Essays on Evaluating the Impacts of Poverty Alleviation and Farmland Acquisition Policies in Rural China

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Statement of Originality

This is to certify that, to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes, except where due acknowledgement is made in this thesis.

I certify that the intellectual content of this thesis is the product of my own work and that any contributions made by others have been explicitly acknowledged.

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Abstract

This thesis comprises three essays on China's poverty alleviation and farmland acquisition policies in rural China. I use panel datasets to explore the household and county-level effects of two poverty alleviation programs—the contiguous poor area (CPA) and targeted poverty alleviation (TPA) programs—and the compulsory farmland acquisition (CFA) policy. While the CPA and TPA programs both aim to resolve poverty in rural areas, they differ in their targets and approaches: CPA focuses on poverty at the regional level, while TPA focuses on poverty at the individual and household levels. In contrast, CFA is not directly related to poverty alleviation but is closely related to the livelihood of farmers.

The CPA strategy is aimed at alleviating poverty in rural regions in China with high concentrations of poverty. The first essay examines the effects of the strategy on county-level economic and income growth based on a panel dataset of more than 500 nationally designated poor counties over 11 years. The results from two difference-in differences methods show that the CPA strategy has contributed to both economic growth and an increase in residents' income but has failed to narrow the urban–rural income gap.

TPA is a poverty alleviation strategy aimed at delivering customised interventions at the household level. The second essay examines its effects on household income based on a household panel survey and non-public administrative data. The results show that TPA has had unfavourable effects on household income. It also discusses the heterogeneous effects arising from the type of poverty and the important role of education of the household head.

The third essay assesses the effect of CFA on household consumption expenditure, which, based on the permanent income hypothesis, is an appropriate measure of household wellbeing. Using household panel survey data, I show that CFA increases the total consumption expenditure of households.

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List of Abbreviations

3SLS	three-stage least squares
ATT	average treatment effect on the treated
CFA	compulsory farmland acquisition
CFPS	China Family Panel Studies
CHARLS	China Health and Retirement Longitudinal Study
CPA	contiguous poor area
DID	difference-in-differences
DID-FE	difference-in-differences with fixed effects
GDP	gross domestic product
IPH	identified poor household
NBSC	National Bureau of Statistics of China
NDPC	nationally designated poor county
OLS	ordinary least squares
PSM	propensity score matching
SDID	synthetic difference-in-differences
SURE	seemingly unrelated regression estimation
TPA	targeted poverty alleviation

Chapter 1: Introduction

The effects of large-scale policies are difficult to capture because of the non-experimental nature of their implementation, the lack of quality data and the difficulty in identifying treatment and control groups. In recent decades, descriptive and correlational studies have shown that China's poverty alleviation and farmland acquisition policies have succeeded in achieving their aims. However, gaps remain in the evidence, making it critical to re-examine the true effects of these policies and arrive at accurate conclusions.

This thesis aims to show the effects of three policies implemented in rural China over the past two decades—the contiguous poor area (CPA), targeted poverty alleviation (TPA) and compulsory farmland acquisition (CFA) policies. While the CPA and TPA strategies are both aimed at alleviating poverty in Chain, they take different approaches and tackle different aspects of poverty. The CPA strategy focuses on regions with high concentrations of poverty, which are often characterised by challenging natural conditions, inadequate infrastructure and limited access to resources. The main goal of this strategy is to stimulate the overall development of these areas, thereby lifting entire regions out of poverty. In contrast, TPA focuses on poverty at the individual and household levels, with the aim of accurately identifying and providing customised assistance to impoverished individuals and households according to their specific needs. Given the multifaceted nature of poverty in China, meaning that a single approach is unable to effectively address all aspects of the issue, the central government has adopted two different strategies (M. Y. Liu et al., 2020) to tackle poverty from both microeconomic (individual and household) and macroeconomic perspectives. CFA refers to the state exercising its statutory authority to appropriate collectively owned land for public development purpose. An integral component of this process involves the state engaging in transactions with rural collectives, during which the state purchases the land and subsequently leases it to development entities. Concurrently, economic compensation is provided to the farmer from whom the land has been requisitioned.

In this thesis, I draw data from a range of sources to construct several panel datasets and employ compatible techniques, including the careful identification of treatment and control groups, to make causal inferences about each policy. To examine the effects of the CPA strategy, which was introduced in late 2011, I gather data on over 2,000 Chinese counties from the *China Statistical Yearbooks* from 2008 to 2018. Given that the CPA strategy represents only one of

China's poverty alleviation strategies at the county-level and beyond, I exclude interference from a parallel strategy known as nationally designated poor counties (NDPCs). Using a synthetic difference-in-differences (SDID) approach (Arkhangelsky et al., 2021), I find evidence that the CPA strategy has boosted county-level economic growth and the income of rural residents but has failed to narrow the urban–rural income gap. The results show the effectiveness of large-scale geographical targeting strategies such as the CPA in resolving geographical poverty, suggesting that they should continue to be implemented.

In my study of the TPA strategy, which was initiated in 2013, I combine household administrative data with survey data from the China Family Panel Studies (CFPS) for several counties of Gansu province, enabling a detailed examination of the effectiveness of the TPA strategy at the household level. I adopt a difference-in-differences (DID) approach based on propensity score matching (PSM) (PSM-DID) (Heckman et al., 1997) to estimate the effects of the strategy on household income growth between 2013 and 2016. The results indicate that TPA was ineffective in its early stage, implying that the government should increase its funding for TPA and revise its allocation mechanisms.

To examine the effects of China's CFA policy, I construct a household panel dataset from 2011 to 2018 based on the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative survey of China's middle-aged and older residents. I utilise several DID-based empirical tools to capture the effect of the policy on the total consumption expenditure and expenditure patterns of CFA-affected households, showing that CFA increases households' total consumption expenditure. While I find correlations between household consumption expenditure patterns and household characteristics such as budget, financial assets, education, age and marital status, CFA appears to have had no effect on household expenditure patterns. The results indicate that households characterised by middle-aged and older people benefit from farmland acquisition, most likely through compensation payments, implying that policymakers should consider maintaining or increasing compensation to ensure the ongoing positive outcomes for rural households affected by CFA.

Chapter 2: Escaping the Trap of Geographical Poverty: Effects of the Contiguous Poor Area Policy Among Nationally Designated Poor Counties

Chapter 2 examines the effect of the CPA poverty alleviation strategy, which is based on geographic targeting, in China's recent wave of poverty alleviation plans. Specifically, it examines the effects of the CPA strategy on gross domestic product (GDP) per capita, rural residents' income and the rural-urban income gap. Drawing on a panel dataset of over 500 poor counties from 2011 to 2018, I employ the SDID approach to estimate the effects of the CPA strategy. The findings suggest that over the study period, the CPA strategy increased GDP per capita and rural income by 8.3% and 6.1%, respectively. Moreover, dynamic benefits of the CPA strategy in terms of GDP and income growth were observed over time. However, the CPA policy has not effectively narrowed the urban–rural income gap. These results are relatively robust to other estimators, including traditional DID and DID with fixed effects (DID-FE).

2.1 Introduction

The geographical or spatial poverty trap has been the subject of a longstanding discourse on persistent poverty in China, particularly in rural areas, where impoverished populations show a distinct spatial distribution that has persisted over several decades. These populations are concentrated primarily in the mountainous and hilly areas of central and western China (L. Guo & Jiang, 1995; Jiang et al., 1988; Y. Liu et al., 2017; Y. Liu & Xu, 2016; Wan, 2007). The underlying reasons for the concentration of poverty in particular regions include the lack of adequate natural resources, fragile environments, unfavourable conditions, frequent natural disasters and poor access to coastal areas with strong economic growth (Blank, 2005; Emran & Hou, 2013; Glauben et al., 2012; Jalan & Ravallion, 2002; Tian et al., 2018).

Alleviating spatial poverty is critical for eliminating individual poverty. The interaction between spatial and individual poverty is complex. Spatial and individual poverty differ in terms of their formation mechanisms and countermeasures; for example, spatial poverty often results from unfavourable external macroeconomic conditions, while individual poverty results from unfavourable individual characteristics, requiring specific alleviation strategies (Ravallion & Wodon, 1999; Zhou & Huang, 2022). However, these two types of poverty are mutually reinforcing; for instance, disadvantaged geographical locations are related to regional economic underdevelopment, which contributes to individual poverty through its effect on socioeconomic conditions (Barbier & Hochard, 2019; Zhou & Huang, 2022).

China has implemented various development-oriented policies to alleviate poverty in different regions across the country. In recent decades, two programs have been implemented at the regional level (i.e. county and above) to address poverty: the NDPC and the CPA programs. The NDPC program was initiated in 1986 with the aim of improving the living conditions and economic development of the poorest counties in China. Under this program, the central government provides designated poor counties with financial and other support. In 2011, the central government introduced the CPA program, which was based on the NDPC program, to eliminate poverty from persistently poor areas. Under this policy, the government invests in education, medical care, culture, employment, social security, beneficial industries, critical infrastructure and environmental protection. Both the NDPC and the CPA programs have significantly reduced China's poverty rate, which has declined from over 97% in 1978 to less than 1% in 2020 (National Bureau of Statistics of China [NBSC], 2021). However, the extent to which the CPA policy, which is targeted at geographical poverty, is currently responsible for poverty reduction is a matter of interest because the nominal GDP nearly doubled over the study period (2011–2018).

This study is based on three DID methods—DID, DID-FE and SDID—to estimate the effects of the CPA program on GDP, rural income and the urban–rural income gap. The dynamic effects of the policy on these variables of interest are also investigated. The analysis is based on a 10-year panel dataset comprising approximately 500 NDPCs. A quarter of these NDPCs are also designated CPAs (referred to as 'CPA-NDPCs'), while the remainder are NDPCs only.

SDID was employed to compare CPA-NDPCs and NDPCs in terms of the effect of the CPA program on GDP per capita and rural residents' income. The results show the CPA policy has had a significant effect on GDP per capita and rural residents' income. Specifically, at the county level, GDP per capita increased by 8.3%, while rural per capita income increased by 6.8% over the study period. Moreover, the program exhibited dynamic benefits, where the longer the exposure of CPAs to the program, the greater its effect, particularly on GDP per capita. However, the CPA program showed no significant effect on narrowing the income gap between urban and rural areas.

This thesis is related to the literature on poverty alleviation policies in China, particularly those targeting impoverished areas at the county level from 1986 to 2010 (e.g. Liu & Ma, 2019; Meng, 2013; Park & Wang, 2010; Park et al., 2002; Qin & Chong, 2018; Ravallion & Chen, 2007). Previous findings on the effectiveness of place-based policies in promoting economic and income growth are contradictory, and there is a need to further explore this issue. This thesis is also related to research on the CPA strategy in China's poverty alleviation plan for 2011–2020 (S. Li et al., 2018; J. Qian & Ma, 2022; Wu et al., 2022). Previous studies have assessed the effects of the CPA program on economic and income growth, primarily based on the PSM-DID method, and have consistently found a positive causal relationship. However, some studies relied on nationwide county-level samples in the early stages of policy implementation (S. Li et al., 2018), while others covered only a few dozen counties in specific provinces (J. Qian & Ma, 2022; Wu et al., 2022). A further issue is poor study design in terms of identifying treatment and control groups, potentially leading to an overestimation of policy effects. Moreover, the critical parallel trend assumption to ensure validity of the DID estimator has not been rigorously tested, nor have the dynamic effects of the policy. Therefore, this thesis is aimed at exploring the medium-term, long-term and dynamic effects of the CPA policy based on a redesigned sample identification strategy and a larger sample size.

The remainder of this chapter proceeds as follows: Section 2.2 provides background information on the CPA policy; Section 2.3 reviews the related literature; Section 2.4 describes the data used and the empirical strategy; Section 2.5 reports the empirical results; and Section 2.6 concludes the chapter.

2.2 Institutional Background

The CPA strategy is a regional poverty alleviation strategy initiated by the Chinese government in 2011 in its Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020) (State Council, 2011). The CPA strategy targets 14 CPAs comprising 680 counties in China's central and western regions, which are characterised by their fragile environments. Of these 680 counties, 431 are NDPCs (Zuo, 2019).

To fundamentally transform CPAs, the central government has implemented a range of supportive strategies, including monetary transfers, tax relief, investments, financial services, industrial development, land use reform, environmental restoration and human capital development. These strategies are aimed at improving living conditions and agricultural production, support the growth of beneficial industries, accelerate the construction of vital regional infrastructure, protect and improve the environment and promote the provision of basic public services throughout the regions. Additionally, State Council departments and local governments at all levels are required to coordinate and implement a range of livelihood projects related to education, health, culture, employment and social security to enhance the economic and social development of these regions.

According to the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020), the previously implemented NDPC program was to remain unchanged following the implementation of the new CPA program, which was administered using additional funds, thus did not affect the funding of the NDPC program (State Council, 2011). Therefore, the effect of the CPA program (i.e. with no interference from the NDPC program) could be evaluated by basing both the treatment and control groups on NDPCs.

The identification of a CPA is based on four key principles: (i) the geographical contiguity of counties (i.e. scattered counties are excluded from CPAs); (ii) similarity between counties in terms of climate, environment, industries, customs and poverty factors; (iii) poverty based on three economic indicators—net income of rural residents, general budget revenue and regional GDP per capita—which must be lower than those of western China for the period 2007–2009; and (iv) administrative integrity (i.e. one county cannot be simultaneously included in two CPAs).

2.3 Related Literature

Theoretical analyses and empirical evidence show that regional economic growth can be compromised by unfavourable geography. Geography matters for economic development through factors such as transportation costs and access to high-value natural resources (Bird et al., 2002; Gallup et al., 1999; Henderson et al., 2001). Geographic factors can lead to and reinforce the cycle of regional inequalities (Krugman, 1999). Jalan and Ravallion (2002) term this phenomenon the 'geographical poverty trap' in which certain regions or areas are caught in a persistent cycle of poverty because of their geography, hindering economic development and growth.

Since the economic reforms of the mid-1980s, the Chinese government has responded to geographical poverty at the policy level. In recognition of the unequal distribution of poverty across the country, the central government initiated a large-scale poverty alleviation plan with a specific focus on the county level, known as the poor county or NDPC program, in 1986. However, some researchers questioned the effectiveness of these programs (e.g. Park et al., 2002; Rozelle et al., 1998). As a revision to the initial plan, the central government launched a large-scale poverty alleviation program known as the 8–7 Plan, which represented the country's first comprehensive poverty alleviation plan with clearly defined objectives, targets, measurement frameworks and timelines. The following two poverty alleviation plans to take effect were the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2001–2010) and the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020).

The poverty alleviation plans from 1986 to 2020 have all predominantly aimed to identify and invest in impoverished populations at the county level. However, the plans differed in terms of their increasingly precise identification of impoverished counties and allocation of resources (Shen, 2022). The second plan, the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2001–2010), shifted the focus to the village level, prioritising the allocation of resources to impoverished villages within counties. The 2011–2020 poverty alleviation plan further improved the accuracy of identification and allocation of resources from the village level to the household level. As mentioned, the poverty alleviation plans have focused on geographical poverty at the county and regional levels. Additional funds for poverty alleviation have primarily been invested in 14 geographically constrained CPAs for critical infrastructure construction, industrial development, environmental protection and livelihood projects.

Previous studies on China's geographic poverty alleviation efforts have mainly focused on the 8-7 Plan (1994–2000) and the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2001–2010). The findings on the effectiveness of these regional policies in terms of GDP and income growth are mixed. For example, Park et al. (2002) found that poor counties experienced a moderate increase in per capita income during the periods 1985–1992 and 1992–1995. Using the regression discontinuity method, Meng (2013) found that the 8–7 Plan increased rural income in poor counties by an average of 38% between 1994 and 2000. In contrast, the 2001–2010 program has been found to have had no effect on economic and income growth (e.g. C. Liu & Ma, 2019; Park & Wang, 2010; Qin & Chong, 2018). This may reflect the increasing complexity involved in lifting the remaining impoverished populations out of poverty through large-scale plans because poverty alleviation is hindered by issues such as targeting errors and regional inequalities (Liu & Ma, 2019; Park & Wang, 2010; Qin & Chong, 2018; Ravallion & Chen, 2007).

This raises the question: Do geographical and county-based poverty identification and assistance policies still meet the requirements for alleviating rural poverty in China? The findings of previous empirical studies do not support this. However, the third wave of poverty alleviation, the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020), provides an opportunity to re-examine the effects of geographical targeting (namely CPAs) and show whether it is still effective in China's current economic climate.

There have been several attempts to evaluate the effectiveness of the CPA program on regional economic and income growth. For example, S. Li et al. (2018) used PSM-DID to show that the CPA program increased county-level GDP and deposits per capita from 2011 to 2015. J. Qian and Ma (2022) and Wu et al. (2022) also found that the CPA program positively influenced economic growth in southern Xinjiang and Yunnan provinces, respectively. Nevertheless, I argue that these studies have overestimated the true effect of the CPA on economic and income growth. Specifically, S. Li et al. (2018) did not account for the effects of the NDPC program in their primary analysis, basing their treatment and control groups on whether a county was included in one of the 14 CPAs. Given that the NDPC program was still being implemented, the true effects of the CPA policy were likely to have been overestimated because most CPA counties were also NDPCs. To address the potential confounding effects of the NDPC program, the authors then excluded NDPCs from their analysis. However, this raises a concern about external validity because, by doing so, they shifted their focus from NDPCs to counties that were relatively less poor. Without further evidence, it is unclear whether the effectiveness of the CPA policy in non-NDPCs can be extrapolated to NDPCs given their different socioeconomic conditions. Similarly, in their studies on the effect of the CPA policy in Xinjiang and Yunnan provinces, respectively, J. Qian and Ma (2022) and Wu et al. (2022) did not account for the additive effect of the NDPC program. Therefore, the question of whether the CPA policy promotes economic growth in poor counties remains.

2.4 Data and Methodology

2.4.1 Data Sources

The data employed in this research were gathered from county-level statistical yearbooks from 2008 to 2018. Linear and cubic interpolation methods were used to fill in missing values.[1] After eliminating counties with imbalanced records, such as those with more than a year of missing data, an 11-year panel dataset comprising 512 counties was created.

Table 2.1 presents the summary statistics of the important economic and social indicators in the baseline year (2011). The table comprises three panels that correspond to the three research questions: (i) what is the causal effect of CPA policy on counties' GDP? (ii) What is the causal effect of CPA policy on rural residents' income? (iii) Does CPA policy narrow the income gap between urban and rural areas? Panel A shows the effect of the CPA program on GDP per capita; Panel B shows the effect of the CPA program on rural residents' income; and Panel C shows the effect of the CPA program on rural–urban income ratio. The outcome variables are shown in the first row of each panel: *lnpercapitaGDP* is the natural logarithm of GDP per capita by county (Panel A); *lnincome_rural* is the natural logarithm of rural residents' average income by county (Panel B); and *rural/urban* is the average rural–urban income ratio within a county (Panel C). The covariates are identical for all three panels: *GDP_primary/GDP* and *GDP_secondary/GDP* represent the proportion of value added to the GDP by the primary and secondary industries, respectively, reflecting the industrial structure of each county. *hospital_bed_density* represents the number of hospital beds per 1,000 people in each county, reflecting the availability of medical resources. *deposit_per_capita* and *budget_expenditure* represent deposit balance and government expenditure per capita, respectively, reflecting the financial status of residents and county governments.

The number of observations differs between the three panels because of differing data availability for the outcome variables. Panel A contains the highest number of observations (512 counties). Panel B is based on only 355 counties because of the limited availability of rural income data. The number of observations is further reduced to 108 in Panel C and observations

[1] Missing values were imputed using the Stata command *mipolate*. The linear method interpolates missing values using linear specifications and the known values of variables before and after any missing values. The cubic method specifies the exact fit of a cubic curve to data points before and after any missing values. In this paper, the linear method was used to interpolate missing values for GDP, number of hospital beds and residents' deposits, while the cubic method was used to interpolate missing budget values, which have an S-shaped distribution.

are concentrated in four provinces (Henan, Hubei, Hunan and Shanxi) because of the lack of data on urban resident income.

Table 2.1 Baseline summary statistics of outcome variables and covariates (2011)

Variable	Control group (CPA = 0)			Treatment group (CPA = 1)			Mean diff.
	Mean (SD)	Min.	Max.	Mean (SD)	Min.	Max.	(1) − (0)
Panel A: Effect of CPA on GDP per capita							
lnpercapitaGDP	9.82 (0.44)	8.09	11.15	9.20 (0.44)	8.12	10.83	-0.62***
GDP_primary/GDP	0.24 (0.15)	0.01	0.74	0.28 (0.10)	0.05	0.75	0.04***
GDP_secondary/GDP	0.46 (0.18)	0.06	0.88	0.36 (0.14)	0.06	0.83	-0.10***
hospital_bed_density	2.47 (0.82)	0.91	6.99	2.41 (1.06)	1.20	8.34	-0.06
deposit_per_capita	11.51 (5.75)	3.14	31.61	7.28(3.50)	0.16	21.64	-4.23***
budget_expenditure	5.16 (2.90)	1.62	18.12	4.53 (2.91)	1.11	25.82	-0.62*
N	113			399			
Panel B: Effect of CPA on rural residents' income							
lnincome_rural	8.37 (0.25)	7.73	8.75	8.22 (0.24)	7.42	8.75	-0.15***
GDP_primary/GDP	0.21 (0.12)	0.01	0.61	0.27 (0.09)	0.05	0.52	0.06***
GDP_secondary/GDP	0.49 (0.16)	0.11	0.88	0.36 (0.14)	0.10	0.83	-0.13***
hospital_bed_density	2.44 (0.91)	0.95	6.99	2.31 (0.93)	1.20	7.17	-0.13
deposit_per_capita	11.97 (6.22)	3.14	31.61	7.56 (3.58)	0.23	21.64	-4.41***
budget_expenditure	4.34 (1.95)	1.62	10.32	4.11 (2.36)	1.11	25.82	-0.23
N	74			281			
Panel C: Effect of CPA on urban–rural income ratio							
rural/urban	0.29 (0.08)	0.17	0.41	0.30 (0.06)	0.14	0.43	0.01
GDP_primary/GDP	0.18 (0.12)	0.01	0.38	0.25 (0.09)	0.06	0.52	0.07***
GDP_secondary/GDP	0.52 (0.16)	0.28	0.88	0.39 (0.15)	0.10	0.83	-0.13***
hospital_bed_density	2.55 (0.81)	1.31	5.38	2.66 (0.94)	0.89	5.60	0.12
deposit_per_capita	13.81 (8.08)	5.60	31.61	9.74 (3.46)	4.83	21.64	-4.06**
budget_expenditure	3.80 (1.67)	1.62	7.82	3.58 (1.30)	1.12	7.16	-0.22
N		31			77		

Note: CPA: contiguous poor area; *lnpercapitaGDP*: natural logarithm of gross domestic product (GDP) per capita; *GDP_primary/GDP*: proportion of value added to the GDP by the primary industry; *GDP_secondary/GDP*: proportion of value added to the GDP by the secondary industry; *hospital_bed_density*: number of hospital beds per 1,000 people; *deposit_per_capita*: deposit balance per capita; *budget_expenditure*: government expenditure per capita; *lnincome_rural*: natural logarithm of rural residents' average income; *rural/urban*: average rural–urban income ratio. All variables reflect annual values at the county level, and all monetary values, except *lnpercapitaGDP* and *lnincome_rural*, are measured in 1,000 CNY. The final column shows the mean difference between the two groups. *** $p < .01$, ** $p < .05$, * $p < .1$.

There is a clear pattern that the average GDP of impoverished counties was lower than the national average over the same period. According to the *2012 China Statistical Yearbook* (NBSC, 2012), the national GDP per capita in 2011 was 35,181 CNY (approximately 5,445 USD at the 2011 average exchange rate), which was higher than that of the treatment and control groups in this study. The national average contribution of primary industry to GDP was 4.6%, much lower than that of the treatment (28%) or control (24%) groups in this study. Conversely, the national average contribution of secondary industry to GDP was 51.6%, higher than that of the treatment (36%) and control (46%) groups. The number of hospital beds per 1,000 people nationally was 3.81, higher than that in the treatment (2.41) and control (2.47) groups. The national deposit balance per capita was 26,974 CNY (4,176 USD at the average 2011 exchange rate), much higher than that of the control group (11,508 CNY) (1,781 USD) or the treatment group (7,277CNY) (1,126 USD). National government expenditure per capita was 8,108 CNY (1,255 USD), higher than that of the control group (5,156 CNY) (798 USD) and treatment group (4,534 CNY) (702 USD). Furthermore, Table 2.1 shows that the treated group was more underdevelopment than the control group likely because of geographical disadvantage.

Table 2.2 presents the baseline mean differences between the overall observations of the 512 counties (Panel A in Table 2.1) and the two subsets (i.e. Panels B and C in Table 2.1). The null hypothesis posits no difference between the overall observation and the two subsets. The penultimate column presents the mean difference between Panels A and B, showing that only government budget expenditure per capita was statistically different from zero ($p < .05$). The final column presents the mean difference between Panels A and C, showing that all five covariates pertaining to counties' economic and social conditions significantly differed from zero in the baseline year. Given this, the results of Panel C should be interpreted as evidence for the sample counties only rather than extrapolating them to other counties.

Table 2.2: Baseline mean test of covariates (2011)

Variable	Panel A (Overall sample)	Panel B	Panel C	Mean diff.	
	(1)	(2)	(3)	(1)-(2)	(1)-(3)
GDP_primary/GDP	0.27	0.26	0.23	0.01*	0.04***
	(0.12)	(0.10)	(0.10)		
GDP_secondary/GDP	0.38	0.38	0.43	-0.002	-0.05***
	(0.15)	(0.15)	(0.16)		
hospital_bed_density	2.42	2.33	2.62	0.09	-0.21**
	(1.02)	(0.92)	(0.90)		
deposit_per_capita	8.21	8.47	10.91	-0.26	-2.70***
	(4.46)	(4.62)	(5.50)		
budget_expenditure	4.67	4.16	3.64	0.51***	1.03***
	(2.92)	(2.28)	(1.41)		
N	512	355	108		

*** p<.01, ** p<.05, * p<.1

Note: Standard deviations are in parentheses.

2.4.2 Identification Strategy

Given the concurrent implementation of the NDPC and CPA programs during the study period, it is important to address the potential interference of the NDPC program on the outcomes. To mitigate the influence of the NDPC program, non-NDPCs were excluded from the dataset. Tibet was also excluded because of limited data availability; thus, the analysis was conducted on only 13 of the 14 CPAs. Therefore, the treatment group comprised NDPCs allocated to one of the 13 CPAs (n = 399), while the control group comprised NDPCs not allocated to a CPA (n = 113) (see Figure 2.1).

Figure 2.2 illustrates the identification strategy, which accounts for the potential effect of the NDPC program to avoid the overestimation of results, unlike previous research on the effect of CPA on GDP and income growth (S. Li et al., 2018; J. Qian & Ma, 2022; Wu et al., 2022). Previous researchers distinguished treatment and control counties based only on whether they were assigned to one of the 14 CPAs, disregarding whether they had already been affected by the NDPC program. This could be a confounding factor when estimating outcomes, which could be influenced by both policies. For instance, as shown in Figure 2.2, it is possible to conduct a comparison on Groups A and B, Groups A and D, Groups C and B or Groups C and D. Given that the majority of counties in CPAs had become NDPCs after 2001, a comparison of Groups A and D, for example, would be likely to overestimate the treatment effects because it would evaluate the effect of both the CPA and the NDPC programs rather than the CPA program alone.

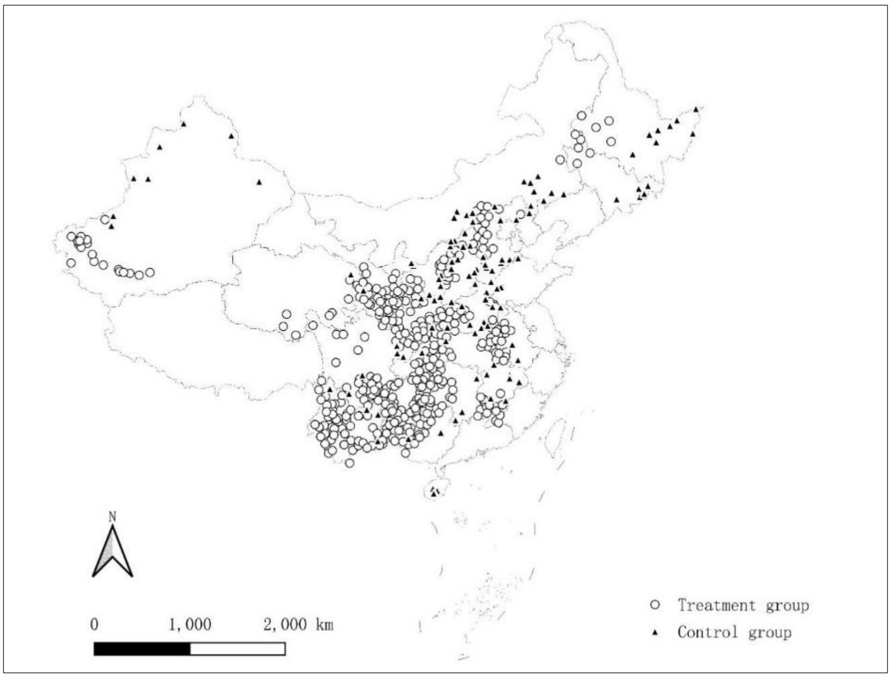
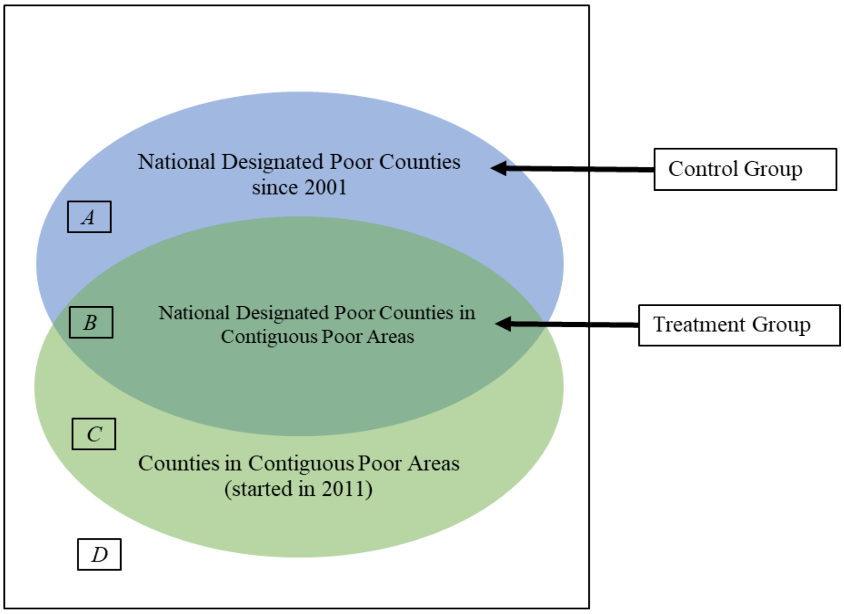


Figure 2.1: Distribution of treatment and control counties.



Policy (CPA & NDPC)	CPA	Non-CPA
NDPC	Treatment group (*B*)	Control group (*A*)
Non-NDPC	Excluded (*C*)	Excluded (*D*)

Figure 2.2: Identification of treatment and control groups.

Note: CPA: contiguous poor area; NDPC: nationally designated poor county.

This identification strategy design can be explained from the perspective of the timelines of the NDPC and CPA programs. As shown in Figure 2.3, the list of NDPCs has undergone two adjustments in the past 2 decades. The first adjustment occurred in 2001 when China implemented its Outline for Development-oriented Poverty Reduction for China's Rural Areas (2001–2010) and transferred all 33 key counties in the eastern region to the central and western regions, meaning that there were no longer any key counties designated to the eastern region. At the same time, the Tibet Autonomous Region was identified as a special support region and enjoyed the same treatment as NDPCs but did not occupy the NDPC county quota. This adjustment led to a total of 592 NDPCs nationwide. The second adjustment occurred in 2011, in which 38 counties were replaced, but the total number remained at 592. In this study, the treatment and control groups were established in areas that were identified as NDPCs in both 2001 and 2011. This ensured that the samples in both groups had similar levels of economic development and had been subject to the same regional poverty alleviation policies (apart from the CPA program).

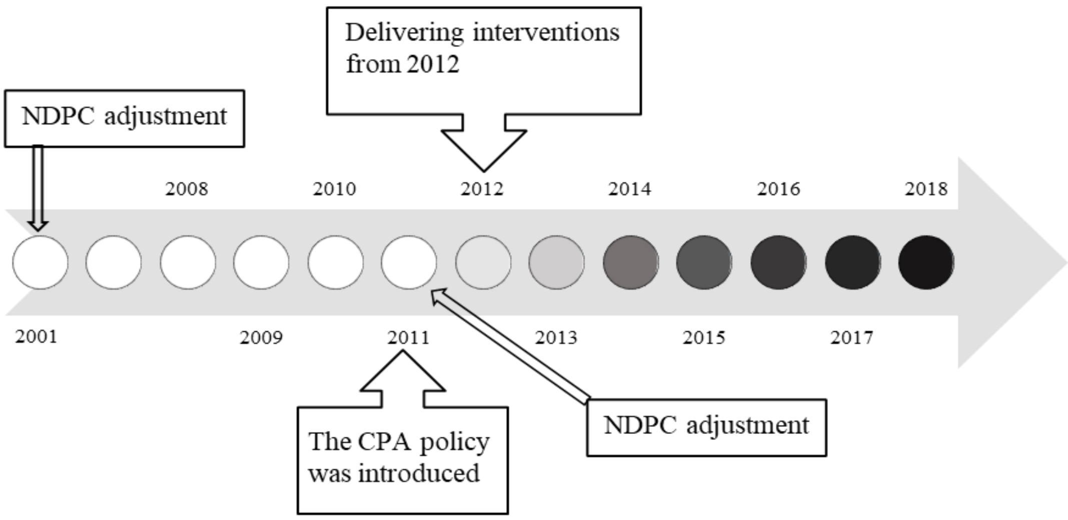


Figure 2.3: Timeline of the CPA program.

Notes: CPA: contiguous poor area; NDPC: nationally designated poor county.

One compelling reason to control for the potential effect of the NDPC program on the outcomes of interest is that the program continued to apply to the newly announced CPA counties. Funding of the CPA program primarily came from newly added central government funds (State Council, 2011). In other words, the CPA program was aimed at strengthening the government's anti-poverty endeavours by providing additional attention and resources to impoverished areas. Additionally, admission to the NDPC program was independent of admission to the CPA program. This means that already established NDPCs could also be eligible for the CPA policy if they met the enrolment requirements. Ongoing debates on the effectiveness of the NDPC program primarily focus on whether the policy has had a positive or neutral effect on counties' economic growth (e.g. L. Huang & Yang, 2018; C. Liu & Ma, 2019). There is currently no evidence to support the notion that the program has had a negative effect. Therefore, to prevent overestimation, it is crucial to account for the potential effect of the NDPC program when estimating the effects of the CPA program.

2.4.3 Effects of the CPA Program

As discussed previously, the essential aim of this study is to examine the relationship between the CPA policy and economic outcomes at the county level and further explore the dynamic effects of the policy. Three DID regressions—traditional DID, DID-FE and SDID—were adopted to estimate the effect of the CPA program on GDP per capita, income of rural residents and the rural–urban income ratio for each county. For the traditional DID regression, the following equation was used:

$$Outcome_{i,j,t} = \alpha_i + \sum_t \beta_{i,t} \times Year_t + \zeta CPA_{j,t} + \sum_t \eta_{i,t} \times Year_t \times CPA_{j,t} + \tau_i X_{j,t} + \varepsilon_{i,j,t}, \tag{2.1}$$

where $Outcome_{i,j,t}$, represents one of the three outcome variables—GDP per capita ($i = 1$), rural residents' average income ($i = 2$) and average rural–urban resident income ($i = 3$)—for county j in year t (2008–2018, excluding 2011, the baseline year). By excluding observations from 2011, all estimates can be compared with the baseline year. $Year_t$ is a set of dummies that control for time variations affecting both the treatment and the control groups across the 10 years. $CPA_{j,t}$ is a treatment dummy that equals one if county j is included in one of the 13 CPAs. $\eta_{i,t}$ represents the coefficients of interest in year t. $X_{j,t}$ represents a set of covariates regarding counties' socio-economic conditions.

The 11 years from 2008 to 2018 include those before and after the implementation of the CPA program in 2011. The pre-intervention period comprises three years (2008, 2009 and 2010), while the post-intervention period comprises seven years (2012–2018). By including the pre-intervention data in the regressions, the parallel trend assumption can be tested for the three outcome variables.

To check the robustness of the DID model based on ordinary least squares (OLS), two additional methods were adopted to estimate the treatment effects for the same outcomes and independent variables. The first was a DID-FE regression based on province fixed effects:

$$Outcome_{i,j,t} = \theta_i + \sum_t \iota_{i,t} \times Year_t + \kappa CPA_{j,t} + \sum_t \lambda_{i,t} \times Year_t \times CPA_{j,t} + \tau_i X_{j,t} + \mu_{i,k} + \varepsilon_{i,j,t} \quad , \tag{2.2}$$

where k represents province, and $\mu_{i,k}$ represents the province fixed effects, which capture unobserved and time-invariant factors at the province level. The choice of province-level fixed effects is rooted in the administrative structure and governance of the region under study. In China, provincial governments play a pivotal role in the region's governance landscape including poverty alleviation. Differences in provincial socio-economic statuses and policies can lead to varying poverty alleviation inputs, which are unobserved in this study. Incorporating province-level fixed effects is thus a conscious decision to ensure that the model captures not just the direct effects of poverty-alleviation measures but also the indirect effects stemming from provincial policies, strategies, and resource allocation mechanisms.

The second method used to test robustness was SDID, which combines the advantages of the synthetic control and DID methods by calculating the weights of the control units to adjust the pre-treatment balance between the treated and control units. Compared with traditional DID, SDID can provide robust estimates and reduce bias by improving the pre-intervention balance (i.e. by allowing for unequal unit and time weights for control units in the pre-intervention period) (Arkhangelsky et al., 2021).

In a policy evaluation setting with j units and t time periods, the traditional DID method yields the average treatment effects through a minimisation framework (e.g., OLS). $Y_{j,t}$ is the outcome of unit j at time t. $Treatment_{j,t}$ denotes the binary treatment status of unit j at time t. α_j and β_t denote the fixed effects of unit and time, respectively. The effect of receiving the treatment, denoted as $\hat{\tau}^{DID}$, is the output of an optimisation problem that minimises the difference between the outcomes and the fitted models:

$$\hat{\tau}^{DID} = \arg\min_{\alpha,\beta,\mu,} \left\{ \sum_j \sum_t \left(Y_{j,t} - \mu - \alpha_j - \beta_t - \tau Treatment_{j,t} \right)^2 \right\} \tag{2.3}$$

The SDID method permits the input of unit weights (i.e. $\widehat{\omega}_j^{SDID}$) and time weights (i.e. $\hat{\lambda}_t^{SDID}$) into the conventional DID framework:

$$\hat{\tau}^{SDID} = \arg\min_{\alpha,\beta,\mu,} \left\{ \sum_j \sum_t \left(Y_{j,t} - \mu - \alpha_j - \beta_t - \tau Treatment_{j,t} \right)^2 \widehat{\omega}_j^{SDID} \hat{\lambda}_t^{SDID} \right\}, \quad (2.4)$$

where the two weights, $\widehat{\omega}_j^{SDID}$ and $\hat{\lambda}_t^{SDID}$, are used to match the trends of the treatment and control groups using an optimisation problem (Abadie et al., 2010; Arkhangelsky et al., 2021). In this paper, I use the *SDID* Stata command written by Pailañir and Clarke (2022) to estimate the average treatment effects on NDPCs covered by the CPA policy.

2.4.4 Parallel Trends in the Pre-intervention Period

The DID method was based on the parallel trend assumption for the outcome of interest during the pre-intervention period. This critical assumption was tested by including the pre-treatment data in Equations (2.1) and (2.2), which generated binary variables for the pre-treatment years ($Year_{pre}$), treatment status ($CPA_{j,pre}$) and the interaction between year and treatment dummy ($Year_{pre} \times CPA_{j,pre}$). As shown in the next section, the statistical non-significance of these pre-intervention interaction terms suggests that the parallel trend assumption holds. Figure 2.4 shows the trends over time for the three evaluated dependent variables.

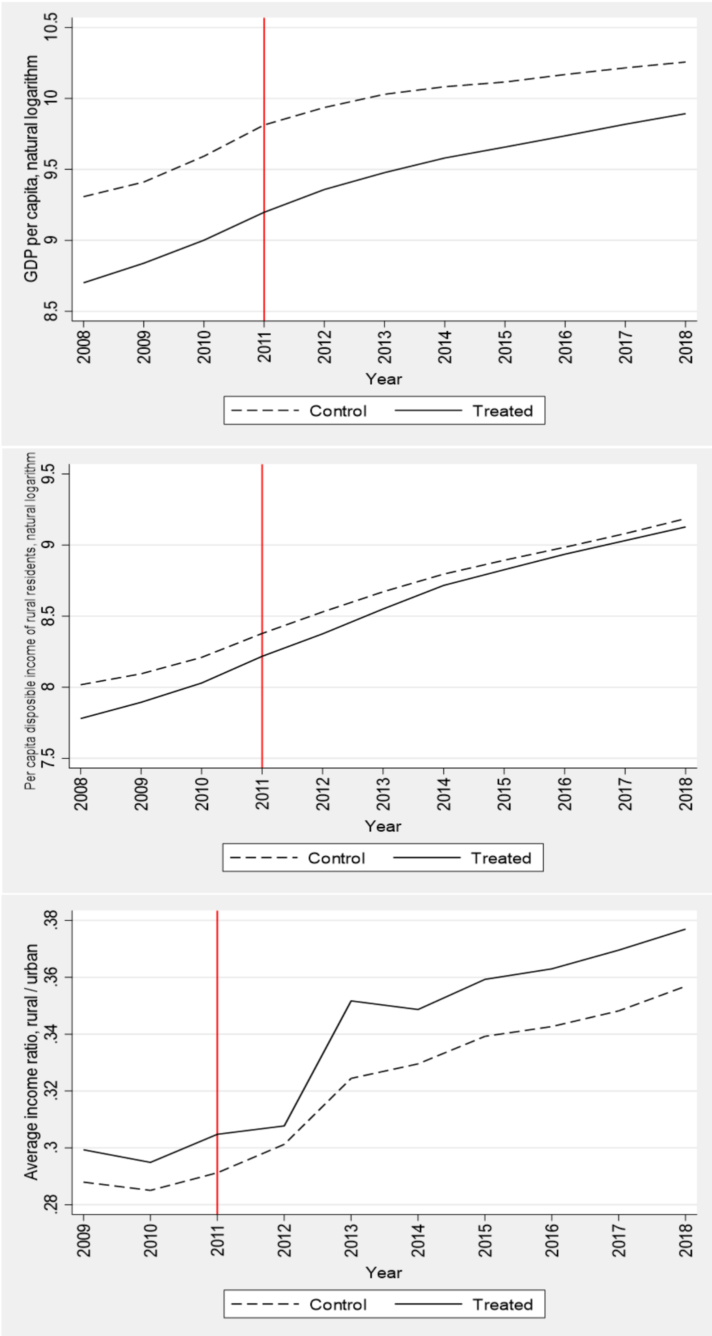


Figure 2.4: Trends of the three dependent variables over time.

2.5 Results

This section presents the empirical results generated by the DID methods discussed in Section 2.4. For each of the following subsections, the traditional DID method serves as the baseline, while DID-FE and SDID are used as robustness checks for the traditional DID method.

2.5.1 Effect of CPA Program on GDP Per Capita

First, the effect of the CPA program on counties' overall GDP per capita was estimated. The treatment group comprised 399 CPA-NDPCs, while the control group comprised 113 NDPCs. This dataset is considered representative because it covers 399 of the 440 (over 90%) of the CPA-NDPCs in the 13 CPAs (excluding Tibet).

Table 2.3 presents the estimated effects of the CPA program on NDPCs using the three DID-based methods: Column (1) reports the DID regression results from Equation (2.1), Column (2) reports the DID-FE regression results from Equation (2.2), and Column (3) reports the SDID regression results from Equation (2.4). First, the regression results show that the parallel trend assumption was satisfied for GDP per capita because the three interaction terms prior to 2011 (i.e. *CPA_year2008*, *CPA_year2009* and *CPA_year2010*) were statistically non-significant; thus, the null hypothesis of zero is not rejected.

The results show that the CPA program has had significant effects on GDP per capita. As shown in Column (1), the estimated coefficient for the interaction variable (i.e. *CPA_year2018*) is 0.25167 ($p < .01$). This indicates that the CPA program increased the average GDP per capita of treated counties by 28.6% compared with the baseline year (2011). Column (2) shows that the effect was also significant at the 1% level for the DID-FE regression model. The effect size was 0.2644, indicating a 30.3%[2] increase in GDP per capita for CPA counties compared with the baseline year.

The estimations also show the dynamic effects of the CPA policy—the longer that counties received additional resources, the stronger the effect of the policy on their GDP per capita. Based on the DID and DID-FE methods, this positive effect was non-significant at the 5% and 1% levels, respectively, in the first 2 years following the implementation of the CPA policy. However, in subsequent years, the effect was significant at the 1% level for both methods. In addition, the effect size continued to increase over the post-intervention period (i.e. 2012 to 2018).

While the SDID method can estimate the average treatment effect, it cannot estimate the dynamic effects. The average treatment effect on the treated (ATT) derived from the SDID is lower than the effects derived from the DID and DID-FE methods; nevertheless, it is consistent

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[2] $(e^{0.2644} - 1) \times 100\% \approx 30.3\%$.

with the estimates of the other two methods in terms of direction. The estimated overall effect size is 0.07984 ($p < .01$). This indicates that the CPA program increased the GDP per capita of the treated counties by 8.3% compared with control counties. Moreover, there was a strong correlation between GDP growth and the contribution to GDP by secondary industries, which were more capable than primary industries in driving GDP growth. The estimated correlation coefficients for the proportion of added value from secondary industries to GDP were both statistically and economically significant. For example, based on the DID-FE model, the coefficient was 1.53477, indicating that a 1% increase in the proportion of added value from secondary industries to GDP was associated with a 1.5% increase in GDP per capita. The size of this correlation was much greater than that of the proportion of the value added from primary industries to GDP.

Table 2.3: Effect of the CPA program on per capita GDP at the county level

GDP per capita (natural logarithm)	**(1)**			**(2)**			**(3)**		
	DID			**DID-FE**			**SDID**		
	Coefficient	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**
year2008	−0.28063	(−6.86)	***	−0.26445	(−7.58)	***			
year2009	−0.20526	(−5.03)	***	−0.20371	(−5.85)	***			
year2010	−0.11290	(−2.77)	***	−0.10888	(−3.13)	***			
year2012	0.03282	(0.81)		0.02708	(0.78)				
year2013	0.05569	(1.36)		0.04558	(1.31)				
year2014	0.07922	(1.93)	*	0.06031	(1.72)				
year2015	0.06527	(1.58)		0.03401	(0.96)				
year2016	0.05368	(1.29)		0.01170	(0.33)				
year2017	0.02604	(0.62)		−0.02827	(−0.78)				
year2018	0.01325	(0.31)		−0.05495	(−1.48)	*			
CPA	−0.33660	(−10.25)	***	−0.23884	(−8.35)	***			
CPA_year2008	−0.28150	(−0.61)		−0.02546	(−0.64)				
CPA_year2009	−0.01401	(0.30)		0.01802	(0.46)				
CPA_year2010	0.00820	(0.18)		0.00703	(0.18)				
CPA_year2012	0.03917	(0.85)		0.04624	(1.17)				
CPA_year2013	0.07793	(1.69)	*	0.08537	(2.16)	**			
CPA_year2014	0.12376	(2.68)	***	0.13381	(3.39)	***			
CPA_year2015	0.16830	(3.65)	***	0.17517	(4.43)	***			
CPA_year2016	0.19910	(4.31)	***	0.20933	(5.29)	***			
CPA_year2017	0.22951	(4.97)	***	0.23674	(5.98)	***			
CPA_year2018	0.25167	(5.44)	***	0.26444	(6.66)	***			

GDP per capita (natural logarithm)	**(1)**			**(2)**			**(3)**		
	DID			**DID-FE**			**SDID**		
	Coefficient	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**
ATT							0.07984	(4.74)	***
GDP_primary/GDP	0.76114	(14.33)	***	0.13352	(2.45)	**			
GDP_secondary/GDP	1.86035	(46.35)	***	1.53477	(39.25)	***			
hospital_bed_density	0.05478	(15.08)	***	0.04206	(12.64)	***			
deposit_per_capita	0.02447	(33.33)	***	0.02589	(34.37)	***			
budget_expenditure	0.01920	(19.27)	***	0.02234	(23.08)	***			
Constant	8.25901	(190.20)	***	8.48186	(212.15)	***			
Province fixed effects	No			Yes			No		
N	5,632			5,368			5,632		
F-test	638.57			726.01					
R-squared	0.7476			0.7329					

Notes: CPA: contiguous poor area; GDP: gross domestic product; DID: difference-in-differences; DID-FE: difference-in-differences with fixed effects; SDID: synthetic difference-in-differences; ATT; average treatment effect on the treated; *GDP_primary/GDP*: proportion of value added to the GDP by the primary industry; *GDP_secondary/GDP*: proportion of value added to the GDP by the secondary industry; *hospital_bed_density*: number of hospital beds per 1,000 people; *deposit_per_capita*: deposit balance per capita; *budget_expenditure*: government expenditure per capita. *** $p < .01$, ** $p < .05$, * $p < .1$.

2.5.2 Effect of the CPA Program on Rural Residents' Income

The effect of the CPA program on GDP per capita reflects the influence of the policy on counties' overall economy. However, this does not necessarily imply that the policy is successful in improving the wellbeing of impoverished people. To explore whether the policy has achieved its goal of alleviating rural poverty, the effect of the policy on rural residents' income was investigated. Given the relative lack of data on rural residents' income, the size of both the treatment and the control groups is smaller than that in the previous analysis. Therefore, for this estimation, there were 281 counties in the treatment group and 74 counties in the control group across 12 CPAs (excluding the three-prefecture area of southern Xinjiang).

Table 2.4 reports the effects of the CPA program on rural residents' income by county. Similar to Table 2.3, Column (1) in Table 2.4 shows the regression results from the DID regression in Equation (2.1), Column (2) shows the results of the DID-FE regression in Equation (2.2), and Column (3) shows the results of the SDID regression in Equation (2.4).

The statistical non-significance of the interaction terms *CPA_year2009* and *CPA_year2010* implies that the parallel trend assumption held in the 2 years prior to the baseline year. However, the assumption was violated when including the year 2008. The estimated coefficient for the interaction term *CPA_year2008* was significant at the 1% level for both the DID and the DID-FE methods. I argue that the risk of violating the parallel trend in 2008 is small because the effects exhibit a clear pattern of being negative in the pre-intervention period and mostly positive in the post-intervention period. More importantly, the negative effect becomes weaker closer to the baseline year (2011) and strengthens from 2011 until 2017. The opposite signs of the pre-intervention and post-intervention effects boosts confidence in the efficacy of the program in increasing rural residents' income.

The results show that the CPA program is positively correlated with rural residents' income at the county level. The estimated coefficients for *CPA_year2018* were 0.07830 for the DID method and 0.12247 for the DID-FE method, indicating that the CPA program increased rural residents' income by 8.1% and 12%, respectively, compared with the baseline year.

Table 2.4: Effect of the CPA program on rural residents' income at the county level

Rural resident income (natural log)	**(1)**			**(2)**			**(3)**		
	DID			**DID-FE**			**SDID**		
	Coefficient	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**
year2008	−0.36226	(−10.30)	***	−0.32551	(−13.21)	***			
year2009	−0.27264	(−7.76)	***	−0.25872	(−10.52)	***			
year2010	−0.16736	(−4.78)	***	−0.15628	(−6.37)	***			
year2012	0.16019	(4.57)	***	0.14166	(5.77)	***			
year2013	0.31581	(8.99)	***	0.27910	(11.34)	***			
year2014	0.45860	(13.01)	***	0.39623	(16.02)	***			
year2015	0.57807	(16.28)	***	0.48606	(19.47)	***			
year2016	0.68114	(19.04)	***	0.56438	(22.38)	***			
year2017	0.79630	(21.97)	***	0.65178	(25.40)	***			
year2018	0.93241	(25.37)	***	0.75478	(28.89)	***			
CPA	−0.11062	(−3.94)	***	−0.07723	(−3.83)	***			
CPA_year2008	−0.10751	(−2.73)	***	−0.10759	(−3.90)	***			
CPA_year2009	−0.05498	(−1.40)		−0.05494	(−1.99)	*			
CPA_year2010	−0.02468	(−0.63)		−0.02619	(−0.95)				
CPA_year2012	−0.00407	(−0.10)		−0.01124	(−0.41)				
CPA_year2013	0.03447	(0.88)		0.04366	(1.58)				
CPA_year2014	0.07699	(1.96)	*	0.08954	(3.25)	***			
CPA_year2015	0.08740	(2.22)	**	0.10864	(3.94)	***			
CPA_year2016	0.10523	(2.67)	***	0.13085	(4.74)	***			
CPA_year2017	0.10393	(2.63)	***	0.13151	(4.76)	***			
CPA_year2018	0.07830	(1.98)	**	0.12247	(4.42)	***			

Rural resident income (natural log)	**(1)**			**(2)**			**(3)**		
	DID			**DID-FE**			**SDID**		
	Coefficient	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**
ATT							0.06616	(2.89)	***
GDP_primary/GDP	0.84484	(15.70)	***	0.18178	(4.24)	***			
GDP_secondary/GDP	0.69350	(19.17)	***	0.20881	(7.44)	***			
hospital_bed_density	0.02129	(6.38)	***	0.01091	(4.36)	**			
deposit_per_capita	0.00007	(−0.11)		0.00677	(12.96)	***			
budget_expenditure	−0.01396	(−11.55)	***	−0.01054	(−10.91)	***			
Constant	7.86325	(202.22)	***	8.14479	(281.51)	***			
Province fixed effects	No			Yes			No		
N	3,905			3,905			3,905		
F-test	663.74			1,305.26					
R-squared	0.8165			0.7962					

Notes: CPA: contiguous poor area; GDP: gross domestic product; DID: difference-in-differences; DID-FE: difference-in-differences with fixed effects; SDID: synthetic difference-in-differences; ATT; average treatment effect on the treated; *GDP_primary/GDP*: proportion of value added to the GDP by the primary industry; *GDP_secondary/GDP*: proportion of value added to the GDP by the secondary industry; *hospital_bed_density*: number of hospital beds per 1,000 people; *deposit_per_capita*: deposit balance per capita; *budget_expenditure*: government expenditure per capita *** $p < .01$, ** $p < .05$, * $p < .1$.

There is also evidence of the dynamic effects of the CPA program on rural residents' income. The DID estimates shown in Column (1) of Table 2.4 show that the effect size continued to expand in the post-intervention period until 2017. From 2015 to 2018, the effect was significant at the 5% level. The coefficients estimated in DID-FE method shown in Column (2) confirm the dynamic pattern.

Unlike the dynamic effects observed for GDP per capita, both dynamic gains and dynamic losses exist for rural residents' income from 2008 to 2018. For example, as shown in Column (1), the effect size continued to expand in the post-intervention period until 2016, then decreased from 0.10523 in 2016 to 0.07830 in 2018. This implies an overall increase of 11.1% and 8.1% in 2016 and 2018, respectively, in rural residents' income. In Column (2), the turning point appeared in 2017, when the effect size reached a maximum of 0.13151, representing a 14.1% increase in rural residents' income. The effect size then slightly decreased to 13% in 2018.

The ATT estimate derived from SDID confirms the positive effect of the policy on rural residents' income during the research period. The estimated coefficient is 0.06616 (p < .01), indicating that by 2018, the CPA program had increased rural residents' income by 6.8%.

Apart from the main finding of causality between the CPA policy and growth in rural residents' income, the correlations between the specific years and rural residents' income are also interesting for two reasons. First, the estimated coefficients for each year are significant, both economically and statistically at the 1% level. Second, there is a positive correlation between time and rural residents' income; that is, the correlation between the year and income is always greater than that for the previous year. This indicates that, on average, rural residents' income has increased monotonically by year in our study locations.

2.5.3 Effect of the CPA Program on Rural–Urban Income Ratio

Reducing the income gap between urban and rural residents is essential for reducing poverty (Bergstrom, 2020). This is also a long-term goal of the Chinese government's poverty alleviation programs. Building on the investigation of the effects of the CPA program on GDP and rural residents' income, the effect of the program on the rural–urban income gap was also investigated.

The index used to estimate the rural–urban income gap was the ratio of per capita annual income of rural residents to that of urban residents, measured at the county level. Given the shortage of income data for urban and rural residents, the observation units analysed were a subset of the original 512 counties, comprising 108 counties located in four provinces (Henan, Hubei, Hunan and Shanxi). Among these, 77 treatment counties were distributed in six CPAs (Dabie Mountain Area, Luoxiao Mountain Area, Lvliang Mountain Area, Qinba Mountain Area, Wuling Mountain Area and Yan–Taihang Mountain Area).

Table 2.5 reports the effects of the CPA program on the rural–urban income ratio in the counties under study. First, the parallel trend assumption for rural–urban income ratio in the pre-intervention period was tested. This assumption held for at least 3 years prior to program implementation because the three pre-intervention interaction terms of interest were statistically non-significant for both the DID and the DID-FE models, supporting the null hypothesis of zero effect.

Next, the effect of the CPA program on the rural–urban income ratio was estimated for the post-intervention period. The results consistently show that the policy had no effect on narrowing the rural–urban income ratio in the selected counties. For example, as reported in Columns (1) and (2), all estimated coefficients in the post-intervention period were statistically non-significant. This indicates that the CPA program had no effect on the rural–urban income ratio. The ATT estimates support the null hypothesis of zero effect on the treatment counties between 2011 and 2018.

While the estimates show that the CPA program did not help narrow the rural–urban income gap in our study areas, a favourable trend was observed in that the income gap has decreased over time. For example, since 2014, the estimates based on the DID-FE model showed significance at the 5% or 1% level, and the effect size has increased monotonically each year. This suggests that from 2014 to 2018, there was a sustained increase in the per capita income of rural residents relative to that of urban residents at the county level. The non-exclusivity of the CPA suggests that while certain counties were designated as treatment areas, interventions or benefits stemming from the CPA could also reach or influence the non-treatment counties. Given that, the spill-over effects could be a highly plausible reason for the non-significant estimates.

Table 2.5: Effect of the CPA program on rural–urban income ratio at the county level

Rural–urban income ratio	**(1)**			**(2)**			**(3)**		
	DID			**DID-FE**			**SDID**		
	Coefficient	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**
year2008	−0.02325	(−1.48)		0.00034	(0.03)				
year2009	−0.02370	(−1.51)		−0.01166	(−0.89)				
year2010	−0.01915	(−1.23)		−0.01058	(−0.81)	**			
year2012	0.02611	(1.67)	*	0.01426	(1.10)				
year2013	0.05853	(3.73)	***	0.03919	(3.00)				
year2014	0.07390	(4.69)	***	0.04512	(3.42)	**			
year2015	0.09351	(5.88)	***	0.05536	(4.15)	***			
year2016	0.10675	(6.66)	***	0.05935	(4.39)	***			
year2017	0.13343	(8.27)	***	0.07293	(5.31)	***			
year2018	0.15820	(9.64)	***	0.08510	(6.04)	***			
CPA	−0.00361	(−0.27)		−0.01089	(−0.99)				
CPA_year2008	−0.01515	(−0.82)		−0.01723	(−1.12)				
CPA_year2009	−0.00245	(−0.13)		−0.00233	(−0.15)				
CPA_year2010	−0.00270	(−0.15)		−0.00436	(−0.28)				
CPA_year2012	−0.01066	(−0.58)		−0.00731	(−0.48)				
CPA_year2013	0.01461	(0.79)		0.01594	(1.04)				
CPA_year2014	0.00419	(0.23)		0.00874	(0.57)				
CPA_year2015	0.01731	(0.93)		0.01555	(1.01)				
CPA_year2016	0.01922	(1.04)		0.01693	(1.10)				
CPA_year2017	0.01750	(0.95)		0.01462	(0.95)				
CPA_year2018	0.01975	(1.07)		0.01542	(1.00)				

Rural–urban income ratio	(1)			(2)			(3)		
	DID			DID-FE			SDID		
	Coefficient	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**	**Coefficient**	**(*t*-statistic)**	**Sig.**
ATT							−0.00677	(−0.51)	
GDP_primary/GDP	0.28783	(9.71)	***	0.04017	(1.45)				
GDP_secondary/GDP	0.10602	(5.64)	***	−0.02205	(−1.30)				
hospital_bed_density	0.00626	(3.57)	***	−0.00288	(−1.78)				
deposit_per_capita	−0.00055	(−1.83)	**	0.00086	(3.26)				
budget_expenditure	−0.01731	(−16.76)	***	−0.00678	(−6.91)	***			
Constant	0.24545	(12.61)	***	0.33250	(19.45)	***			
Province fixed effects	No			Yes			No		
N	1,188			1,188			1,188		
F-test	37.38			17.94					
R-squared	0.4557			0.2647					

Notes: Given the shortage of income data, the dataset used for estimating the rural–urban income ratio was a subsample of the whole panel dataset, comprising 108 counties from four provinces (Henan, Hubei, Hunan and Shanxi). CPA: contiguous poor area; GDP: gross domestic product; DID: difference-in-differences; DID-FE: difference-in-differences with fixed effects; SDID: synthetic difference-in-differences; ATT; average treatment effect on the treated; *GDP_primary/GDP*: proportion of value added to the GDP by the primary industry; *GDP_secondary/GDP*: proportion of value added to the GDP by the secondary industry; *hospital_bed_density*: number of hospital beds per 1,000 people; *deposit_per_capita*: deposit balance per capita; *budget_expenditure*: government expenditure per capita *** $p < .01$, ** $p < .05$, * $p < .1$.

2.6 Conclusion

In this study, a panel dataset was used to examine the performance of the CPA program, a geographic poverty alleviation strategy introduced in the most recent wave of China's poverty alleviation plans, the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2011–2020). The NDPC program, which is targeted at county-level poverty, was implemented prior to the CPA program and was still active following the implementation of the CPA policy. While this presented a challenge in terms of distinguishing the effect of the CPA policy alone, it also brought a benefit. The objectives and interventions of the NDPC and CPA programs are partially aligned, meaning that failure to exclude the effect of the NDPC program may result in an overestimation of the effect of the CPA policy. However, if the NDPC program could be appropriately integrated into the evaluation of the CPA program, it may enhance the efficacy of the evaluation. This goal was accomplished by constructing treatment and control groups from NDPCs.

Based on a series of DID approaches, the analysis revealed that the CPA program yielded significant positive effects on GDP and rural per capita income. These results were relatively robust to the DID-FE and PS-weighted DID methods. For example, based on the PS-weighted DID method, the CPA program increased GDP per capita by 8.3% and rural income by 6.8% in CPA-NDPCs compared with pure NDPCs from 2011 to 2018. This finding was robust to different model specifications, including the DID and DID-FE approaches.

To examine whether the CPA program yielded dynamic benefits for CPA-NDPCs, the effect of the policy was estimated from 2012 to 2018. The results show that the policy has had a dynamic effect on both economic and income growth. The effect on GDP per capita continued to increase over time (although the increment size decreased). The dynamic effect on per capita rural income showed a similar trend; however, the effect size decreased slightly in 2018.

In contrast, the CPA program has failed to narrow the rural–urban income gap. However, because of limited data availability, this evaluation was based on only four provinces: Henan, Hubei, Hunan and Shanxi. In addition, since CPA is non-exclusive, there may be spillover effects that lead to the underestimation of the actual impact. Therefore, the results should not be generalised without further analysis and additional evidence.

Together, these empirical findings confirm the value of geographic targeting for poverty alleviation in the context of China and contribute to the literature by providing robust empirical evidence on the efficacy of China's CPA policy. These results imply that the CPA policy is effective for alleviating spatial poverty and should continue to be implemented. In addition, given that secondary industries play a significant role in promoting the growth of GDP and farmers' income, the government should invest in these industries. Nevertheless, given the limited availability of data, our evaluation focuses on the economic and income outcomes at the county level. Future researchers could explore the direct effects of the policy on poverty reduction at both regional and individual levels and empirically investigate the mechanisms underlying the effectiveness of such geographical targeting schemes.

Chapter 3: Evaluation of the Initial Effects of China's Targeted Poverty Alleviation Strategy: The Example of Gansu Province

The TPA program had been the primary household-level anti-poverty strategy in China since 2013. Chapter 3 evaluates the effectiveness of this strategy for increasing the income of rural households in Gansu province in the early years of its implementation (2013–2016). Using a combination of DID and PSM methods, I estimate the effects of the program. The findings indicate that the program has had an overall negative effect on the income growth of lower-income households and no significant effect on higher-income households. The effect size is heterogeneous depending on the type of poverty at the household level, with a stronger effect on education-induced poverty. Further, the empirical results highlight the importance of the education of the household head in generating income.

3.1 Introduction

China has experienced a rapid reduction in poverty for decades. Based on the current national rural poverty line, which is 2,300 RMB (1.8 USD) per day (at the 2010 purchasing power parity exchange rate), the number of rural people living in poverty was 770 million in 1978 compared with 82 million in 2013, representing a decrease in the poverty rate from 60.5% to 8.5% (NBSC, 2019). Arguably, economic growth plays a crucial role in promoting the welfare of citizens and reducing poverty (Ravallion, 2011; Roemer & Gugerty, 1997; Yan, 2016; Yao, 1999); however, to some extent, poverty is also the product of specific social and economic policies (Alcock, 1997). Therefore, government interventions are as important as economic growth in the fight against poverty (Škare & Družeta, 2016).

Given the importance of public interventions in reducing poverty, the Chinese government has run a comprehensive campaign to reduce rural poverty since the mid-1980s after realising the insufficient power of overall economic growth in assisting those still living in poverty in rural area. Moreover, the focus of anti-poverty policies has shifted from the county level to the village and household levels to improve their efficacy. Against this backdrop, this paper evaluates the effects of the TPA strategy, which has been the dominant strategy in China's most recent poverty reduction plan since 2013.

The core principle of TPA is to identify the underlying causes of poverty for each household and implement corresponding measures. Millions of government employees have been mobilised to achieve this goal and combat rural poverty. Besley and Kanbur (1990) emphasised that while the administrative and information costs of targeted strategies can be high, these strategies are ideal for delivering targeted interventions to impoverished people. Previous studies on the effectiveness of the TPA in improving the economic conditions of households are based on three main methods: regression analysis (Xiao et al., 2022; Zhu et al., 2019), decomposition analysis (Fang & Zhang, 2021; X. Li & Li, 2021) and qualitative methods (Guo et al., 2022). Few studies have focused on the effects of TPA on income; for example, Tang et al. (2022) found that TPA narrowed the urban–rural income gap at the prefecture city level. The lack of empirical research on the direct correlation between TPA and a change in income for targeted households hinders the understanding of the importance and necessity of China's targeted strategy at the household level.

To identify the effect of TPA on household income, I drew on household survey data from two sources from 2013 to 2016, which includes the year the TPA program commenced, based on data availability. I employed PSM to construct counterfactuals from a panel survey dataset and DID to capture the effect for the entire sample.

This chapter aims to answer three questions: (i) What is the effect of TPA on household income? (2) Does the effect depend on the type of poverty? (3) Are household characteristics correlated with income growth?

The findings of this study indicate that (i) the effect is heterogeneous for households with different initial income levels and causes of poverty; (ii) the ATT is significantly negative for lower-income households and non-significant for higher-income households; and (iii) the education level of the head of treated households is positively correlated with income growth.

This study contributes to the existing literature in two ways. First, it investigates the effectiveness of China's latest poverty alleviation policy through an analysis of household data, making it one of the first attempts to explore the effects of poverty alleviation strategies using household-level panel data. Second, it reveals the heterogeneous effects of the TPA strategy in the early years of its implementation depending on the cause of poverty.

The remainder of this chapter is structured as follows: Section 3.2 reviews the related literature; Section 3.3 presents the institutional background; Section 3.4 describes the methodology and data used; Section 3.5 discusses the results, and Section 3.6 concludes the chapter.

3.2 Literature Review

Improving the level of targeting in poverty alleviation policies is one means of assisting deeply impoverished populations. Theoretically, targeted measures are more effective because they deliver customised interventions to meet the individual needs of impoverished people and optimise the efficient use of limited resources; however, in practice, they are challenging to implement because of imperfect information and insufficient political support (Lavallée et al., 2010; Smolensky et al., 1995).

Despite the debate on the adoption of either universal or targeted programs, the literature shows both desirable and undesirable outcomes from targeted programs in developing countries. For example, Iqbal et al. (2015) evaluated the effects of microcredit, a self-targeted program, for impoverished populations in Pakistan. The authors surveyed 263 customers of selected microfinance institutions, finding that microfinance plays a positive role in reducing poverty in terms of fulfilling basic needs, improving living standards and increasing self-employment. Similar results were found for a microcredit program in Bangladesh (Pomi, 2019).

Studies of a nationwide conditional cash transfer program known as PROGRESA, founded in Mexico in 1997, have found that it has had a moderate effect on household wellbeing. Unlike the self-targeted microfinance program in Pakistan (Iqbal et al., 2015), PROGRESA identifies people living in poverty through proxy means testing and geographical targeting. Empirical studies have shown that the overall effects of the program on household income and consumption are modest in the short term (Angelucci & Attanasio, 2009); however, in the long term, targeted households could achieve permanently higher consumption rates by investing their payments in productive assets (Gertler et al., 2012).

Unlike other targeted anti-poverty policies or programs that use methods such as proxy means testing, geographical targeting and self-targeting to identify impoverished people (Grosh, 1994; Lavallée et al., 2010; Smolensky et al., 1995), China's TPA focuses not only on accuracy in identifying impoverished populations but also on delivering multilevel programs to meet the needs of individuals and providing one-on-one help by mobilising millions of public officials to build connections with identified poor households (IPHs). The Chinese government proposed its TPA program in November 2013 and implemented it in late 2014/early 2015. Since 2016, there has been considerable research on the TPA program (e.g., Davie et al., 2021; Guo et al., 2022; Y. Li et al., 2016; Si, 2020; J. Wang et al., 2016; Wang & He, 2018; Yang & Liu, 2021;

Zhou et al., 2018). These studies elaborate on the concepts, mechanisms and necessity of TPA (Davie et al., 2021; Y. Li et al., 2016; Y. Liu et al., 2017; Wang & He, 2018; Yang & Liu, 2021) but also point to its practical challenges in terms of the accurate identification of impoverished households (Y. Li et al., 2016; Qian, 2016) and the sustainability of policy implementation and performance (Si, 2020).

The effectiveness of TPA has also been analysed in qualitative case studies. G. Zhang et al. (2019) investigated two villages in Fujian province, finding that the goals of TPA had been largely achieved and that the program had mitigated traffic conditions. Rogers et al. (2020) examined poverty resettlement projects in Shaanxi and Gansu provinces, finding that resettled households (both IPHs and non-IPHs) had a reduced financial burden; however, resettlement could create conflicts in local societies. Viewing poverty as the result of excessive population or inadequate resources, Y. Guo and Wang (2021) investigated a TPA-based labour transfer program[3] in a north-western county, finding that it not only reduced the vulnerability of impoverished people but also contributed to improving the livelihood capitals (i.e. human capital, natural capital, financial capital, social capital and physical capital) of the remaining population in the county.

A small number of studies have attempted to quantitatively examine the correlation between TPA and socioeconomic outcomes. Most of these have focused on the sub-initiatives of the TPA program, finding mixed results. For example, Xiao et al. (2022) used formal econometric models to assess the effects of infrastructure on the income of impoverished families. They found that investment in electricity and irrigation significantly contributed to households' agricultural income by increasing participation in agricultural labour. However, given that this was a quasi-experiment, which requires the accurate identification of treatment and control groups and the careful selection of econometric methods, the authors' use of simple OLS regressions to estimate the effects may have been inadequate to capture causality. C. Chen and Pan (2019) focused on the health poverty alleviation project, an integral component of the TPA program implemented in 2016, finding that it decreased impoverished households' financial risk by reducing their out-of-pocket payments. H. Zhang et al. (2020) examined the effect of a solar photovoltaic project on county-level income, finding that the project immediately increased per capita disposable income and that the effect size grew in the subsequent 2–3 years.

[3] Poverty alleviation through labour transfer was implemented by the Chinese government as part of anti-poverty efforts in rural areas. Under this policy, rural residents are provided with training and employment opportunities in urban areas.

L. Zhang et al. (2020) analysed the effects of the TPA's resettlement project in a county in central China, finding that the project increased participants' income and labour supply. Those who were more competitive in the labour market received greater benefits because relocation eliminates the mismatch in the labour market by increasing work opportunities. M. Y. Liu et al. (2021) evaluated the effects of the TPA's industrial development program on the livelihood capital of farmers in Guizhou, Sichuan and Gansu provinces from 2014 to 2017. They found that the program brought more benefits to non-impoverished people than to impoverished people, although this effect was not statistically significant in Gansu province.

A practical challenge in quantitatively evaluating the sub-initiatives of the TPA is identifying the treatment and control groups because a single IPH commonly receives multiple sub-initiatives of the TPA at the same time. This creates difficulty in accurately extracting the treatment effects of a specific sub-initiative or project, potentially weakening or confounding the treatment effects. For example, in estimating the effects of specific programs, C. Chen and Pan (2019) (the health poverty alleviation project), H. Zhang et al. (2020) (the photovoltaic project) and M. Y. Liu et al. (2021) (industrial development) did not control for the potential effects of other sub-initiatives or projects that were being simultaneously implemented.

Another challenge when evaluating the household-level effects of TPA is constructing a counterfactual group. The official database for IPHs is the National Poverty Alleviation and Development Information System (NPADIS); however, this database contains only IPH information, creating an obstacle to finding an appropriate control group for IPHs. The existing literature has addressed this issue in two ways: changing the composition of the control group or leveraging additional datasets to construct counterfactuals. Examples of the former include L. Zhang et al. (2020), who identified the treatment group as IPHs that participated in the resettlement project and the control group as IPHs that did not participate in the project, and Xiao et al. (2022), who considered infrastructure a continuous rather than a binary independent variable and evaluated the effects within the IPHs. This was followed by C. Chen and Pan (2019), who combined the NPADIS dataset with the New Rural Cooperative Medical Scheme dataset, which contains the information of non-participants. It should be noted that this challenge is only relevant when conducting evaluations at the household level. Changing the evaluation to a higher level such as the county level could rectify the issue of inadequate household-level data (e.g., H. Zhang et al., 2020); nevertheless, this would limit the understanding of microlevel effects.

The review of the literature indicates that the overall effects of the TPA on the wellbeing of IPHs in China remain underexplored. The research presented in this chapter is based on Gansu province, a typical impoverished region of China. In general, the interventions received by IPHs can be categorised into three types: skills training, agricultural subsidies and education support. Selected households receive a mix of interventions depending on their specific circumstances. The function of the assigned government officers at this stage is to assist these households in understanding and selecting programs that are most suitable for their needs. The research presented here evaluates the effect of TPA on a household-level outcome: per capita net income.

3.3 Institutional Background

3.3.1 Background of China's Poverty Alleviation Program

Since the establishment of the People's Republic of China in late 1949, the Chinese government has persistently fought rural poverty (Rozelle, et al, 2003; Yan, 2016). A retrospective view shows the clear change in China's anti-poverty strategies over the last few decades. There have been five poverty reduction stages prior to the introduction of the TPA program.

The first stage was between 1949 and 1978, when poverty was prevalent and persistent in rural China. Government anti-poverty campaigns were primarily focused on resolving basic food and clothing shortages at the national level and re-establishing agricultural production that had been destroyed by war and inappropriate development policies (e.g. the Great Leap Forward) (Fan & Chan-Kang., 2005; Y. Liu et al., 2018). While living conditions in the 1970s were much better than those in the 1950s, political factors prior to 1978 hindered the effectiveness of poverty reduction campaigns. Political struggles during this period suppressed production incentives. Meanwhile, the 'agriculture first' policy impeded industrial development, thus was detrimental to poverty reduction (Yao, 2000). By the end of 1977, there were more than 770 million impoverished rural populations in China (based on the 2010 poverty line) (NBSC, 2019).

The second stage was between 1978 and 1985, when poverty reduction campaigns were driven by land and market reforms. Land reforms were focused on transforming the collective agricultural system into a system in which individual households were contracted for agricultural production, stimulating the enthusiasm of farmers (Lin, 1992), while market-based reforms at the macroeconomic level contributed to rural development, helping to alleviate poverty (Yan, 2016).

The third stage, 1986 to 1993, was characterised by the emergence of a dedicated government agency to address poverty. Prior to 1985, poverty alleviation had been a by-product of macroeconomic improvement; that is, impoverished populations benefited from overall economic growth rather than from a particular poverty alleviation project (Khan & Riskin, 1998). While GDP continued to increase into the mid-1980s, poverty reduction began to slow (Gustafsson & Shi, 1998; Yao, 1999). This was a result of inequality and imbalanced development impeding the effectiveness and efficiency of overall economic development in further eliminating poverty (Ahmad & Wang, 1991; Ravallion & Chen, 1998; Ravallion & Chen, 2007; Yan, 2016). Unlike previous poverty alleviation strategies, which were non-specific and largely driven by overall economic development, poverty alleviation activities from 1986 to 1993 were more targeted, organised and planned. A key event occurred in 1986, when the central government established the State Council Leading Group on Economic Development in Poor Areas to lead the nation's poverty alleviation. During this period, poverty reduction was significant. By the end of 1993, the poverty rate had fallen to half that of 1986 (based on the 1978 poverty line) (NBSC, 2019). Nevertheless, the poverty alleviation projects at this stage could not completely eradicate poverty because of the government's lack of experience in policy implementation and fiscal shortages (Yan, 2016). The unequal regional development that had begun in the 1980s led to impoverished populations being concentrated in specific areas, widening the disparities between eastern and western China (Fan, 1997; Lakshmanan & Hua, 1987; Yan, 2016).

The fourth stage, spanning from 1994 to 2000, was aimed at addressing unequal development and absolute poverty in rural China. To this end, the central administration introduced the the 8–7 Plan in 1994, which aimed to meet the food and clothing needs of 80 million rural inhabitants by 2000. The 8–7 Plan established 11 goals[4] to address the basic needs of impoverished populations, build infrastructure and improve education and health (Yan, 2016). This marked the first anti-poverty program with clear objectives, goals and methods. While

[4] The 11 goals of the 8–7 Program were as follows: (i) achieve a per capita net income of at least 500 CNY (in 1990 prices) for the vast majority of poor households; (ii) provide a half to full *mu* of high-yield basic farmland per capita in places with suitable conditions; (iii) provide an average of 1 *mu* of forest orchard or crops per household; (iv) send an average of one labourer per family to work in a non-agricultural sector; (v) provide an average of one aquaculture or other family business per household; (vi) provide an average of one fenced pasture per household in pastoral areas; (vii) ensure adequate drinking water in impoverished townships; (viii) provide electricity to impoverished townships; (ix) provide basic universal primary education to eliminate illiteracy; (x) provide adult vocational and technical education and skills training in impoverished townships; and (xi) improve medical and health conditions in poor townships to prevent and cure endemic diseases (Yan, 2016).

evaluation methods have varied, studies have highlighted the positive effect of the 8–7 Plan on poverty reduction (Meng, 2013; S. Wang et al., 2004).

During the third and fourth stages, the central administration had identified hundreds of counties as NDPCs. By the end of 1993, 592 NDPCs had been identified, and these were the basic targets of poverty alleviation strategies, including monetary payments, infrastructure construction and other supportive activities. During this period, comprehensive improvements were made to agriculture, roads, electricity, telecommunications, hospital facilities and schools, and the number of people living in poverty declined. By the end of the 8–7 Program, the number of rural people living below the poverty line had fallen from 80 million to 32 million (NBSC, 2019). However, new challenges were emerging in terms of assisting the remaining poor populations.

The fifth stage was guided by the Outline for Development-oriented Poverty Reduction for China's Rural Areas (2001–2010). In this new plan, poverty alleviation strategies were adjusted, including a crucial change in which the focus of poverty alleviation work shifted to the western provinces and downward to villages given that impoverished populations were geographically dispersed and increasingly concentrated in villages rather than in counties (Yan, 2016). In total, 150,000 villages in counties designated as both impoverished and non-impoverished were identified as poor.

Previous anti-poverty efforts in rural China faced two major issues. The first is the 'return to poverty' phenomenon in which many previously impoverished people fall back into poverty because of disease, natural disasters or burdensome education expenditures (Yan, 2016). To some extent, this phenomenon indicates the unsustainable effects of previous poverty alleviation efforts. The second issue is chronic or persistent poverty, which has proven to be intractable in previous poverty alleviation activities. Wan and Zhang (2013) decomposed poverty in China, finding that chronic poverty accounts for over 85% of all types of poverty. In response to these issues and to fulfil its political promise to resolve absolute poverty by 2020, the central government then turned to TPA, which focuses on the accurate identification of poor households and targeted actions depending on the type of poverty to achieve the goal of poverty alleviation.

3.3.2 Participation in the TPA Program

Several criteria are used to identify households as poor, thus eligible to receive interventions. According to an official central government document, the selection criteria are divided into two major components. The first is per capita net annual income, which is set at 2,300 CNY (in 2010 prices). The second considers other household issues such as the presence of illness in family members, the presence of school-age children (who bring a financial burden to the household) and housing difficulties. Households facing any of these issues are more likely to be considered eligible for the program, even if their per capita net income is higher than 2,300 CNY (X. Li et al., 2022).

The Chinese central government has outlined several steps for the identification of genuinely impoverished households to ensure they receive appropriate interventions (see Figure 3.1). First, households must apply to their village committee, which then makes a democratic assessment and creates an initial list of impoverished households. Next, the village committee and a government-appointed administrative team announce the results to the village and submit the list to the township government. After reviewing the list of impoverished households, the township government again announces the list in the village before submitting the final list to the county government.

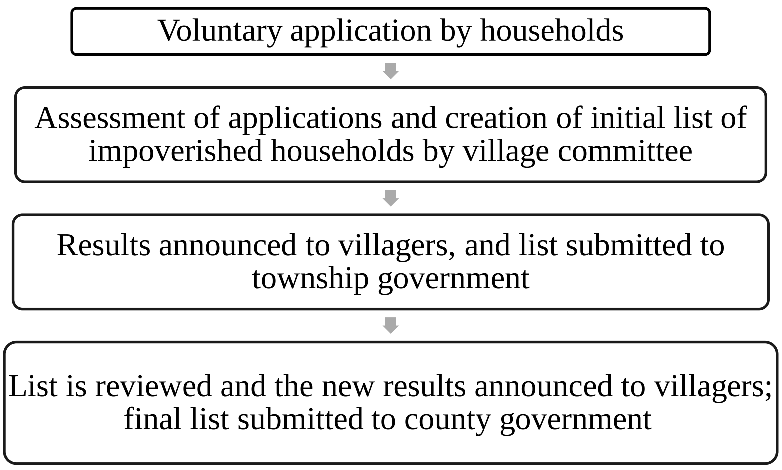

Figure 3.1: Procedure for identifying poor households.

There remain concerns that some eligible households may not participate in the program because of endogenous factors. For example, impoverished families with illiterate or elderly family heads may have difficulty understanding the policy and navigating the application process. Further, while some households possess the labour capacity to enhance their living conditions, they may lack the motivation to apply for the program. The TPA approach offers a solution for addressing such unanticipated situations. Although households themselves must initially apply for the program, autonomous village committees and stationed cadres are obligated to evaluate each household's circumstances and provide assistance throughout the application process. Given that village committees function as autonomous administrative entities that maintain close relationships with the rural households under their jurisdiction, thus possess a more comprehensive understanding of each household's unique situation than that possessed by any other government agency, I posit that most eligible households are effectively identified and supported.

However, not all impoverished households are enrolled in the TPA program for two reasons. First, although the central government aims to assist all impoverished rural populations, it assigns a quota to the number of impoverished households in each province, resulting in some eligible households not being enrolled. Based on its preliminary data, the central government redistributed the task of lifting 70.17 million impoverished people out of poverty to 28 provinces by excluding Beijing, Shanghai and Tianjin. In each province, quotas are further assigned to lower administrative areas. However, inaccuracies in identifying poor households may have led to some cities, counties and villages receiving an insufficient quota, meaning that some poor households will be excluded, and others receiving an excessive quota, meaning that some ineligible households will be included (Y. Li et al., 2016).

Second, impoverished households may fail to receive assistance from the TPA program because of corruption. Rural China is more relations based compared with urban China. A survey conducted by Y. Li et al. (2016) implied the existence of corruption, which hindered the accurate identification of poor households and impeded the effectiveness of the program. These findings were confirmed by Sun et al. (2021) in a case study.

These inaccuracies in identifying poor households provided the opportunity to construct a control group comprising households that would have been eligible for but were not enrolled in the TPA program. The data collected for this study confirm the existence of an identification problem because thousands of additional households were enrolled in the re-identification process.

3.3.3 Interventions

From 2014 to 2016, the Chinese government implemented four types of interventions to eligible households: the provision of livestock (e.g. cows and goats) worth up to 10,000 CNY per household; loans of up to 50,000 CNY with discounted interest rates; the provision of vocational training programs to school-age children costing 1,500 CNY per student; and the provision of agricultural skills training programs costing 150 CNY per capita.

In addition to these interventions, eligible households are also prioritised in terms of non-exclusive assistance and development programs. An empirical study of TPA conducted by X. Li et al. (2022) indicates that regardless of their income status (i.e. income poor, multidimensionally poor or non-poor), enrolled households received more public assistance than did non-enrolled poor households. Given that direct comparisons of the effects of individual interventions are not possible given their various applications, the effects of the TPA interventions as a bundle are rigorously assessed in this study.

3.4 Methodology and Data

This study was based on a combination of DID and PSM to examine the causal relationship between the TPA program and the income of enrolled poor households. The selection of the PSM-DID approach was motivated by three key factors. First, the non-experimental nature of the study necessitated careful consideration of the chosen methodology to minimise bias resulting from the non-random selection of treatment and control groups, which is beyond the capability of traditional DID and DID-FE methods. Second, the dataset included observations from both the pre-intervention and the post-intervention periods, making it amenable to the application of DID. Finally, because the data were drawn from multiple sources, the use of PSM at baseline permitted greater comparability between the treatment and control groups (Khandker et al., 2009).

Other commonly used DID-based methods such and DID-FE and SDID are not as ideal as PSM-DID in addressing data issues. In this study, there were significant differences between the treated and untreated observations in the raw data; therefore, pairing treated and untreated units was critical for minimising the baseline imbalances between the control group (untreated observations) and the treatment group, which is beyond the capability of the DID-FE and SDID methods.

3.4.1 Data

In this study, household-level data were drawn from two sources. The data for the treatment group were collected from several counties in Gansu province. Gansu has long been considered representative of poor areas in China because of its entrenched poverty (Y. Liu et al., 2017; Montalvo & Ravallion, 2010; Ravallion & Chen, 2007). Gansu is located in the arid region of north-western China (see Figure 3.2), where natural disasters are frequent and the ecosystem is fragile, limiting agricultural production. Economically, Gansu is largely dependent on less diversified agriculture, which, combined with its underdeveloped infrastructure, limits its integration and growth opportunities compared with more prosperous regions. In addition, a large proportion of ethnic minorities in Gansu live in remote areas, where they have limited access to services such as education and medical care. These factors have historically led to high levels of poverty in Gansu, making it emblematic of the broader poverty problem in China.

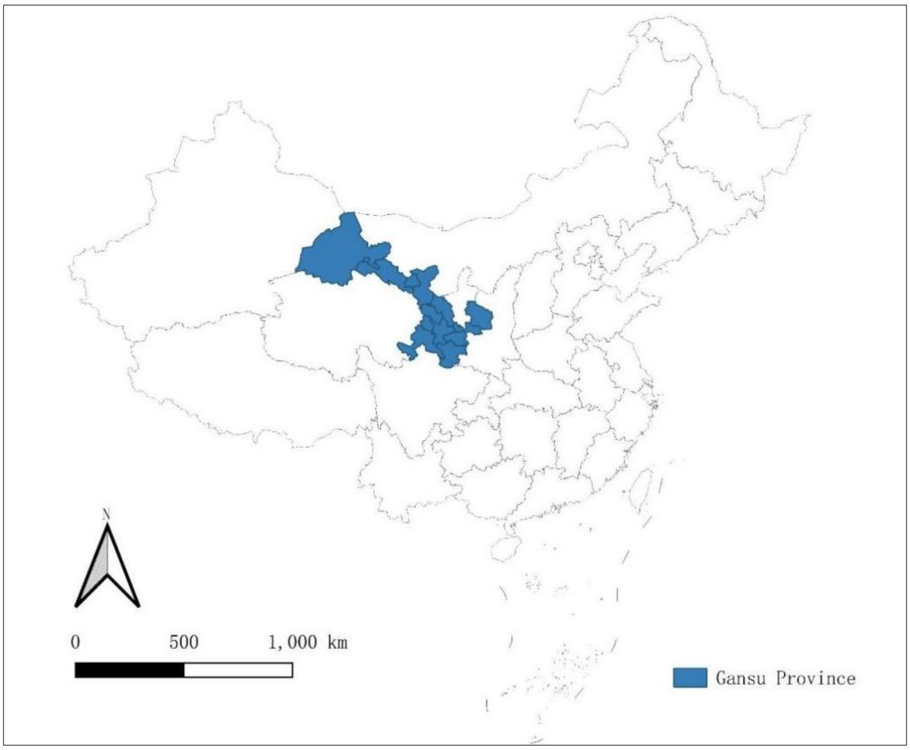

Figure 3.2: Location of Gansu province.

The dataset used in this study covered more than 18,800 designated poor households for the years 2013 and 2016. This is an administrative dataset that was originally collected by the office for poverty relief of local governments. The household variables in this dataset included per capita net income, the health status of family members, the number of school-age children, enrolment in medical insurance programs, housing difficulties and family size.

To construct a suitable control group, data were drawn from the CFPS, a nationally representative survey of Chinese families and individuals, for 2014 and 2016. The CFPS data were limited to Gansu province to ensure comparability with the treatment group. While TPA is implemented nationwide, local governments at the provincial level tailor specific measures based on households' actual circumstances (C. Liu et al., 2018). Therefore, an additional advantage of this restriction is the elimination of provincial differences in the main TPA methods.

To match the 2013 treatment group, 2014 CFPS data were adjusted using the increasing rate of per capita net income of the rural population in Gansu province[5]. After cleaning and matching, this dataset contained data from nearly 500 rural households in Gansu province.

Table 3.1 presents the summary statistics of unmatched observations from both groups (The next subsection describes in detail how the control group is constructed). Unsurprisingly, the mean values of most household characteristic variables were significantly different before matching because the observations in the original datasets of both groups had different distributions. Specifically, the CFPS dataset pertains to the overall population, while the treatment group dataset pertains to poor households. Matching with replacement led to the final data being balanced because it allowed for the repetition of observations in the control group; therefore, one control group household could serve as a counterfactual for multiple treatment group households. In this case, the true average values of the control group should be weighted based on the frequency of observations in the control group. At this stage, it was infeasible to calculate frequency weights using statistical software. Nevertheless, the weighted mean differences between the key characteristic variables shown in Table 3.2 indicate that the mean differences were significantly reduced after matching.

[5] . The method employed took the following form: $\text{income}_{2013} = \text{original income}_{2014}/(1 + \text{Increasing rate of per capita net income in 2014})$. Where the "Increasing rate of per capita net income" was derived from the official statistical yearbook for Gansu province.

Table 3.1 Summary statistics of unmatched observations

	Treatment group Mean	Std. dev.	Control group Mean	Std. dev.	Diff. C-T
Change in per capita income, 2016 vs 2013	1553	1664	2783	12592	1230***
Income, per capita	2577	800	7450	6531	4873***
Family size	4.27	1.47	4.41	1.64	0.14**
Proportion of capable labour force within a household	0.67	0.26	0.45	0.29	-0.23***
Proportion of family members with chronic diseases within a household	0.14	0.22	0.14	0.21	0.003
Proportion of school-age child within a household	0.21	0.20	0.15	0.21	-0.06***
The highest education level of the head of household	1.37	0.65	0.93	1.05	-0.44***
N	18566		481		

* p<.1; ** p<.05; *** p<.01

3.4.2 Empirical Strategies

3.4.2.1 Control Group Identification

A critical issue in evaluating the TPA program was identifying the counterfactuals. Given that the compliance rate of the program is 100%, the treatment status is the same as the program's assignment. However, defining a counterfactual was problematic for two reasons. First, the implementation of the program was non-random, and second, the program was implemented nationwide. Nonetheless, counterfactuals may be identified by examining the spatial or temporal rollout, meaning households that were eligible for the program but did not enrol because of insufficient poverty alleviation resources or inaccurate identification.

Although the TPA program aims to accurately identify impoverished households, inaccuracies in the identification process still exist in practice (Deng, 2014; Y. Li et al., 2016; Y. Liu et al., 2018; Sun et al., 2021). As a result, a control group could be constructed using data from unidentified households. The first reason for inaccurate identification is that the provincial government estimates the total quantity and distribution of impoverished households, then assigns a quota to each county based on its preliminary estimation. Consequently, the quota that each village receives may not correspond to the actual number of impoverished households. The second reason relates to intentional relationship-based manipulation in which local administrative agents, instead of complying with the established methods for identifying impoverished households, favour households containing their relatives. Thus, some eligible households may be excluded because each village has a cap on the number of assisted households. Our dataset revealed the inaccurate identification of impoverished households, as illustrated in Figure 3.3.

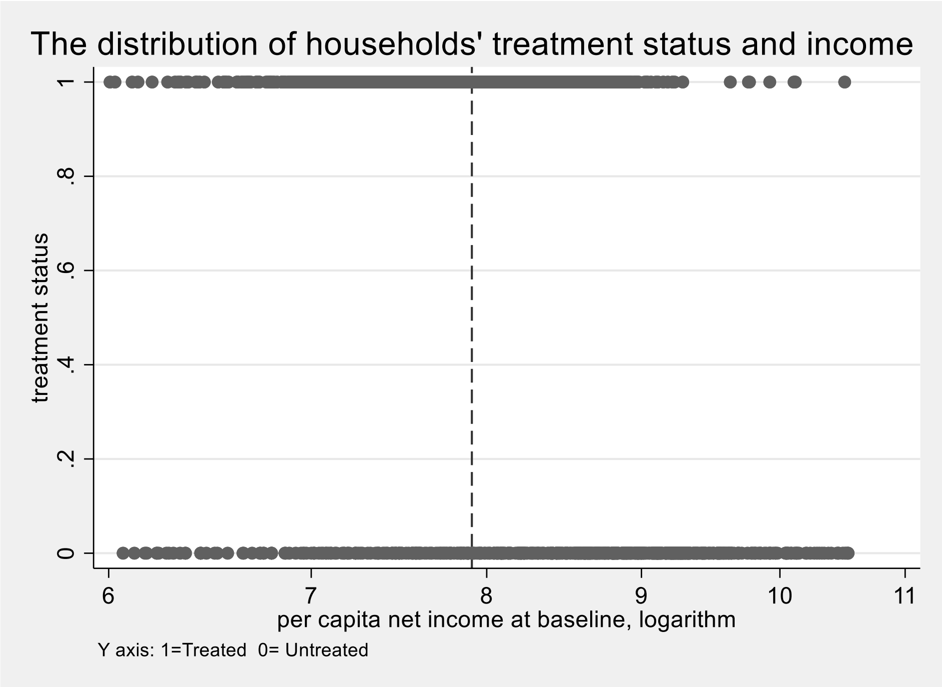

Figure 3.3: Distribution of treatment status and income in the baseline year.

Notes: The dashed line is the poverty line.

The control group was constructed using the CFPS dataset. First, the CFPS dataset was reduced by excluding observations from urban areas and other provinces, leaving only the rural areas of Gansu province. Then, households that had received any TPA-related funds from the government during the research period were excluded.

After filtering out observations with missing or abnormal values, nearest neighbour matching with replacement was used to match designated poor households with the constructed counterfactuals (non-poor households with the closest propensity score). This matching method involved pairing the treated observations (designated poor households) with untreated observations based on the predicted propensity score. Because the control group was smaller than the treated group, the matching algorithm allowed for replacement, permitting untreated observations to be matched to multiple treated observations to ensure all treated data could be utilised. To explore whether different matching algorithms would yield different treatment effects, two commonly adopted algorithms—radius matching and kernel matching—were used. The results show that the treatment effects were similar for both matching algorithms (see Table 3.3).

The TPA selection criteria for impoverished households include whether they live below the poverty line, have school-age children, suffer from chronic diseases or experience housing difficulties. For this study, two variables—income in 2013 and the proportion of school-age children—were selected for PSM. These two variables correspond to the identification indicators of impoverished households mentioned in the previous section (i.e., the selection criteria for identified impoverished households: per capita net annual income, which is set at 2,300 CNY in 2010 prices, the presence of school-age children that bring a financial burden to the household.). Table 3.2 shows the balance of the key selection variables after matching. The difference in the two key selection variables between the treatment and control groups narrowed after matching.

Table 3.2: Covariate balance before and after matching

	Raw		Matched	
Number of obs.	19,047		37,132	
Treated obs.	18,566		18,566	
Control obs.	481		18,566	
	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Per capita income at household level, logarithm	-1.079	0.032	0.073	0.919
Proportion of school-age child within a household	0.356	0.145	1.459	1.429

To facilitate the distribution of assistance to IPHs, each household is classified as one of 13 poverty types or causes (see Appendix A). Village committees and local cadres assess the poverty type of each IPH by visiting and interviewing them about the primary factors constraining their ability to improve their financial status based on the official guidelines.

Figure 3.4 illustrates the six most prevalent causes of poverty in our IPH dataset: (i) lack of agricultural technologies or work skills (skills scarcity); (ii) shortage of production funds (funds scarcity); (iii) chronic or major diseases or disabilities (health issues);[6] (iv) financial burden arising from school and related expenses (education burden); (v) inadequate labour because of age or other reasons (labour scarcity); and (vi) labour ability but lack of willingness (insufficient motivation). The small proportion of IPHs that did not fall under one of these six poverty types were grouped as 'other' and excluded from the empirical analysis.

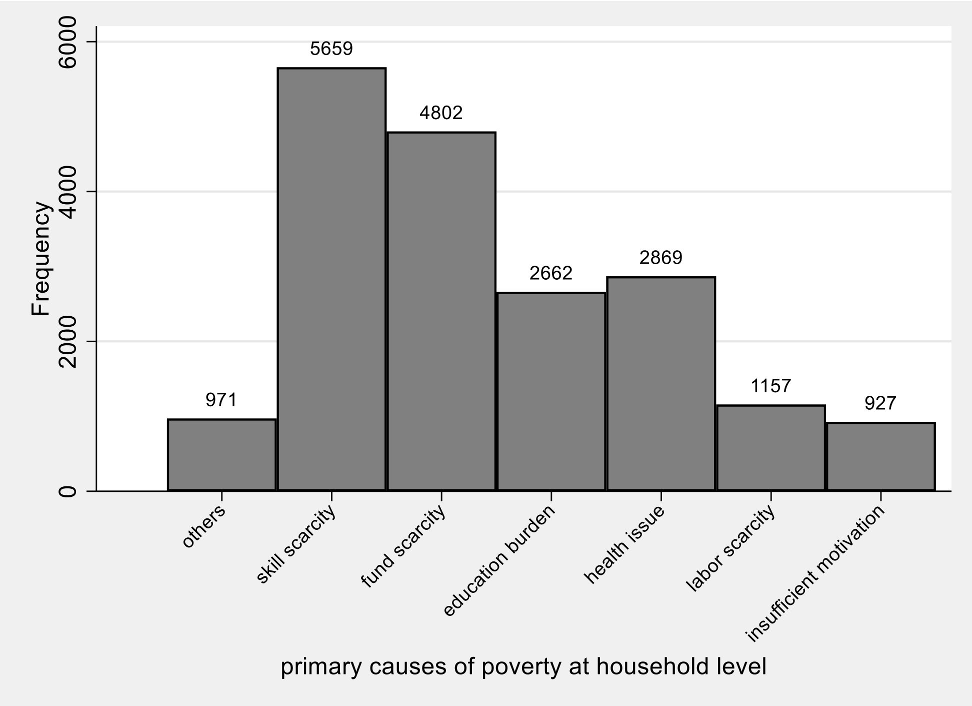

Figure 3.4: Identified causes of household-level poverty.

3.4.2.2 Empirical Model

In this study, the effect of the TPA program on per capita net income at the household level was estimated. Given that the treatment status relates to household-level characteristics, self-selection bias was possible. Thus, the DID method was used to eliminate self-selection bias and account for unobserved household factors. However, the DID model may be compromised by the non-randomness of non-experimental studies. A common solution to this concern is to combine PSM with the DID model (Heckman et al., 1997). Combining DID and PSM yields an ATT estimate as follows:

[6] This category combines two identified causes of poverty in the raw data—disability and chronic or major diseases (see Appendix A).

$$\text{ATT} = E_{p(x)|D=1}\left[E\left(Y^{1i}\middle|D_i = 1, p(X_i)\right) - E\left(Y^{0i}\middle|D_i = 0, p(X_i)\right)\right]$$

The internal validity of DID depends on the parallel trend assumption, which requires that in the absence of treatment, the difference between the treatment and control groups remains unchanged over time. In the context of this study, factors that could lead to differences in income growth between the two groups include macroeconomic conditions and household characteristics. To control for macroeconomic conditions, the control group was limited to households in rural areas of Gansu province, where the treated households were also located. This geographical restriction ensured similarity in administrative policies and the level of development between the treatment and control groups. Evidence suggests that over 87% of the counties in Gansu province were identified as poor in previous poverty alleviation actions, reflecting the prevalent underdevelopment in rural Gansu (Zhang et al., 2021).

In addition, PSM enhances the similarity of household characteristics and eligibility for TPA between the treatment and control groups, thereby improving the internal validity of the DID method. Given that anti-poverty programs were mainly implemented at the village and county levels before the TPA program, households in both groups had the opportunity to benefit from these programs if they had similar economic conditions.

In summary, by applying a geographical restriction and a matching method, it is reasonable to expect similarities in income changes between the two groups before the implementation of TPA. Figures 3.5 and 3.6 illustrate these similarities by comparing rural residents' per capita income and income growth rate, respectively, in the counties from which data were collected, other counties in the province and the overall province. The trends are consistent terms of direction and size.

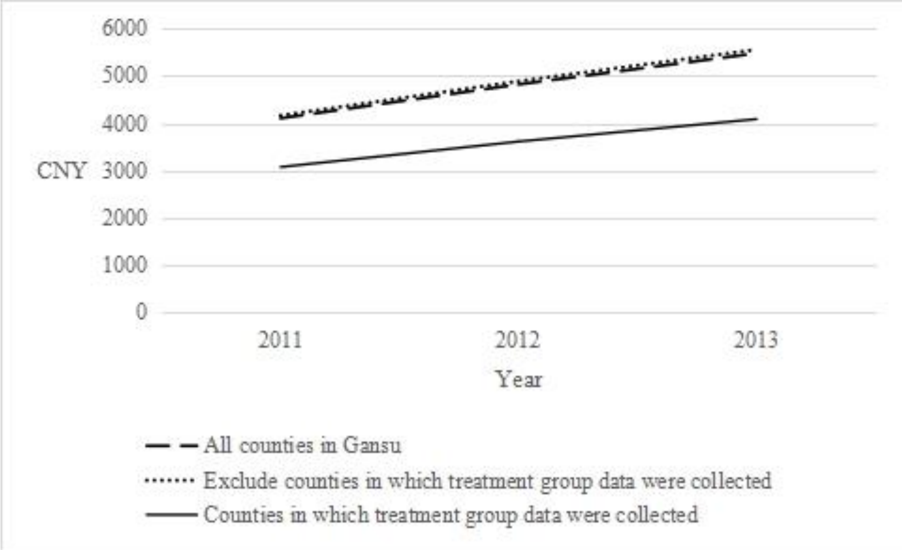

Figure 3.5: Per capita income in rural Gansu prior to the implementation of targeted poverty alleviation.

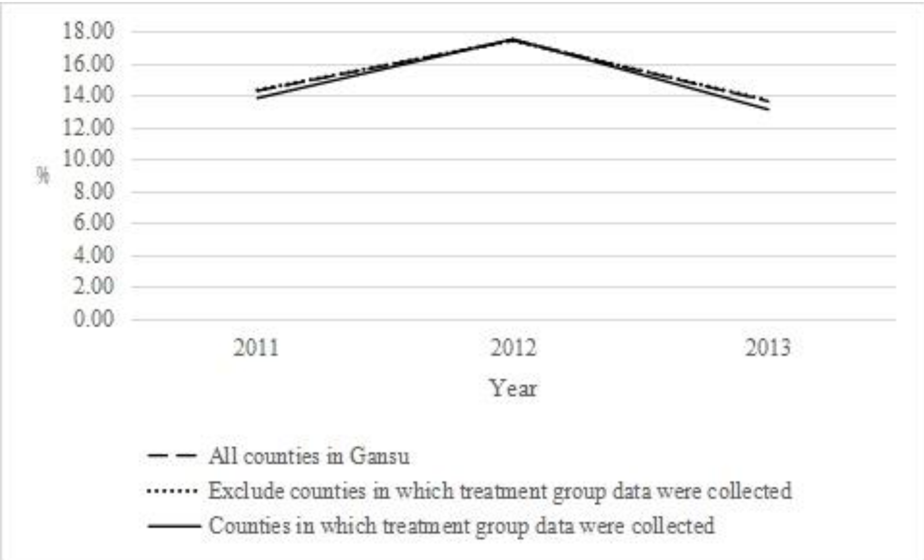

Figure 3.6: Per capita income growth in rural Gansu prior to the implementation of targeted poverty alleviation.

Testing for the parallel trend assumption typically requires pre-intervention data, which were unavailable for the treatment group in this study. To overcome this limitation, county-level data on the per capita net income of the rural population were used for the treatment group. While this alternative method has limitations, it did provide some information about the trend. It is only the trend in income before the commencement of TPA in 2014 that is of interest for this study because the post-intervention data may not accurately reflect the income growth rate of the treatment group because of the program effects.

Figure 3.7 illustrates the per capita net income trends for the treatment and control groups. The curve for the control group represents the logarithmic per capita net income derived from the CFPS dataset, while the curve for the treatment group represents the natural logarithm of county-level per capita net income collected from the local statistics office of the treatment households. The year 2013 marks the introduction of the TPA scheme, which was implemented in 2014. While the data used for the trend comparison were more macro than those used in the regressions, this approach enabled the observation of trends in income growth for both groups.

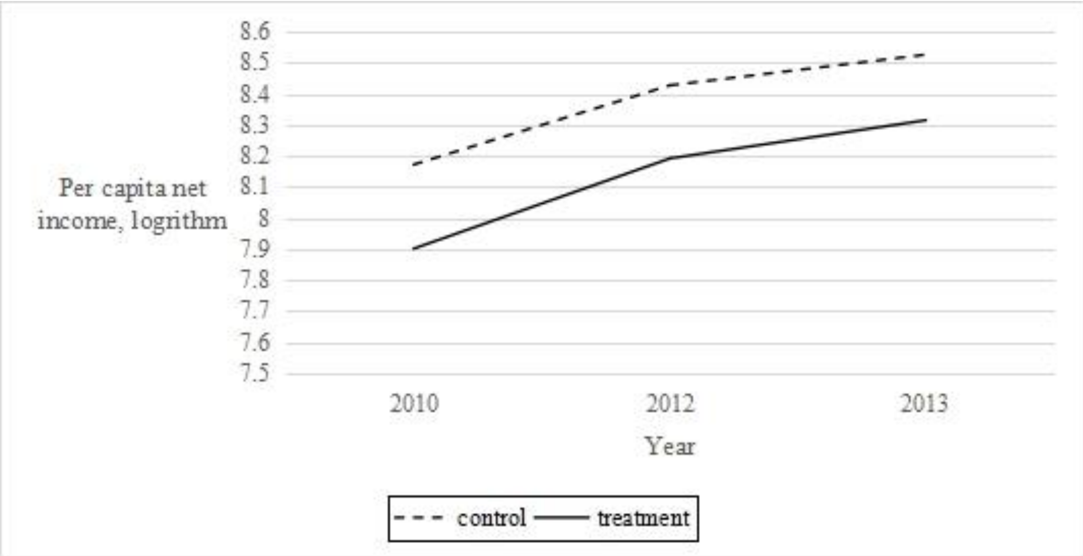

Figure 3.7: Trends in per capita net income.

Figure 3.8 shows the propensity score distribution of the treatment and control groups before and after matching. After matching, the density and propensity scores of observations in both groups were similarly distributed. Figure 3.9 presents the distribution of the baseline per capita income before and after matching and shows that the difference in the distribution of this key variable between the two groups reduced significantly after matching.

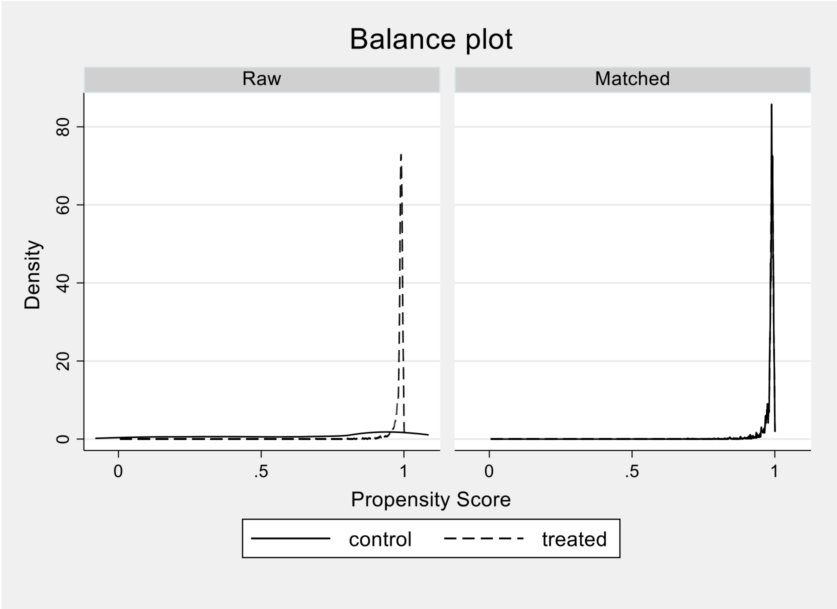

Figure 3.8: Kernel density plot: Propensity scores in raw and matched data.

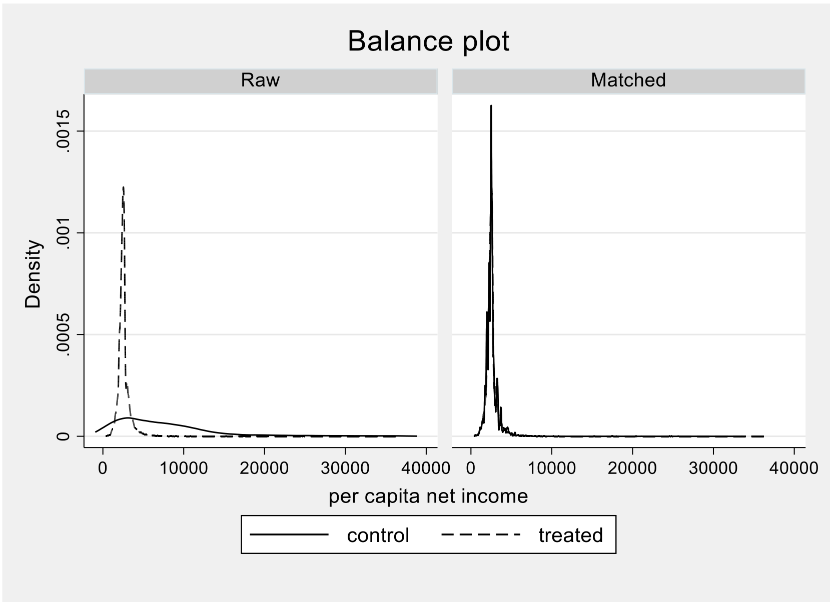

Figure 3.9: Kernel density plot: Baseline income in raw and matched data.

The propensity score for being enrolled was calculated using the following logit model:

$$\text{Log}\left\{\frac{\Pr(Treat_i=1|X_i)}{1-\Pr(Treat_i=1|X_i)}\right\} = \alpha_0 + \alpha_1 lnincome_{baseline_i} + \alpha_2 psc_i, \tag{3.1}$$

where $lnincome_{baseline_i}$ denotes per capita net income at baseline, and pbh_i ,pcl_i and psc_i denote the proportion of family members with poor health, the proportion of family members of working age and the proportion of family members of school age, respectively, in household i. These two variables correspond to the selection criteria for IPHs.

The effect of the program on household-level per capita net income was tested using the following DID model:

$$\text{Log}\, income_i = \alpha + \gamma_1\, Treat_i + \gamma_2 Time_i + \theta Treat_i \times Time_i + \epsilon_i \tag{3.2}$$

The main variable of interest here is $Treat_i \times Time_i$, which captures the average treatment effect of the TPA on the treated.

3.4.2.2.1 Overall Treatment Effects

To incorporate PSM, the standard DID regression in Equation (3.2) above was transformed into the following model (H. Li et al., 2011; Meng, 2013):

$$\Delta \log income_i = \log income_i{}^{16} - \log income_i{}^{13} = \beta_0 + \beta_1 Treat_i + \epsilon_i{}^{16} - \epsilon_i{}^{13} \tag{3.3}$$

3.4.2.2.2 Heterogeneous Treatment Effects

Equation (3.4) was used to test whether households with relatively better outcomes benefit more than other households by stratifying households according to their baseline outcome variables. Additionally, matched observations were divided according to quantile income to examine whether the effects of TPA varied with a difference in households' initial economic conditions:

$$\Delta \log income_i{}^q = \beta_0{}^q + \beta_1{}^q Treat_i + \epsilon_i{}^{16^q} - \epsilon_i{}^{13^q}, \tag{3.4}$$

Where q denotes the subgroups of the observations divided by income. Instead of running 10 regressions, observations were grouped into three subgroups: higher-, middle- and lower-income groups.

The causes of poverty were then incorporated into the regression model by grouping the treated observations into six subgroups based on their primary documented cause of poverty, then re-estimating Equation (3.3) for these subgroups:

$$\Delta \log income_i{}^r = \beta_0{}^r + \beta_1{}^r Treat_i + \epsilon_i{}^{16^r} - \epsilon_i{}^{13^r}, \tag{3.5}$$

Where r denotes the subgroups according to the primary cause of poverty (education burden, funds scarcity, health issues, labour scarcity, skills scarcity and insufficient motivation).

Further, quantile-based estimations were conducted on the basis of Equation (3.5):

$$\Delta \log income_i{}^{r,q} = \beta_0{}^{r,q} + \beta_1{}^{r} Treat_i + \epsilon_i{}^{16^{r,q}} - \epsilon_i{}^{13^{r,q}}, \tag{3.6}$$

where the superscripts are identical to those in the abovementioned equations.

3.4.2.2.3 Correlation Estimation

Next, household characteristics, including the education level of the household head, the presence of school-age children and the presence of disability in a family member, were tested for their contribution to the outcomes of the treatment group using the following model:

$$\Delta \log income_i = \theta_0 + \theta_1\ hsize_i + \theta_2 edu_i + \theta_3 pbh_i + \theta_4 psc_i + \theta_5 pcl_i + \theta_6 \log income_i{}^{13} + \gamma_1 education_i + \gamma_2 fund_i + \gamma_3 health_i + \gamma_4 labor_i + \gamma_5 skill_i + \epsilon_i \tag{3.7}$$

The outcome variable is identical to that in Equation (3.3). The independent variables are $hsize_i$ (family size), edu_i (education level of the household head); pbh_i (proportion of unhealthy family members), psc_i (proportion of school-age children) and pcl_i (proportion of capable working-age family members) of household i. Log $income_i{}^{13}$ denotes the baseline income of household i prior to the intervention. The remaining variables, $education_i, fund_i$, $health_i$, $labor_i$ and $skill_i$, are binary variables denoting the causes of poverty in household i. While six major types of poverty were identified from the raw data (education burden, funds scarcity, health issues, labour scarcity, skills scarcity and insufficient motivation), one was excluded from Equation (3.7). Thus, the coefficients γ_1 to γ_5 capture the difference in outcomes compared with the excluded group (i.e. the group of treatment households that lacked self-development motivation).

3.5 Results

3.5.1 ATT

The first estimation was whether the TPA had any effect on households' per capita income. Table 3.3 presents the empirical results of Equation (3.2). From 2013 to 2016, the growth in per capita income of households enrolled in the TPA program was approximately 0.25 log points lower than that of households in the control group. This represents a 22% lower growth rate for treatment households compared with controls ($p < .01$).

Table 3.3: Average treatment effect on the treated (ATT): whole sample

Δlnincome	Coef.	St. Err.	t-value	p-value	[95% Conf.	Interval]	Sig.
ATT	-0.25	0.089	-2.81	0.005	-0.424	-0.076	***
Radius Matching	-0.23	0.056	-4.15				***
Kernel Matching	-0.24	0.094	-2.52	0.012	-0.421	-0.052	**
Mean dependent var.	0.429		SD dependent var.	0.418			
N	19,047						
N-treatment	18,566						
N-control	481						
Matches:							
Requested	= 10						
Min	= 10						
Max	= 34						

*** p<.01, ** p<.05, * p<.1
Notes: The row of ATT is obtained from nearest neighbor matching, N= 10. Two commonly used matching algorithms, radius matching and kernel matching, are adopted to examine whether the form of algorithm would change the ATT.

However, the effect size changed when the effect was examined according to the different income quantiles. Table 3.4 shows the stratified ATT estimators of Equation (3.3). Households with incomes in the lowest and second-lowest quantiles were allocated to the lower-income group, those with incomes in the highest and second-highest quantiles were allocated to the upper-income group, and the remaining households were allocated to the middle-income group. The results show that the TPA program had a greater effect on the lower-income group compared with the other two groups. The estimated coefficient for the lower-income group was −0.637, indicating that the treated households' growth in per capita income was about 47% lower than that of controls. The effect size shrinks as income increases. The effect sizes for the middle-income and upper-income groups were −0.167 and −0.133, respectively; however, these estimates were both statistically non-significant.

Table 3.4: Average treatment effect on the treated (ATT): quantile regression

	Lower quantiles	Middle quantiles	Upper quantiles
Δlnincome			
ATT			
Treatment	-0.637***	-0.167	-0.133
	(-6.75)	(-1.07)	(-1.16)
N	3810	11428	3809
treated	1	1	1
control	0	0	0
neighbour	10	10	10
k_nnmin	10	10	10
k_nnmax	30	21	18

*** p<.01, ** p<.05, * p<.1

Notes: Nearest neighbour matching, N= 10. Lower quantiles are the 1st and the 2nd, the middles are the 3rd to the 8th, and the uppers are the 9th and the 10th. T statistics are in parentheses

3.5.2 Causes of Poverty and Household Outcomes

Equation (3.5) was also employed to explore the heterogeneous effects of TPA on household income depending on the six major causes of poverty. Table 3.5 shows that the effects were statistically significant for all six household subgroups at the 10% significance level and for five of the subgroups at the 5% significance level. The effect size was highest in the education burden subgroup and similar for the remaining five subgroups. The effect of TPA on the income of households in the education burden group was −0.646, indicating that growth in per capita income for treated households was approximately 47.6%[7] lower than that of controls. The growth in per capita income for households in the insufficient motivation, funds scarcity, skills scarcity, labour scarcity and health issues groups were approximately 25%[8], 23.4%[9], 22.6%[10], 19.2%[11] and 18.7%[12], respectively, lower than that of controls. While the previous section showed that the overall treatment effect was statistically significant for lower-income households but non-significant for higher-income households, it did not consider the primary

[7] $(e^{-0.646} - 1) \times 100\% \approx 47.6\%$
[8] $(e^{-0.288} - 1) \times 100\% \approx 25.0\%$
[9] $(e^{-0.266} - 1) \times 100\% \approx 23.4\%$
[10] $(e^{-0.256} - 1) \times 100\% \approx 22.6\%$
[11] $(e^{-0.213} - 1) \times 100\% \approx 19.2\%$
[12] $(e^{-0.207} - 1) \times 100\% \approx 18.7\%$

cause of poverty of these households. As shown in Tables 3.5 and 3.6, this result holds for the estimations based on the six causes of poverty.

Table 3.5: Average treatment effect on the treated (ATT) by poverty causes

	(1) Skill scarcity	(2) Fund scarcity	(3) Education burden	(4) Health issues	(5) Labour scarcity	(6) Insufficient motivation
ATT						
treatment	-0.256**	-0.266**	-0.646***	-0.207*	-0.213**	-0.288**
	(-3.21)	(-3.10)	(-7.30)	(-2.56)	(-2.86)	(-3.19)
N	6630	5773	3633	3840	2128	1898
treated	1	1	1	1	1	1
control	0	0	0	0	0	0
k_nneighbor	10	10	10	10	10	10
k_nnmin	10	10	10	10	10	10
k_nnmax	33	15	14	17	13	13

* p<.1; ** p<.05; *** p<.01
Notes: Nearest neighbour matching, N= 10. T statistics are in parentheses.

Table 3.6 Average treatment effect on the treated (ATT) by cause and income level

	(1)	(2)	(3)	(4)	(5)	(6)
	Skill scarcity		Fund scarcity		Education burden	
Δlnincome	lower	upper	Lower	upper	lower	upper
ATT						
treatment	-0.684***	-0.139	-0.600***	-0.0637	-0.667***	-0.035
	(-8.07)	(-1.19)	(-7.28)	(-0.47)	(-5.31)	(-0.24)
N	1423	1530	1045	1605	627	806
treated	1	1	1	1	1	1
control	0	0	0	0	0	0
k_nneighbor	10	10	10	10	10	10
k_nnmin	10	10	10	10	10	10
k_nnmax	12	12	17	12	12	11
k_robust	2	2	2	2	2	2
	(7)	(8)	(9)	(10)	(11)	(12)
	Health issues		Labour scarcity		Insufficient motivation	
Δlnincome	lower	upper	Lower	upper	lower	upper
ATT						
Treatment	-0.471***	-0.127	-0.565***	-0.111	-0.541***	-0.033
	(-4.60)	(-0.95)	(-5.92)	(-1.05)	(-4.52)	(-0.23)
N	686	1041	443	803	376	689
treated	1	1	1	1	1	1
control	0	0	0	0	0	0
k_nneighbor	10	10	10	10	10	10
k_nnmin	10	10	10	10	10	10
k_nnmax	13	11	12	12	11	11
k_robust	2	2	2	2	2	2

* p<.1; ** p<.05; *** p<.01
Notes: Nearest neighbour matching, N= 10. T statistics are in parentheses.

Next, I compared the magnitude of the change in income among households in the six subgroups. Table 3.7 shows the *t*-test results for the mean difference in per capita income growth between the treated households, indicating the existence of heterogeneous treatment effects depending on the type of poverty. At the 5% significance level, the pairs with statistically significantly different effect sizes were skills scarcity and education burden, skills scarcity and health issues, skills scarcity and labour scarcity, funds scarcity and health issues, funds scarcity and insufficient motivation, education burden and health issues, education burden and insufficient motivation, health issues and labour scarcity, health issues and insufficient motivation, and labour scarcity and insufficient motivation. Only two pairs—skills scarcity and education burden, and funds scarcity and insufficient motivation—were statistically insignificant in terms of their mean differences.

Table 3.7: Heterogeneous effects among the six poverty type subgroups

	Skill scarcity	Fund scarcity	Education burden	Health issues	Labour scarcity	Insufficient motivation
Skill scarcity	0					
Fund scarcity	0.043 ***	0				
Education burden	-0.005	0.048 ***	0			
Health issues	0.089 ***	0.132 ***	0.084 ***	0		
Labour scarcity	0.043 ***	0.086 ***	0.038 ***	0.046 ***	0	
Insufficient motivation	0.061 ***	0.018	0.066 ***	0.149 ***	0.104 ***	0

* p<.1; ** p<.05; *** p<.01
Note: Differences defined as column-line. T-Test for the mean differences in income among six-cause subgroups.

Similar results were found for the lower-income group (see Table 3.8). Although the treatment effects were non-significant for upper-income households, the effect sizes were also heterogeneous (see Table 3.9).

Table 3.8: Heterogeneous effects among the six poverty type subgroups: lower quantiles

	Skill scarcity	Fund scarcity	Education burden	Health issues	Labour scarcity	Insufficient motivation
Skill scarcity	0					
Fund scarcity	-0.032 *	0				
Education burden	-0.050 **	-0.017	0			
Health issues	-0.166 ***	-0.134 ***	-0.117 ***	0		
Labour scarcity	-0.079 **	-0.047	-0.029	0.087 **	0	
Insufficient motivation	0.060 *	0.092 ***	0.110 ***	0.226 ***	0.139 ***	0

* p<.1; ** p<.05; *** p<.01
Note: Differences defined as column-line. T-Test for the mean differences in income among six-cause subgroups and lower quantiles.

Table 3.9 Heterogeneous effects among the six poverty type subgroups: upper quantiles

	Skill scarcity	Fund scarcity	Education burden	Health issues	Labour scarcity	Insufficient motivation
Skill scarcity	0					
Fund scarcity	0.089 ***	0				
Education burden	-0.009	-0.098 ***	0			
Health issues	-0.059 ***	-0.148 ***	-0.050 **	0		
Labour scarcity	-0.043*	-0.131 ***	-0.033	0.017	0	
Insufficient motivation	-0.014	-0.103 ***	-0.005	0.045	0.029	0

* p<.1; ** p<.05; *** p<*.01*
Note: Differences defined as column-line. T-Test for the mean differences in income among six-cause subgroups and upper quantiles.

3.5.3 Correlation Between Household Characteristics and Income

Next, the correlations between household-level characteristics and per capita income growth were estimated. The education level of household heads and the proportion of unhealthy family members were significantly and positively correlated to income growth, while the proportion of school-age children, household size and initial income level were significantly and negatively correlated to income growth. Table 3.10 shows the empirical results of Equation (3.7).

Table 3.10: Correlation between household characteristics and income growth

Δlnincome	Coef.	St. Err.	t-value	p-value	[95% Conf.	Interval]	Sig.
Hsize	-0.01	0.002	-5.05	0	-0.014	-0.006	***
Edulevel	0.071	0.004	16.96	0	0.063	0.079	***
Pbh	0.111	0.016	6.84	0	0.079	0.142	***
Psc	-0.146	0.017	-8.78	0	-0.179	-0.114	***
Pcl	-0.005	0.013	-0.37	0.709	-0.03	0.021	
lnincome13	-0.558	0.011	-51.63	0	-0.58	-0.537	***
Education	0.091	0.014	6.38	0	0.063	0.119	***
Fund	0.057	0.013	4.44	0	0.032	0.082	***
Health	0.129	0.014	9.17	0	0.102	0.157	***
Labour	0.109	0.016	6.76	0	0.077	0.141	***
Skill	0.073	0.013	5.79	0	0.049	0.098	***
Constant	4.686	0.087	54	0	4.516	4.856	***
Mean dependent var.	0.433						
SD dependent var.	0.388						
R-squared	0.154						
Number of obs.	18076						
F-test	299.09						
Prob > F	0						

*** p<.01, ** p<.05, * p<.1

The education level of household heads was positively correlated to income growth (0.071), indicating that with each level of education (primary school, junior high school, senior high school, etc.), the growth in per capita income is 7.4%[13] higher than that of the lower education level. The coefficient for the proportion of unhealthy members was 0.111, suggesting that the maximum difference in the income growth between households with zero unhealthy members and households with unhealthy members is 11.7%[14]. The proportion of school-age children in households was negatively correlated with income growth (−0.146), indicating that the maximum difference in income growth between households with and without school-age children is 13.6%[15]; however, given that the value of the variable cannot reach 1 (which would mean that all family members in a household are school-age children), the actual correlation size is less than 13.6%. Household size was negatively correlated to the outcome (−0.01), signifying a maximum of 1% growth in per capita income. This is economically insignificant, despite being statistically significant at the 1% level. Initial income was negatively correlated with the outcome (−0.558), indicating that a 1% change in initial income level is associated

[13] $(e^{0.071} - 1) \times 100\% \approx 7.4\%$
[14] $(e^{0.111} - 1) \times 100\% \approx 11.7\%$
[15] $(e^{-0.146} - 1) \times 100\% \approx 13.6\%$

with a 0.56% change in per capita net income in the opposite direction. This is consistent with the smaller size of the treatment effect for higher-income households in the previous analysis.

The remaining coefficients for the categorical dummy variables (i.e. $education$, $fund$, $health$, $labor$ and $skill$) were significant and suggest a non-zero correlation between the primary causes of being poor and income growth. These coefficients reflect differences in per capita income growth compared with the motivation-induced poverty group.

3.6 Discussion

3.6.1 Non-positive Effects

In this study, the average effects of TPA on income growth were negative for lower-income households and non-significant for higher-income households. To some extent, these results are consistent with the concerns of some authors (Y. Li et al., 2016; Sun et al., 2021) regarding the inaccurate identification of impoverished households and the inefficient distribution of resources, indicating that less-impoverished households outperform more-impoverished households in making better use of programs to generate income.

Moreover, the non-positive effect may be the result of various factors. One reason may be the inaccuracy in delivering specific assistance. Designing and offering targeted assistance to individual households is costly, both financially and in terms of human resources, and requires high professional competence. These requirements are beyond the ability of many lower-level government employees involved in providing assistance. As a result, many assistance measures rely on higher-level agencies with sufficient capacity to allocate resources. Therefore, household-level targeting, which was intended to improve the effectiveness of poverty alleviation programs, is not fully effective.

Another reason may be related to the TPA assessment mechanisms. The aim of the plan was to lift most of the remaining impoverished population out of poverty by 2020. In practice, however, the goal is to eliminate poverty at the county level. A county is identified as non-poor if its poverty headcount falls below 3%. From the local government perspective, reducing the poverty headcount is the highest priority, while the means of achieving the goal is less important. Despite the importance of causality, local governments are not concerned about this if they can reduce the poverty headcount through non-targeted measures, especially given that accurate measures are difficult and costly to implement. Thus, increasing the income of poor households is not the focus of local governments.

Furthermore, the phenomenon of spillover effects is pivotal in elucidating the observed negative outcomes. Under the TPA framework, specific assistances were earmarked exclusively for qualifying treated households (i.e., IPHs), thus facilitating direct benefits for these households. At the micro level, the TPA's intervention facilitated tangible benefits for individual households. However, at the macro level, villages having treated households have also been reshaped by the TPA in terms of cultural tradition and economic condition. For instance, the introduction of local cadres, tasked with aiding identified indigent households, also served as conduits of market intelligence, potentially enhancing household economic prospects. In locales where IPHs were concentrated, there might be prioritization by local administrative bodies towards infrastructure enhancement, such as road development. Consequently, in these villages, non-treated households with an inherent capacity to leverage these improved conditions may have inadvertently reaped the benefits of TPA’s broader village-level impacts indirectly.

In addition, specific programs provided by TPA may take longer to generate returns. One of the goals of the plan is to help poor households develop sustainably, namely by giving them the ability to self-sustain and self-develop. Indeed, a major household-level intervention in the study area during the study period was the provision of training programs, which would not generate an immediate return like other strategies such as cash transfers or agricultural loans.

3.6.2 Heterogeneous Treatment Effects by Type of Poverty

The heterogeneous effects according to type of poverty may reflect the inaccuracy of delivering specific treatments or the intrinsic characteristics of households. Again, this indicates the importance of considering the type of poverty when providing support. It also provides an insight into how poverty type influences the effect of poverty alleviation programs in the short term (i.e. 3 years). A prominent example is education-induced poor households, which have a significantly slower rate of income growth compared with other types of poverty. This may be attributed to the nature of education, the returns of which take time. Additionally, local governments may be more inclined to allocate limited funds to other poverty alleviation measures because the returns from investing in education cannot be immediately reflected in their performance records.

3.6.3 Importance of Household Heads

The education level of the household head plays an important role in household income. As the principal person of the family, the head of the household has the power to decide on family affairs, which may affect their decision to access state-run poverty alleviation programs.

In the context of this study, the household head's education level may determine whether they understand and take advantage of the opportunities provided by poverty alleviation projects and their ability to cooperate with government personnel assigned to assist them. Given that the average education of the household head is just above primary school level, it may be worthwhile investing in their education, irrespective of age, so they can better understand and utilise the opportunities and resources offered, especially for those with a low education level (e.g. illiterate, semi-literate and primary education level).

3.7 Conclusion

This study explored the latest wave of poverty alleviation programs in China in an underdeveloped province to provide new evidence of its early-stage effects on household income. These effects were obtained using a PSM-DID method. The major findings are that (i) the effects are heterogeneous for households with different initial income levels and causes of poverty; (ii) the effect is significantly negative for lower-income households and non-significant for higher-income households; and (iii) the education level of the household head is positively correlated to income growth.

The findings of this study offer several important policy implications regarding the implementation of TPA efforts in China. A key insight is that the effects of TPA are different depending on households' initial income level and causes of poverty. Lower-income households experienced a negative effect of TPA on income, while higher-income households experienced no significant effect on income. This finding reflects previous concerns about the unequal distribution of resources, with less impoverished households often benefiting more than the most impoverished households. To address this issue, policymakers should consider revising resource allocation to ensure more equitable distribution, especially towards those most in need. The study also highlights the role of education of household heads in improving household income, suggesting the importance of helping less-educated household heads better understand and utilise the available resources and opportunities.

This study is one of the few to explore the effects of poverty alleviation programs using household-level data; however, it was limited by the availability of data in two respects. First, the data covered only the first 3 years of TPA, thus could only represent its short-term effects. Second, the lack of household survey data for the untreated neighbours of the treatment group impeded examination of the potential spillover effects of TPA, which would be beneficial for gaining a deeper insight into TPA.

Chapter 4: Effect of Compulsory Farmland Acquisition on the Expenditure of Middle-aged and Older Farmers in Rural China

Chapter 4 evaluates the effect of CFA on household expenditure by leveraging panel household survey data between 2011 and 2018 in rural China. The effects of CFA were estimated using DID, PSM-DID and PS-weighted DID. The results indicate that the average effect of CFA on total consumption expenditure is positive and significant but is non-significant for categorical consumption expenditures. There is also a significant correlation between household consumption expenditure patterns and household characteristics such as spending budget, financial assets, education, age and marital status. However, CFA is uncorrelated to expenditure patterns.

4.1 Introduction

China has experienced rapid economic growth over the past few decades, as evidenced by its remarkable progress in industrialisation and urbanisation. Farmland acquisition became an inevitable route to acquiring land for extensive infrastructure construction and urbanisation. Much of the farmland in rural China is owned by village collectives rather than by the state. Thus, legislated land requisition in rural areas changes the ownership of land from being collectively owned to being state owned in the interests of the public. Farmers who have had their farmland expropriated represent a sizeable group in China. According to Pan and Wei (2011), with every hectare of farmland expropriated, the number of farmers who lose their land increases by 21, and this number is growing at a rate of 2.5 million to 3 million every year.

Cultivated land is both a crucial source of income and a form of social insurance[16] for rural residents, thus plays a critical role in the welfare of rural households in China (M. Cai, 2016). Song et al. (2015) decomposed the functions of cultivated land in China, finding that three of these functions—provision of food, generation of income and defence against unemployment for rural labourers—are closely related to the welfare of rural households. The authors examined the changes in cropland functions from 1985 to 2012, finding that the food provision

[16] Under the dual welfare structure, land provides rural residents with both a source of income and social insurance. Under the perception that land cultivation offers a last resort for generating income, rural residents often migrate to cities for higher-income jobs, thereby promoting rural labour mobility in China. When rural residents become too old to farm, they can generate income by renting out their land to farmers. Thus, land ownership functions as a pension for elderly people in rural areas. When rural land is expropriated, villagers lose their source of social security as well as an income-generating asset (M. Cai, 2016).

function has weakened over time because food needs are mainly fulfilled by the market; however, the other two functions have continued to strengthen. As a source of natural capital and agricultural output, farmland assures the livelihood of farmers.

Given their dependence on farmland and lack of employment opportunities, farmers who have lost their land are considered a vulnerable group (Song et al., 2015; Xie, 2019). Previous studies on CFA have generated mixed findings (e.g. Alhassan et al., 2018; Ghatak et al., 2013; Le & Nguyen, 2020; H. Nguyen, 2014; T. T. Nguyen et al., 2019; Quansah et al., 2020; Shee & Maiti, 2019), including in the context of China (A. Chen, 2020; C. Li et al., 2018; J. Liu & Zhou, 2012; Z. Qian, 2015; Development Research Center of the State Council, 2009; D. Wang et al., 2019). However, few studies have explored the causal relationship between CFA and household livelihood, primarily because of the lack of data on rural China.

This study focuses on middle-aged and older farmers who have yet to move out of their homes after experiencing CFA. This group typically relies on agriculture for their livelihoods and tends to lack adaptability or employment opportunities, making them susceptible to the negative effects of farmland expropriation. Household panel survey data were used to evaluate the effects of CFA on livelihood in terms of consumption expenditure. The relationships between expenditure patterns and household characteristics are also explored. This study aims to answer the following two questions: How does CFA affect household expenditure? and What factors are related to household consumption expenditure patterns? The estimation is based on DID, with kernel-based PSM-DID and propensity score weighting employed to check the robustness of the estimates.

While income is widely adopted as a variable to represent livelihood (e.g. C. Li et al., 2018; Z. Qian, 2015; D. Wang et al., 2019), in this study, the one-time payment for farm acquisition meant that the income variable was not smooth. Thus, estimating the change in and patterns of household expenditure was a more suitable method of assessing the change in livelihood (Noll, 2007). I further argue that consumption expenditure is an appropriate indicator of livelihood based on the permanent income hypothesis.

This study generated the following findings. First, the average effect of CFA is positively significant for total consumption expenditure but is non-significant for categorical consumption expenditure. The mechanism for this may be that farmers who have lost their land will reduce (increase) their consumption expenditure if they believe that the compensation payment is lower (higher) than the income that would have been generated by the farmland. Second, there is a significant correlation between CFA and households' consumption expenditure patterns. Third, some household characteristics (spending budget, financial assets, education, age and marital status) are significantly correlated to consumption expenditure. Therefore, this study contributes to the existing literature by providing empirical evidence of the causal relationship between CFA and household livelihood in terms of consumption expenditure based on household-level panel data.

The remainder of this chapter is structured as follows: Section 4.2 introduces the institutional background of CFA in China; Section 4.3 reviews the related literature; Section 4.4 presents the data and identification strategy for the treatment and control groups; Section 4.5 discusses the theoretical models and empirical methods; Section 4.6 presents the results; and Section 4.7 discusses the results and concludes the chapter.

4.2 Institutional Background

Compulsory land acquisition is stipulated and regulated by the *Land Administration Law of the People's Republic of China*. Early criticism of CFA mainly emphasised its outdated and inadequate compensation (Chan, 2003). In response to this, the Chinese government reformed its land acquisition procedures and amended the law in 2004, improving it in the process.

4.2.1 Land Expropriation in Rural Areas

The acquisition of farmland in China is compulsory and distinguished by unique legal requirements. Farmland rights are divided into three types: the right to own land, the right to manage land and the right to contract land. The principal entities endowed with farmland ownership are village collectives, while the right to manage and contract land is endowed to farmers. However, farmers are permitted to contract out their right to land management and receive rent in return.

Under the existing law, farmland that is collectively owned cannot be developed for construction purposes until it has been expropriated by the state. This process, known as CFA, is required before any public construction projects can be conducted. Through CFA, the government acquires farmland from village collectives and farmers and transforms it into state-owned land for the purpose of public projects.

Figure 4.1 shows the three stages of CFA according to the *Land Administration Law*.

Preliminary investigation and public consultation	**Report the plan and await approval**	**Implementation of expropriation**
• Preliminary investigation • Public consultation • Signing agreement	• The government that intends to acquire the land shall submit the materials collected from previous stage to upper government with the approval authority for approval according to the law.	• Announce the final decision of farmland acquisition to the public once the plan is approved. • Negotiate with the expropriated individual who have not signed agreement. • The farmland expropriation will be enforced by the court If the land-expropriated individual rejects any agreement. And the individual will be compensated according to the original compensation plan

Figure 4.1: Process of farmland expropriation in rural areas.

In the first stage, the government agency that intends to expropriate farmland must investigate the status of the farmland and issue a report clarifying the scope of expropriation and the compensation, resettlement and security plans for the farmers who collectively own the land. The government then needs to publicise the report in the township and village from which the land is being expropriated for at least 30 days. If the majority of the rural collective whose land is being expropriated object to the plan, the government is required to hold a public hearing about compensation and resettlement. Next, the government agency at or above the county level that intends to implement the expropriation must measure the area of the expropriated farmland and open a specific account to ensure that compensation is fully paid. In the final step of the first stage, members of the collective who agree to the expropriation sign a compensation and resettlement agreement, while information about those who do not agree is recorded.

In the second stage, the government agency that intends to acquire the land must submit the plan and any reports created in the previous stage to the appropriate authority and request approval. Once the application has been approved, the land changes from being collectively owned to being state owned. The right of land contracting for those who have lost their land is replaced by the right to obtain compensation.

In the third stage, the government at or above the county level that intends to acquire the land must announce its approval and begin the acquisition process. The government must also negotiate with members of the collective who have yet to sign an agreement. In the event that the negotiation fails, non-consensual individuals are ordered to hand over the title to the land and are compensated according to the original compensation plan. The government can further apply to the court to force these individuals to vacate the land if necessary.

Rural residents and farmers have little control over the decision-making processes in CFA, hindering them from making optimal choices. Under CFA, individual farmers have little bargaining power and are often unable to decide whether to accept the offer. Rather, the main determinants are the location of the farmland and the public development plan. For example, in the public interest, farmland that is close to urban areas may be expropriated to accommodate the expansion of cities, while those close to planned highways or railways may be expropriated for road construction. Farmland in areas with higher population density and economic status is more likely to be expropriated. This enabled the construction of counterfactuals in this study by controlling for factors such as the location and socioeconomic conditions of villages.

4.2.2 Compensation for Expropriated Farmland

In China, compensation for farmland acquisition is regulated by the *Land Administration Law*. According to Article 47, compensation comprises four components: compensation for expropriated farmland, compensation for crops on the farmland, compensation for non-crop plants and infrastructure affiliated with the farmland (e.g. trees, flowers, greenhouses, hydropower facilities, etc.) and compensation for resettlement (A. Chen, 2020). Compensation for expropriated farmland and resettlement is based on the average annual output value of the farmland in the 3 years preceding acquisition. The compensation amount for these two components is calculated by multiplying the average annual output on a case-by-case basis. Compensation for crops and other plants and infrastructure is based on their current market value.

4.3 Literature Review

4.3.1 Farmland Acquisition and Farmers' Livelihoods in Developing Countries

Farmland acquisition inevitably affects the livelihoods of households in developing countries; however, these effects are debated in the literature. For example, using the Spearman's rank correlation coefficient, Alhassan et al. (2018) investigated the correlation between land acquisition and the livelihoods of 560 randomly selected farming households in Ghana, finding that farmland acquisition was negatively correlated with household income, food production, health, nutrition and social cohesion but positively correlated with education and employment. They also found that land acquisition threatened farming households because the disadvantages of losing land outweighed the advantages. However, Quansah et al. (2020) found the opposite in Pru, an underdeveloped region in Ghana with poor infrastructure and inadequate access to clean water. Based on data collected from 332 farmers in five communities in the Pru district, the authors found that large-scale land acquisition had a significant positive effect on the income of surveyed farmers.

Ghatak et al. (2013) surveyed households in Singur, India, that had lost their land to industrial development and unaffected households in neighbouring villages to compare household-level economic outcomes, finding that the crop-related income of affected households dropped significantly compared with their unaffected counterparts; however, there was no difference in labour-generated income. The authors further suggest that under-compensation is responsible for the economic hardships of households that have lost land. Shee and Maiti (2019) analysed the change in the welfare of households affected by an industrial development project in West Bengal. They conducted a stratified random sampling survey on affected households in the project area and unaffected households in the non-project area, finding that the labour-generated income of affected households increased by 26.5%. Nevertheless, the absence of econometric causal inference hinders the explanation of the difference between affected and unaffected households arising from land acquisition.

In a survey of 100 households in a peri-urban town in Ethiopia (Dires et al., 2021), most respondents reported challenges such as food insecurity, social problems and family disintegration after experiencing farmland expropriation. Based on a survey of 173 randomly selected households in Delta State in Nigeria, Adepoju et al. (2018) revealed that the size of the expropriated land and lack of compensation had negative effects on household welfare in terms of expenditure. The implications of this study are clear: the larger the farmland being expropriated, the lower the expenditure of households, and households that received compensation had a higher expenditure than those that did not.

The limitations of descriptive or correlational research as described above are apparent in that they cannot establish whether there is a causal relationship between farmland acquisition and changes in farmers' livelihoods. Confounding factors in different countries may mean that the effects of land expropriation on individual households' livelihoods are inseparable from the country's land system, administration and economic structure.

Among developing countries, Vietnam is more comparable to China in terms of farmland acquisition because it has a similar farmland system and development path. In both countries, land is owned by collectives, and farmers are entitled to use or contract their land. Similar to China, Vietnam has also adopted development-oriented farmland acquisition (i.e. acquiring farmland for the purpose of promoting economic development, urbanisation or infrastructure expansion), where the decision to acquire farmland is largely independent of household characteristics (H. Nguyen, 2014). Researchers have used household survey data to explore the correlation between farmland acquisition and household livelihoods in Vietnam. Unsurprisingly, mixed and even contrary results are found in the empirical literature. Using household survey data from peri-urban areas of Hanoi, Tuyen et al. (2014) found no negative effect of farmland loss on either income or consumption expenditure. They further revealed the indirect positive effect of farmland loss on household welfare through the taking up of non-agricultural livelihoods. In contrast, based on nationwide household survey data on both affected and unaffected households and an OLS model, Le and Nguyen (2020) found that farmland acquisition negatively affected household food expenditure, with a 1% increase in land acquisition resulting in a 0.22% decrease in food expenditure. They further revealed that barriers to participating in the non-agricultural labour market accounted for the adverse effects because affected households were unable to fill the income gap caused by the loss of agriculture activities.

4.3.2 CFA and Farmers' Livelihoods in China

A. Chen (2020) conducted in-depth case studies in several regions across China and argued that the effects of land expropriation are multifarious and sensitive to certain conditions. The author found that changes in household livelihoods following CFA are shaped by compensation and employment opportunities. Consistent findings can be found in the descriptive and correlational literature. For example, the Development Research Center of the State Council (2009) surveyed 1,106 rural households whose farms had been acquisitioned in Beijing, Jiangsu, Shandong and Sichuan in 2009. The survey showed an overall increase in the average income of these households; however, nearly a quarter of surveyed households experienced a decrease in income following land acquisition. The survey also indicated the challenges for farmers obtaining employment in non-agricultural industries and the significance of age and education in reducing barriers to employment. Ding et al. (2018) employed an income transition matrix and a regression model to investigate income mobility, defined as the change in a rural household's income group, following farmland acquisition. The findings from 429 households in Hubei and Yunnan provinces revealed that income mobility differed among households and was closely linked to education and working ability. The authors suggest that investment in human capital to improve farmers' working ability and social security schemes would be feasible solutions to prevent farming households from falling into poverty following land acquisition.

The literature reveals mixed findings on the effect of CFA on farmers' livelihoods. For example, many authors are sceptical about the sustainability of farmers' livelihoods following CFA or indicate that farmers have a high possibility of falling into poverty because of a lack of resources (C. Li et al., 2018; J. Liu & Zhou, 2012; Z. Qian, 2015), especially for vulnerable groups such as elders and women (Tong et al., 2019). However, some studies have found a positive correlation between CFA and farmers' income (Development Research Center of the State Council, 2009; J. Liu & Zhou, 2012; D. Wang et al., 2019). A recent study found that the extent to which farmers benefited from or were disadvantaged by land requisition was determined by multiple factors, including the compensation package offered, the farmer's reliance on agriculture to earn a living, their non-agricultural skills and social networks and competitiveness in the labour market (A. Chen, 2020).

A small body of research has focused on the causal relationship between CFA and household livelihood. In the context of China, this research can be separated into two strands. The first is based on theoretical models to infer the effects of CFA on household livelihoods. For example, Ju et al. (2016) based their study on the utility maximisation model of consumption to show the change in farmers' income resulting from land acquisition. By comprising budget change resulting from land acquisition into budget constraint, they found that the compensation paid for expropriated land is positively correlated to subsequent household income and negatively correlated to non-agricultural labour input. Nevertheless, their empirical findings, which were based on OLS regressions, were mixed and inconsistent with their theoretical model. Their initial estimations were based on data from the 2013 CHFS, showing a positive correlation between household income and land acquisition. However, in their own survey of a county, the authors found a non-significant correlation. The findings from both datasets showed no correlation between compensation price and non-farm labour input.

The second strand of research is based on the use of econometric methods. Guo et al. (2019) adopted structural equation modelling to evaluate the effect of CFA on farmers' capital in Sichuan province based on survey data from 240 rural households. The authors found that CFA positively affected households' physical capital while negatively affected households' financial capital through the amount of compensation paid for expropriated farmland. D. Wang et al. (2019) used PSM to estimate the effects of CFA on farmers' income and happiness based on a rural household sample of the China Household Income Project in 2013. The authors found that CFA had a positive effect on household income. However, they did not control for regional or village fixed effects, which may have led to the problem of heterogeneity because factors that determine whether farmers benefit or suffer from land acquisition are likely to differ by region, village or even household (A. Chen, 2020).

This review of the existing literature shows that the findings on the effects of the CFA on farmers' livelihoods are mixed, partly because of the attention paid to fluctuations in income. I argue that consumption expenditure is a better indicator of household livelihood based on the permanent income hypothesis. I estimate the effects of CFA on income using PSM-DID and the PS-weighted DID approaches.

4.4 Data and Identification Strategy

4.4.1 CHARLS

Conducted by the National School of Development at Peking University, CHARLS aims to collect a nationally representative sample of Chinese middle-aged and older residents. CHARLS is based on two components: a panel survey of households and individuals and a baseline survey of communities and villages. Starting from 2011, participants in the survey were followed up every 2–3 years.

In this study, I leverage four waves of survey data from 2011 to 2018. Table 4.1 shows the summary statistics of communities used to calculate the propensity scores for the treatment group and household characteristics used for multivariate analysis. Figure 4.2 demonstrates the time points of CHARLS and the partitioning of the pre-intervention, post-intervention and baseline periods.

Table 4.1: Summary statistics: mean baseline characteristics

	Treatment	Control	Overall	Difference
Community characteristics				C-T
Urban planning area	1.8352	1.8354	1.8353	
Socioeconomic condition	3.3704	3.4849	3.4671	**
Distance to (km):				
kindergarten	4.5438	3.2483	3.4494	***
primary school	1.2596	1.4522	1.4223	*
junior middle school	6.0011	5.2772	5.3896	***
senior high school	34.9101	25.5245	26.9817	***
post office	7.0232	6.2981	6.4107	**
library	23.5134	23.4172	23.4321	
police station	7.0232	4.5254	4.5442	
bank	6.5175	5.6451	5.7805	***
theatre	26.7183	28.0891	27.8763	
nursing home	15.9651	17.1543	16.9697	
convenience store	0.2339	0.2787	0.2718	
farmers' market	6.5810	6.1950	6.2549	
supermarket	8.6589	7.9936	8.0969	
Household characteristics				
Total expenditure (CNY)	8813	9582	9463	
Productive assets (1,000 CNY)	2.3021	2.9618	2.8594	
Financial assets (1,000 CNY)	8.6304	8.5163	8.5340	
Medical insurance	0.9620	0.9223	0.9285	***
Pension	0.8577	0.7823	0.7940	***
Highest education	3.8380	3.8136	3.8174	
Area of leased farmland (mu)	1.4324	0.7273	0.8368	**
Average age	57.26	58.39	58.22	***
Marriage status	0.8423	0.8064	0.8119	**
Income from (logarithm):				
cropping and foresting	7.7192	6.5854	6.7614	***
livestock and fishery	3.2390	2.9622	3.0052	**
rental	0.5582	0.6019	0.5951	
wage	2.2011	2.2686	2.2581	
business	0.0528	0.0601	0.0590	
N	710	3863	4573	

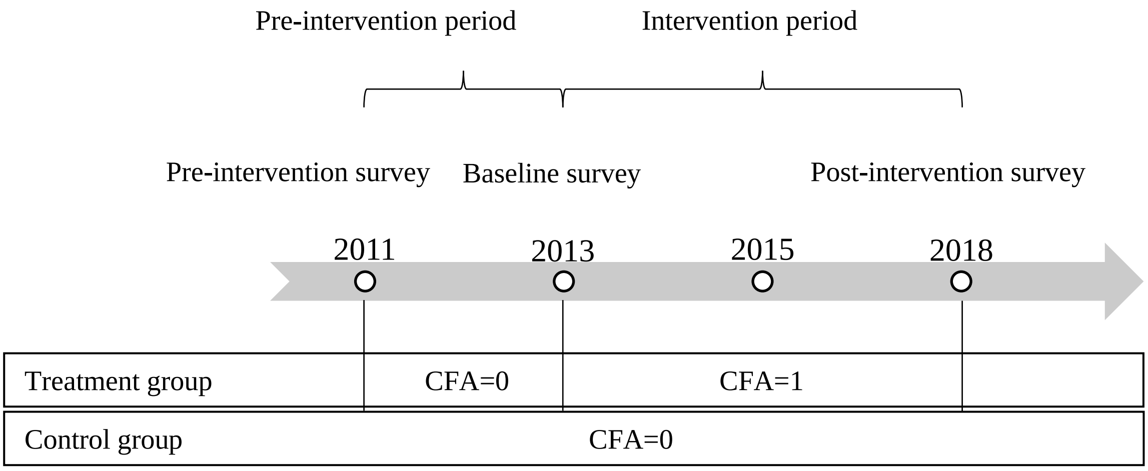

Figure 4.2: Timeline of the China Health and Retirement Survey

Notes: Data were collected at four time points: 2011, 2013, 2015 and 2018. The treatment group comprises households that had experienced compulsory farmland acquisition (CFA) between 2014 and 2018. The control group comprises households that had not experienced CFA since 2000. There is no information about CFA prior 2000 because of the lack of data availability.

4.4.2 Identification Strategy

Treatment and control households were identified using specific criteria. The treatment group comprises households that were subject to CFA between 2014 and 2018, while the control group comprises households that were not subject to CFA before 2018.

Given the need for variables that clearly indicate households' treatment status in the panel dataset, a mixed identification strategy was adopted. Table 4.2 shows the selection criteria for the treatment and control groups. First, observations were restricted to households located in rural areas that were entitled to farmland in the baseline year (2013) and had completed all waves of the CHARLS survey. However, excluding observations with missing variables substantially reduced the number of eligible observations; therefore, to prevent the further loss of observations, the requirement for completion of all waves of the CHARLS survey was relaxed to include only those for the baseline and post-treatment years (i.e. 2013 and 2018). To ensure the consistency of individual observations regarding social relationships and socioeconomic status, it was also a requirement that the addresses of individual households were the same in 2013 and 2018.

Table 4.2: Identification criteria for treatment and control groups

	Criteria
For both groups	1) Located in rural areas and 2) Entitled with farmland in baseline survey (2013) and 3) The address in 2018 survey is the same as in 2013 and Participated at least two waves of survey (2013 & 2018).
Treatment group	1) Report farmland acquisition in 2015 or 2018 survey. and 2) Did not report any farmland acquisition prior to 2013.
Control group	1) Did not report farmland acquisition before 2015 according to the survey record. and 2) Did not observe decrease of farmland area entitled to the respondent and his/her spouse in a household in 2018 record relative to the record in 2015. and 3) Did not receive any compensation relative to land acquisition or enrolled in pension program targeting land-lost individuals.

Next, the treatment group was constructed by including households that had reported compensation for CFA in the 2015 and 2018 CHARLS surveys. This identification strategy would mean the loss of some treated households, including (i) those who had been subject to CFA but either intentionally or unintentionally failed to report compensation and (ii) those who had received compensation more than 12 months before completing the survey (given that the survey question on compensation relates only to the preceding 12 months and the interval between surveys is 2–3 years).

Identification of the control group was less straightforward because of the survey was changed between the first three rounds (i.e. 2011, 2013 and 2015) and the fourth round (2018). In the first three rounds of the survey, respondents were directly asked whether they had experienced CFA; however, this question was removed from the 2018 survey. Therefore, the identification of control households was based on their answers to survey questions both before and after 2015. Specifically, individual households were assigned to the control group if they:

- did not report farmland acquisition before 2015
- did not report a significant decrease in their farmland entitlement in 2018 compared with 2015 (i.e., the farmland area was non-zero in 2015, but was zero in 2018; or the area was reduced by no less than 2 acres (approximately 0.165 acres))
- did not report compensation for farmland acquisition in either the 2015 or the 2018 surveys.

Figure 4.3 presents the change in consumption expenditure of the two groups over time. The sample adopted was the observations matched through PSM (the details of PSM is presented in the next section). The figure shows that the expenditure trends for both groups were almost parallel in the pre-intervention period (2011–2013) but deviated in the post-intervention period. This implies that CFA may have had an effect on expenditure. Effect size was estimated using a formal econometric framework, discussed in the following sections.

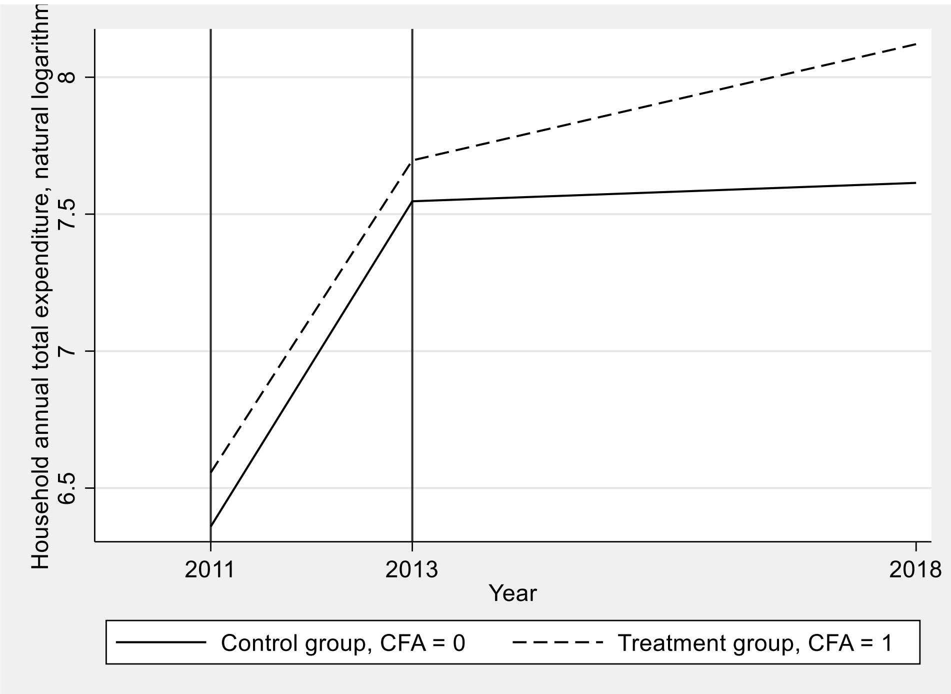

Figure 4.3: Household consumption expenditure trends.

Note: CFA: compulsory farmland acquisition.

4.5 Methodology

This section presents two theoretical models explaining why expenditure is an ideal indicator of household livelihood and linking expenditure change with consumption patterns. The empirical methods designed to answer the research questions are also discussed.

4.5.1 Theoretical Frameworks

4.5.1.1 Permanent Income Hypothesis and Household Consumption

Farmland is crucial for the welfare of farmers in China, although its importance is changing with China's socioeconomic evolution (Ma et al., 2020). Given that CFA breaks the connection between farmers and their land and that farmers have no choice in the decision, it is reasonable to treat CFA as an external economic shock to farmers. However, it is unclear whether this shock is positive or negative in terms of consumption expenditure. While CFA involves the expropriation of land, a productive asset that could constantly generates cash flow, the compensation paid for expropriated farmland can be regarded as paying farmers discounted value of aggregated future income from the farmland.

The permanent income hypothesis states that an individual's current spending is consistent with their expected life-time income (Friedman, 1957). The following model was adopted to illustrate how CFA influences household expenditure by affecting their exogenous wealth and endogenous income (S. Cai & Park, 2016):

$$\max_{\{c_{t+k}\}_0^\infty} U_t = E_t \left[\sum_{k=0}^{\infty} \beta^k u(c_{t+k}) \right]$$

$$s.t.\ \ w_{t+k+1} = (1+r)w_{t+k} + x_{t+k} - c_{t+k}$$

This model assumes that a typical household will attempt to maximise its utility through its lifetime consumption and that its needs and preferences are conditional on information in period t, denoted E_t. The subscripts t and k refer to observed periods and unobserved future periods. w, x and c denote wealth, income and consumption, respectively. r denotes fixed real interest rate, while k is the future discount rate, denoted β^k.

By assuming quadratic preferences (Hall, 1978), S. Cai and Park (2016) derive the following expression for consumption, permanent income, current wealth and future income:

$$c_t = r \left[w_t + \sum_{k=0}^{\infty} \left(\frac{1}{1+r} \right)^{k+1} E_t x_{t+k} \right] \equiv y_t^p ,$$

where c_t is current consumption; w_t is current wealth; x_{t+k} is current income flow if $k = 0$ and future income flow if $k > 0$; and y_t^p is the annual value of permanent income at time t.

In the context of this study, the fluctuations in consumption following CFA would depend on household wealth and future income. Assume that the transaction for expropriated land is completed at period t, and the compensation the household receives is w^c, where c refers to compensation. The predicted income flow from the expropriated farmland, including cropping and renting, will be $x_{t+k}^{predict}$, which is a subset of income flow x_{t+k}. Then, the optimal consumption at period t will be:

$$u'(c_t^1) = \beta(1+r)E_t[u'(c_t^1)]$$

By adding wealth and income changes induced by CFA, current consumption could be rewritten as:

$$c_t^1 = r\left[w_t + w^c + \sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t(x_{t+k} - x_{t+k}^{predict})\right] \equiv y_t^{p,1},$$

where c_t^1 is one's current consumption expenditure at the current period, and w_t and w^c are current wealth and compensation from CFA, respectively. $\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t(x_{t+k} - x_{t+k}^{predict})$ is the total expected future income. $x_{t+k}^{predict}$ denotes the expected change in income after losing farmland. This equation implies that one's current consumption expenditure is determined by one's current wealth and expected income flow.

The following equation combines the changes in wealth (i.e. w^c) and income flow (i.e. $x_{t+k}^{predict}$) to demonstrate how CFA affects current consumption:

$$c_t^1 = r\left[w_t + \sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k} + w^c - \sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict}\right] \equiv y_t^{p,1}$$

The equation above implies that, *ceteris paribus*, the change in household consumption depends on the relative amount of compensation (w^c) and the change in expected income flow ($\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict}$).

The income flow of households unaffected by CFA (i.e. the control group) is expressed as:

$$\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ unaffected},$$

while the income flow of CFA-affected households (i.e. the treatment group) is expressed as:

$$\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ affected}$$

The difference in expected future income between the households in the treatment group and their corresponding counterfactuals is expressed as:

$$\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ unaffected-affected} = \sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ unaffected} - \sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ affected} = \sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t (x_{t+k}^{predict,\ unaffected} - x_{t+k}^{predict,\ affected}),$$

where $\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ unaffected-affected}$ denotes income change induced only by CFA. This change is deemed negative by assuming that, *ceteris paribus*, CFA equates to loss of income from farmland. Based on the above equations regarding the relationships between current consumption expenditure, wealth and expected income flow, we would expect an increase in consumption expenditure at any period after t if the individual is optimistic about their future long-term income; that is, the value of the compensation (w^c) is greater than the decrease in expected future income flow ($\sum_{k=0}^{\infty}\left(\frac{1}{1+r}\right)^{k+1} E_t x_{t+k}^{predict,\ unaffected-affected}$).

In addition to attributing changes in consumption expenditure to changes in wealth and expected income, as discussed above, the income uncertainty induced by CFA will also affect households' consumption expenditure. Farmland provides a steady income to rural households, either through cropping or renting, and defends against unemployment of rural transferred labourers [17] (Song et al., 2015) in rural China. However, the expropriation of farmland undermines the relationship between farming households and farmland, increasing income uncertainty, especially for those more dependent on agricultural income (Xie, 2019). Thus, CFA deprives farming households of a relatively stable income source, and farmers who have lost their land often face challenges in transitioning to new employment (X. Huang et al., 2017; Xie, 2019). The permanent income hypothesis has been used in numerous studies to theoretically show the negative effect of income uncertainty on consumption behaviour (Blanchard & Mankiw, 1988; Skinner, 1988), especially for individuals with little wealth (N. Wang, 2003). Empirical studies from China and other countries show that income

[17] In the context of China, rural transferred labourers refers to the movement of labourers from rural to urban areas in search of better economic opportunities. This labour transfer can involve rural workers migrating temporarily or permanently to cities to take up jobs in the manufacturing, construction or service sectors.

uncertainty either decreases household consumption or increases precautionary savings (Ben-David et al., 2018; Carroll, 1994; Chamon et al., 2013; Kraay, 2000).

4.5.1.2 Household Consumption Patterns

A simplified model was developed in this study to illustrate how one-time compensation payments for CFA affect households' expenditure decisions. By assuming that household i aims to maximise the utility of four types of consumption expenditure and that the utility function is concave, a rational strategy for household i is to allocate its budget to the available consumption categories to maximise the total utility of its consumption expenditure, as described by the following model:

$$Max\ \alpha_i U_{it}^{Short}\left(e_{it}^{c\&b}, e_{it}^{t}, e_{it}^{d}, e_{it}^{e\&t}, e_{it}^{h}, e_{it}^{o}\right) + (1-\alpha_i) U_{it}^{Long}\left(e_{it}^{c\&b}, e_{it}^{t}, e_{it}^{d}, e_{it}^{e\&t}, e_{it}^{h}, e_{it}^{o}\right)$$

$$s.t.\ e_{it}^{n} + e_{it}^{l} + e_{it}^{h} + e_{it}^{o} \leq e_{it}^{total},$$

where U_{it}^{Short} is the immediate utility that household i obtains from its expenditures in year t, and U_{i}^{Long} is the utility that can only be obtained in the future. The inputs $e_{it}^{c\&b}$, e_{it}^{t}, e_{it}^{d}, $e_{it}^{e\&t}$, e_{it}^{h} and e_{it}^{o} denote expenditure on clothing and bedding, travel, durable goods, education and training, health care and other (e.g. groceries, communication, transportation and beauty), respectively, of household i in year t. The variable e_{it}^{total} denotes the budget constraint of household i. The weights α_i and $1-\alpha_i$ represent the preference for either short-term or long-term utility. Assuming that the utility functions are concave and that the budget constraint is quasi-convex, interior solutions can be obtained by solving first-order conditions with respect to the input variables.

Assuming that both the treatment and control groups have been properly randomised, I expect that, *ceteris paribus*, the average total expenditure of all households was identical prior to CFA. CFA then causes a shock to treatment households and results in an increase in income or cash flow. This increase in income or cash flow can be divided into two categories: the first is the temporary, one-time increase from monetary compensation, and the second is the permanent or repeatable increase gained from interest and other sources related to CFA (e.g. households have more cash to invest in human capital, generating future returns). Consequently, targeted households face three possible scenarios in terms of their post-CFA livelihoods: better off, no change or worse off. Any changes in expenditure patterns would only occur if the effects of

CFA on livelihood are significant. Thus, we would observe a change in the share of expenditure for each category in treatment households relative to control households.

4.5.2 Empirical Model

4.5.2.1 ATT of CFA on Household Consumption Expenditure

In this quasi-experimental study, I used PSM to randomly select affected households. Given that CFA is not random, evaluating the effects of CFA on household consumption expenditure requires econometric techniques to mimic randomisation. Specifically, the main determinants of CFA are beyond the household and include location of the farmland and the level of local economic development.

In the context of this research, selection bias refers to the non-randomness of external decisions to acquire farmland for development purposes. These decisions are closely related to two factors. The first is the state of the local economy: intuitively, demand for land would increase if the local economy was undergoing expansion, meaning that a farming household located in such a place is more likely to have its farmland being expropriated to fulfil the need for land. The second is the location of farmland; that is, whether it is within the area of the local development plans.

Given the development-oriented nature of CFA, it is necessary to adopt PSM because CFA participation is conditional on the location of farmland. Thus, a matching algorithm was run using village-level characteristic variables (see Table 4.1) to enable a comparison of affected and unaffected households in terms of their probability of being enrolled in CFA. The propensity score for the control observations was estimated using the following logit model:

$$pscore_k(CFA_k = 1|\boldsymbol{Z}_k) = \frac{\exp(\boldsymbol{\beta z'})}{1+\exp(\boldsymbol{\beta z'})}, \tag{4.1}$$

where the outcome variable $pscore_k$ is the probability of individual household k being enrolled in CFA, given the vector of its characteristics $\boldsymbol{Z}_k$ (the variables under community characteristics in Table 4.1).

To further control for unobserved regional and family characteristics that may be related to consumption behaviours, the DID method was used to estimate ATT. This compound approach combines PSM with DID, controlling for both unobserved time-invariant heterogeneities and the potential selection bias arising from observable characteristics. In the context of this study, unobserved time-invariant factors affecting household consumption expenditure include households' risk and personal consumption preferences. For example, a household's risk preference determines its savings behaviour, in turn affecting its expenditure. Households with a higher risk preference tend to spend more and save less in the short run (e.g. Mazzocco, 2004). In contrast, personal consumption preferences affect expenditure patterns through the personal preferences of each household member (e.g. some members may spend more on travelling). Observable characteristics related to selection bias, such as location, determine whether a farmland will be expropriated. For example, farmland located in a suburb may have a higher likelihood of being expropriated compared with farmland located in a remote region because the former has greater access to transportation and markets, which is attractive for certain industries.

Under this combined approach, DID estimates are calculated for the treatment households and matched control households within the common support. To utilise the full information from the data, the kernel matching method was applied. Unlike other common matching techniques in which treated units are matched with only some control units (e.g. nearest neighbour matching and calliper matching), kernel matching matches each treated unit with a weighted average of all control units. In this way, each observation in the control group is assigned a weight according to the kernel function (Mu & van de Walle, 2011). However, the kernel matching approach may be sensitive to the choice of bandwidth. To check the robustness of the default bandwidth of 0.06, the estimation was also conducted at bandwidths of 0.01 and 0.1, showing that it was robust to different bandwidths (see Appendix B). The effect of the treatment for each treatment household was obtained from the following equation:

$$DID_i = \left(y_{i,post}^{treated} - y_{i,pre}^{treated}\right) - \sum_j w_{ij}\left(y_{j,post}^{control} - y_{j,pre}^{control}\right), i \in I, \quad (4.2)$$

where I represents the whole sample; $y_{i,pre}^{treated}$ and $y_{i,post}^{treated}$ denote the consumption expenditure of treatment household i in the pre-intervention and post-intervention periods, respectively; $y_{j,pre}^{control}$ and $y_{j,post}^{control}$ denote the consumption expenditure of control household j in the pre-intervention and post-intervention periods, respectively; and w_{ij} is the weight calculated by PSM of control household j to treatment household i.

After applying PSM to the observations, I estimated the average treatment effect using the following DID regression model:

$$y_k = \alpha_0 + \alpha_1 CFA_k + \alpha_2 Time_k + \theta CFA_k \times Time_k + \boldsymbol{\beta X}'_k + \varepsilon_k, k \in K, \quad (4.3)$$

where the outcome variable y_k denotes the consumption expenditure of household k (k is an element of set K, which consists of the matched observations of both treatment and control households). The dummy variable CFA_k indicates whether a household is affected or unaffected by CFA. $Time_k$ is a time dummy indicating the pre-acquisition and post-acquisition periods. Correspondingly, θ is the PSM-DID estimator for ATT. The vector $\boldsymbol{X}'_{kt}$ is the set of time-variant variables that may be correlated to consumption expenditure as listed in Table 4.4 (i.e., the variables for household characteristics).

To check the robustness of the estimation using the PSM-DID method, PS-weighted DID was employed for the same observations. As shown by Hirano et al. (2003), weighted least squares regression yields a fully efficient estimator by weighting the control observations based on their propensity scores. Specifically, the weights of the control observations are given by their predicted propensity scores:

$$p_{ij} = \frac{pscore_j}{1 - pscore_j} \quad (4.4)$$

The regression specifications from the PS-weighted DID method remain similar to those from the PSM-DID method, with the only difference being the weights denoted by p_{ij}:

$$y_k = \alpha_0 + \alpha_1 CFA_k + \alpha_2 Time_k + \theta CFA_k \times Time_k + \boldsymbol{\beta X}'_k + \varepsilon_k, \text{ with weights } p_{ij} \quad (4.5)$$

In this specification, p_{ij} represents the weights calculated according to the propensity scores. The PS-weighted DID estimates were obtained by running the weighted least squares regression using the calculated weights.

4.5.2.2 Change in Consumption Patterns of Treatment Households

In this study, changes in household consumption patterns were examined by dividing annual expenditure into six mutually exclusive categories: clothing and bedding, travel, durable goods, education and training, health care and other. This classification and the definition of each category is based on the CHARLS questionnaire. For example, clothing and bedding refers to clothing, footwear, hats and bedding for individuals' basic needs. Travel refers to long-distance travel usually associated with leisure and entertainment. Durable goods include furniture, electrical and electronic appliances (e.g. refrigerators, washing machines, televisions and computers), musical instruments (e.g. pianos) and other durable goods. Education and training refer to tuition and training, which may have long-term effects on individuals' knowledge, skills and career prospects. Healthcare expenditure includes direct and indirect medical expenses, excluding those covered by China's free public healthcare system, reflecting an individual's level of concern about their health and medical needs. 'Other' includes expenditure on beauty (e.g. make-up, facials, massages), the maintenance and repair of vehicles and appliances, communication products and public transportation.

To estimate the potential effect of CFA on household consumption expenditure patterns, the Engel curve (Panikkassery, 2020) was adopted for cross-sectional data in the post-intervention period (i.e. 2018). The regression model is specified as follows:

$$S_{mk} = \theta_m + \gamma_1 EXP_k + \gamma_2 CFA_k + \boldsymbol{\tau H}'_k + u_{mk}, \tag{4.6}$$

where S_{mk} represents the expenditure share of category m in household k; EXP_k is the total expenditure of household k; and the vector $\boldsymbol{H}'_k$ represents the socioeconomic and demographic factors of household k.

The above equation consists of five regressions that correspond to the five expenditure categories. A seemingly unrelated regression estimation (SURE) was adopted to deal with all regressions simultaneously. Meanwhile, three-stage least squares (3SLS) based on the Hausman test was adopted to reveal any endogeneity that may exist between total expenditure and expenditure share. Income was used as the instrumental variable for expenditure. If endogeneity exists, the SURE results will be inconsistent, and 3SLS results will be consistent. In the absence of endogeneity, SURE is more efficient than 3SLS.

4.6 Results

4.6.1 Average Treatment Effects of CFA on Household Expenditure

The effect of CFA on households' total consumption expenditure and its seven subcategories was estimated. As argued previously, based on the permanent income hypothesis, consumption expenditure is not only a comprehensive indicator of a household's present livelihood but also reflects the household's expected future livelihood.

I adopted three methods based on the DID approach. Table 4.3 presents the estimates of the mean effects of CFA on total and categorical expenditure using simple DID, kernel-based PSM-

DID and PS-weighted DID, as previously discussed. For the simple DID method, the sample adopted was the observations in the treatment and control groups with common support determined by the propensity scores. In other words, the sample for the DID estimates was the same as those for the kernel-based PSM-DID and PS-weight DID. The difference between the simple DID and the other DID methods was the algorithm that matches treated observations with their control group counterparts. Moreover, because kernel-based PSM may be sensitive to different bandwidths, I checked the robustness of the default bandwidth of 0.06 by conducting the PSM-DID estimation using bandwidths of 0.01 and 0.1 (see Appendix B). This shows that the estimated coefficients were robust to different bandwidths.

The estimation captured the effects of CFA on household expenditure during the study period. Outcome variables were transformed into their natural logarithmic forms. Table 4.3 shows that the average treatment effect of CFA on households' total consumption expenditure was positively significant, with a significance level of 5% for the DID estimator and 1% for PSM-DID and PS-weighted DID estimators. The full results of the PS-weighted DID estimation are available in Appendix C.

Table 4.3: Effect of CFA on total and categorical consumption expenditure

	DID	sig.	PSM-DID	sig.	PS-weighted DID	sig.
consumption expenditure on:						
total	0.360	**	0.359	***	0.365	***
	(2.49)		(3.45)		(2.69)	
cloth and bedding	-0.025		-0.010		-0.024	
	(-0.14)		(-0.08)		(-0.14)	
travelling	0.002		0.006		0.008	
	(0.03)		(0.10)		(0.10)	
durable goods	0.049		0.060		0.053	
	(0.28)		(0.48)		(0.31)	

education and training	0.006	-0.031	-0.010
	(0.03)	(-0.22)	(-0.05)
healthcare	0.300	0.302**	0.290
	(1.63)	(2.31)	(1.62)
others	0.049	0.011	-0.002
	(0.27)	(0.08)	(-0.01)
N		4572	

*** p<.01, ** p<.05, * p<.1

Notes: CFA: compulsory farmland acquisition. The sample consists of 710 treated households and 3862 controlled households. All observations are within the scope of common support as determined by propensity score matching. The variables used for kernel propensity score matching are distances to nearest public facilities and departments (e.g., kindergarten, primary school, junior middle school, post office, library, police station, theatre, nursing home, convenience store, farmers' market, and supermarket), measured by kilometer. The covariates included in the regressions are the value of productive assets (1,000 CNY), the value of financial assets (1,000 CNY), a dummy variable indicating whether (the core member of a household) having pension, the highest education level of the head of a household, a dummy variable indicating the marital status of the head of a household, the area of rented farmland (measured by mu), the average age of the head of a household and his/her spouse, incomes from rental, wage, business, cropping and farming, livestock and fishery. T-statistics are in parentheses.

The effects estimated by the three methods are almost identical in magnitude. DID, PSM-DID and PS-weighted DID estimated effect sizes of 0.36, 0.359 and 0.365, respectively. The effect size of 0.36 indicates that the total expenditure of CFA-affected households (the treatment group) was approximately 43.3%[18] higher than that of unaffected households (the control group) from 2013 to 2018 (the pre-treatment and post-treatment periods, respectively). The effect size increased slightly to 44% using the PS-weighted DID method.

According to the regression results, while the effect of CFA on total household consumption expenditure was statistically significant, the effects of CFA on the different expenditure categories were not. Thus, at the aggregate level, CFA significantly influences households' consumption expenditure, but the categorical effects may not. The inability to statistically detect the individual disaggregated effects may be due to their small effects. This may also be attributable to the uneven effect of the policy on the different consumption categories. For example, Table 4.3 shows that, based on the PSM-DID method, the effect of CFA on healthcare

[18] $(e^{0.36} - 1) \times 100\% \approx 43.3\%$.

expenditure is significant. While the effect was not significant based on the PS-weighted DID method, it approached the 10% significance level.

To explore the correlations between household characteristics and consumption expenditure, I focused on the PS-weighted DID estimates for total expenditure (see Appendix C for the full results for the categorical consumption expenditure). Table 4.4 shows the results of the PS-weighted DID regression in which the dependent variable was logarithmic total expenditure. Apart from the positive effect of CFA on total expenditure, other factors such as financial assets, education level and marital status were positively correlated with households' total expenditure. Financial assets were positively correlated with total expenditure, and these correlations were both statistically and economically significant. The effect size of 0.014 indicates that total consumption expenditure increases by an average of 1.4% with each 1,000 CNY increase in the value of household financial assets. The significantly positive effect of marital status indicates that households comprising married couples have an average of 68.5% higher expenditure than those comprising single people, reflecting that two people cost more than one. Unsurprisingly, income, regardless of its source, was significantly and positively correlated with expenditure. According to the estimation, a 1% increase in income from rental, wages, business activities and cropping and forestry activities was associated with an approximate increase in total consumption expenditure of 0.05%, 0.02%, 0.1% and 0.04%, respectively. Moreover, age was negatively correlated with consumption expenditure, indicating that older people are less likely to spend compared with younger people. On average, each additional year of age was correlated with a 3.8% decrease in total expenditure. This negative correlation is consistent with previous studies such as that by Heshmati et al. (2019), who revealed an inverse U-shape of expenditure with age. The sample in this study comprises rural residents with a mean age of 58 years, who have passed the peak of the U-shaped curve; thus, their consumption expenditure will be declining.

Table 4.4: Effects of CFA on total consumption expenditure: PS-weighted DID

Total expenditure, natural logarithm	Coef.	St.Err.	p-value	Sig.
CFA	0.0036	0.1034	0.9726	
Time	0.0421	0.0634	0.5067	
CFA×Time	0.3706	0.1365	0.0066	***
Productive assets	0.0001	0.0001	0.3352	
Financial assets	0.0014	0.0007	0.0302	**

Pension	0.4439	0.0891	0.0000	
Highest education	0.0605	0.0245	0.0135	**
Rented farmland	-0.0081	0.0070	0.2477	
Average age	-0.0383	0.0047	0.0000	***
Marriage	0.6601	0.1040	0.0000	***
Income from (natural logarithm):				
rent	0.0496	0.0131	0.0001	***
wage	0.0219	0.0076	0.0039	***
business	0.0987	0.0179	0.0000	***
crop and forestry	0.0374	0.0118	0.0015	***
livestock and fishery	0.0108	0.0093	0.2447	
Constant	8.3127	0.3626	0.0000	***
Mean dependent var	7.632		SD dependent var	2.679
R-squared	0.097		N	9145
F-test	33.73		Prob > F	0

*** p<.01, ** p<.05, * p<.1

Notes: CFA: compulsory farmland acquisition. The results in this table depict from PS-weighted DID regression model. The dependent variable is the natural logarithm of household total consumption expenditure (measured by 1,000 CNY). *CFA* is a binary variable indicating treatment status. *Time* is the time dummy indicating post-treatment period. *Productive assets* and *Financial assets* are the value of productive assets and Financial assets measured by 1,000 CNY, respectively. *Pension* is a binary variable indicating whether core family members have pension. *Highest education* is the highest education level of the head of a household. *Rented farmland* is the area of farmland rented by a household, measured by mu. *Average age* is the average age of the head of a household and his/her spouse. *Marriage* is a binary variable indicating the marital status of the core member of a household. *rent*, *wage*, *business*, *crop* and *forestry*, and *livestock and forestry* are household income (originally measured by CNY and has transformed into natural logarithm) from rental, wage, self-business, crop and forestry activity, livestock and forestry, respectively. T-statistics are in parentheses.

4.6.2 Factors Associated with Households' Consumption Expenditure Patterns

Consumption expenditure was divided into six categories. Table 4.5 shows the mean share of each expenditure category and the expenditure quantiles in the post-treatment period. For observations in the first quartile, only the expenditure on clothing and bedding differed significantly between the two groups. For observations in the second quartile, the share of expenditure on durable goods, education and training and 'other' was significantly different between the two groups. For observations in the fourth quartile, only the expenditure on the 'other' category differed significantly between the two groups. No significant differences were found in the third quartile. However, the significant differences found in the quantile comparisons are mitigated by examining the whole sample. The two groups showed no significant differences in their consumption expenditure patterns in terms of either the whole sample or for most quantile subgroups. To some extent, the results are consistent with the non-significant effects of CFA on households' categorical consumption expenditures in the previous analysis.

Consumption expenditure by category shows some trends along the expenditure quantiles. For example, spending on clothing and bedding consistently declined with an increase in expenditure for both groups. A similar pattern can be seen in the expenditure on education and training and travel.

Healthcare expenditure was prominent, accounting for more than half of total consumption expenditure. This may explain the significant positive correlation between medical insurance and expenditure on health care. Enrolment in medical insurance programs is voluntary in rural China; those with a greater need for medical care will be more motivated to have medical insurance, thus will be systematically different from non-participants in terms of their health and medical expenses.

Table 4.5: Mean comparison tests

	Control group (CFA = 0) (1)	Treatment group (CFA = 1) (2)	Difference: (1) − (2)	*t*-statistic	Sig.
Clothing and bedding					
Q1	0.374	0.306	0.068	(1.857)	*
Q2	0.221	0.226	−0.006	(−0.299)	
Q3	0.144	0.151	−0.007	(−0.557)	
Q4	0.089	0.094	−0.005	(−0.457)	
All	0.196	0.183	0.013	(1.288)	
Travel					
Q1	0.001	0.005	−0.004	(−1.203)	
Q2	0.008	0.001	0.007	(1.576)	
Q3	0.010	0.006	0.004	(0.732)	
Q4	0.023	0.020	0.003	(0.389)	
All	0.011	0.008	0.003	(0.979)	
Durable goods					
Q1	0.022	0.021	0.001	(0.110)	
Q2	0.083	0.044	0.039	(2.415)	**
Q3	0.082	0.094	−0.012	(−0.851)	
Q4	0.061	0.054	0.007	(0.582)	
All	0.065	0.057	0.008	(1.129)	
Education and training					
Q1	0.010	0.020	−0.010	(−1.161)	
Q2	0.039	0.060	−0.021	(−1.811)	*
Q3	0.111	0.119	−0.007	(−0.427)	

	Control group (CFA = 0)	Treatment group (CFA = 1)	Difference: (1) − (2)	*t*-statistic	Sig.
	(1)	(2)			
Q4	0.163	0.149	0.014	(0.666)	
All	0.085	0.094	−0.009	(−1.086)	
Health care					
Q1	0.528	0.569	−0.041	(−1.068)	
Q2	0.552	0.560	−0.008	(−0.326)	
Q3	0.527	0.486	0.520	(1.614)	
Q4	0.506	0.546	−0.039	(−1.340)	
All	0.528	0.536	−0.008	(−0.517)	
Other					
Q1	0.041	0.027	0.014	(0.939)	
Q2	0.058	0.083	−0.025	(−2.020)	**
Q3	0.099	0.117	−0.018	(−1.242)	
Q4	0.069	0.039	0.030	(2.840)	***
All	0.020	0.022	−0.002	(−0.499)	

Notes: CFA: compulsory farmland acquisition; *Clothing and bedding:* household expenditure on clothing and bedding; *Travel*: household expenditure on long-distance travel; *Durable goods*: household expenditure on furniture, electrical and electronic appliances and other durable goods; *Education and training*: household expenditure on education and training; *Health care*: household expenditure on medical goods and services and fitness expenses; *Other*: household expenditure on beauty (e.g. make-up, facials, massages), maintenance and repair of vehicles and appliances, communication products and public transportation. Q1 to Q4 are quantiles containing a quarter of the sample. *** $p < .01$, ** $p < .05$, * $p < .1$.

To select between the 3SLS and SURE models, endogeneity of total expenditure was tested using the Hausman test, which failed to reject the null hypothesis of no systematic difference between 3SLS and SURE (see Table 4.6), indicating that SURE is the more efficient model. Therefore, SURE was used to estimate the effect of CFA on household consumption expenditure patterns. The estimated results of 3SLS are available in Appendix D.

Table 4.6: Hausman test of endogeneity

	Chi-square	p-value
Q1	0.97	1.0000
Q2	1.94	0.9998
Q3	0.12	1.0000
Q4	2.88	0.9983

Notes: Null hypothesis is the difference in coefficients is not systematic. Alternative hypothesis is the difference is systematic.

Table 4.7 presents the estimated coefficients of CFA on four expenditure quantiles using the SURE method. Overall, CFA was not significantly correlated with household consumption expenditure patterns. Only some coefficients were significant. For example, the correlation between CFA and expenditure on clothing and bedding was negatively significant in the first quartile, indicating that CFA-affected households tended to spend less on clothing and bedding compared with unaffected households. CFA-affected households in the second quartile tended to spend less on durable goods but more on education and training compared with unaffected households.

Table 4.7: Correlation between CFA and household expenditure patterns

	Q1		Q2		Q3		Q4	
	CFA	Sig.	CFA	Sig.	CFA	Sig.	CFA	Sig.
Clothing	-0.0788	***	-0.0036		0.0090		0.0030	
	(-6.09)		(-0.20)		(0.72)		(0.30)	
Traveling	0.0031		-0.0070	*	-0.0032		-0.0004	
	-1.07		(-1.66)		(-0.66)		(-0.05)	
Durables	-0.0006		-0.0343	**	0.0106		-0.0069	
	(-0.05)		(-2.12)		(0.78)		(-0.60)	
Education	0.0093		0.0226	**	0.0036		-0.0180	
	-1.09		(1.97)		(0.21)		(-0.89)	
Healthcare	0.0528		0.0052		-0.0376		0.0403	
	-1.44		(0.20)		(-1.54)		(1.43)	
Others	-0.0158		0.0249	**	0.0160		-0.0332	
	(-1.12)		(1.98)		(1.10)		(-3.06)	***

*** p<.01, ** p<.05, * p<.1

Notes: CFA: compulsory farmland acquisition. SURE is conducted on propensity matched sample in 2018. All observations are within the scope of common support as determined by propensity score matching. T-statistics are in parentheses.

Table 4.8 reports the estimated coefficients from the SURE model on the whole sample rather than by quantile. The dependent variables in the six equations are the share of consumption expenditure for the six categories described above. The results show that CFA had no significant correlation with the share of consumption expenditure in the six categories. This is consistent with the results of previous analyses that the effects of CFA on categorical consumption expenditure are non-significant.

Total consumption expenditure was significantly correlated with the share of expenditure in five of the six categories; however, these correlations were too small to be considered economically significant. Specifically, for each 1,000 CNY increase in total expenditure, the share of expenditure on clothing and bedding, health care and ‘other’ decreased by 0.12%, 0.03% and 0.02%, respectively. In contrast, the share of expenditure on travel and education and training increased by 0.01% and 0.02%, respectively, for the same increase in total consumption expenditure.

The value of productive assets was significantly correlated to the share of expenditure on travel; however, the average size of the correlation was less than 0.01% for every 1,000 CNY increase in asset value. The value of financial assets was significantly and positively correlated to the share of consumption expenditure in all categories except education and training and ‘other’; however, these effect sizes were also small. For every 1,000 CNY increase in the value of financial assets held by a household, the share of expenditure on clothing and bedding, travel, durable goods and health care increased by 0.03%, 0.01%, 0.01% and 0.08%, respectively. Health care represented the largest share of expenditure among these four categories.

Education was positively correlated with travel expenditure and negatively correlated with healthcare expenditure. The former may reflect that more highly educated people tend to prioritise travel more than do less-educated people. The latter may reflect that education reduces healthcare costs by positively influencing one’s health-related behaviours and attitudes, thus reducing the need for health care, as suggested by Feinstein et al. (2006).

Age was significantly and negatively correlated with expenditure in three of the six categories. For each unit increase in age, expenditure on clothing and bedding, education and training and ‘other’ decreased by 0.48%, 0.28% and 0.19%, respectively. The effect of age on expenditure on travel and durable goods was non-significant, while its effect on healthcare spending was positive, increasing by 1.02% for each unit increase in age. These findings are consistent with those in the literature (e.g. Y.-P. Chen & Chu, 1982; Cook & Settersten, 1995) that older people spend more on health and less on clothing, education and recreation.

The correlations between marital status and expenditure patterns are similar. For example, marital status was negatively correlated with spending on clothing and bedding, education and training and ‘other’ and positively correlated with spending on health care. On average, compared with households in which the main family member is single, those with married couples spend 8.26% more on health but 3.25%, 2.81% and 0.03% less on clothing and bedding, education and training and ‘other’, respectively. The fact that households with married couples tend to allocate more of their funds to health indicates that marriage has a positive effect on the health behaviours of older populations (Schone & Weinick, 1998).

Table 4.8: Household characteristics and consumption expenditure patterns

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of expenditure					
	Clothing/bedding	Travel	Durable goods	Education/training	Health care	Others
Total expenditure	−0.00121***	0.00010***	−0.00010	0.00018**	−0.00031**	−0.00021***
	(−11.85969)	(3.56069)	(−1.34209)	(2.11231)	(−2.19848)	(−3.18079)
CFA	−0.01521	−0.00205	−0.00780	0.00701	0.01235	0.00032
	(−1.51046)	(−0.75813)	(−1.11435)	(0.84219)	(0.87626)	(0.04770)
Productive assets	0.00001	0.00004***	−0.00001	−0.00002	−0.00000	−0.00001
	(0.23586)	(7.07388)	(−0.76134)	(−0.81259)	(−0.06072)	(−0.79802)
Financial assets	0.00033***	0.00013***	0.00011**	0.00009	−0.00080***	0.00008
	(4.01913)	(5.95226)	(1.99131)	(1.33362)	(−6.92702)	(1.47156)
Pension	−0.02685***	−0.00234	0.00038	0.00336	0.02220*	0.00447
	(−2.84574)	(−0.92236)	(0.05825)	(0.43052)	(1.68080)	(0.71987)
Highest education	0.00084	0.00179***	0.00014	−0.00054	−0.00587*	−0.00057
	(0.34074)	(2.70136)	(0.08122)	(−0.26383)	(−1.70127)	(−0.35110)
Rented farmland	−0.00073	−0.00017	0.00010	0.00071	−0.00083	0.00112**
	(−1.02081)	(−0.88334)	(0.19220)	(1.21161)	(−0.83204)	(2.38062)
Average age	−0.00480***	−0.00008	0.00014	−0.00277***	0.01024***	−0.00194***
	(−10.27332)	(−0.61013)	(0.42514)	(−7.17441)	(15.66581)	(−6.29560)
Marriage	−0.03534***	0.00010	−0.00331	−0.02919***	0.08434***	0.00055
	(−3.65933)	(0.03785)	(−0.49322)	(−3.65900)	(6.24008)	(0.08733)
Constant	0.52769***	0.00647	0.05794**	0.26202***	−0.10159**	0.17907***
	(15.15306)	(0.69100)	(2.39470)	(9.10691)	(−2.08422)	(7.81496)
N	4,839					

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of expenditure					
	Clothing/bedding	**Travel**	**Durable goods**	**Education/training**	**Health care**	**Others**
R-squared	0.0545	0.0292	0.0016	0.0147	0.0748	0.0153
F-statistics	27.83	14.53	0.77	7.21	39.02	7.50
Prob > *F*	0.0000	0.0000	0.6553	0.0000	0.0000	0.0000

Notes: *Total expenditure*: household total expenditure (in 1,000 CNY). *CFA*: compulsory farmland acquisition, a binary variable indicating treatment status; *Productive assets*: value of productive assets (in 1,000 CNY); *Financial assets*: value of financial assets (in 1,000 CNY). *Pension*: a binary variable indicating whether core family members have pension; *Highest education*: highest education level of household head; *Rented farmland*: the area of farmland rented by a household (in *mu*); *Average age*: average age of household head and spouse; *Marriage*: a binary variable indicating the marital status of the household head. *t*-statistics are in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.

4.7 Discussion and Conclusion

This chapter presented a study on the effect of CFA on household expenditure in rural China, with a focus on middle-aged and elderly people. Following the permanent income hypothesis, consumption expenditure was adopted as an indicator of household livelihood. To capture the relationship between CFA and consumption expenditure at the household level, PSM and PA-weighting methods were adopted within the DID framework. The total consumption expenditure of CFA-affected households was nearly 40% higher than that of unaffected households between 2013 and 2018, indicating that CFA during this period positively affected household livelihoods. A possible reason for this may be that the compensation paid to households for expropriated farmland exceeded their expected future income from their farmland and offset the risk of income uncertainty arising from land loss.

A study of expenditure patterns based on the SURE framework revealed that CFA is not significantly correlated with consumption expenditure patterns, consistent with the non-significant effect of CFA on categorical expenditure. This indicates that CFA was not associated with a negative shock to the consumption behaviours of households during the research period.

Other findings are consistent with the existing literature. For example, households with higher total consumption expenditure allocate more to essentials such as clothing and bedding. Those with well-educated core members tend to spend more on long-distance travel and less on health care. Households with older core members spend more on health care and less on clothing and bedding, education and training and other expenses unrelated to health care. Marriage is positively associated with spending on health care and negatively associated with spending on clothing and bedding and education and training.

The findings of this study have significant implications for policymakers, especially in the context of CFA in China. The positive effects of CFA suggest that compensation for acquired farmland exceeds households' expectations of future income from their farmland, thus improving their livelihoods. Therefore, policymakers should maintain or increase compensation levels to ensure the continued positive outcomes for rural households affected by CFA. Moreover, the correlations between household characteristics and expenditure patterns (e.g. older people spending more on health care) underline the importance of considering demographic factors in policies. Such insights could improve the targeted support for farmers subject to CFA to further support the specific needs of these households.

By leveraging household panel survey data, this study captured the positive relationship between CFA and household expenditure in China between 2013 and 2018. It also revealed the correlations between household characteristics and consumption expenditure patterns. However, the exact mechanisms underlying the positive effects could not be explored because of limited data. Future researchers could address this shortcoming if data on CFA compensation and households' income expectations become available.

Chapter 5: Conclusion

This thesis has highlighted the effects of three policies enacted in China over the past 2 decades—CPA, TPA and CFA—on affected households. I gathered and analysed data from multiple sources, creating panel datasets compatible with the DID framework. Depending on the characteristics of the data, several methods of causal inferences based on DID (e.g. SDID, DID-FE, PSM-DID and PS-weighted DID) were used.

Chapter 2 presented the use of a panel dataset to examine the CPA strategy, a targeted geographic poverty alleviation strategy in China. The study aimed to distinguish the effects of the CPA program from the concurrent county-level NDPC program. By constructing treatment and control groups among NDPCs and employing an SDID approach, the analysis shows that the CPA program significantly increased per capita GDP by 8.3% and rural income by 6.8% in CPA-NDPCs compared with pure NDPCs between 2011 and 2018. The results were robust across different model specifications such as DID and DID-FE. The study also shows evidence of the policy's dynamic benefits on economic and income growth, although the effect size decreased slightly in 2018. However, the CPA program did not significantly narrow the urban–rural income gap, and the evaluation was limited to four provinces because of limited data availability. The findings support the effectiveness of geographical targeting for poverty alleviation in China, providing robust empirical evidence of the efficacy of the CPA program.

Chapter 3 examined the early-stage effects of TPA in China's latest poverty alleviation campaign, with a focus on the underdeveloped representative province of Gansu. Using a combination of DID and PSM, the study showed that TPA negatively affected lower-income households but had no significant effect on higher-income households. This may be attributable to the inaccurate identification of impoverished households, costly and complex assistance measures and assessment mechanisms that prioritise the poverty headcount over growth in household income. The effects were also heterogeneous according to the type of poverty, highlighting the need to consider the type of poverty and the intrinsic characteristics of households when providing support. Additionally, the education of the household head plays a significant role in the household's ability to access and understand the opportunities provided by poverty alleviation programs.

Chapter 4 investigated the effect of CFA on the expenditure of households comprising middle-aged and elderly residents in rural China, based on the argument that expenditure is a better indicator of household livelihood. The relationships between household characteristics, including whether they had been affected by CFA, and consumption patterns were also explored. Estimations based on PSM-DID and PS-weighted DID revealed the positive effect of CFA on household consumption expenditure between 2013 and 2018, indicating that the compensation paid for expropriated farmland surpassed households' expected future income from their farmland and offset the risk of income uncertainty arising from land loss. Using the SURE framework, the study also revealed a non-significant correlation between CFA and consumption expenditure patterns, suggesting that CFA does not cause a shock to the consumption behaviours of farmers. Other results align with the existing literature on the relationships between household characteristics and expenditure patterns, such as the effect of education, age and marital status on various spending categories.

In summary, this thesis makes a notable contribution to the existing literature by addressing several gaps in the literature on the effect of poverty alleviation policies in rural China. However, because of limitations in data availability, numerous intriguing questions remain for future research endeavours. For instance, it is crucial that future researchers further examine the direct effects of the CPA policy on poverty reduction at both the regional and individual levels and investigate the mechanisms underlying the effectiveness of such targeted geographic schemes. The results of the TPA study were derived from the policy's early stages, precluding a comprehensive understanding of the effects of TPA. Additionally, the absence of data on untreated neighbouring households hindered the assessment of potential spillover effects. This study could be improved by obtaining more detailed information on the specific interventions received by each family. Finally, the CFA study was constrained by the lack of data on compensation levels and households' income expectations, necessitating further research in this area.

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Appendix A

Table A1: Identified causes of poverty

Causes	Meaning
Skill scarcity	Impoverished households may lack the necessary skills or technology to increase productivity or engage in higher-income occupations.
Fund scarcity	Impoverished households may not have sufficient funds to invest in education, health, or productive activities, limiting their income growth.
Education burden	The financial strain caused by the cost of education can lead to household debt, which may ultimately result in poverty for the affected families.
Chronic or major diseases	Chronic or major diseases may prevent impoverished households from working while increasing medical expenses, further reducing family income.
Labor scarcity	Families may lack sufficient labor to maintain production or income sources, particularly in rural areas.
Insufficient motivation	Impoverished households may lack the motivation for self-improvement and development, preventing them from escaping poverty.
Disability	Disabilities may prevent impoverished households from working, affecting their income sources.
Backward transportation conditions	Poor transportation conditions in impoverished areas may prevent households from easily accessing markets, education, and medical resources, limiting their income and quality of life.
Natural disasters	Natural disasters may lead to loss of housing, crops, and property for impoverished households.
Farmland scarcity	In rural areas, impoverished households may lack sufficient arable land to grow crops, resulting in lower income levels.
Lack of water	Water resource shortages may cause impoverished households to face challenges in agriculture, drinking water, and sanitation, affecting their quality of life and income.
Marriage and funeral expenses	In some regions, the high costs of marriage and funeral rituals may burden impoverished households with heavy debt.
Other	This category includes various other causes that may lead to poverty.

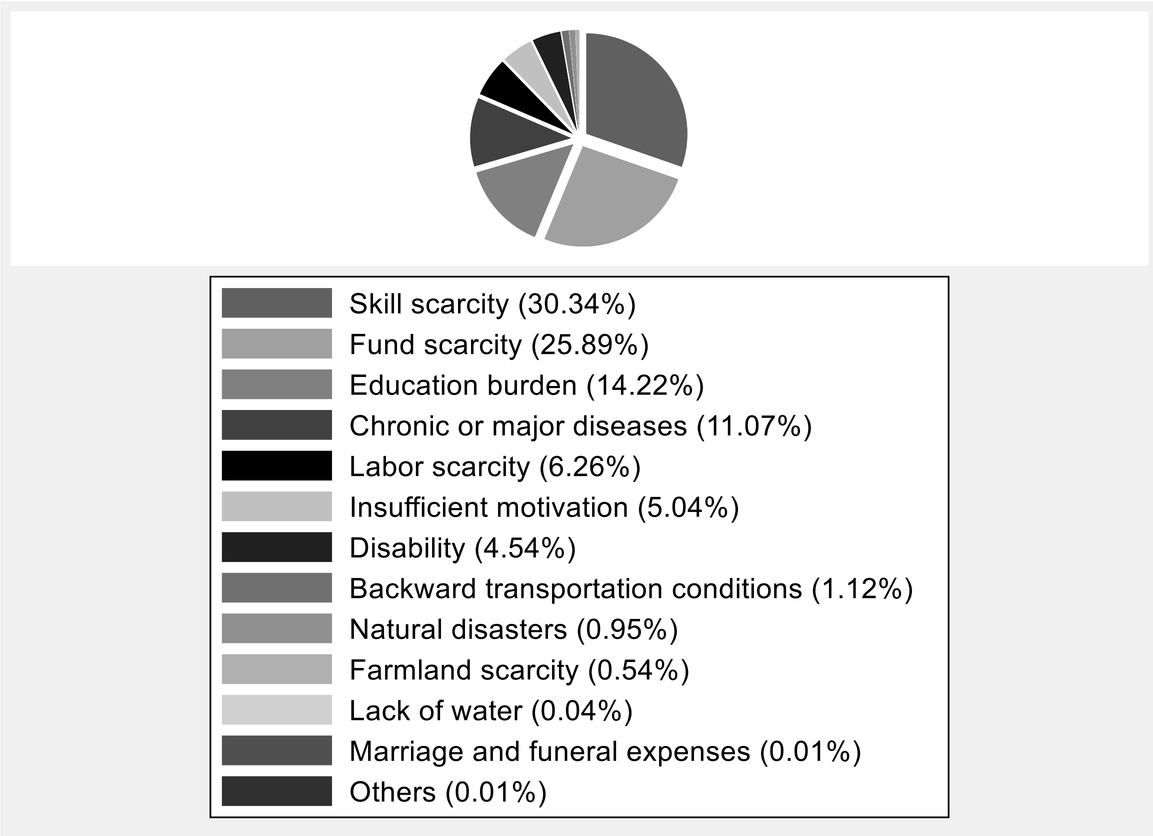

Figure A1: Identified causes of poverty in the raw data.

Appendix B

Table B1: Effect of CFA on total expenditure (bandwidth = 0.1)

Outcome var.	lnexp	S. Err.	t	P>t
Baseline				
Control	7.2840			
Treated	7.3770			
Diff (T-C)	0.0940	0.0750	1.25	0.2100
Follow-up				
Control	7.3540			
Treated	7.8010			
Diff (T-C)	0.4480	0.0750	6	0.000***
Diff-in-Diff	0.3540	0.1050	3.37	0.001***

Note: Estimations based on kernel-based propensity score matching with difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table B2: Effect of CFA on total expenditure (bandwidth = 0.01)

Outcome var.	lnexp	S. Err.	t	P>t
Baseline				
Control	7.3940			
Treated	7.3690			
Diff (T-C)	-0.0250	0.0730	-0.3400	0.7320
Follow-up				
Control	7.4580			
Treated	7.7930			
Diff (T-C)	0.3360	0.0730	4.61	0.000***
Diff-in-Diff	0.3610	0.1030	3.52	0.000***

Note: Estimations based on kernel-based propensity score matching with difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Appendix C

Table C1: Effects of CFA on clothing and bedding expenditure

lnexpcb	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CFA	.1778	.1211	1.47	.1421	-.0596	.4152	
Time	-.2349	.0747	-3.14	.0017	-.3814	-.0885	***
CFA×Time	-.0212	.1721	-0.12	.9019	-.3586	.3162	
Productive assets	.0001	.0002	0.60	.5505	-.0003	.0005	
Financial assets	.005	.0015	3.42	.0006	.0021	.0079	***
Pension	.2247	.1079	2.08	.0374	.0132	.4363	**
Highest education	.0424	.0289	1.47	.1421	-.0142	.0991	
Rented farmland	-.0111	.0054	-2.05	.0407	-.0217	-.0005	**
Average age	-.0674	.0056	-12.01	0	-.0784	-.0564	***
Marriage	.0614	.1227	0.50	.617	-.1792	.302	
rent	-.0005	.0194	-0.03	.9792	-.0385	.0375	
wage	.0645	.0109	5.93	0	.0432	.0858	***
business	.1678	.024	6.99	0	.1207	.2148	***
crop and forestry	.0563	.0137	4.12	0	.0295	.0831	***
livestock and fishery	.0171	.0119	1.44	.1492	-.0061	.0404	
Constant	7.455	.425	17.54	0	6.622	8.2881	***

Mean dependent var	4.4990	SD dependent var	3.1505
R-squared	0.0903	Number of obs	9145
F-test	39.6680	Prob > F	0.0000
Akaike crit. (AIC)	45863.7680	Bayesian crit. (BIC)	45977.7034

Note: Estimations are based on propensity score–weighted difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table C2: Effects of CFA on travel expenditure

lnexpt	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CFA	.006	.0584	0.10	.9179	-.1085	.1206	
Time	-.0323	.0356	-0.91	.3637	-.102	.0374	
CFA×Time	.0088	.0828	0.11	.9151	-.1535	.1712	
Productive assets	.0007	.0001	6.12	0	.0005	.0009	***
Financial assets	.0024	.0009	2.71	.0067	.0007	.0042	***
Pension	-.043	.0533	-0.81	.4196	-.1476	.0615	
Highest education	.0314	.0147	2.14	.0324	.0026	.0601	**
Rented farmland	-.0012	.0015	-0.80	.4234	-.0042	.0018	
Average age	-.0021	.0026	-0.80	.4233	-.0071	.003	
Marriage	-.0023	.053	-0.04	.9653	-.1062	.1016	
rent	.0264	.0112	2.36	.0181	.0045	.0482	**
wage	.0046	.0055	0.84	.4028	-.0062	.0154	
business	.049	.0243	2.01	.0443	.0013	.0967	**
crop and forestry	-.0144	.0076	-1.89	.0588	-.0292	.0005	*
livestock and fishery	.0175	.0058	2.99	.0028	.006	.0289	***
Constant	.314	.1992	1.58	.1149	-.0764	.7044	

Mean dependent var	0.3085	SD dependent var	1.4802
R-squared	0.0193	Number of obs	9145
F-test	10.4907	Prob > F	0.0000
Akaike crit. (AIC)	32489.5402	Bayesian crit. (BIC)	32603.4756

Note: Estimations are based on propensity score–weighted difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table C3: Effects of CFA on durable goods expenditure

lnexpd	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CFA	-.1264	.1265	-1.00	.3177	-.3745	.1216	
Time	-.4258	.074	-5.75	0	-.5708	-.2807	***
CFA×Time	.0551	.17	0.32	.7461	-.2782	.3883	
Productive assets	-.0003	.0001	-1.79	.0739	-.0006	0	*
Financial assets	.0029	.0014	2.02	.0439	.0001	.0058	**
Pension	.0124	.1058	0.12	.9064	-.195	.2199	
Highest education	.0702	.0293	2.40	.0165	.0128	.1275	**
Rented farmland	.005	.0056	0.89	.3731	-.006	.0161	
Average age	-.0059	.0053	-1.11	.2652	-.0163	.0045	
Marriage	.0154	.1142	0.13	.8926	-.2085	.2393	
rent	.0163	.0181	0.90	.3675	-.0192	.0518	
wage	.0221	.0118	1.87	.062	-.0011	.0452	*
business	.0473	.0311	1.52	.1281	-.0136	.1082	
crop and forestry	.0305	.0128	2.39	.0168	.0055	.0556	**
livestock and fishery	.0483	.0124	3.91	.0001	.024	.0725	***
Constant	1.2415	.415	2.99	.0028	.4279	2.0551	***

Mean dependent var	1.4307	SD dependent var	2.9796
R-squared	0.0173	Number of obs	9145
F-test	7.0079	Prob > F	0.0000
Akaike crit. (AIC)	45671.0299	Bayesian crit. (BIC)	45784.9653

Note: Estimations are based on propensity score–weighted difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table C4: Effects of CFA on education and training expenditure

lnexpedu	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CFA	.2822	.1473	1.92	.0555	-.0066	.5709	*
Time	-.6237	.0817	-7.63	0	-.7839	-.4636	***
CFA×Time	-.0079	.1998	-0.04	.9683	-.3997	.3838	
Productive assets	-.0003	.0002	-1.59	.1111	-.0006	.0001	
Financial assets	.0004	.0015	0.24	.8076	-.0025	.0032	
Pension	-.1078	.1261	-0.86	.3924	-.355	.1393	
Highest education	.024	.0332	0.73	.4684	-.0409	.089	
Rented farmland	-.0024	.0052	-0.46	.6423	-.0125	.0077	
Average age	-.0473	.0064	-7.37	0	-.0599	-.0347	***
Marriage	-.191	.134	-1.42	.1542	-.4537	.0718	
rent	-.0483	.0207	-2.33	.0198	-.0889	-.0077	**
wage	.022	.0138	1.60	.1098	-.005	.0491	
business	.1744	.0386	4.52	0	.0987	.2501	***
crop and forestry	.042	.0161	2.61	.009	.0105	.0735	***
livestock and fishery	.0368	.0145	2.53	.0113	.0083	.0652	**
Constant	4.5324	.482	9.40	0	3.5875	5.4773	***

Mean dependent var	1.8428	SD dependent var	3.3931
R-squared	0.0393	Number of obs	9145
F-test	15.3941	Prob > F	0.0000
Akaike crit. (AIC)	48221.5635	Bayesian crit. (BIC)	48335.4989

Note: Estimations are based on propensity score–weighted difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table C5: Effects of CFA on healthcare expenditure

lnexph	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CFA	.138	.1297	1.06	.2874	-.1162	.3922	
Time	.4296	.0798	5.39	0	.2732	.5859	***
CFA×Time	.295	.179	1.65	.0994	-.0559	.6459	*
Productive assets	-.0004	.0002	-1.93	.0532	-.0008	0	*
Financial assets	0	.0008	0.04	.9686	-.0016	.0017	
Pension	.5831	.1162	5.02	0	.3553	.8109	***
Highest education	.0281	.031	0.91	.3651	-.0327	.089	
Rented farmland	-.0115	.0067	-1.73	.0836	-.0246	.0015	*
Average age	-.0024	.0058	-0.40	.6857	-.0138	.0091	
Marriage	.7389	.1231	6.00	0	.4977	.9801	***
rent	.0744	.0184	4.04	.0001	.0383	.1105	***
wage	-.0116	.0116	-1.00	.3177	-.0344	.0112	
business	-.0076	.0327	-0.23	.8161	-.0717	.0565	
crop and forestry	.0274	.0146	1.87	.061	-.0013	.056	*
livestock and fishery	.011	.0126	0.88	.381	-.0136	.0356	
Constant	4.5325	.4473	10.13	0	3.6558	5.4092	***

Mean dependent var	6.0150	SD dependent var	3.2752
R-squared	0.0327	Number of obs	9145
F-test	11.9495	Prob > F	0.0000
Akaike crit. (AIC)	46900.3334	Bayesian crit. (BIC)	47014.2688

Note: Estimations are based on propensity score–weighted difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table C6: Effects of CFA on other expenditure

lnexpo	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CFA	.1336	.1323	1.01	.3128	-.1258	.393	
Time	-.5715	.0778	-7.35	0	-.724	-.4191	***
CFA×Time	-.0006	.1841	-0.00	.9974	-.3614	.3602	
Productive assets	-.0004	.0002	-1.71	.0864	-.0008	.0001	*
Financial assets	.0033	.0014	2.27	.0229	.0005	.0061	**
Pension	.1095	.1149	0.95	.3406	-.1158	.3349	
Highest education	.0686	.0316	2.17	.03	.0067	.1306	**
Rented farmland	.0072	.0072	1.00	.3163	-.0069	.0213	
Average age	-.033	.0058	-5.70	0	-.0443	-.0216	***
Marriage	.0698	.1204	0.58	.5621	-.1662	.3058	
rent	.0103	.0192	0.54	.5911	-.0273	.0479	
wage	.0786	.0128	6.13	0	.0534	.1037	***
business	.1257	.0344	3.65	.0003	.0583	.1932	***
crop and forestry	.0583	.0142	4.09	0	.0304	.0862	***
livestock and fishery	.0141	.0133	1.06	.2884	-.012	.0403	
Constant	3.2063	.4442	7.22	0	2.3356	4.077	***

Mean dependent var	2.1184	SD dependent var	3.1960
R-squared	0.0532	Number of obs	9145
F-test	21.1617	Prob > F	0.0000
Akaike crit. (AIC)	46873.1673	Bayesian crit. (BIC)	46987.1027

Note: Estimations are based on propensity score–weighted difference-in-differences; CFA: compulsory farmland acquisition. *** $p < .01$, ** $p < .05$, * $p < .1$.

Appendix D

Table D1: Household characteristics and overall consumption expenditure patterns

	(1)	(2)	(3)	(4)	(5)	(6)
	the share of expenditure on					
	clothing and bedding	travelling	durables	education and training	healthcare	others
Total expenditure	-0.00121***	0.00010***	-0.00010	0.00018**	-0.00031**	-0.00021**
	(-11.85969)	(3.56069)	(-1.34209)	(2.11231)	(-2.19848)	(-3.18079)
CFA	-0.01521	-0.00205	-0.00780	0.00701	0.01235	0.00032
	(-1.51046)	(-0.75813)	(-1.11435)	(0.84219)	(0.87626)	(0.04770)
Productive assets	0.00001	0.00004***	-0.00001	-0.00002	-0.00000	-0.00001
	(0.23586)	(7.07388)	(-0.76134)	(-0.81259)	(-0.06072)	(-0.79802)
Financial assets	0.00033***	0.00013***	0.00011**	0.00009	-0.00080***	0.00008
	(4.01913)	(5.95226)	(1.99131)	(1.33362)	(-6.92702)	(1.47156)
Pension	-0.02685***	-0.00234	0.00038	0.00336	0.02220*	0.00447
	(-2.84574)	(-0.92236)	(0.05825)	(0.43052)	(1.68080)	(0.71987)
Highest education	0.00084	0.00179***	0.00014	-0.00054	-0.00587*	-0.00057
	(0.34074)	(2.70136)	(0.08122)	(-0.26383)	(-1.70127)	(-0.35110)
Rented farmland	-0.00073	-0.00017	0.00010	0.00071	-0.00083	0.00112**
	(-1.02081)	(-0.88334)	(0.19220)	(1.21161)	(-0.83204)	(2.38062)
Average age	-0.00480***	-0.00008	0.00014	-0.00277***	0.01024***	-0.00194**
	(-10.27332)	(-0.61013)	(0.42514)	(-7.17441)	(15.66581)	(-6.29560)
Marriage	-0.03534***	0.00010	-0.00331	-0.02919***	0.08434***	0.00055
	(-3.65933)	(0.03785)	(-0.49322)	(-3.65900)	(6.24008)	(0.08733)
Constant	0.52769***	0.00647	0.05794**	0.26202***	-0.10159**	0.17907**
	(15.15306)	(0.69100)	(2.39470)	(9.10691)	(-2.08422)	(7.81496)
N	4839					

Note: Estimations are based on three-stage least squares. CFA: compulsory farmland acquisition. *z*-statistics are given in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table D2: Household characteristics and consumption expenditure patterns, 1st quartile

	(1)	(2)	(3)	(4)	(5)	(6)
	the share of expenditure on					
	clothing and bedding	travelling	durables	education and training	healthcare	others
Total expenditure	0.0027	0.0002	-0.0002	-0.0002	-0.0028	0.0007
	(0.9291)	(0.9899)	(-0.6062)	(-0.7460)	(-0.9286)	(0.9121)
CFA	-0.2163	-0.0065	0.0120	0.0203	0.1961	-0.0507
	(-1.2673)	(-0.5328)	(0.4997)	(1.0562)	(1.0999)	(-1.0807)
Productive assets	-0.0001	-0.0000	-0.0000	0.0000	0.0001	-0.0000
	(-0.3052)	(-0.3433)	(-0.0195)	(0.1517)	(0.4281)	(-0.5214)
Financial assets	0.0004	-0.0001	0.0000	-0.0000	-0.0002	-0.0002
	(0.3036)	(-0.5917)	(0.0645)	(-0.2755)	(-0.1229)	(-0.4689)
Pension	-0.0630	0.0035	0.0021	-0.0043	0.0636	0.0126
	(-0.6998)	(0.5472)	(0.1656)	(-0.4275)	(0.6758)	(0.5094)
Highest education	0.0027	-0.0004	0.0040	0.0013	-0.0111	0.0008
	(0.1108)	(-0.2276)	(1.1663)	(0.4549)	(-0.4373)	(0.1179)
Rented farmland	0.0025	0.0002	-0.0008	-0.0008	-0.0021	0.0019
	(0.2470)	(0.3325)	(-0.5329)	(-0.6590)	(-0.1993)	(0.6740)
Average age	-0.0000	0.0005	0.0002	-0.0012	-0.0002	0.0015
	(-0.0031)	(0.6983)	(0.1527)	(-0.9950)	(-0.0151)	(0.4978)
Marriage	-0.1165	-0.0125	0.0124	0.0091	0.1432	-0.0371
	(-0.7738)	(-1.1583)	(0.5848)	(0.5373)	(0.9100)	(-0.8965)
Constant	-1.1622	-0.1500	0.1363	0.2273	2.1585	-0.4812
	(-0.5054)	(-0.9093)	(0.4197)	(0.8754)	(0.8984)	(-0.7608)
N	927					

Note: Estimations are based on three-stage least squares. CFA: compulsory farmland acquisition. *z*-statistics are given in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table D3: Household characteristics and consumption expenditure patterns, 2nd quartile

	(1)	(2)	(3)	(4)	(5)	(6)
	the share of expenditure on					
	clothing and bedding	travelling	durables	education and training	healthcare	others
Total expenditure	0.0008	0.0000	0.0001	-0.0001	-0.0011	0.0001
	(1.3299)	(0.6578)	(0.5704)	(-0.8799)	(-1.3548)	(0.8841)
CFA	0.0340	-0.0059	-0.0308*	0.0169	-0.0347	0.0301*
	(0.5495)	(-1.1595)	(-1.6498)	(1.0188)	(-0.4212)	(1.7987)
Productive assets	0.0005	-0.0000	0.0002	-0.0000	-0.0009	0.0000
	(0.4190)	(-0.0377)	(0.6828)	(-0.1014)	(-0.5452)	(0.0428)
Financial assets	0.0009	0.0000	0.0000	-0.0002	-0.0008	0.0001
	(1.5671)	(0.7366)	(0.0271)	(-1.1839)	(-1.0396)	(0.9186)
Pension	0.0130	-0.0003	-0.0052	-0.0137	-0.0027	0.0088
	(0.2126)	(-0.0678)	(-0.2823)	(-0.8321)	(-0.0326)	(0.5310)
Highest education	0.0116	0.0018	0.0006	-0.0059	-0.0122	-0.0018
	(0.7424)	(1.4122)	(0.1280)	(-1.4179)	(-0.5854)	(-0.4285)
Rented farmland	0.0022	-0.0001	-0.0002	-0.0008	-0.0025	0.0016
	(0.4974)	(-0.3489)	(-0.1139)	(-0.6612)	(-0.4193)	(1.3579)
Average age	-0.0044	0.0006**	0.0006	-0.0027***	0.0069	-0.0013
	(-1.2497)	(2.1912)	(0.5780)	(-2.8718)	(1.4448)	(-1.3322)
Marriage	-0.0664	0.0080	-0.0530***	-0.0023	0.1394	-0.0181
	(-1.0451)	(1.5267)	(-2.7599)	(-0.1322)	(1.6435)	(-1.0520)
Constant	-1.6783	-0.1295	-0.1882	0.6176	3.0162	-0.2423
	(-0.9431)	(-0.8870)	(-0.3499)	(1.2930)	(1.2698)	(-0.5020)
N	1330					

Note: Estimations are based on three-stage least squares. CFA: compulsory farmland acquisition. *z*-statistics are given in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table D4: Household characteristics and consumption expenditure patterns, 3rd quartile

	(1)	(2)	(3)	(4)	(5)	(6)
	the share of expenditure on					
	clothing and bedding	travelling	durables	education and training	healthcare	others
Total expenditure	-0.0014	-0.0011	0.0003	0.0004	0.0028	-0.0009
	(-0.3318)	(-0.3306)	(0.3096)	(0.3186)	(0.3311)	(-0.3299)
CFA	-0.0269	-0.0311	0.0184	0.0126	0.0316	-0.0068
	(-0.1247)	(-0.1848)	(0.3760)	(0.2212)	(0.0755)	(-0.0490)
Productive assets	-0.0032	-0.0026	0.0017	0.0006	0.0060	-0.0026
	(-0.2805)	(-0.2992)	(0.6440)	(0.1969)	(0.2727)	(-0.3490)
Financial assets	0.0001	-0.0002	0.0002	-0.0001	-0.0001	-0.0002
	(0.0431)	(-0.1081)	(0.4505)	(-0.2101)	(-0.0135)	(-0.1295)
Pension	0.0917	0.0755	0.0079	-0.0145	-0.2352	0.0711
	(0.2544)	(0.2684)	(0.0962)	(-0.1524)	(-0.3357)	(0.3065)
Highest education	0.0617	0.0459	-0.0120	-0.0234	-0.1098	0.0334
	(0.3407)	(0.3251)	(-0.2931)	(-0.4890)	(-0.3119)	(0.2865)
Rented farmland	-0.0002	0.0005	0.0008	0.0020	-0.0043	0.0018
	(-0.0178)	(0.0481)	(0.2715)	(0.5606)	(-0.1659)	(0.2063)
Average age	-0.0194	-0.0124	0.0037	-0.0004	0.0420	-0.0134
	(-0.4011)	(-0.3291)	(0.3349)	(-0.0291)	(0.4475)	(-0.4310)
Marriage	-0.2073	-0.1403	0.0563	0.0046	0.4008	-0.0964
	(-0.3717)	(-0.3226)	(0.4455)	(0.0315)	(0.3698)	(-0.2686)
Constant	10.8757	8.1924	-2.2039	-2.2483	-20.5316	7.0128
	(0.3432)	(0.3314)	(-0.3070)	(-0.2687)	(-0.3333)	(0.3437)
N	1319					

Note: Estimations are based on three-stage least squares. CFA: compulsory farmland acquisition. *z*-statistics are given in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.

Table D5: Household characteristics and consumption expenditure patterns: 4th quartile

	(1)	(2)	(3)	(4)	(5)	(6)
	the share of expenditure on					
	clothing and bedding	travelling	durables	education and training	healthcare	others
Total expenditure	0.000003	0.000004*	0.000001	0.000000	-0.000015*	0.000000
	(1.331525)	(1.691778)	(0.562257)	(0.026561)	(-1.697328)	(0.343015)
CFA	0.015472	0.016474	-0.003216	-0.016393	-0.015740	-0.030496**
	(0.763722)	(0.665135)	(-0.239440)	(-0.730922)	(-0.188158)	(-2.454959)
Productive assets	0.000002	0.000038	-0.000018	-0.000035	0.000042	-0.000012
	(0.091727)	(1.251135)	(-1.083086)	(-1.275282)	(0.405016)	(-0.756676)
Financial assets	0.000345**	0.000370**	0.000217**	0.000282*	-0.001545***	0.000108
	(2.423137)	(2.120991)	(2.290911)	(1.783626)	(-2.625201)	(1.239805)
Pension	0.024914	0.043057	-0.012736	0.021444	-0.141859	0.009280
	(0.883388)	(1.248716)	(-0.681035)	(0.686813)	(-1.218110)	(0.536607)
Highest education	0.002336	0.001028	-0.004075	0.003126	-0.005967	0.000771
	(0.502446)	(0.180943)	(-1.321895)	(0.607385)	(-0.310834)	(0.270490)
Rented farmland	0.000394	0.000855	-0.000285	0.000177	-0.003845	0.001219
	(0.309727)	(0.550116)	(-0.337557)	(0.125814)	(-0.732515)	(1.563733)
Average age	-0.001437	0.001656	0.000163	-0.001741	0.002304	-0.000499
	(-1.090065)	(1.027956)	(0.186397)	(-1.193201)	(0.423366)	(-0.617333)
Marriage	0.000521	0.040473	0.011375	-0.086236***	0.023263	0.001211
	(0.019036)	(1.210515)	(0.627288)	(-2.848407)	(0.206008)	(0.072210)
Constant	0.018031	-0.326837	0.033106	0.291809	1.129435	0.064955
	(0.098301)	(-1.457362)	(0.272175)	(1.436968)	(1.491101)	(0.577475)
N	1263					

Note: Estimations are based on three-stage least squares. CFA: compulsory farmland acquisition. *z*-statistics are given in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.