Less Poor is More Equal: Evidence from the Targeted Poverty Alleviation in China

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Abstract

This study evaluates the impact of the Targeted Poverty Alleviation (TPA) program in 2015 on urban-rural income inequality in China. Income inequality is defined as the ratio of the urban net income to rural net income, both in per capita form. Using the county-level data from 2010 to 2019, the main finding suggests that the program leads to a 3.8% reduction in the urban-rural income ratio in poverty counties, compared with non-poverty counties, which implies a discernible convergence in income levels. I discuss that the significant increase in rural income per capita, improved rural employment, and more government spending largely contribute to the narrowing urban-rural inequality in poverty counties.

Keywords: poverty alleviation, urban-rural income inequality, county governments

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To make the pie bigger, or to improve the way pie is divided?[1] That is a question about efficiency and equity. Over the past three decades of hardworking efforts, China has transformed from one of the worlds most underdeveloped countries to a high middle-income economy. The country has achieved a historic milestone in poverty alleviation by lifting over 770 million people out of absolute poverty, accounting for nearly 70% of global poverty reduction during the same period.[2] This remarkable achievement is illustrated in figure 1(a), which shows a dramatic decline in the poverty rate from 88.1% in 1981 to just 0.2% in 2019.[3] However, these efforts have also contributed to an unintended consequence: increasing regional inequality (Jones et al., 2003; Chan et al., 2014), particularly the widening urban-rural divide (Zhao, 1999; Sicular et al., 2007; Zhou and Song, 2016). As shown in figure 1(b), while income levels in both urban and rural areas steadily increases alongside the countrywide growth, the gap between them also enlarges. The growing income disparity, if left unaddressed, risks undermining the progress made in poverty alleviation (Yao et al., 2004; Iniguez-Montiel, 2014) and could pose challenges to social stability. Consequently, the focus has shifted towards the equitable distribution of income and wealth across regions.

In response to these challenges, the Chinese government launched the Targeted Poverty Alleviation (TPA) program in 2015, with the explicit goal of eradicating absolute poverty and reducing economic disparities in underdeveloped regions. Unlike earlier poverty alleviation efforts, which often prioritized overall growth and overlooked the deepening rural-urban divide, the TPA program adopts a more targeted approach. It identifies impoverished households and directly addresses the root causes of poverty through tailored support measures. Given that the majority of the poverty-stricken population resides in rural areas (Park et al., 2002), the TPA program is expected to significantly improve rural income levels. If the program demonstrates a rural-oriented character, its impact on urban income may remain limited. Therefore, a natural expectation arises: the TPA program will contribute to narrowing the urban-rural income gap. Besides, this is also closely aligned with the guideline of "common prosperity".

[1] See from `http://www.qstheory.cn/international/2022-12/19/c_1129218316.htm`.

[2] See from `http://www.china.org.cn/chinese/2021-06/02/content_77513397.htm`.

[3] Data obtained from the World Bank and Global Extreme Poverty, see `https://pip.worldbank.org/home`.

This study aims to empirically test whether the TPA program has succeeded in achieving this anticipated outcome. In the empirical analysis, I assess the impact of the Targeted Poverty Alleviation (TPA) program on urban-rural income inequality using a Difference-in-Differences (DID) approach. Income inequality is measured as the ratio of the urban net income per capita to rural net income per capita. Given that the TPA program primarily targets poverty counties, I leverage the variation in the poverty status to estimate the program effect on the income ratio. However, an outstanding concern of endogeneity occurs in the estimation because the poverty status is largely related to economic conditions years before the program. The process of the designation is not considered random. If ignored, the endogeneity would bias the estimation from a standard DID model. Thus, I employ the Propensity Score Matching (PSM) method to match comparable counties with different poverty statuses to reduce pre-program differences.

After balancing pre-program differences using the PSM weights, the main findings of this study reveal that the TPA program reduces the income ratio in poverty counties by 3.8% relative to non-poverty counties. Importantly, the use of the PSM weights corrects a 77% overestimation observed in the unweighted model, demonstrating the necessity of addressing initial imbalances. In addition, the event-study design not only confirms the parallel trends assumption, further validating the robustness of the standard DID approach, but also displays a downward trend in the income ratio. Therefore, the TPA program has effectively reduced urban-rural income inequality in poverty counties.

A key concern with place-based programs like the TPA program is the potential extending effect on neighbouring non-poverty counties (Lu et al., 2019), which could lead to an underestimation of the true impact. To address this, I incorporate a proxy for such extending effect into the model. The results indicate that non-poverty counties within the same prefecture are not significantly affected by the program implementation in neighbouring poverty counties. This finding reinforces that the observed reduction in urban-rural income inequality is a direct consequence of the TPA program, rather than being driven by external or indirect factors.

I explore three mechanisms that help explain the main finding of this study. First, I build on the rural-oriented nature of the TPA program and hypothesize that its implementation primarily benefits the targeted group–the rural poor (Rozelle et al., 1998; Montalvo and Ravallion, 2010; Meng, 2013). To test this, I examine changes in both urban and rural net income per capita following the program. The results show that the TPA program significantly increases rural net income per capita in poverty counties, while urban net income per capita remains unaffected. The size of the income increase is approximately 8.3% of the poverty line at the time.

Second, I present evidence that the increase in rural incomes is linked to improved job opportunities in rural areas. Similar to the income channel, the TPA program significantly boosts rural employment in poverty counties, while urban employment remains unaffected. This improved rural labour market is further reflected in a rise in agricultural production, suggesting that the program directly supports rural livelihoods. Both the income and employment channels reinforce the rural-oriented design of the program and its targeted impact on poverty alleviation.

Last, I examine the role of county governments, which act as the core administrative units responsible for implementing the program (Fan et al., 2000; Zhu et al., 2021). My finding reveals a significant increase in fiscal expenditure per capita in poverty counties relative to non-poverty counties following the program. This result highlights the crucial role of local governments in allocating resources and ensuring the successful execution. Their active involvement in the program reflects their commitment to achieving its poverty reduction objectives.

This study contributes to the literature in the following ways. First, it directly adds to the growing body of research on China's poverty alleviation efforts. Since the Chinese government officially initiated poverty alleviation programs in 1986, previous studies have examined program efficiency through lens such as economic development or income increase (Rozelle et al., 1998; Montalvo and Ravallion, 2010; Meng, 2013; Zhang et al., 2021, 2023), political influence (Li and Wu, 2022; Han et al., 2022), infrastructure (Qin and Chong, 2018; Xiao et al., 2022), or environmental influence (Yuan and Wang, 2021). This study offers a novel perspective by introducing urban-rural income inequality as the central focus of analysis. It addresses a critical gap in the literature by highlighting how the TPA program contributes not just to poverty alleviation but also in narrowing the urban-rural income divide.

Second, the main finding in this study provides the evidence that a better income distribution can be achieved by specifically raising the income levels of the targeted group, suggesting the rural-oriented nature of the TPA program. While previous poverty alleviation programs succeeded in lifting individuals out of poverty, they also exacerbated urban-rural income inequality (Ravallion and Chen, 2007; Zhang, 2021). In contrast, the TPA program distinguishes itself through its precision-targeted approach, which focuses on increasing rural income levels and enhancing rural employment, while leaving urban income largely unaffected. At the county level, the analysis confirms that neighbouring non-poverty counties remain unaffected by the program, even within the same prefecture, underscoring the place-based and well-targeted design of the intervention. These findings align with broader evidence from supportive policies that aim to reduce inequality by delivering resources to disadvantaged groups without inducing unintended spillover effects (Dahl and Lochner, 2012; Chetty and Saez, 2013; Li, 2014; Bastian, 2020).

It should be noted that this study is different itself from (Tang et al., 2022; Zhou et al., 2023) in several key aspects. First, the county-level sample provides finer details than the prefecture-level data.[4] Using county-level data not only provides a larger number of observations and greater degrees of freedom but also ensures a more accurate capture of variations in poverty status designation at the county level, given that the TPA program's designation of poverty status took place at the county level. Second, I apply stringent criteria in sample selection by excluding coastal provinces in the east region and county-level districts (*"qu"*). Coastal provinces in East China are historically at the forefront of economic development in the country, thus their exclusion prevents potential overestimation of the program effect by focusing on regions more representative of the national landscape. Similarly, the exclusion of county-level districts ensures that the analysis focuses on the "real" county-level comparisons, minimizing potential confounding factors from different layers of administration. Last, I incorporate time trends in the analysis to address concerns regarding differences in initial conditions between poverty counties and non-poverty counties. While propensity score matching (PSM) helps minimize differences between them, weighted samples may still

[4]In China, a prefecture is usually the direct leader of several counties.

present challenges in achieving optimal comparability. I ensure that the estimation remains robust and unbiased conditional on the inclusion of different time trends, thereby enhancing the reliability of the study's findings.

The subsequent sections of this paper are organized as follows: Section 1 provides an overview of the Targeted Poverty Alleviation program. Section 2 builds the conceptual framework for this study and explain why the program works on reducing the urban-rural income inequality. Sections 3 and 4 describe the data sources and methodology for the empirical analysis, with the results outlined in Section 5. Section 6 discusses some potential mechanisms to explain the primary findings, while Section 7 concludes.

1 Background: Targeted Poverty Alleviation

Poverty alleviation in China has historically been closely tied to rural development, as over 80% of the population resided in rural areas in 1978. I briefly summarize the historic account of poverty alleviation in the Appendix A.1, which lays a groundwork for future works.

In earlier decades, the "broad and general" approach adopted in poverty alleviation may have been effective when a substantial share of the population lived below the poverty line. However, it became increasingly inefficient as the poverty rate declined. Local officials often lacked clarity about the exact number of poverty-stricken individuals within their jurisdictions due to ambiguous criteria. And eligible households failed to receive necessary assistance. Therefore, the challenge of uplifting the remaining impoverished population was particularly difficult, considering that these individuals had remained in poverty despite previous programs. Given this situation, the Targeted Poverty Alleviation program was launched in 2015, marking China's final phase in the fight against poverty.[5] The TPA program introduces a clear and systematic identification process for poverty-stricken individuals. The local governments are required to establish a comprehensive database detailing impoverished households through in-depth inquiries at the grassroots level. This database is frequently updated to ensure accuracy by adding or removing beneficiaries as circumstances changed.[6] This shift

[5]The concept of "targeted poverty alleviation" was introduced during president Xi Jinping's visit in 2013. See from `http://cpc.people.com.cn/n1/2022/0625/c444826-32456402.html`.

[6]The central government also revised the poverty line to align with current development standards and

represented a significant improvement in poverty alleviation practices by targeting individual households and identifying the specific causes of their poverty. In short, the TPA program is tailored to support the rural poor directly with more effective allocation of resources. At the same time, the urban-rural inequality is expected to narrow under this framework of "common prosperity".

Counties serve as the core administrative unit in the TPA program.[7] Officially designated as "national poverty alleviation and development priority counties", or simply "poverty counties", these areas are the primary recipients of fiscal transfers from higher levels of government and bear the responsibility for alleviating poverty at the grassroots level. In 2014, 592 counties are designated, approximately 20% of the total county-level administrative units in China.[8] The list of those poverty counties is accessible on the official website of the National Rural Revitalization Administration.[9] Though the exact criteria of the designation does not become public, counties with disadvantaged economic conditions, such as higher percentages of the poverty-stricken population, are more likely to be designated. Table A1 summarizes the distribution of poverty counties, with an average ratio of 28% across 21 middle and western provinces. However, they are discernibly different in the distribution of poverty counties: the two southwestern provinces (Guizhou and Yunnan) exhibit poverty county ratios of around 57%, while Heilongjiang in a northeastern region records the lowest ratio at 11%. Figure 2 presents the overall geographic distribution of poverty counties (indicated by black dots) in China, primarily concentrated in the inland middle and western regions. In contrast, coastal provinces in the east do not host any poverty counties, owing to their robust economic performance. It is important to note that the absence of a "poverty county" designation does not imply the complete absence of poverty-stricken individuals in those regions. Still, both table and figure underscore the regional disparities prevalent in China.

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price levels. In 2015, the annual net income threshold was set at 2800 RMB, approximately $2.2 per day. See `http://politics.people.com.cn/n1/2015/1215/c70731-27932806.html`.

[7] Counties here encompass all count-level administrative units, including county-level cities. For brevity, "counties" will be used to refer to all such units.

[8] Counties in the Xizang Autonomous Area, also known as Tibet, are not included in the list due to their highest average altitudes and unique culture. Instead, they belong to another development program.

[9] Formerly known as the State Council Leading Group Office of Poverty Alleviation and Development before February 2021.See from `https://nrra.gov.cn/art/2012/3/19/art_50_23706.html`.

In practice, poverty counties extend targeted support to villages and poverty-stricken individuals through multiple aspects. These include direct assistance for improving livelihoods, enhancing agricultural production, and providing access to essential services such as healthcare and education. Beyond household-level interventions, local governments in poverty counties also undertake significant infrastructure development projects aimed at fostering long-term economic growth. These efforts include constructing highways to improve connectivity, providing electricity in some remote rural areas, and renovating dilapidated houses. Those initiatives not only address immediate needs but also lay the foundation for sustainable rural development by creating better economic opportunities and living conditions.

2 Conceptual Framework

In this section, I develop a conceptual framework grounded in the existing literature and economic theories to explain how the Targeted Poverty Alleviation program could reduce urban-rural income inequality. I begin with a simple model where ID_i denotes the urban-rural income difference in county i. The income difference can be expressed as a function of urban and rural net income per capita:

$$ID_i = F(U_i, R_i)$$

where U_i and R_i represent the urban and rural net income per capita, respectively, and $F(\cdot)$ is a continuous and differentiable function. To ensure that income differences respond as expected to changes in income, the partial derivatives of $F(\cdot)$ with respect to U_i and R_i satisfy the following conditions:

$$\frac{\delta F(\cdot)}{\delta U_i} > 0; \quad \frac{\delta F(\cdot)}{\delta R_i} < 0$$

These conditions imply that an increase in urban income deepens income inequality, while an increase in rural income narrows the gap.

The implementation of the TPA program introduces an exogenous intervention in a representative poverty county, potentially influencing both urban and rural income levels. Specifically, let $U_i = U(p_i)$ and $R_i = R(p_i)$, where p_i is a binary indictor that equals 1 if county i is designated as poverty county. The impact of the TPA program on urban-rural income inequality can then be expressed as:

$$\frac{\delta ID_i}{\delta p_i} = \overbrace{\frac{\delta F(\cdot)}{\delta U_i}\frac{\delta U(p_i)}{\delta p_i}}^{\text{spillover effect}} + \overbrace{\frac{\delta F(\cdot)}{\delta R_i}\frac{\delta R(p_i)}{\delta p_i}}^{\text{direct effect}}$$

This framework provides a theoretical foundation for understanding how the TPA program could reduce urban-rural income inequality. Based on this decomposition, the TPA program primarily targets rural poverty, focusing on improving income levels in rural areas. In the model, this implies no spillover effect, or $\frac{\delta U(p_i)}{\delta p_i} = 0$. In practice, the majority of poverty-stricken individuals reside in mountainous central and western regions, where public infrastructure remains underdeveloped and resources are relatively scarce (Liu et al., 2017; Xiao et al., 2022). The program prioritizes these underprivileged households as its main beneficiaries (Chen et al., 2009; Qin et al., 2021). Local governments often facilitate the targeted interventions, including relocation from isolated and remote ares to places with better access to employment opportunities, education, and essential services (Zhang et al., 2023). These measures are narrowly focused on the rural poor and do not extend to groups outside the targeted population, reflecting the program's rural-oriented nature.

Second, the program also improves the productivity by providing training sessions. During the TPA program, poverty alleviation coordinators, many of whom are local civil servants, are matched with poverty-stricken households and provided training or employment information, thereby assisting villagers in securing better-paying jobs (Zhang et al., 2021). The improved productivity usually translates into a wage rise, even with reduced working hours (Bandiera et al., 2017). The income gains generated under the TPA program are predominantly concentrated within the agricultural sector, which remains the primary livelihood for many rural households (Rozelle et al., 1998; Montalvo and Ravallion, 2010). By increasing the earnings of farming-dependent households, the program enhances rural income levels. In the model, this is represented as $\frac{\delta R(p_i)}{\delta p_i} > 0$. Under the assumption of no spillover effect on urban income, the increase in rural income leads to a narrowing of urban-rural income inequality.

Lastly, the implementation tends to improve bureaucratic management in rural areas. Within the current political structure in China, local leaders' career prospects are closely tied to their performance of governance (Li and Zhou, 2005; Bardhan, 2020), incentivizing efforts in poverty alleviation once their districts are classified as poverty counties. Furthermore, under the national anti-corruption campaign, increased transparency in governance has reduced the likelihood of staying in poverty (Han et al., 2022). New village officials, typically more educated and open-minded than their predecessors, have positively influenced village development, leading to increased registrations of low-income villagers, individuals with disabilities, and recipients of poverty subsidies (He and Wang, 2017). Coordinators in the TPA program are required to pay regular visits and identify the causes of poverty for each targeted household. Some might leverage their positions within local government organizations to more effectively aid households in overcoming poverty (Zhang et al., 2021).

3 Data

I exploit multiple data sources in this study to conduct an empirical analysis. The first source is county-level data from *China Statistical Yearbook (County-level)*, compiled annually by the National Bureau of Statistics of China. These yearbook data encompass various indicators, including local GDP per capita, the agricultural share of GDP, the industrial share of GDP, fiscal conditions, and more. I adjust monetary indicators among them to the 2010 price level, using provincial consumer price index. With the yearbook data, I could match the treatment status with county characteristics.

I select 2019 as the endpoint of the study period for two primary reasons. First, the data collection concludes just before the global outbreak of COVID-19 in early 2020. The pandemic introduced significant disruptions, such as lockdowns and quarantine policies, which could distort economic growth patterns and complicate the interpretation of program effects. Second, the Targeted Poverty Alleviation (TPA) program officially completed in 2020. Using 2019 as the endpoint avoids potential distortions from an intensified push in the final year to meet its targets, promising a more consistent evaluation of the program effect.

The second data source consists of information extracted from the county annual *Statistical Communique on National Economic and Social Development* and the *Report on the Work of the Government*. These sources complement some missing values found in the yearbook data. Despite this, certain indicators were still absent from local government reports.

The last source is geographic data, including each county's longitude and latitude, obtained from National Geomatics Center of China. Besides, each county is matched with the relief degree of land surface (RDLS) data to account for altitude differences in the region (You et al., 2018).[10]

To ensure regional comparability, I first excluded eight eastern provinces where no poverty counties are located.[11] I then excluded five additional provinces due to extensive missing data.[12] Finally, I omitted city districts within prefectures, referred to as "*qu*," because they lack significant rural areas. Including these districts could introduce noise and overestimate the treatment effect. As a result, my sample consists of 1,183 counties, including 415 designated poverty counties and 768 non-poverty counties.

The focus of this study is the income ratio within a county, calculated as the ratio of urban net income per capita to rural net income per capita (Zhang, 2021).[13] Each year officers from the local Bureau of Statistics conduct a household sample survey to record economic and livelihood-related indicators. For instance, a selected urban household reports wage, operational income, property income, and transfer income, collectively referred to as household total income. Urban net income per capita is estimated by subtracting personal tax and social security contributions from the sum, divided by the number of family members. This income ratio, presented in the aforementioned form, is advantageous as it remains unaffected by provincial and yearly price level variations, serving as a reasonable proxy for urban-rural income inequality on average.

Figure 3 visually illustrates the trends in the income ratio between poverty and non-

[10] Data on China's RDLS can be accessed at `https://www.geodoi.ac.cn/doi.aspx?Id=887`.

[11] These wealthier provinces include Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, and Guangdong.

[12] Yunnan, Xinjiang, Gansu, and Qinghai were removed for this reason, while Xizang (Tibet) was excluded as it was not part of the TPA program, as explained in the background section.

[13] The term "county" itself is a broader concept than in casual conversation, referring not only to the core/urban area but also the surrounding rural regions. The official name for the urban area is "town/county district," signifying the dual structure within Chinese counties.

poverty counties over the period 2010 to 2019. The vertical line marks the year of program implementation in 2015, while the connected lines represent the respective trends for the two groups. As shown, non-poverty counties consistently maintain a smaller income ratio compared to poverty counties throughout the study period. Importantly, the trends for both groups appear roughly parallel prior to 2015. However, poverty counties exhibit a more pronounced decline in the income ratio after 2015, suggesting a stronger reduction relative to non-poverty counties, despite the downward trend observed in both groups.

Table 1 provides summary statistics at the county level prior to the implementation of the TPA program. The table reports sample means and standard deviations, with the final column showing the unconditional differences between poverty and non-poverty counties. Significant disparities are evident across several dimensions. Urban income in poverty counties reaches to 3.35 times rural income, compared to a ratio of 2.39 in non-poverty counties, consistent with the earlier illustration. Differences in GDP per capita and sectoral composition further highlight the economic disadvantage of poverty counties, which tend to be less industrialized and economically weaker. This economic gap extends to the fiscal domain, as poverty counties generate lower fiscal revenue per capita compared to non-poverty counties, although government expenditure per capita remains similar. Geographically, poverty counties tend to have greater altitude variations and are located farther from the nearest ports, reinforcing the notion that these counties are typically situated in mountainous or remote areas.

4 Identification Strategy

This study investigates how implementing the TPA program in poverty counties influences urban-rural income inequality within those areas. To accomplish this, I leverage the variation in the designation status of poverty counties and employ a Difference-in-Differences (DID) model to estimate the causal effect. The assumption underpinning this model is the consistency of the treatment status. Some poverty counties may have been removed from the official list of poverty areas due to improvements in income levels or other economic factors before the termination of the TPA program. However, this does not necessarily mean they are no longer part of the program. Official sources indicate that a final survey would still be conducted to identify any potential errors and rectify them.[14] Therefore, these counties were effectively considered to be part of the program until 2020. And based on this, I assume that poverty counties receive the treatment throughout the post-program period.

However, another major challenge in the DID model is the outstanding differences in trends between poverty and non-poverty counties before the implementation of the program. Poverty counties, designated as such by the central government due to their weaker economic conditions, typically require greater financial support compared to non-poverty counties. This inherent distinction is evident in the comparison of variables presented in the last column of table 1, which calculates the unconditional differences. Failure to address this pre-existing imbalance could bias the estimation results.

4.1 Propensity Score Matching

To mitigate the concern of pre-existing differences between poverty and non-poverty counties, I augment the simple DID model with the Propensity Score Matching (PSM) strategy. It involves matching observations with similar characteristics but in different groups by estimating the probability of treatment assignment for each observation (Rosenbaum and Rubin, 1983). In this paper, I employ a logit regression model to predict the score, $\pi_i = Pr_i(NP = 1|X_i)$, representing the likelihood of being treated, with a set of covariates. Next, I use the default kernel matching strategy and maintain the weights for poverty counties as one, while assigning inverse probability weights for non-poverty counties as $\pi_i/(1-\pi_1)$ (Ertefaie and Stephens, 2010). The covariates used to predict propensity scores are designed to capture pre-existing differences between poverty and non-poverty counties, ensuring that the comparisons reflect initial conditions prior to the implementation. These covariates include GDP per capita, agricultural share, fiscal revenue per capita, Relief Degree of Land Surface (RDLS), and the distance to the nearest port, all measured during the period from 2010 to 2014.

Figure A4 illustrates the kernel density distributions of the propensity scores for the

[14] See `http://paper.people.com.cn/zgjjzk/html/2020-04/15/content_1983276.htm` and `https://www.xinshao.gov.cn/xsxfpb/xfpcx/202401/58408dec99524431928f75a1a8c5c6e0.shtml`.

treatment and control groups. Before matching, the kernel density of propensity scores reveals a clear separation: the distribution of non-poverty counties is concentrated closer to the origin, while that of poverty counties is clustered slightly to the left of 1. This pattern reflects the strong predictive power of the selected covariates in determining the poverty county designation, as the distributions align well with the actual classification of poverty and non-poverty counties. Besides, the improved alignment of the density curves following matching confirms the effectiveness of the PSM strategy in balancing observable differences. Table A2 further presents this improvement by presenting the revised pre-program comparisons. The table reveals that the disparities between poverty and non-poverty counties have been largely reduced across most covariates, except for expenditure per capita and saving per capita.

4.2 PSM-DID Model

The previous sections applies the PSM weights to address the comparability between poverty and non-poverty counties, which significantly improve balance across observable characteristics. Building on this foundation, I employ a baseline PSM-DID model as the identification strategy. This model leverages two key sources of variation: (1) whether a county is designated as a poverty county, and (2) whether the Targeted Poverty Alleviation (TPA) program has been implemented. The model is specified as follows:

$$y_{ipt} = \beta NP_i \times Post_t + \delta_1 x'_{i,10} \times Post_t + \delta_2 g(x'_{i,10}, t) + \kappa_i + \theta_p \times \eta_t + \epsilon_{ipt} \tag{1}$$

where y_{ipt} represents the outcome of interest in county i, province p in year t; NP_i is the treatment dummy that equals 1 if county i is designated as a poverty county; $Post_t$ is the post-program dummy that equals 1 if the program is in effect ($t \geq 2015$).

I incorporate county-level fixed effects (κ_i) to account for unobserved and time-invariant heterogeneity, such as geographic features. However, trends in outcomes may differ across provinces or initial conditions, potentially biasing the results. I introduce year-province fixed effects ($\theta_p \times \eta_t$) to absorb variations specific to provinces and time periods. Furthermore, I include the interaction between county-level controls (GDP per capita in 2010, agricultural share in 2010, and fiscal revenue per capita in 2010) and different time dummies to account for differential trends driven by initial county-level differences ($x'_{i,10} \times Post_t$ and $g(x'_{i,10}, t)$), following approaches used in Gentzkow (2006); Li et al. (2016); Lu et al. (2023). The function $g(\cdot)$ captures the form of the time trend (linear, quadratic, or cubic). ϵ_{ipt} represents unobserved shocks to the outcome of interest. In summary, β captures the causal effect of being designated as a poverty county under the TPA program on urban-rural income inequality. Standard errors are clustered at the county level to account for within-county correlation over time.

In the baseline model, it is important to ensure that the estimation of β remains conditionally uncorrelated with the error term. However, there exists another potential source of bias from any extending effect that poverty counties may have exerted on non-poverty counties. If this case indeed exists but remains unaccounted for, it could lead to an underestimation of the program effect. Following the literature (Miguel and Kremer, 2004; Lu et al., 2019), I assume that any potential extending effect is confined within the same prefecture, excluding cross-prefecture or cross-province influences. Consequently, the localized effect under consideration operates at the prefecture level, with its model represented as follows:

$$\begin{aligned} y_{ipt} =& \alpha NC_c \times Post + \beta NP_i \times Post_t + \\ & \delta_1 x'_{i,10} \times Post_t + \delta_2 g(x'_{i,10}, t) + \kappa_i + \theta_p \times \eta_t + \epsilon_{ipt} \end{aligned} \tag{2}$$

where NC_c will be 1 only if a prefecture has at least one poverty county under its administration. The rest settings follow Eq.(1). In this model, α represents the potential spillover effect from poverty counties to non-poverty counties in the same prefecture during the TPA program. Thus, $\alpha + \beta$ is the revised program effect.

4.3 The Even-Study Design

In contrast to the previous models that rely on a single key interaction term to estimate the causal effect, an event study design could assess the effect each year and serve as a robustness check. This approach differs from the baseline model because (1) the year dummies in an event study design are typically divided into lag years (before the program) and lead years (after the program) to indicate whether and for how long a program is implemented, and (2) the interaction terms between year dummies and the treatment dummy are derived to validate the practice of the baseline model by showing no pre-program differences and then estimate the program effect by year. By setting 2015 as the reference year, Eq.(2) describes the event study model as follows:

$$
\begin{aligned}
y_{ipt} = \sum_{j=-1}^{-5} \beta_j NP_i \times Lag_{jt} + \sum_{k=1}^{4} \beta_k NP_i \times Lead_{kt} + \\
\delta_1 x'_{i,10} \times Post_t + \delta_2 g(x'_{i,10}, t) + \kappa_i + \theta_p \times \eta_t + \epsilon_{ipt}
\end{aligned}
\tag{3}
$$

where y_{it}, NP_i, and $Post_t$ are already defined above; Lag_{jt} is a lag dummy that is only equal to 1 if year t is exactly $|j|$ year(s) before 2015;[15] $Lead_{jt}$ is a lead dummy that is only equal to 1 if year t is exactly k year(s) after 2015.[16] The setting of the controls and types of fixed effects are the same as in Eq.(1). Then, β_j and β_k display the change of the outcome in poverty counties as to non-poverty counties each year before and after the TPA program. I expect β_j to be not significant but β_k to be significantly negative. The expectation has twofold implications: First, the insignificance of β_j validates the parallel trend in poverty and non-poverty counties, a critical assumption in using a DID model; Second, the program takes effect in poverty counties by significantly declining the urban-rural income difference.

5 Empirical Results

In this section, I present empirical evidence on the effectiveness of the TPA program in reducing urban-rural income inequality. Each specification in this study will include the PSM weights unless otherwise noted. I begin by showing the results from the standard DID model, which serves as the baseline outcome. Then, the event-study design illustrates the annual effects observed in the post-implementation period. Finally, I conduct several robustness checks to ensure the consistency and reliability of the baseline results.

[15] Mathematically, $Lag_{jt} = \mathbb{1}(t = 2015 - |j|)$, $j \in \{-1, -2, -3, -4, -5\}$.

[16] Also, $Lead_{kt} = \mathbb{1}(t = 2015 + k)$, $k \in \{1, 2, 3, 4\}$.

5.1 The PSM-DID Results

Using Eq.(1) outlined in the previous section, table 2 presents the estimates derived from the PSM-DID model, with the natural log of the income ratio within a county as the outcome of interest. Standard errors are clustered at the county level and reported in parentheses. All specifications include county fixed effects and province-year fixed effects. Across all the columns, the estimates are significantly negative. In column (1), the unweighted estimate is presented for comparison, while column (2) incorporates the PSM weights to balance pre-existing disparities between poverty and non-poverty counties. The difference in magnitude reveals that omitting PSM weights would overestimate the program effect by at least 77%. Columns (3) and (4) introduce additional controls: an interaction term between 2010 control variables and the post-program time dummy, as well as a cubic time trend. Despite these inclusions, the estimated magnitudes remain largely unchanged, suggesting the robustness of the results. For further verification, able A3 in the Appendix presents estimations using linear and quadratic time trends. These results remain highly consistent with the main findings.

As both NP_i and $Post_t$ are binary variables, the coefficient of their interaction term ($NP_i \times Post_t$) captures the causal effect of the TPA program on urban-rural income inequality in poverty counties. The preferred specification in column (3) reveals a 3.8% reduction in the income ratio relative to non-poverty counties following the program.[17] This result is consistent with figure 3, which illustrates a steeper decline in the income ratio for poverty counties after 2015. A back-of-the-envelope calculation shows that the program decreases the income ratio by approximately 0.09 in poverty counties, based on the mean value observed in non-poverty counties. In the Discussion section, I will further assess the influence on rural income to provide a more comprehensive understanding of the mechanisms driving this outcome. However, it is important to interpret this estimate with caution, as it reflects the average treatment effect on the treated counties (poverty counties) rather than the entire sample.

[17] $e^{-0.039} - 1 \approx -0.038$

5.2 The Event-Study Results

Next, I display the estimates with their 95% confidence intervals for each year in figure 4, relying on Eq.(3).[18] The vertical axis depicts the estimates of β_j and β_k, representing the yearly difference in the income ratio between poverty counties and non-poverty counties relative to the reference year, 2015. The pre-program estimates are statistically insignificant, suggesting that poverty and non-poverty counties demonstrate similar trends in the income ratio prior to the implementation when applying the PSM weights. This validates the parallel trends assumption essential for the DID framework, further affirming the robustness of the baseline results.

In the post-program period, the coefficients β_k turn significantly negative, indicating a strong and consistent program effect in reducing the income ratio. The event study findings not only corroborate the causal impact of the TPA program but also reveal an interesting pattern: the magnitude of the effect grows progressively larger as the program approaches its conclusion. This suggests that the program effect intensifies over time, likely reflecting cumulative benefits from targeted interventions. Overall, these results confirm the effectiveness of the TPA program in narrowing the urban-rural income divide.

5.3 Robustness Checks

In this section, I perform several robustness checks to strengthen the validity of the main findings. A key concern arises from the place-based nature of the TPA program, as the designation of poverty counties might indirectly influence neighbouring non-poverty counties. For example, farmers in non-poverty counties may relocate to nearby poverty counties to take advantage of program benefits. If such extending effects exist, the baseline estimates could underestimate the true program effect. To address this concern, I conduct the analysis by estimating the potential extending effect using the specification in Eq.(2). Table 3 presents the results. Across the specifications, the extending effect is found to be statistically insignificant, regardless of the inclusion of different control variables. This suggests that neighbouring non-poverty counties are not significantly affected by the program, reinforcing

[18] In the Appendix, table A4 documents the yearly estimates from the equation.

the precision and targeting effectiveness of the place-based policy. Moreover, the coefficient $\hat{\beta}$ remains consistent in both sign and magnitude compared to the baseline outcome, indicating that the standard DID model does not suffer from underestimation of the program effect.

To further reinforce the robustness of the baseline results, I conduct additional checks summarized in table 4. First, I address concerns regarding the clustering of standard errors. In columns (1) and (2), I re-estimate β from Eq.(1) by clustering the standard errors at the prefecture and province levels, respectively. The estimates remain consistent with the baseline results, confirming that the program effect is not sensitive to the clustering strategy. Next, in column (3), I extend the analysis by exclusively including western provinces in the sample.[19] The results yield a slightly larger estimate than the baseline, suggesting that the TPA program is even more effective in relatively underdeveloped regions. In column (4), I replace the natural log of the income ratio with its level form as the outcome of interest. The estimate remains significantly negative, affirming the robustness of the baseline findings to alternative outcome specifications. Lastly, in column (5), I perform a falsification test by assuming the TPA program was implemented in 2013. Using the sample from 2010 and 2014, I find no significant effect from this "placebo" program. This result again validates the assumption of parallel trends between poverty and non-poverty counties in the pre-treatment period.

To rule out any potential spurious program effect, I conduct an additional test by randomly assigning poverty status to counties and estimating the program effect under this random assignment. In my sample, 415 out of 1172 counties are designated as poverty counties, representing approximately 35% of the total. To replicate this, I generate a binary treatment variable where each county has a 35% probability of being assigned as a poverty county. This random assignment does not consider any underlying factors, ensuring it is purely random. In this test, the PSM weights are no longer applicable, as the assignment lacks the actual targeting criteria. Therefore, the results should be directly comparable to column (1) of Table 2, which reports the unweighted estimate. I then repeat the regression in Eq.(1) 1,000 times and document the distribution of the key estimates in Figure 5. The hori-

[19] These provinces include Neimeng, Sichuan, Ningxia, Guangxi, Guizhou, Chongqing, and Shaanxi.

zontal axis displays the estimated coefficients, and the vertical axis represents the fraction of observations within each bin. The solid line depicts the kernel density estimate. The results show that the simulated program effects are minimal and statistically insignificant, with the vast majority of estimates clustering around zero. This pattern stands in stark contrast to the baseline estimate of -0.069, which lies considerably outside the simulated distribution.

Taken together, these robustness checks confirm the reliability of the baseline results and underscore the robustness of the estimated program effect on reducing urban-rural income inequality.

6 Discussions

Following the empirical evidence that the TPA program has reduced urban-rural income inequality in poverty counties, I will discuss the mechanisms in this section through which the program effect could be attributed to the implementation.

6.1 Income Level

Based on the conceptual framework, I investigate a potential channel through which the TPA program tends to deliver greater benefits to impoverished individuals compared to their wealthier counterparts (Rozelle et al., 1998; Montalvo and Ravallion, 2010; Chen et al., 2009; Qin et al., 2021). Given that the program adopts a targeted and place-based approach, I hypothesize that the decline in urban-rural income inequality arises primarily from a larger increase in rural income levels within poverty counties. However, this narrowing of the income gap does not necessarily imply a change in urban income. This deduction aligns with the inherently rural orientation of the program. Therefore, if urban income also increases or decreases, it could indicate a spillover effect from rural to urban areas within a county.

To test this hypothesis, I use the same specification as in Eq.(1), replacing the outcome variable with rural net income per capita and urban net income per capita, respectively. Table 5 presents the estimation results. In columns (1) and (2), the program leads to a significant increase of 2.4% in rural net income per capita in poverty counties relative to non-poverty counties. This effect remains robust after controlling for time trends. By contrast, the non-significant estimates in columns (3) and (4) suggest that urban income remains largely unaffected, regardless of poverty designation. These findings indicate no evidence of a spillover effect and provide strong support for the hypothesis that the program solely benefits rural areas.

The results further underscore the rural-oriented nature of the TPA program. Given that the average rural income per capita in non-poverty counties is 9,665 RMB, the estimated program effect translates into an increase of approximately 232 RMB in rural income per capita for residents in poverty counties. This is equivalent to 8.3% of the poverty line at that time. Besides, the magnitude of this effect is more than double that of the program evaluated by Meng (2013), which examines another poverty alleviation program implemented between 1994 and 2000.

6.2 Employment Structure

While the income mechanism provides a direct explanation for the baseline results, I explore deeper into understanding the origin of the increased rural income levels here. An apparent explanation for the rise in rural income levels could be attributed to the expansion of job opportunities for the rural labour force. To evaluate this claim, I analyze the change in the number of employees per thousand persons in rural areas, the industrial sector, and the tertiary sector, using the same framework in Eq.(1).

Table 6 presents the results in columns (1) to (3), the change in the number of employees across different categories. The findings indicate that the program led to an increase in the number of rural employees in poverty counties compared to non-poverty counties. This expansion of job opportunities for the rural labour force may translate into higher income levels over time. Since the industrial and tertiary sectors are predominantly located in urban areas, changes in their employee numbers serve as proxies for urban employment. In line with the rural-oriented nature of the program, there is no significant change observed in urban employment, consistent with the lack of impact on urban income. While some data may be missing, potentially leading to biased estimations, the overall narrative still suggests that improved outcomes in the rural labour market serve as a plausible mechanism for the observed results.

Additionally, I examine how the program influences agricultural production in poverty counties, which may result from an improved rural labour market. To proxy agricultural production, I use GDP per capita of the primary sector as the outcome variable in Eq.(1). In column (4), the estimate of the program effect is insignificant. However, the coefficient for the interaction term between GDP per capita in 2010 and the post-program dummy is significantly negative. This suggests that the causal effect on agricultural production may be absorbed by the initial economic conditions of poverty counties. To address this, I exclude the control variables and re-estimate the model in column (5). The new specification yields a positive and significant estimate, indicating that agricultural production has indeed increased in poverty counties. This finding highlights the rural-oriented focus of the TPA program and further explains the narrowing of urban-rural income inequality: the boost of agricultural production. The result underscores the effectiveness of the program in addressing income disparities through targeted support to the rural economy.

6.3 Government Spending

Since the primary implementation of the TPA program is concentrated in poverty counties, county governments receive intergovernmental transfers to facilitate the execution under the existing fiscal system.[20] They should ensure the delivery of targeted interventions, such as infrastructure improvement (Fan et al., 2000). As a result, the program may lead to an increase in government spending in these counties.

To test this, I use Eq.(1) to estimate the program effect on fiscal expenditure per capita. The result is presented in column (6) of Table 6. The significantly positive coefficient indicates that, following the implementation of the TPA program, poverty counties increases their government spending by approximately 3% relative to non-poverty counties. This magnitude aligns with findings from Zhu et al. (2021), which document a comparable reduction in government spending when counties exit the program.

[20] See more in Appendix A.1.

7 Conclusion

In this study, I evaluate the effect of the Targeted Poverty Alleviation program on urban-rural income difference in China, leveraging the county-level data from 2010 to 2019. Before the implementation of the program, poverty counties and non-poverty counties were different across various dimensions, including economic development and sectoral composition. I rely on the Propensity Score Matching method to minimize these pre-program imbalances and then employ a Difference-in-Differences model to estimate the effect.

The baseline finding reveals that the TPA program led to a 3.8% greater decline in urban-rural income inequality, measured by the ratio of urban net income per capita to rural net income per capita, within poverty counties relative to non-poverty counties. The event-study analysis corroborates the finding showing consistent results over time and further validating the causal interpretation.

Importantly, the analysis demonstrates that the observed reduction in income inequality is concentrated in poverty counties, as the program does not exhibit spillover effects on neighbouring non-poverty counties within the same prefecture. This finding reinforces the place-based nature of the TPA program and highlights its precision in targeting impoverished regions. Additional robustness checks confirm the stability and reliability of the baseline results.

To explore the mechanisms behind the observed decline in income inequality, I examine changes in rural income, employment, and government spending. First, I find that the rural net income per capita in poverty counties increases by 2.4% relative to non-poverty counties, while urban incomes remain largely unaffected, underscoring the programs rural focus. Second, employment opportunities improve in poverty counties, but this improvement is concentrated in rural sectors rather than urban-based secondary or tertiary employment. Together, these results affirm the rural-oriented nature of the TPA program. Finally, I identify a significant increase in government spending per capita within poverty counties during the program period, highlighting the pivotal role of county governments in implementing and sustaining the program.

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Tables

Table 1: Statistical Description Before the Program

	Non-Poverty counties	Poverty counties	Unconditional Differences
Urban-Rural Income Ratio	2.39	3.35	-0.97***
	(0.67)	(0.89)	(0.02)
ln(GDP per capita)	10.08	9.48	0.60***
	(0.64)	(0.49)	(0.02)
Agricultural Share	0.20	0.26	-0.06***
	(0.11)	(0.11)	(0.00)
Industrial Share	0.50	0.40	0.10
	(0.15)	(0.15)	(0.00)
ln(Revenue per capita)	7.07	6.48	0.59***
	(0.90)	(0.71)	(0.02)
ln(Expenditure per capita)	8.30	8.30	0.00
	(0.60)	(0.48)	(0.02)
ln(Saving per capita)	9.50	9.10	0.41***
	(0.52)	(0.52)	(0.01)
ln(Primary School Students)	4.16	4.24	-0.08***
	(0.33)	(0.34)	(0.01)
ln(High School Students)	3.83	3.84	-0.01
	(0.30)	(0.35)	(0.01)
RDLS	0.76	1.17	-0.40***
	(1.06)	(1.00)	(1.06)
Distance to the Closet Port (km)	570.74	588.65	-17.91*
	(316.75)	(293.93)	(8.42)

Note: This table documents the statistical description of variables before the TPA program in poverty and non-poverty counties (2010-2014). Standard deviations are reported in parentheses, while *, **, and *** in the last column denote significance levels at 10%, 5%, and 1% respectively.

Table 2: Baseline Results: the PSM-DID Estimates

	Unweighted	PSM Weighted		
	(1)	(2)	(3)	(4)
NP × Post	-0.069***	-0.039***	-0.039***	-0.039***
	(0.007)	(0.010)	(0.011)	(0.011)
Controls in 2010 × Post			✓	✓
Cubic Time Trend				✓
County FE	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓
Observations	10475	8150	8150	8150

Note: Coefficients are estimated through Eq.(1), weighted by the PSM score except in column (1). The dependent variable across all columns is the natural log of the income ratio defined in the main text. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. Only column (4) adds the cubic time trend of the controls. County and year-province fixed effects are all controlled. The standard errors are clustered at the county level and reported in parentheses, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

Table 3: Potential Effect on Non-Poverty Counties

	(1)	(2)
Extending Effect	0.005	0.005
	(0.014)	(0.014)
NP × Post	-0.040***	-0.040***
	(0.011)	(0.012)
Controls in 2010 × Post	✓	✓
Cubic Time Trend		✓
County FE	✓	✓
Province × Year FE	✓	✓
Observations	8150	8150

Note: Coefficients are estimated through Eq.(2) with the PSM score weights. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. Then they are interacted with the post dummy. Column (2) adds the cubic time trend of the controls. County and year-province fixed effects are all controlled. The standard errors are clustered at the county level and reported in parentheses, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

Table 4: Other Robustness Checks

	Cluster at Prefecture	Cluster at Province	Western Provinces	Income Ratio	If TPA Started in 2013
	(1)	(2)	(3)	(4)	(5)
NP × Post	-0.039***	-0.039**	-0.043**	-0.179***	
	(0.013)	(0.014)	(0.018)	(0.040)	
NP × Post_{2013}					-0.023
					(0.015)
Controls in 2010 × Post	✓	✓	✓	✓	
County FE	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓
Observations	8150	8150	2941	8150	3736

Note: Coefficients are estimated through Eq.(1), weighted by the PSM score. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. In columns (1) and (2), the standard errors are clustered at the prefecture and province level. In column (3), only western provinces are considered in the specification. The dependent variable is the natural log of the income ratio defined in the main text, except in column (4). In column (5), I assume the TPA program started in 2013 and only use the sample from 2010 to 2014 for regression. County and year-province fixed effects are all controlled, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

Table 5: Change in Urban and Rural Income

	Rural Income		Urban Income	
	(1)	(2)	(3)	(4)
NP × Post	0.0240**	0.0240**	-0.0090	-0.0087
	(0.0101)	(0.0101)	(0.0085)	(0.0085)
Controls in 2010 × Post	✓	✓	✓	✓
Cubic Time Trend		✓		✓
County FE	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓
Observations	8875	8875	8153	8153

Note: Coefficients are estimated through Eq.(1), weighted by the PSM score. The dependent variable is rural net income per capita in columns (1) and (2) and urban net income per capita in columns (3) and (4), both at the 2010 price level and then being transformed in the natural log form. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. Then they are interacted with the post dummy. Only columns (2) and (4) add the cubic time trend of the controls. County and year-province fixed effects are all controlled. The standard errors are clustered at the county level and reported in parentheses, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

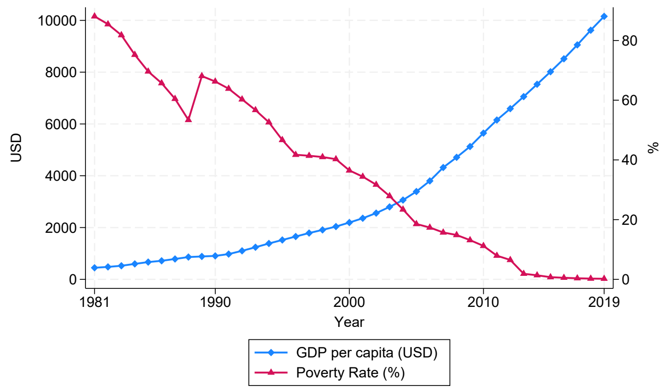
Table 6: Change in Employment, Primary Sector, and Fiscal Expenditure

	Rural Employees	Industrial Employees	Tertiary Employees	Primary Sector		Fiscal Expenditure
	(1)	(2)	(3)	(4)	(5)	(6)
NP × Post	0.034**	-0.018	0.001	0.020	0.036**	0.030**
	(0.014)	(0.062)	(0.046)	(0.014)	(0.016)	(0.015)
Controls in 2010 × Post	✓	✓	✓	✓		✓
County FE	✓	✓	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓	✓	✓
Observations	5759	6406	6406	8904	8904	8907

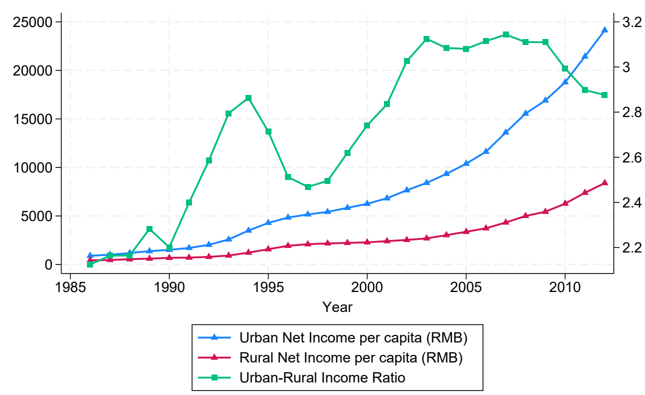
Note: Coefficients are estimated through Eq.(1), weighted by the PSM score. The outcome is rural employees per ten thousand persons in column (1), industrial employees per ten thousand persons in column (2), tertiary employees per ten thousand persons in column (3), GDP per capita of primary sector in columns (4) and (5), fiscal expenditure per capita in column (6), all being transformed in the natural log form. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. County and year-province fixed effects are all controlled, as well as the cubic time trend of controls in 2010. The standard errors are clustered at the county level and reported in parentheses, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

Figures

Figure 1: GDP per capita, Poverty Rate, and Income in China



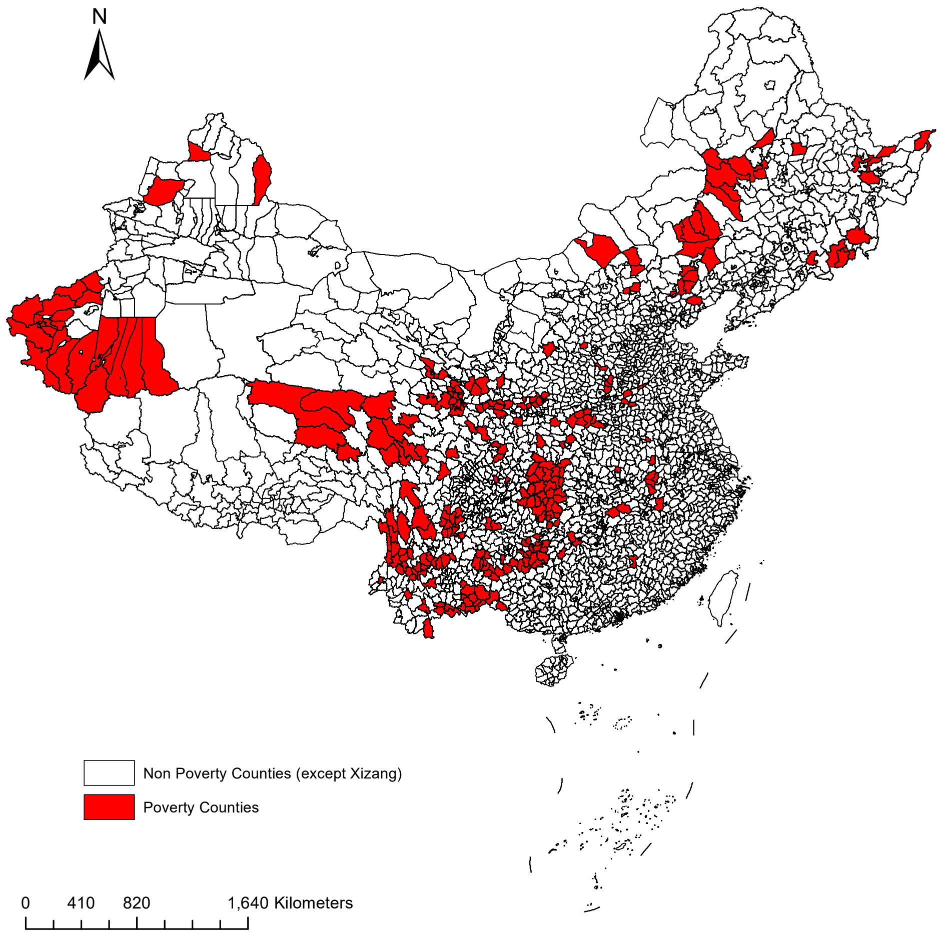
(a) Economic Growth and Poverty Alleviation



(b) Income and Income Inequality

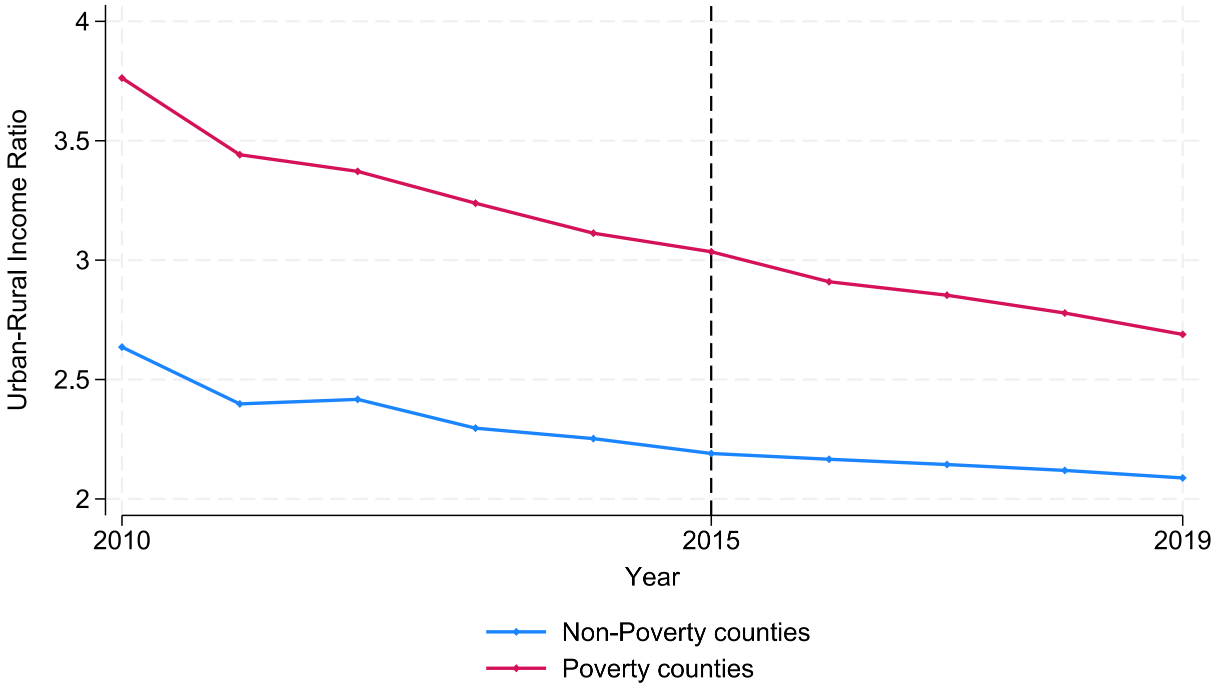
Note: Data are obtained from the World Bank and Global Extreme Poverty and National Bureau of Statistics. In (a), GDP per capita (plotted in the left vertical axis) has been adjusted in the 2015 US dollar, while the poverty rate (plotted in the left vertical axis is the percentage of the population living on less than 1.90 US dollars per day in the 2011 PPP. In (b), urban and rural net income per capita (plotted in the left vertical axis) are under the current price, while the urban-rural income ratio (plotted in the right vertical axis) is measured by the ratio of urban net income per capita to rural net income per capita.

Figure 2: Distribution of Poverty Counties in China



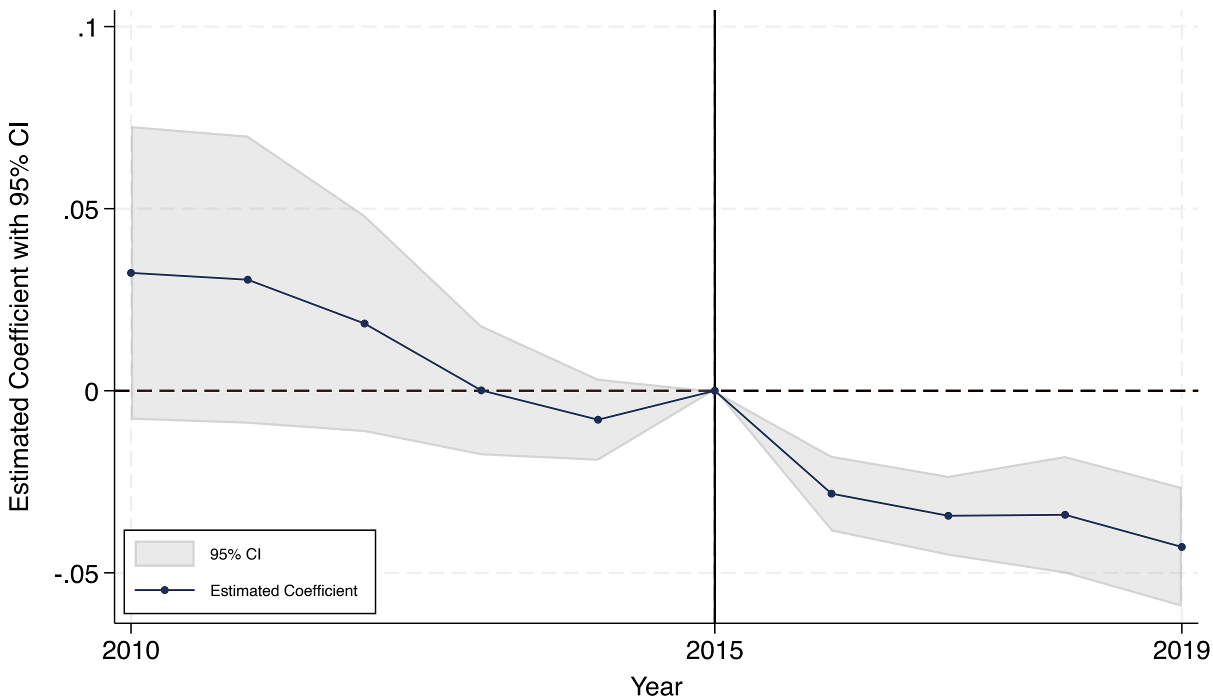
Note: The figure plots the distribution of poverty counties in China. The red colour suggests being designated as a poverty county in 2014, otherwise not. It should be noted that Xizang is not included in the Targeted Poverty Alleviation program and serves as an exception.

Figure 3: Trends In Urban-Rural Income Ratio from 2010 to 2019



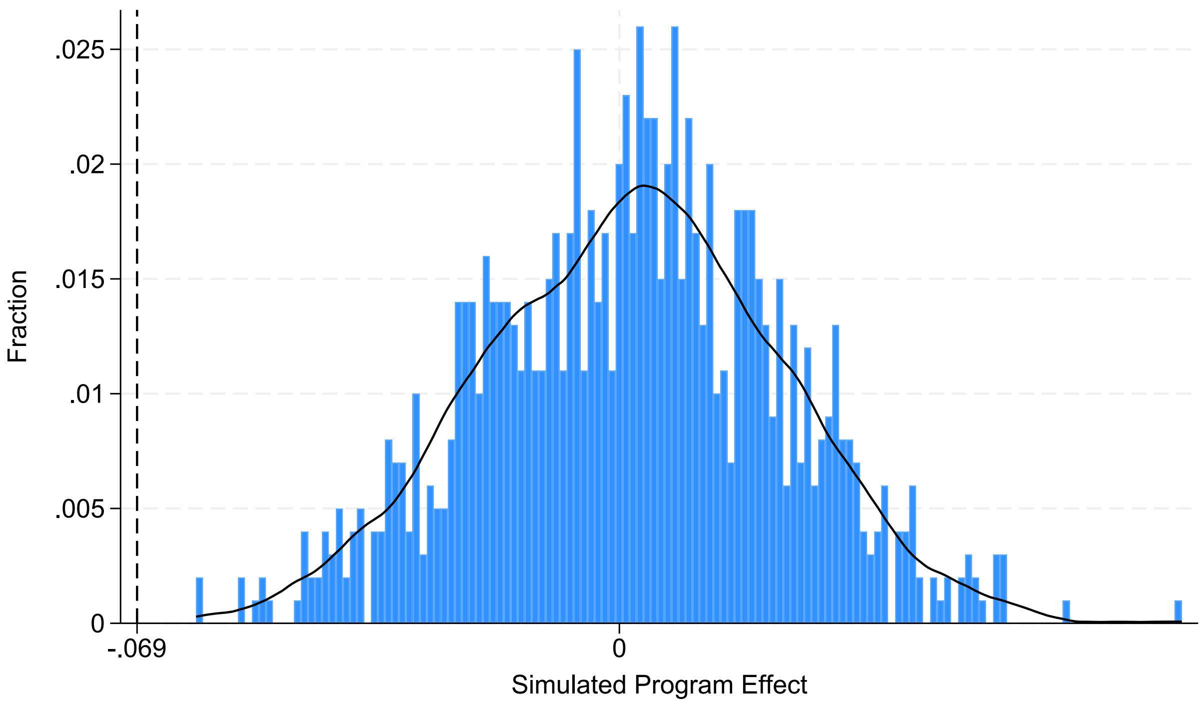
Note: All data are from *China Statistical Yearbook (County-level)*. The urban-rural income ratio is calculated by the urban net income per capita over the rural net income per capita. The red line represents poverty counties defined in the main text, while the blue line represents those non-poverty counties in only 21 provinces with at least one poverty county.

Figure 4: The Event-Study Analysis of the Income Ratio (log)



Note: Coefficients and their 95% confidence intervals in each year are the estimated coefficients through Eq.(3), weighted by the PSM score. The dependent variable is the natural log of the income ratio defined in the main text. The vertical line stands for the reference year, 2015. The standard errors are clustered at the county level

Figure 5: Estimates from Randomly Assigning Treatment



Note: By randomly assigning the status of poverty county and repeating the regression described in Eq.(1) 1000 times, the estimated coefficients are plotted on the horizontal axis, while the vertical axis is the fraction of each bin. Besides, a kernel density estimate is provided as the solid line. By comparison, the placebo estimates follow the distribution around 0, which is significantly away from the baseline estimate.

A Appendix

A.1 Poverty Alleviation since 1978

In stark contrast to its current status, China was among the most underdeveloped countries in the world during the 1970s, with the majority of its population leading a frugal and modest life.[21] The economic transformation commenced following the 1978 opening-up reforms when the central government made the pivotal decision to prioritize economic development and integrate into the global market. Among many challenges, the most urgent was to improve the quality of life for the Chinese people.

The initial phase of market-oriented reforms (19781986) brought significant benefits to rural farmers, marking a fundamental departure from the previous centrally planned framework. A key element of this reform was the introduction of the household responsibility system, which decentralized agricultural production by granting households contractual rights over land use. This system proved highly effective in boosting agricultural productivity and improving farmers' living standards (Li et al., 1998; McMillan et al., 1989). Until 1986, the Chinese government formally initiated poverty alleviation programs. (I) The first round from 1986 to 1993 was spearheaded by the Leading Group for Economic Development (the Leading Group), which identified poverty counties across the nation based on a variety of economic indicators. While the program demonstrated an overall positive impact, it also uncovered instances of malpractice, particularly concerning the politicization and economic gains associated with being designated as a poverty county (Park et al., 2002). Local officials sought to include districts that did not meet the criteria for poverty-stricken status, driven by the allure of substantial financial transfers from higher levels of government. Consequently, subsequent rounds adopted a more cautious approach to targeting and classification. (II) The second round, also known as the 8-7 Plan, spanned from 1994 to 2000, with the ambitious objective of uplifting 80 million rural poor out of poverty within 7 years.[22] The State Council augmented the work-for-dole funds and the poverty-alleviation-discount funds by 1

[21] According to the World Bank, China's GDP per capita in 1970 was $113.2 in current USD, ranking 154th out of 170 countries with available data.

[22] In Chinese, 10 million is *"qian wan"*, so 80 million is *"8 qian wan"*. The official announcement of the plan: `https://www.gov.cn/gongbao/shuju/1994/gwyb199412.pdf`.

billion RMB each. Furthermore, adjustments were made to promote regional equilibrium, whereby poverty alleviation funds for the six more affluent coastal provinces remained static, enabling the surplus funds to be channelled to the less developed central and western regions. (III) The third round started in the early 2000s and witnessed the implementation of a more comprehensive and quantifiable criterion of poverty status. Known as the "631 index", it encompassed the poverty population (60%), rural income per capita (30%), and per capita GDP and fiscal revenues (10%).[23] This phase focused on contiguous poor areas, including ethnic minority regions, historical revolutionary bases, border areas, and underprivileged zones, aligning with the Western Development strategy of 2000.[24]

In terms of financial support, the central government has consistently increased fiscal funds allocated for poverty alleviation, subject to annual audits conducted by the Ministry of Finance. As depicted in figure A1, cumulative funds during the initial phase before 1985 barely surpassed 3 billion RMB, before witnessing a surge to over 20 billion RMB between 1985 and 1993. Since the turn of the 21st century, funds surged significantly even over 100 billion RMB. The initial five years of the most recent phase (2011-2015) witnessed an expenditure that exceeded the total accumulated amount from 2001 to 2010 by 45 billion RMB. In summary, the pronounced growth of funds over the years attests to the Chinese government's resolute commitment to eradicating absolute poverty nationwide.

[23] See `http://cn.chinagate.cn/povertyrelief/2012-08/09/content_26182170.htm`.

[24] The Western Development strategy is a large-scale program to reduce regional imbalance by boosting economic development in the western areas of mainland China.

A.2 Table

Table A1: Provinces with Poverty Counties in 2014

Province	Number of Poverty Counties	Total Number of Counties	Ratio
Hebei	39	171	0.228
Shanxi	35	119	0.294
Neimeng	31	102	0.304
Jilin	8	60	0.133
Heilongjiang	14	128	0.109
Anhui	19	105	0.181
Jiangxi	21	100	0.210
Henan	31	158	0.196
Hubei	25	103	0.243
Hunan	20	122	0.164
Guangxi	28	110	0.255
Hainan	5	24	0.208
Chongqing	14	38	0.368
Sichuan	36	183	0.197
Guizhou	50	88	0.568
Yunnan	73	129	0.566
Shaanxi	50	107	0.467
Gansu	43	86	0.500
Qinghai	15	43	0.349
Ningxia	8	22	0.364
Xinjiang	27	103	0.262
Total	592	2101	0.282

Note: The total number of counties in each province is from *China Statistical Yearbook 2014* and the list of poverty counties from `http://nrra.gov.cn/art/2012/3/19/art_50_23706.html`.

Table A2: Statistical Description After Matching

	Non-Poverty counties	Poverty counties	Weighted Differences
ln(GDP per capita)	9.49	9.49	0.00
	(0.40)	(0.49)	(0.06)
Agricultural Share	0.24	0.26	-0.01
	(0.11)	(0.11)	(0.02)
Industrial Share	0.41	0.39	0.02
	(0.14)	(0.15)	(0.02)
ln(Revenue per capita)	6.32	6.45	-0.12
	(0.66)	(0.69)	(0.09)
ln(Expenditure per capita)	8.16	8.27	-0.11*
	(0.43)	(0.45)	(0.06)
ln(Saving per capita)	9.25	9.10	0.15***
	(0.40)	(0.52)	(0.06)
ln(Primary School Students)	4.22	4.21	0.01
	(0.32)	(0.33)	(0.81)
ln(High School Students)	3.86	3.84	0.02
	(0.30)	(0.33)	(0.04)
RDLS	0.88	1.01	-0.13
	(0.54)	(0.68)	(0.08)
Distance to the Closet Port (km)	530.47	544.36	-13.90
	(195.31)	(252.70)	(0.64)

Note: This table documents the statistical description of variables before the TPA program in poverty and non-poverty counties (2010-2014), weighted by the PSM score. Standard deviations are reported in parentheses, while *, **, and *** in the last column denote significance levels at 10%, 5%, and 1% respectively.

Table A3: Baseline Results with Different Time Orders

	Linear Trend		Quadratic Trend	
	(1)	(2)	(3)	(4)
NP × Post	-0.039***	-0.039***	-0.039***	-0.039***
	(0.011)	(0.011)	(0.011)	(0.011)
Controls in 2010 × Post		✓		✓
County FE	✓	✓	✓	✓
Province × Year FE	✓	✓	✓	✓
Observations	8150	8150	8150	8150

Note: Coefficients are estimated through Eq.(1), weighted by the PSM score. The dependent variable across all columns is the natural log of the income ratio defined in the main text. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. Then they are interacted with the post dummy. Columns (1) and (2) use the linear trend of the controls, while columns (3) and (4) use the quadratic trend. County and year-province fixed effects are all controlled. The standard errors are clustered at the county level and reported in parentheses, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

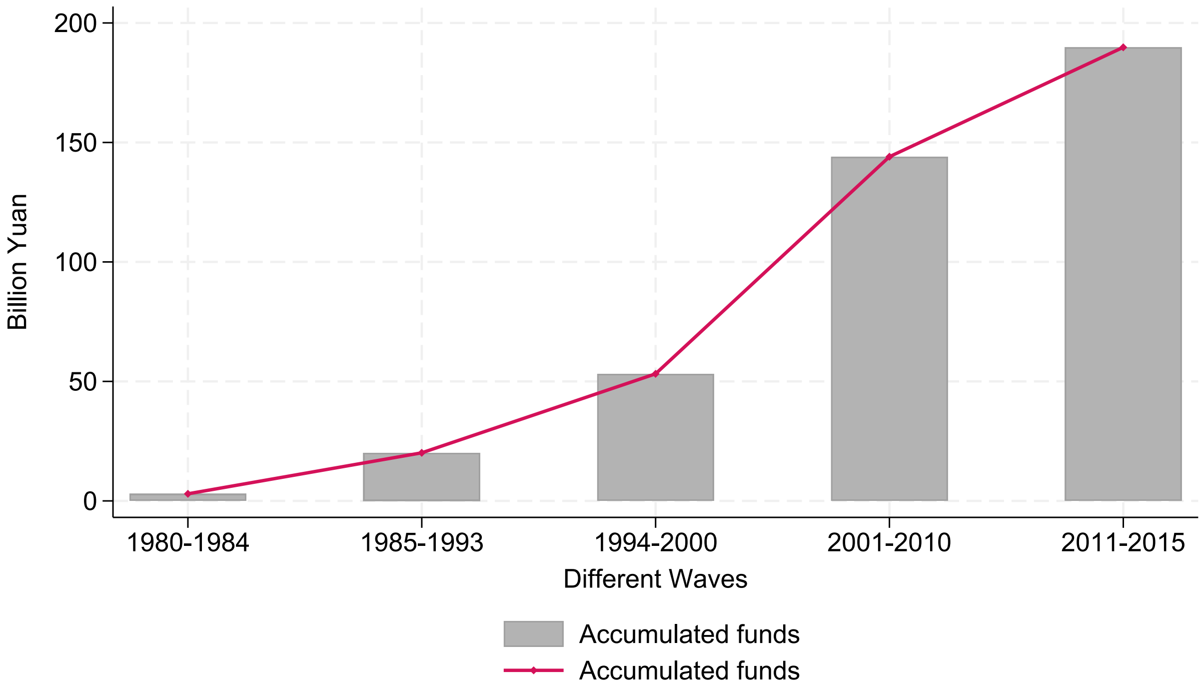
Table A4: Detailed Estimates from the Event-Study Design

	(1)	(2)	(3)
5-Year Prior	0.033*	0.032	0.037
	(0.019)	(0.021)	(0.023)
4-Year Prior	0.031*	0.030	0.032
	(0.019)	(0.020)	(0.021)
3-Year Prior	0.019	0.018	0.018
	(0.014)	(0.015)	(0.015)
2-Year Prior	0.000	0.000	-0.001
	(0.008)	(0.009)	(0.009)
1-Year Prior	-0.008	-0.008	-0.008
	(0.005)	(0.006)	(0.005)
1-Year After	-0.028***	-0.028***	-0.027***
	(0.005)	(0.005)	(0.005)
2-Year After	-0.034***	-0.034***	-0.033***
	(0.006)	(0.006)	(0.006)
3-Year After	-0.034***	-0.034***	-0.033***
	(0.008)	(0.008)	(0.009)
4-Year After	-0.043***	-0.043***	-0.043***
	(0.008)	(0.008)	(0.010)
Controls in 2010 × Post		✓	✓
Cubic Time Trend			✓
County FE	✓	✓	✓
Province × Year FE	✓	✓	✓
Observations	8150	8150	8150

Note: Coefficients and their 95% confidence intervals in each year are the estimated coefficients through Eq.(3), weighted by the PSM score. The dependent variable is the natural log of the income ratio defined in the main text. Controls include GDP per capita in 2010, agricultural share in 2010, fiscal revenue per capita in 2010. Then they are interacted with the post dummy. Then they are interacted with the post dummy. Only column (3) adds the cubic time trend of the controls. County and year-province fixed effects are all controlled. The standard errors are clustered at the county level and reported in parentheses, while *, **, and *** denote significance levels at 10%, 5%, and 1% respectively.

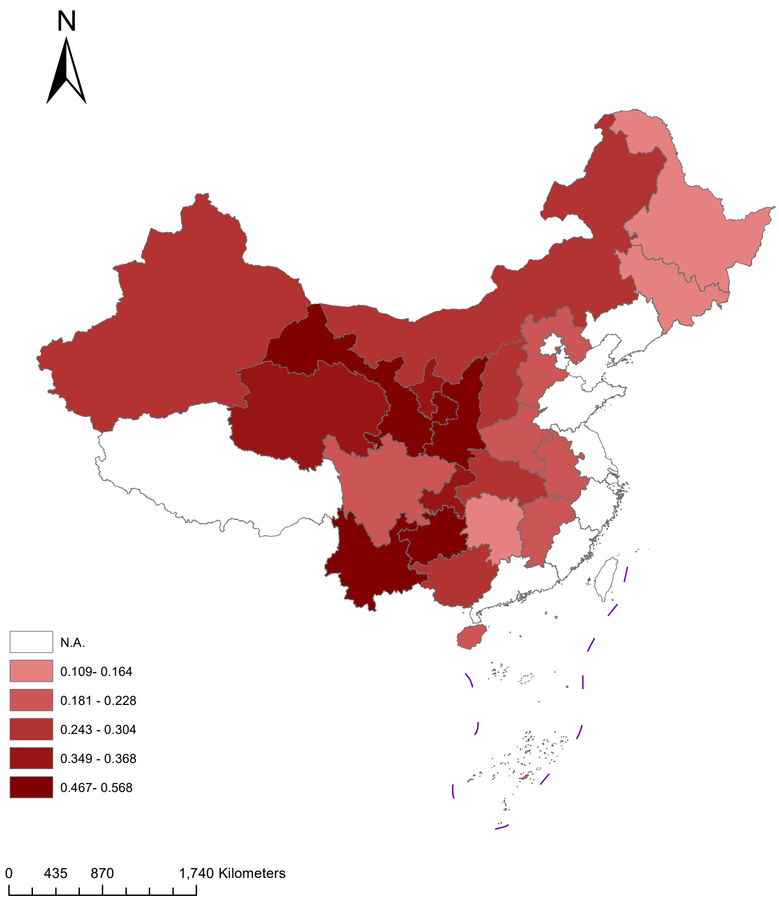
A.3 Figures

Figure A1: Fiscal Funds for Poverty Alleviation in Each Wave



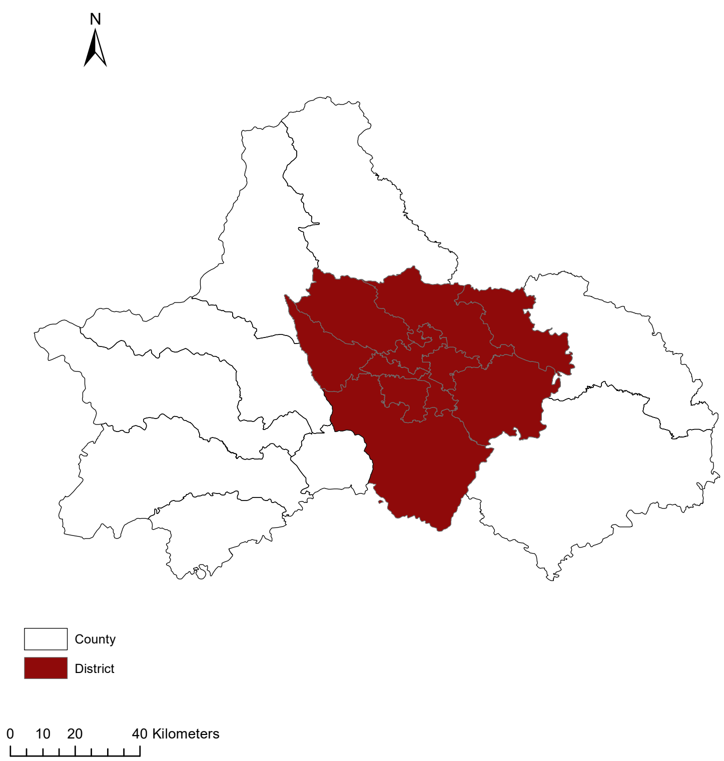
Note: Data are collected from an official report which lists the fiscal funds for poverty alleviation in each wave. The latest wave only displays the funds accumulated during 2011 and 2015, not 2020. See from `http://f.china.com.cn/2016-09/12/content_39281638.htm`.

Figure A2: The Ratio of Poverty Counties in Each Province



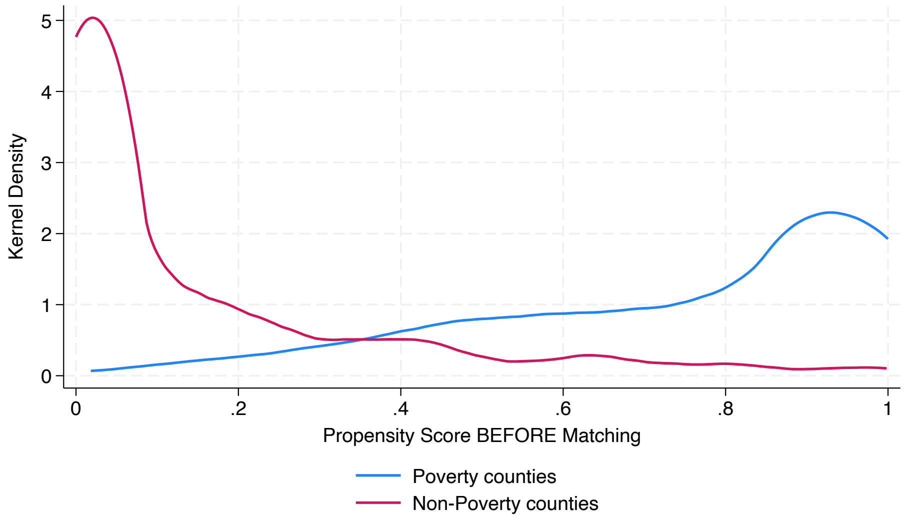
Note: Based on the administrative districts in 2014, the ratio of poverty counties is calculated and presented. The darker red colour represents a higher ratio of poverty counties. Besides, Xizang is an exception as is explained in the previous figure.

Figure A3: Administrative Units of an Example Prefecture

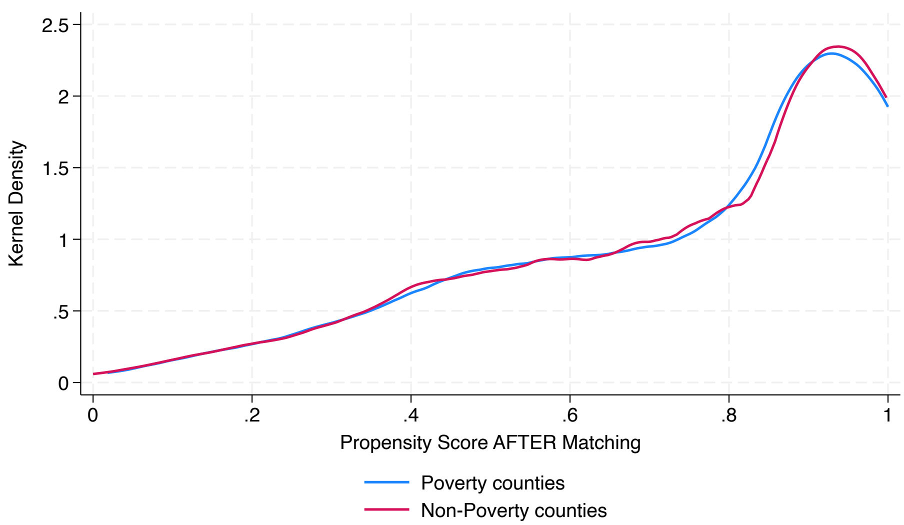


Note: Taking a Chinese prefecture as an example, all of its divisions are county-level in the administrative ranking. However, the dark red area is usually called districts, rather than counties as the rest of county-level divisions. Besides, districts often are the political and economic centre of the prefecture.

Figure A4: The Kernel Density of Propensity Score Before and After Matching



(a) The density of propensity score before matching



(b) The density of propensity score after matching

Note: Based on the kernel matching strategy, individual counties in the treatment and control groups are assigned propensity scores. The upper figure plots the kernel density of the score of the two groups before matching, while the lower plots after matching.