), 209–228.

Lo, A.Y. & Cong, R. (2017) After CDM: domestic carbon offsetting in China. *Journal of Cleaner Production*, 141, 1391–1399.

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

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.

Peng, P. & Mao, H. (2022) The effect of digital financial inclusion on relative poverty among urban households: a case study on China. *Social Indicators Research*, 165, 377–407. Available from: https://doi.org/10.1007/s11205-022-03019-z

Ross Lambie, N. (2010) Understanding the effect of an emissions trading scheme on electricity generator investment and retirement behaviour: the proposed carbon pollution reduction scheme. *Australian Journal of Agricultural and Resource Economics*, 54(2), 203–217.

Shan, Y., Liu, J., Liu, Z., Xu, X., Shao, S., Wang, P. et al. (2016) New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors. *Applied Energy*, 184, 742–750.

Wan, G., Hu, X. & Liu, W. (2021) China's poverty reduction miracle and relative poverty: focusing on the roles of growth and inequality. *China Economic Review*, 68, 101643.

Wang, X., Wang, D. & Wen, T. (2014) Effect of poverty reduction and income growth about loan for rural residents in China. *The Journal of Quantitative & Technical Economics*, 9, 40–55 (In Chinese).

Wen, S., Jia, Z. & Chen, X. (2022) Can low-carbon city pilot policies significantly improve carbon emission efficiency? Empirical evidence from China. *Journal of Cleaner Production*, 346, 131131.

World Bank. (2019) *State and trends of carbon pricing 2019*. Available at: https://documents.worldbank.org/en/publication/documents-reports/documentdetail/191801559846379845/state-and-trends-of-carbon-pricing-2019 [Accessed 22nd March 2023].

Xie, H., Shen, M. & Wang, R. (2014) Determinants of clean development mechanism activity: evidence from China. *Energy Policy*, 67, 797–806.

Yan, Y., Sun, M. & Guo, Z. (2022) How do carbon cap-and-trade mechanisms and renewable portfolio standards affect renewable energy investment? *Energy Policy*, 165, 112938.

Ye, F., Xiong, X., Li, L. & Li, Y. (2021) Measuring the effectiveness of the Chinese certified emission reduction scheme in mitigating CO_2 emissions: a system dynamics approach. *Journal of Cleaner Production*, 294, 125355.

Zhang, G. & Zhang, N. (2020) The effect of China's pilot carbon emissions trading schemes on poverty alleviation: a quasi-natural experiment approach. *Journal of Environmental Management*, 271, 110973.

Zhang, H., Wu, K., Qiu, Y., Chan, G., Wang, S., Zhou, D. et al. (2020) Solar photovoltaic interventions have reduced rural poverty in China. *Nature Communications*, 11(1), 1969.

Zhang, H., Xu, Z., Zhou, Y., Zhang, R. & Cao, J. (2021) Optimal subsidy reduction strategies for photovoltaic poverty alleviation in China: a cost-benefit analysis. *Resources, Conservation and Recycling*, 166, 105352.

Zhang, Y., Guo, S., Shi, X., Qian, X. & Nie, R. (2021) A market instrument to achieve carbon neutrality: is China's energy-consumption permit trading scheme effective? *Applied Energy*, 299, 117338.

Zhang, Y.J. & Cheng, H.S. (2021) The impact mechanism of the ETS on CO_2 emissions from the service sector: evidence from Beijing and Shanghai. *Technological Forecasting and Social Change*, 173, 121114.

Zhang, Y.J., Liu, J.Y. & Su, B. (2020) Carbon congestion effects in China's industry: evidence from provincial and sectoral levels. *Energy Economics*, 86, 104635.

Zhu, J., Fan, Y., Deng, X. & Xue, L. (2019) Low-carbon innovation induced by emissions trading in China. *Nature Communications*, 10(1), 4088.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Zhang, Y.-J., Liu, J.-Y. & Woodward, R.T. (2023) Has Chinese Certified Emission Reduction trading reduced rural poverty in China? *Australian Journal of Agricultural and Resource Economics*, 67, 438–458. Available from: https://doi.org/10.1111/1467-8489.12515