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Across a few prohibitive miles: The impact of the Anti-Poverty Relocation Program in China

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ABSTRACT

Many households are confined to remote rural villages in the developing world. This study examines the Anti-Poverty Relocation Program in China, considering the village-to-town relocation from agricultural to non-agricultural sectors induced by the program. While exploring a novel administrative data set on impoverished people in a Chinese county, we discovered that the program significantly increased the participants' income by 9.61%, driven mainly by the increase in wage income. The empirical findings are consistent with the Roy-model perspective, which states that rural households with comparative advantage in non-agricultural sectors could benefit from relocation to nearby towns. This study provides new evidence that mobility barriers across sectors exist even on a small geographic scale in rural areas. The results of the cost–benefit analysis suggest that relocation of households in remote rural areas is a feasible policy tool for overcoming such mobility barriers.

1. Introduction

To lift nearly 100 million impoverished rural people out of poverty by 2020, China initiated the Targeted Poverty Alleviation (TPA) strategy in 2013.[1] It is one of the largest poverty alleviation programs in history. This paper investigates the influence of the Anti-Poverty Relocation Program (*Yi Di Fu Pin Ban Qian*. Hereinafter referred to as APRP), a major program of TPA strategy, and explores the underlying economic logic behind its effects.

The government launched the APRP to facilitate the relocation of poor households from remote, inhospitable areas to places with more work opportunities and a better life. As it is mainly a within-county relocation program, it moves households from villages to nearby towns or the county center by offering either public housing or housing vouchers.[2] Households can choose either to move into apartments in public housing communities for free or agree on a fixed amount of subsidy (26,000 Yuan per capita) to purchase or build a new house in a preferred location within the county.[3]

Although households only moved a relatively short distance (refer to Figure E8), APRP facilitated substantial changes with regard to participating households in many aspects (refer to Section 2 and Section 5). First, households moved to less geographically isolated places. The Terrain Ruggedness Index, the average slope of the land, and commuting time to the populated area decreased, and the road density increased after relocation. Second, households moved to more developed places. Population density, electricity consumption, and area of built land were higher in destination regions, while poverty rate was lower. Third, access to amenities increased a lot after relocation because households moved to locations close to schools and health care institutions. We also provide suggestive evidence that school quality is higher in destination regions for the housing voucher group.

Among all causes of poverty in rural areas, the APRP potentially tackles two problems: low productivity in agricultural sector relative to non-agricultural sector (Adamopoulos et al., 2022a; Gollin et al., 2014; Lagakos et al., 2020; Lagakos, 2020; Young, 2013) and the cost of remoteness, which prohibits access to market (Aggarwal, 2018; Asher et al., 2018; Brooks and Donovan, 2020; Provenzano, 2020; Redding and Sturm, 2008). By placing households in regions with more non-agricultural economic activities, the APRP aids in supplementing labor force shifts from agricultural to the non-agricultural

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[1] Refer to http://www.xinhuanet.com/politics/leaders/2021-02/25/c_1127140240.htm. In Chinese. Last accessed: Aug 7, 2022.

[2] According to the provisions of the relocation program, there are two types of relocation. The first one is "collective relocation", referred to as public housing relocation throughout this study. The other one is "dispersed relocation", referred to as housing voucher relocation hereinafter.

[3] Households are not allowed to relocate within the same natural village to avoid program abuse. In this research, the term "village" refers to an *administrative village*, which is an area self-governed by a Villagers' Committee. Each administrative village comprises one or more *natural villages*.

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sector. Besides, the APRP increases participating households' market access by directly moving them out of remote areas. However, a positive impact on economic outcomes is not guaranteed. A within-county relocation may not be sufficient in overcoming the mobility barrier across sectors.[4] For example, poor households may lack crucial skills for non-agricultural jobs.

A conceptual framework is thus adopted that accounts for the comparative advantage in sectors, switching costs, and compensating differential in amenities of residence to understand the APRP's impact. Based on the conceptual framework, we hypothesize a positive average treatment effect on the treated (ATT) of the APRP on participating households' economic outcomes. A positive ATT arises because households with comparative advantage in the non-agricultural sector opt for the program and the program reduces switching costs across sectors by improving transportation conditions, access to non-agricultural job opportunities, and the propensity to migrate to other cities.

We test our theoretical predictions with a difference-in-differences (DID) method by utilizing comprehensive and fine-scale administrative panel data of 45,059 impoverished people in an impoverished county in China, comparing participants in the APRP with non-participants who are otherwise identically impoverished. Regarding the difference in the treatment and control groups, we use entropy balancing (Hainmueller, 2012) and inverse-probability-weighting methods (Wooldridge, 2010) in combination with post-double selection of controls (Belloni et al., 2014) to obtain a valid estimation of the ATT. We also incorporate a battery of robustness checks to establish causality, including the Oster test (Oster, 2019) and the permutation test, as well as controlling for other TPA programs and exploiting variation generated by the phase-in nature of the program.

In addition to a positive ATT, we document substantial heterogeneity in the effects, which aligns with our conceptual framework predictions. First, we find that the treatment effect on economic outcomes is smaller for households receiving housing vouchers than those who moved into public housing communities. This heterogeneity can be explained by the fact that households who chose housing vouchers had more kids and relocated to places with better access to educational resources. Higher amenities compensate for wage differences, encouraging some households without a comparative advantage in the non-agricultural sector to participate in the program. Second, moving into public housing communities has no significant positive impact on the labor supply of those with relatively low potential income in the labor market, including women, those who did not work in the previous year, and those with severe health issues. Heterogeneous effects on different groups of people are consistent with the Roy-model perspective, according to which comparative advantage in the non-agricultural sector determines the gain in potential income.

Notably, identifying the critical mechanism that decreases the switching cost from the agricultural to the non-agricultural sector with a short-distance relocation is the primary objective. We exploit the variation that participants who move to the same relocation community may come from different villages. For households in the same relocation community, access to the labor market, geographic conditions, transportation, etc., are all the same after treatment. Variations come before relocation, which is exogenous to households because self-relocation across villages is rare among poor households. Also, any effect of belonging to a particular village is eliminated by comparing participants and non-participants in the same village. Pre-treatment environment determines how restricted and isolated the Identified Poor Households (IPHs) are. With this variation, we find that households from villages with a lower average income, a lower proportion of wage in household income, and a more rugged terrain benefit more from relocation. Overall, access to non-agricultural sectors before treatment, which is in turn affected by geographic conditions, determines the treatment effect. We exclude some potential mechanisms, including extra job opportunities provided post-treatment, exposure to wealthier IPHs, and improved housing quality.

Finally, we conduct a cost–benefit analysis of the APRP by comparing the fiscal expenditure of the program with the increase in participants' life-cycle potential income. A back-of-the-envelope calculation denotes that the APRP generates a net benefit to the economy when the counterfactual per capita income growth rate exceeds 6.45%. Our estimate likely underestimates the long-run benefit on the next generation (Chetty et al., 2016; Chyn, 2018), as we estimate the short-run effect of the program, given data limitations. Besides, the distributional benefit of the APRP, which is potentially substantial, is not considered. Future research is required.

This study is related to a wide range of literature, such as that related to internal migration (e.g., Bryan et al., 2014; Bryan and Morten, 2019; Nakamura et al., 2022; Tombe and Zhu, 2019). In particular, this study enriches the current understanding of internal migration by emphasizing a sectoral switch accompanying spatial movements (e.g., Nakamura et al., 2022; Tombe and Zhu, 2019). In Nakamura et al. (2022), living on a remote Icelandic island was found to impede the development of children with comparative advantage in industries other than fishing. Likewise, our study finds that remote rural areas impose economic costs on adults with a comparative advantage in the non-agricultural sector. We document that mobility barriers across sectors exist even in a "local" context. Even a short-distance relocation may generate a substantial impact on economic outcomes. The reduced-form results in this study are consistent with the structural estimation results in Adamopoulos et al. (2022a), where the local agricultural-to-non-agricultural barrier could be larger in magnitude than the rural-to-urban barrier, especially in remote regions in China. Our findings align with a large literature that underscores the cost of remoteness (e.g., Brooks and Donovan, 2020; Provenzano, 2020; Redding and Sturm, 2008).

This research is also related to a broad strand of literature that focuses on poverty alleviation practices globally (e.g., Chen and Ravallion, 2010; Meng, 2013; Li et al., 2016b). This study aims to understand whether relocating ultra-poor households from remote, segregated villages to nearby towns makes a difference in their economic outcomes. As many households in the developing world are still residing in remote and segregated villages, our findings have broad implications. While previous literature concentrated on the impact of constructing transportation infrastructure in rural areas (refer to e.g., Aggarwal, 2018; Asher and Novosad, 2020; Brooks and Donovan, 2020), this study looks at another type of policy intervention – housing assistance, which is less studied in a rural context – revealing that such an intervention could be beneficial for treated households and the economy. In Asher and Novosad (2020), reduced transportation costs enabled reallocation of workers to the non-agricultural sector. Our results are consistent with theirs in that explicit reduction of the distance between

[4] Previous literature primarily documents the positive impact of migration over long distances (e.g., Fan, 2019; Kinnan et al., 2018; Wu and You, 2020). This literature usually defines internal migration in China as moving to places outside the origin *hukou* (registration) region because *hukou* is one of the most critical barriers to internal migration, imposing strict restrictions on public services for migrants. In contrast, the *hukou* status can be regarded as identical in the same county within each sector.

rural households and towns induces workers into the non-agricultural sector.[5]

In addition, we contribute to the literature that studies the effect of housing assistance policies (e.g., Barnhardt et al., 2017; Jacob and Ludwig, 2012; Kemp, 1990; Orr et al., 2003). Moving impoverished people to low-poverty regions was hypothesized to have positive impacts on economic outcomes (Wilson, 1987). Recent observational evidence outlines location as a core determinant of upward mobility and long-term economic outcomes of future generations (e.g., Chetty et al., 2014; Chetty and Hendren, 2018). This research distinguishes itself from previous literature by targeting housing assistance policy in rural areas.

The remainder of the paper is organized as follows. Section 2 introduces the APRP in China, and Section 3 discusses the data and provides descriptive analysis. Section 4 proposes a conceptual framework for understanding the program effect. Based on the framework, Section 5 proposes three parts of empirical analyses. We first estimate the effects of the APRP. Then, the heterogeneity in the effects is estimated across relocation types and individual characteristics. Finally, we discuss the underlying mechanisms of the APRP. Section 6 provides a cost–benefit analysis, and Section 7 concludes the study.

2. Anti-poverty relocation program in China

Relocation program entitled *Yi Di Ban Qian* (i.e., the APRP) was first launched in 2001, starting in four pilot provinces: Inner Mongolia, Guizhou, Yunnan, and Ningxia. It was gradually phased in another 13 pilot provinces. From 2001 to 2015, the central government invested 36.3 billion Chinese yuan (i.e., approximately 5.2 billion US dollars according to the exchange rate in 2020) and relocated 6.8 million impoverished people in total.[6]

An expanded round of the APRP was launched in 22 provinces in 2016. This wave of the APRP is a major component of the TPA strategy in China, with an unprecedented large scale in China and the world.[7] The annual average investment is about three times the fiscal expenditure of public housing programs in the US in 2017 (17.77 billion dollars v.s. 6.48 billion dollars).[8]

Despite the differentials across regions, the APRP is a within-county relocation program in general, that is, households are relocated within the county.[9] Given the within-county nature of the APRP, two features are worth noting. First, households are often moved from remote, poor rural areas to small towns or county centers instead of big cities. Second, the relocation distance is generally short. Taking the county we study in this paper as an example, households moved to public housing communities that were on average 3.88 km away (crow-flies distance, same below), with the maximum being only 10.48 km. Households who took the voucher moved by a longer distance as they had a larger choice set of destinations. The average relocation distance is 11.04 km, with the maximum being 44.96 km.[10]

2.1. Application and screening

As a major component in the TPA strategy of China, the APRP intends to target IPHs (*Jian Dang Li Ka Hu*), which were first identified by the government in December 2013. The precise identification of poor people was a main concern in the TPA strategy.[11] The IPHs had much lower income levels, smaller family sizes, and worse health conditions compared to non-IPHs.

Among the IPHs, households living in areas with poor living conditions and a fragile ecological environment are on top of the list for the APRP. Household participation in the program is a joint decision of public agencies and the household, combining self-application and approvals from multiple levels of administration. Initially, a household chooses to file an application. Thereafter, the Villagers' Committee screens the households' eligibility. After approval, the list of the approved households is publicly announced in the village for villagers to appraise it. Assume someone who is not on the list argues for their eligibility or questions the eligibility of someone on the list. In that case, the local officials need to double-check those household statuses to ensure the list's validity. Lastly, the Leading Group Office of Poverty Alleviation and Development (LGOPAD) in the county assesses and approves the application. The approved households still have the right to choose not to relocate and give up the housing assistance provided in the program.

Unlike previous poverty alleviation projects that were place-based (e.g., Meng, 2013), the eligibility for relocation is determined by the characteristics of each household. Hence, village characteristics are not decisive in one's application and screening process. Due to village-level determinants that frequently impact households located in the same village, there might be a within-village correlation of participation in the APRP. In the empirical analysis of this study, we control for household fixed effects and cluster the standard error at the village level (or above) to address this issue.

2.2. APRP in Xin County

The data utilized in the study are from Xin County, a county of Xinyang City, Henan Province (refer to Figure A1). It comprises an area of about 1551 km^2, with 17 township-level administrative regions and 205 villages, among which 179 have IPHs as shown in our data.

We compare Xin County in 2015 (i.e., before the APRP) with other counties in China to give a sense of the external validity of our study for other regions. The findings are presented in Table 1 (refer to Appendix D for more details). Xin County is shown to be comparable to the median level of all counties in many key socio-economic variables.

Like other places in the country, the APRP in Xin County includes two types: public housing relocation and housing voucher relocation.

Public housing is provided in collectively built communities. The locations of these communities are selected by the government. According to the national guideline of the APRP, public housing communities are to be located in places near county centers, towns, or factories.

[5] In Asher and Novosad (2020), the road construction program had no significant impact on income or asset holdings. However, this outcome does not necessarily contradict ours because they look at village-level data while we focus on household- and individual-level data. The Roy-model-type selection indicates that the influence on aggregate economic outcomes may not be positive.

[6] Information above is from the National Development and Reform Commission. The Relocation from Inhospitable Areas Program in China. https://www.ndrc.gov.cn/fzggw/jgsj/dqs/sjdt/201803/t20180330_1050716.html. In Chinese. Last Accessed: Aug 7, 2022.

[7] Refer to The 13th Five-Year Plan for Relocations from Inhospitable Areas. http://www.cpad.gov.cn/module/download/downfile.jsp?filename=1704281114592202439.pdf&classid=0, in Chinese. Last accessed: Aug 7, 2022.

[8] The fiscal expenditure of public housing includes public housing capital fund, public housing operating fund, and Choice Neighborhoods grants. Refer to https://www.everycrsreport.com/files/20170623_R44495_27b87275b3c17a4292a6f88619152249d47f1106.pdf for details. Last accessed: Aug 7, 2022.

[9] Cross-county relocation is permitted only in rare cases in some provinces, where households could not be relocated within the county because the whole county was under severe land or natural resource constraints.

[10] Crow-flies distance may mask the rugged geography and transport challenges in remote rural areas. Taking the county we study in this paper as an example, the average relocation distances measured in length of road for the public housing group and the housing voucher group are 7.10 km (83% longer) and 19.25 km (73% longer), respectively. However, the relocation distance is very short compared to inter-city or inter-province migration.

[11] Refer to Appendix C for details on the identification of IPHs.

Table 1
Xin County and other counties in China.

	(1) Xin County	(2) 25th Percentile	(3) 50th Percentile	(4) 75th Percentile
GDP per capita (Yuan)	28631.45	18616.76	27111.63	43429.71
Population density (10,000 Person/km^2)	0.02	0.01	0.02	0.05
Value added in manufactory Sector/GDP	0.42	0.33	0.44	0.53
Deposit per capita (Yuan)	19482.79	13918.46	18999.80	27463.59
Fiscal expenditure per capita (Yuan)	5641.66	4890.41	6599.04	9566.71
Household size	4.81	3.64	4.13	4.69
Housing area (m^2)	109.54	90.44	117.03	143.89
Number of rooms in the House	3.66	2.97	3.80	4.67
Age	36.16	34.55	36.83	39.31
Proportion of males	0.53	0.50	0.51	0.53
Own rural land	0.74	0.42	0.64	0.76
Education (year)	8.15	8.03	8.63	9.44
Currently working	0.64	0.52	0.61	0.69
Proportion of residences without Hukou	0.07	0.09	0.15	0.27
Proportion of those working outside city	0.23	0.03	0.08	0.16
Married	0.69	0.70	0.74	0.77
Number of children	1.83	1.35	1.59	1.82

Notes: This table compares socio-economic variables of Xin County measured in 2015 with the 25th, 50th, and 75th percentile of all counties in China. The data of the first five variables comes from the County Statistical Yearbook of China. The remaining variables are calculated from the 2015 1% National Population Sample Survey of China.

After being informed about the communities' location, the eligible households choose the kind of relocation they want to participate in. The number of eligible households that apply for public housing determines the number of buildings and units.[12] Usually, a building has five or six stories, with two to four units on each floor. The size of the housing unit for each household is capped at 25 square meters per capita.[13] For households of the same size, the unit is primarily assigned by lottery, with households with disabled members having priority for first-floor units. After relocation, the previous homestead is reclaimed by the government with a compensation of 30 yuan per square meter.[14]

Participants who choose a housing voucher receive a subsidy to buy or build a new house. The location of the new house is determined by the household, with a limitation that the household cannot stay in the same natural village as the original residence. The level of subsidy is unrelated to household income but remains at a constant of 26,000 yuan per capita, which is approximately equal to the construction cost of 25 square meters in Xin County. Households may spend more than the subsidy to purchase or build a new house only if they can afford it without borrowing and the per capita residence area is not larger than 25 square meters. Additionally, households may also spend less than the subsidy, keeping the remaining amount for other expenses. To prevent them from spending the housing voucher on anything unrelated to housing, the local government designed a strict acceptance check procedure before providing the subsidy to eligible households. A transaction contract is necessary for those who buy a new house, and an on-site inspection is mandated for those who build a new house to receive the subsidy.[15] After relocation, the government reclaims the previous homestead with a compensation of 50 yuan per square meter.

2.3. The APRP and other poverty alleviation policies

As a component of the TPA strategy, the APRP is simultaneously implemented with other poverty alleviation programs in the TPA strategy. These other programs have been gradually rolled out along with the progress of the TPA strategy.[16] Throughout the sample period, households were covered by multiple poverty alleviation policies. To disentangle the APRP's effect, we control for other poverty alleviation programs (i.e., confounding programs) in the empirical analysis for disentangling the effect of the APRP.

Besides the simultaneous programs in the TPA strategy, some programs are implemented explicitly to supplement the APRP. One such policy is the poverty alleviation workshop (*Fu Pin Che Jian*, i.e., small plants for manufacturing). Poverty alleviation workshops provide job opportunities to both poor and non-poor workers. Jobs offered in these workshops were flexible in working hours, aiming to provide homemakers and elders the chance to earn income in their leisure time. These workshops tend to be located near public housing communities to ensure poverty alleviation, strengthening the relocation effect on households' labor supply and wage income. By 2018, 28 poverty alleviation workshops were conducted in Xin County, which were set up near public housing communities and offered jobs to 410 IPH workers and another 724 non-poor workers. The effects of poverty alleviation workshops may influence the aggregate effect of the APRP, which help clarify the underlying mechanisms of the APRP's treatment effect (refer to Section 5.3 for details).

3. Data and descriptive analysis

3.1. Data and summary statistics

The dataset used in this study is a full-sample administrative poverty population dataset of Xin County, Henan Province, obtained from the National Poverty Alleviation and Development Information System

[12] Housing units are either in a multi-story building or in a detached house. In Appendix B, a summary table of the population, types, and stories of the building of each public housing community in Xin County is provided.

[13] Based on construction cost, the minimum size of a housing unit is 50 m^2. Thus, single-member households are not eligible for housing units in public housing relocation, and they are assigned to the housing voucher group instead. The maximum size of a housing unit is 125 m^2 or 150 m^2. Accordingly, the average size per member is smaller for households with more than five or six members relative to households with fewer members.

[14] Participating households get property rights to the public housing unit assigned to them. The compensation is not included in the benefits side of our cost–benefit analysis in Section 6 because there we focus on labor market impacts.

[15] Due to privacy concerns, the local government cannot provide the transaction contracts to us. Hence, we do not know the exact amount of subsidy spent on housing.

[16] Appendix A provides a more detailed description about these other programs.

Table 2
Summary statistics.

	(1) Control Mean	(2) Housing Voucher Mean	(3) Public Housing Mean	(4) (2)-(1) *t*-statistic	(5) (3)-(1) *t*-statistic	(6) (3)-(2) *t*-statistic
2014						
Net income per capita (Yuan)	2648.01	2484.11	2403.40	−2.11	−5.59	−1.31
Wage income per capita (Yuan)	1719.30	1874.99	1725.57	1.81	0.13	−2.55
Agricultural and business income per capita (Yuan)	373.43	275.19	347.19	−2.33	−1.04	1.40
Property income per capita (Yuan)	20.84	4.35	11.72	−0.98	−0.97	2.17
Transfer income per capita (Yuan)	696.48	429.98	435.14	−5.93	−10.64	0.12
Duration of working in a year (month)	2.92	3.06	2.93	1.17	0.07	−1.00
2018						
Net income per capita (Yuan)	9790.01	8681.73	10028.26	−3.95	1.46	5.37
Wage income per capita (Yuan)	7141.51	7088.34	8050.84	−0.18	5.26	3.83
Agricultural and business income per capita (Yuan)	616.88	628.24	567.66	0.08	−0.66	−0.36
Property income per capita (Yuan)	359.02	253.62	304.70	−3.63	−3.20	1.90
Transfer income per capita (Yuan)	1858.75	1000.64	1306.76	−7.81	−8.64	3.24
Duration of working in a year (month)	5.28	5.38	5.52	0.78	2.91	0.95
Household size (person)	3.16	4.37	3.70	16.87	13.06	−9.71
Number of youths	0.62	1.30	0.92	17.12	12.88	−7.52
Residential area (square meter)	91.03	83.54	78.23	−4.25	−12.67	−3.76
Distance to major road in village (km)	0.58	0.81	0.78	4.93	7.27	−0.60
Age (year)	37.62	31.37	34.17	−12.37	−10.72	4.89
Male (dummy)	0.56	0.51	0.54	−4.08	−2.44	2.21
Education (year)	6.56	6.34	6.32	−2.43	−4.17	−0.20
General labor[a] (dummy)	0.59	0.54	0.56	−4.25	−3.73	1.63
Healthy (dummy)	0.76	0.82	0.78	5.88	3.43	−3.40
Student (dummy)	0.27	0.35	0.31	7.55	5.69	−3.29
Number of households	10751	444	1421			
Number of working age individuals	23402	1327	3666			
Number of individuals	37085	2135	5832			

Notes: Table shows the mean and *t*-statistics.
[a]General labor refers to people who are between 16 and 60 years old, can work, and do not have a vocational qualification certificate.

(NPADIS).[17] The dataset covers all the IPHs in Xin County. As the IPH list is adjusted annually, it is an unbalanced panel dataset, covering 12,616 households (45,059 individuals) from 2014–2018.

The APRP was implemented in Xin County in 2016 and 2017 and mainly targeted IPHs. During this period, 1,909 households (7,786 individuals) were relocated through this program, among which 1,865 households (7,676 individuals) were IPHs.[18] Among the IPH participants, 691 households (37.1%) participated in the APRP in 2016, and the other 1,174 (62.9%) participated in 2017. Among them, 1,421 households (76.2%) moved to public housing communities, and 444 households (23.8%) took housing vouchers. As IPHs are very different from non-IPHs in many aspects, the non-IPHs have been excluded from this study.

The key dependent variables in this study are household-level income and individual-level labor supply. Income variables include total income, wages, operational income (e.g., income from farming and small family business), property income (e.g., rents from land, collective income dividends, and other property appreciation gains), and transfers (e.g., government transfers like minimum living allowance and donations from others). All income data are converted to per capita terms, and labor supply is measured as the number of months spent working in a year. The dataset contains a large set of control variables, namely (1) household demographic structure, (2) land ownership, (3) infrastructure access and social connection, and (4) individual characteristics. Table 2 presents the means of household characteristics measured in 2014 for the control group and the two treatment groups (i.e., columns (1) – (3)). Additionally, we compare the differences between each treatment group and the control group, and the difference between the two treatment groups (i.e., columns (4) – (6)).[19] For the core dependent variables, the summary statistics are provided both before the commencement of the relocation (2014 data) and afterward (2018 data). We see that both the treatment and control groups enjoyed rapid growth in both income and labor supply during a period of rapid poverty reduction in China. A significant difference between the control and treatment groups is also observed, highlighting potential sorting issues in our context.

3.2. Descriptive analysis

Before presenting the conceptual framework and empirical analysis, some descriptive results on how the APRP affects participating households are first provided. For the public housing group, the households are moved to public housing communities built by the local government. For the housing voucher group, we manage to locate 364 households (about 82%) according to the address list provided by the local government. Fig. 1 depicts the spatial distribution of participating households, railways, main roads (excluding township-level roads and village-level roads), the locations of township centers, and the poverty rate of each village. At a first glance, households move to places with lower poverty rates, convenient transportation, and near township centers.

To further illustrate this point, we do a simple comparison, contrasting village-level characteristics of origin villages that participating households came from, together with the destinations that they moved to. We focus on the following variables measured before the treatment: (1) travel time to the nearest city with a population of more than 20,000 in 2015, which is obtained from Nelson et al. (2019); (2) two measurements of terrain ruggedness, including Terrain Ruggedness

17 Refer to Appendix C for more details about the dataset.

18 Some non-IPH households participated in the program via the “Accompanying Relocation” policy, which prevented them from being left behind in remote areas. Non-IPH households need to fund the construction of their house in the public housing community. Afterward, they get to enjoy a publicly-provided infrastructure in the community.

19 Refer to the complete table of all control variables in Table E1.

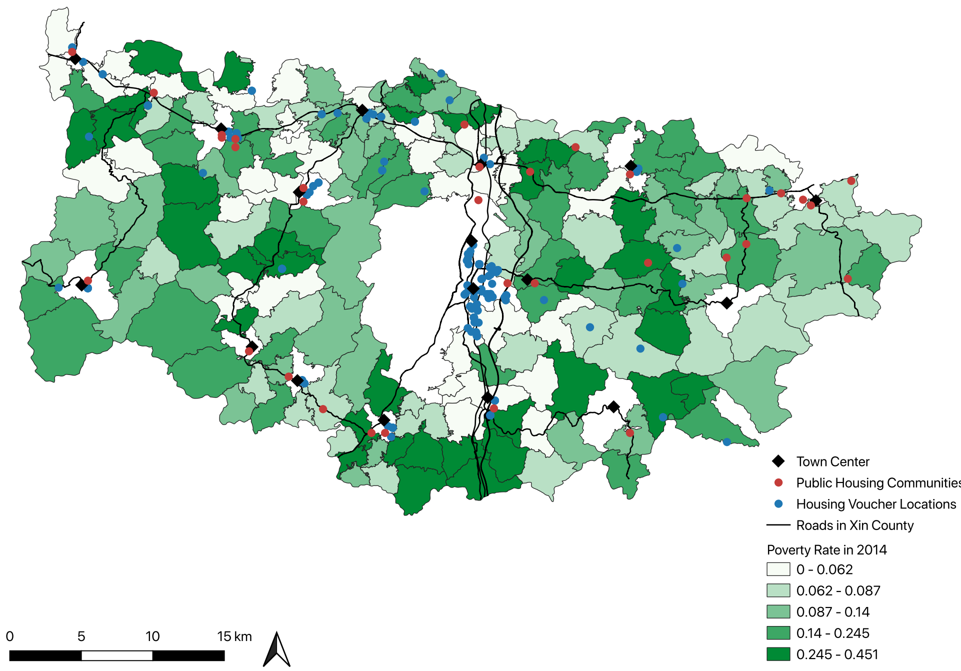


Fig. 1. Locations of relocated households.
Notes: Black lines indicate the main roads in the county, and black diamond marks signify the center of each township. Red dots refer to the locations of public housing communities. Blue dots convey the locations of households relocated through housing vouchers, and the background color of each village highlights the poverty rate of the village in 2014. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Index and average slope, from Nunn and Puga (2012); (3) road density calculated as the total length of railways and main roads per square kilometer in 2013; (4) population density measured by population per square kilometer of land[20]; (5) poverty rate measured by the number of IPHs in 2015 on village population; (6) residential and non-residential electricity consumption in 2015[21]; (7) total area of built land in 2015 is measured by impervious surface from China Land Cover Database (Yang and Huang, 2021). The results are shown in Fig. 2. It turns out that households relocated to places with better geographic conditions, better transportation, and a more developed economy that were proxied by higher population density, lower poverty rate, higher electricity consumption[22] and more built areas.

Fig. 3 depicts the trajectories of income and labor supply of the treatment and control groups. The treatment and control groups have parallel trajectories in income and labor supply before the APRP. After relocation, the treatment group catches up with the control in per capita income and surpasses the control group in labor supply. These descriptive results suggest a positive treatment effect of the program and improved participation in wage jobs after relocation.

4. Conceptual framework

In this section, we incorporate a conceptual framework adapted from the model in Nakamura et al. (2022), with comparative advantages across sectors taken into consideration, to understand the effect and the mechanism of the APRP in China (Roy, 1951; Borjas, 1987).

The conceptual framework is presented in Fig. 4. Consider an economy with two sectors: agriculture and non-agriculture. Households are endowed with comparative advantage q in the non-agricultural sector. The blue solid line ($\bar{Y}_A(q)$) and black dashed line ($\bar{Y}_N(q)$) show the average potential income levels in the agricultural and non-agricultural sectors conditional on q, respectively. Here, two assumptions are considered. First, potential income in the non-agricultural sector is correlated positively with comparative advantage in the non-agricultural sector, that is, $\bar{Y}_N(q)$ is increasing in q. Second, comparative advantage in the non-agricultural sector also means comparative disadvantage in the agricultural sector. Therefore, $\bar{Y}_A(q)$ is decreasing in q.

Switching across sectors is costly, which is measured by m. Such a cost reflects frictions in at least three forms, as discussed in Lagakos (2020). The first one is information friction wherein households do not know the exact return or cost of migration (Bryan and Morten, 2019). The second one is financial friction, including borrowing constraints experienced by poor households (Cai, 2020) and lack of insurance. The third one is institutional friction. Literature signifies that lack of land security impedes internal migration in China (e.g., Ngai et al., 2019; Adamopoulos et al., 2022b,a). With regard to remote rural areas, transportation cost likely exists as well (Asher and Novosad, 2020).

Some households with relatively high comparative advantage in the non-agricultural sector could be limited to the agricultural sector due to the high cost of switching across sectors, leading to misallocation across agricultural and non-agricultural sectors (refer to misallocation region $q \in [\tilde{q}, q^*]$). When households cannot pay for m, even households with a high comparative advantage in the non-agricultural sector may

[20] Due to data limitation, we only have village population in 2017. Hence, here we assume the total population of villages are stable throughout the sample period.

[21] Electricity consumption data comes from the local power bureau. We can only match IPHs to electricity consumption data in a fuzzy way using households' township and the given name of the household head (surnames are omitted due to privacy concerns). Excluding confounding matches leaves the match rate to be only 61.4%. Also, measures on participating households after relocation are not available because cases of changing meters will be confounded with cases of multiple households sharing the same given name, which are dropped in the matching process. Thus, we do not utilize household-level electricity consumption throughout the study. Each electricity consumption record marks the transmission line that supplies the electricity. To get village-level electricity consumption data, we first use the matched data to get a list of village-transmission line pairs. Next, the number of households on each transmission line is used as weights to calculate village-level weighted average electricity consumption.

[22] Previous research revealed strong links between energy consumption and income, opportunity, or well-being. Refer to, e.g., Khandker et al. (2012) and Shi (2019).

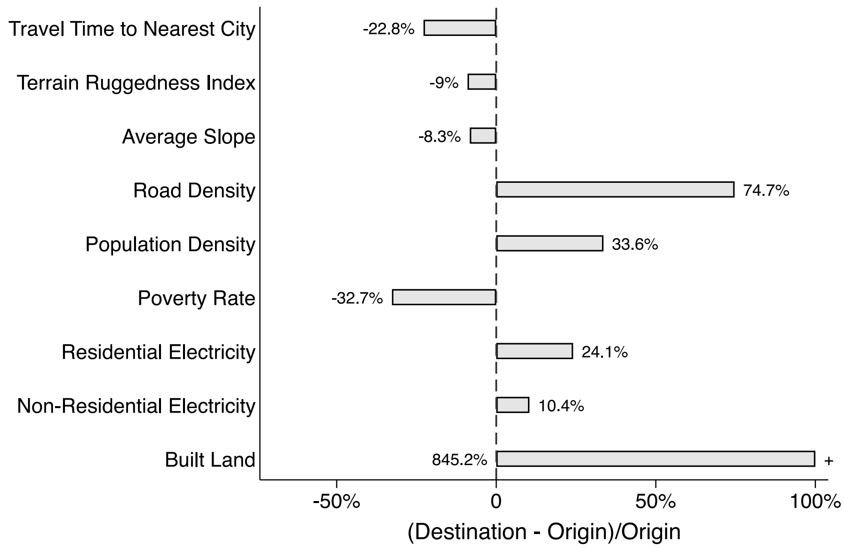
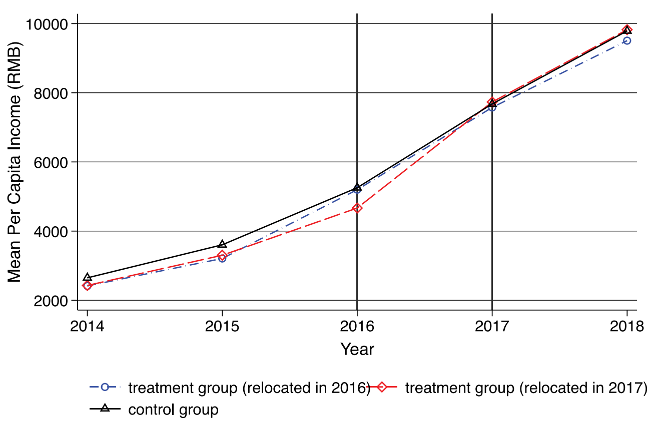
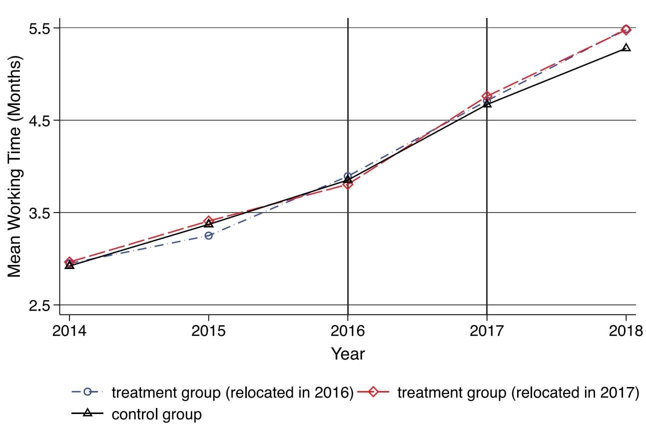


Fig. 2. Destination villages vs. origin villages.
Notes: This figure compares the pre-treatment characteristics of the origin villages of participating households to the destination villages. X-axis indicates the difference in proportion term, that is, we divide the difference by the level of origin villages.



(a) Average per capita income in 2014 – 2018



(b) Average working time (months per year) in 2014 – 2018

Fig. 3. Trajectory of key outcome variables.
Notes: Circle dashed line represents the treatment group that relocated in 2016. The diamond dashed line outlines the treatment group that relocated in 2017, and the triangle line indicates the control group. Per capita income refers to household income per capita. Months working in a year are calculated at the individual level, and the sample is restricted to working-age adults.

still be trapped in the agricultural sector (refer to constraint region $q \mid q > q^*$). The latter case could be prevalent in our context because the relocation cost is substantially greater than the average yearly income of households in our sample,[23] and most impoverished households are under strict credit constraints (Cai, 2020).

The APRP is introduced in this framework in a way that it reduces the perceived switching cost m for households, enabling transitions from the agricultural to the non-agricultural sector. The APRP reduces m for two reasons. First, participants get much better access to the non-agricultural sector in small towns or county centers where they moved to. Second, participants have lower costs for further migration to the coastal region in China because of extra information, encouragement from neighbors, and better access to transportation.

Positive treatment effect on the treated: The rural households with $q > \tilde{q}$ are more likely to pursue the relocation program if they anticipate a potential increase in income, or if they have lower income before the relocation program.[24] These households could obtain a higher lifetime income; therefore, we hypothesize that the treatment effect on the treated (TOT effect) of the APRP is positive. We provide evidence of this claim in Section 5.1.

Amenities compensate wage difference: Labor can be compensated via higher amenities to work in regions with lower wages (Bryan and Morten, 2019). Thus, households with low comparative advantage in the non-agricultural sector may also participate in the program if they are compensated by better amenities. The treatment effect on the treated will be smaller in this case. The APRP provides an opportunity to separate these two types of households (i.e., those maximizing income and those considering amenities) by comparing public housing to housing vouchers. As those who receive housing vouchers can choose the location of the new residence freely, their selection reveals their preference for amenities. If households who take housing vouchers move to places systematically different from those that move into public housing communities, we expect the APRP to have a smaller treatment effect in terms of income on the housing voucher group. We test this hypothesis in Section 5.2.1.

[23] Take the housing voucher as an example, 26,000 Yuan is about 10 times the yearly per capita income of treated households in 2014 (approximately 2,423 Yuan).
[24] The latter case occurs when comparative advantage is positively correlated with absolute advantage.

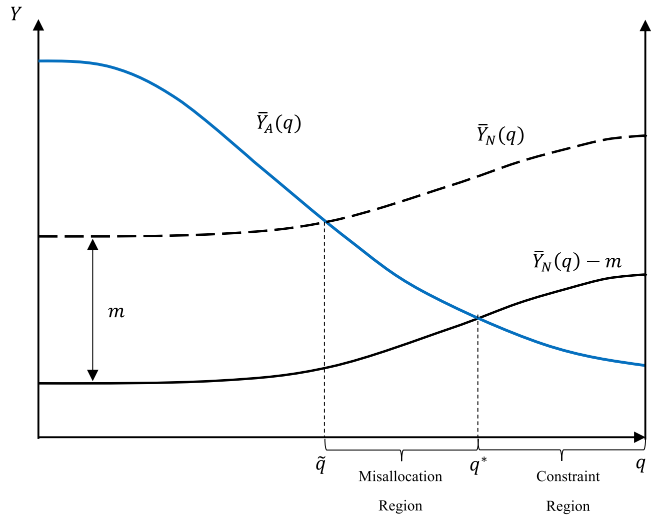


Fig. 4. Sorting based on comparative advantage.
Notes: The blue line indicates the average income in the agricultural sector. The dashed black line represents the average income in the non-agricultural sector. The solid black line highlights the average income net of switching cost m from the agricultural to the non-agricultural sector, and the x-axis indicates the comparative advantage q in the non-agricultural sector. $\tilde{q}$ specifies the level of comparative advantage at which the potential income in agricultural and non-agricultural sectors are the same. q^* outlines the level of comparative advantage at which the potential income in the agricultural sector equals the potential income in the non-agricultural sector net of the switching cost.
Source: Adapted from Figure 8 in Nakamura et al. (2022).

Positive effects on competitive individuals: One reason for a positive treatment effect, when it exists, is that the program encourages those with comparative advantage in the non-agricultural sector to participate. Accordingly, we hypothesize that households with higher potential income in the labor market benefit more from the relocation program. We test this hypothesis in Section 5.2.2.

Cost–benefit comparison: According to Fig. 4, the fiscal relocation cost of those in the misallocation region exceeds the potential income gain, noting that $(q^* - \tilde{q})m > \int_{\tilde{q}}^{q^*} \left(\bar{Y}_N(q) - \bar{Y}_A(q)\right) dq$. Providing relocation subsidies for those in the misallocation region generates net cost; however, potential income gain from relocation exceeds the switching cost for households in the constraint region. Therefore, the aggregate impact of the relocation program relies on the proportion of treated households in the misallocation region and the constraint region. Empirically, it is hard to directly estimate these proportions. In Section 6, we perform a back-of-the-envelope cost–benefit analysis based on our treatment effect estimation and the actual fiscal expenditure of the program for all the participants.

5. Empirical analysis

Based on the dataset described above, we empirically test the hypotheses proposed in Section 4. First,we estimate the treatment effect of the APRP. Second, we identify the heterogeneity in the treatment effects, focusing on the heterogeneity across different relocation types and groups of people. Third, we explore the mechanism of the treatment effect.

5.1. Treatment effect of relocation

The key challenge to the identification of treatment effects is the selection issue concerning APRP participation. To account for this issue, we incorporate a DID method and conduct an event study to test the parallel trend assumption between different groups. Although we cannot reject the parallel pre-trend with raw data, pre-treatment entropy balancing is utilized to get a more precise estimation of the average treatment effect on the treated (ATT). As the weighting method can only control for observed characteristics, unobserved differences between the treated and the control groups are still crucial for the valid estimation of the ATT. We also conduct a series of robustness checks to further validate our results.

5.1.1. Empirical strategy

A DID method is used to estimate the effect of the APRP, and the basic regression specification is:

$$\ln Y_{ht} = \beta_0 + \lambda \cdot APRP_{ht} + \sum_{j=1}^{k} \beta_j X_{j,ht} + \alpha_h + \gamma_t + u_{ht} \tag{1}$$

where Y_{ht} indicates per capita income of household h at year t; $APRP_{ht}$ is the treatment indicator, which is the interaction of the dummy variable D_h, which equals one if household h was in the APRP treatment group and zero otherwise, and the dummy variable D_t (i.e., equals one if time $t \geq t_{h0}$, zero otherwise, and t_{h0} is the year household h relocated). The coefficient λ is the ATT of the program; $X_{j,ht}$ are time-variant observable covariates at the household level, including household demographics, farmland ownership, infrastructure access, and social connections; α_h are household fixed effects, which control for household time-invariant unobservable characteristics, and γ_t are year fixed effects. These effects control for variables constant across households but varying across years. Finally, u_{ht} is the error term.

The comparability of the control and treatment groups is strengthened through pre-treatment balancing. We employ the method of entropy balancing proposed by Hainmueller (2012) and Hainmueller and Xu (2013).[25] Appendix E.1 shows the outcomes of our balancing method on both targeted controls in the treatment equation and the untargeted controls in the outcome equation.

The DID identification depends on the parallel trend assumption that the difference in outcome between the treatment group and the control group would be constant in the absence of treatment. The parallel trend assumption might be violated if those who were originally more disadvantaged were more likely to apply and be selected into the treatment group, which is likely to be true given the discussion in Section 4, and if the more disadvantaged households demonstrate a different development trajectory. We conduct an event study of the APRP to provide evidence for parallel pre-trends, and the empirical model is:

$$\ln Y_{ht} = \beta_0 + \sum_{m=-3}^{2} \lambda_m \cdot D \cdot t_{0+m} + \sum_{j=1}^{k} \beta_j X_{j,ht} + \alpha_h + \gamma_t + u_{ht} \tag{2}$$

where t_{0+m} is a set of dummies indicating a five-year window around the relocation year of the APRP (i.e., from three years before to two years after). t_0 signifies the year when the relocation took place, and $m = -3, -2, -1, 0, 1, 2$. In the regression, we use the group where $m = -1$ as a benchmark. Thus, λ_m measures the treatment effect of assigning a household into the treatment group m years after the relocation compared to the effect one year before the relocation.

5.1.2. Results

Table 3 summarizes the findings of estimating Eq. (1) for the annual household income per capita, and on different sources of income. The coefficient of $APRP_{ht}$ in column (1) reveals that the APRP increases participants' per capita income by 9.61%. Columns (2) through (5) denote that the APRP increased per capita wage, property, and transfer income by 15.5%, 33.8%, and 9.69%, respectively, and did not have a significant impact on agricultural and business income. Given that wage income is the largest source of household income, as shown in

[25] In Section 5.2, we use a more traditional inverse probability weighting method to help construct comparable control groups for various relocation types (Wooldridge, 2010).

Table 3
Treatment effect of the APRP on per capita income.

VARIABLES	(1) Log(per capita income)	(2) Log(per capita wage)	(3) Log(per capita operational income)	(4) Log(per capita property income)	(5) Log(per capita transfer)
$APRP_{ht}$	0.0961***	0.155***	0.0383	0.338***	0.0969***
	(0.0189)	(0.0474)	(0.0808)	(0.125)	(0.0303)
Observations	58,047	57,790	57,629	57,132	58,057
Number of unique_id	11,740	11,738	11,736	11,736	11,740
Adjusted R-squared	0.702	0.255	0.055	0.481	0.257
Balanced	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y

Notes: The reported outcomes are the regression results from estimating equation (1) wherein the control variables selected by the double-selection method include household size, area of woodland, average education level, the number of Dibao recipients, labor force numbers, the number of unhealthy household members (i.e., suffering from chronic diseases, serious illnesses or disabilities), the number of youths under 14 years of age, and the number of people above 65 years. Standard errors in parentheses are clustered at village level, and the number of observations is different between the unbalanced and balanced sample because some households have zero weight in the regression. Numbers of observations are different when controlling for covariates because of missing data, and the complete results with coefficients on control variables are shown in Table E3. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table 2, the increase in per capita income is generally driven by the wage increase.[26]

The treatment effect of about a 10% increase in income (15% in wages) is considerable; still, it lies in a reasonable range compared to previous literature. For example, Bryan and Morten (2019) found that reducing migration costs to the US level increases the productivity of Indonesian workers by 7.1%. Observational return to migration of rural China is about 25% in Lagakos et al. (2020). The large treatment effects can be explained by the conceptual framework in Section 4. According to the framework, the increase in income arises from switching across sectors. Underlying the income gain are huge agricultural productivity gaps that have been documented in previous literature (refer to e.g., Gollin et al., 2014; Lagakos, 2020). Sorting, switching (migration) costs, and other frictions in the market explain such agricultural productivity gaps (refer to a survey in Lagakos, 2020).[27]

Fig. 5 provides the results of the event study. We estimate Eq. (2) for both the balanced and non-balanced samples. Findings confirm that we cannot reject the null hypothesis, stating that the treatment and control groups have the same trajectory of per capita income before the relocation, even without entropy balancing. Notably, the treatment effect estimates based on the balanced sample are larger in magnitude than those based on the unbalanced sample. Such a pattern is consistent with our projection in Section 4 according to which treatment groups should be those who tend to benefit more from the APRP. We also conduct event studies for various income sources (see Figure E3), which yield the same qualitative conclusions as the DID analysis above.

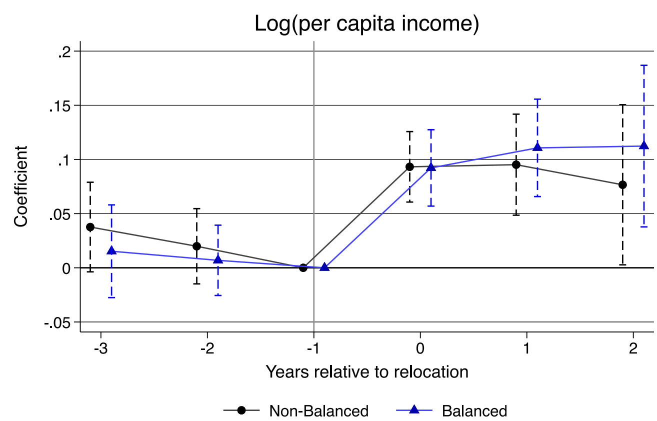


Fig. 5. Treatment effect on per capita income before and after the relocation.
Notes: Each circle and triangle indicates the point estimations of the treatment effect, and each vertical dashed line indicates the 95% confidence interval of the treatment effect. The black line indicates the findings from the non-balanced sample, and the blue line specifies the results from the balanced sample. The confidence interval is calculated based on robust standard errors clustered at the village level, and control variables are the same as in Eq. (1).

5.1.3. Robustness checks

We conduct several robustness checks to further ensure the validity of the causal conclusion.

First, a permutation test of random assignments is used to account for any potential over-rejection problem caused by serial correlation (Bertrand et al., 2004; Chetty et al., 2009; Li et al., 2016a). Details are presented in Appendix E.3.1. The findings suggest that the distribution of estimates from randomly drawn treatment status is located around zero, and the true point estimate is located outside the whole distribution of the 500 placebo estimates, indicating that the findings are not likely to be driven by an over-rejection problem.

Second, we include other types of poverty alleviation programs implemented in Xin County in the regression to account for the potential endogenous take-up of other poverty alleviation policies for the treatment group, as mentioned in Section 2.3. Moreover, the "renovation program for dilapidated houses" (*Wei Fang Gai Zao*, hereinafter referred to as the house renovation program) is also taken into account.[28] The house renovation program is mutually exclusive to the APRP (i.e., those who receive a house renovation subsidy after 2016 should not participate in the APRP). Controlling the house renovation program not only helps address the endogeneity problem but also elucidates the role of living conditions on economic outcomes. We include a set of dummy variables in the main regression assessing whether a household benefits from the programs stated above. Results convey that the effect of the APRP remains stable in controlling for these policies (Appendix E.3.2).

[26] The effect size on property income is quite large in percentage terms. Given that property income only accounts for a small proportion of household income (refer to Table 2), the effect size in monetary terms is small (200.75 Yuan, or about 30 USD). Such an increase in property income may be mechanical. For instance, after moving away, households may rent out the rural land near their original residence. We thank the reviewer for a discussion on this point.

[27] The estimated treatment effect does not take into account the general equilibrium effect that may arise in response to an influx of labor in towns and the county center. However, the general equilibrium effect should be negligible in this context because the treated population is very small compared with the total population of Xin County (about 8,000 vs. 250,000). We thank the reviewer for a discussion on this point.

[28] The house renovation program is included in the infrastructural program mentioned above.

Third, we employ the method proposed by Oster (2019), which exploits insights from Altonji et al. (2005), considering that potential biases from time-variant unobserved characteristics are still concerning. Details of the Oster test are exhibited in Appendix E.3.3. The test results show that all the Oster ratios are either greater than one or negative (refer to Table E6), denoting that the estimated treatment effect is unlikely to be driven by unobserved differences between participants and non-participants.

Finally, we utilize the phase-in nature of the program to compare the effects on households that are relocated in different years. These households are comparable because the timing of relocation is arguably exogenous to households. For households who chose public housing, the timing of relocation is largely determined by the progress of the construction of the public housing communities. For households who chose housing vouchers, half of the townships implemented the program in the same year. With household fixed effects controlled, the effect of the township-specific differences, if any, is absorbed. We conduct a within-treatment group analysis, comparing those who participated first with those waiting to participate in the program. As displayed in Table E7, all treatment effects are similar to those in the baseline results.

5.2. Heterogeneity in effects

In the previous section, the APRP is shown to have significant positive effects on household income. However, the average treatment effect on the treated masks the significant heterogeneity of the program's impact. In this section, we show who benefits from which type of relocation and explain the reasons behind the heterogeneity.

5.2.1. Heterogeneity across relocation types

First, we document the fact that the housing voucher group moved to places with a higher amenities level by comparing the surrounding amenities of the two treatment groups. Based on the geographic information of Xin County in 2018, we calculate the numbers of education and healthcare institutions within a one-kilometer radius of the locations after the relocation, as well as the shortest distance to railways or main roads of the locations.[29] Thereafter, we construct counterfactual statistics based on the village the participants' lived in before the relocation. We use the centroid of the original village as the proxy for the original residence location of the treated households. Finally, we test whether there is a statistically significant difference between the counterfactual statistics and the data after relocation. We summarize the results in Fig. 6. It shows that the public housing group has slightly worse access to educational institutions, and better access to healthcare institutions, compared to before the relocation. The housing voucher group has much better access to these two types of institutions, but both groups reduced the distance to the nearest roads to about 600 m. The difference in the access to educational institutions is consistent with a revealed preference theory where households in the housing voucher group contain more kids and students (refer to Table 2), and thus have a higher preference for localities with better access to educational resources. In Appendix E.4.2, we provide suggestive evidence that the quality of educational institutions around the housing voucher group is also better than that of the public housing group.

Further, we predict that the public housing group experiences have a larger positive impact on household wage income than the housing voucher group based on the prediction in Section 4. Given that wage income is the main income source, the public housing group can also likely have a larger positive impact on per capita income. Moreover,

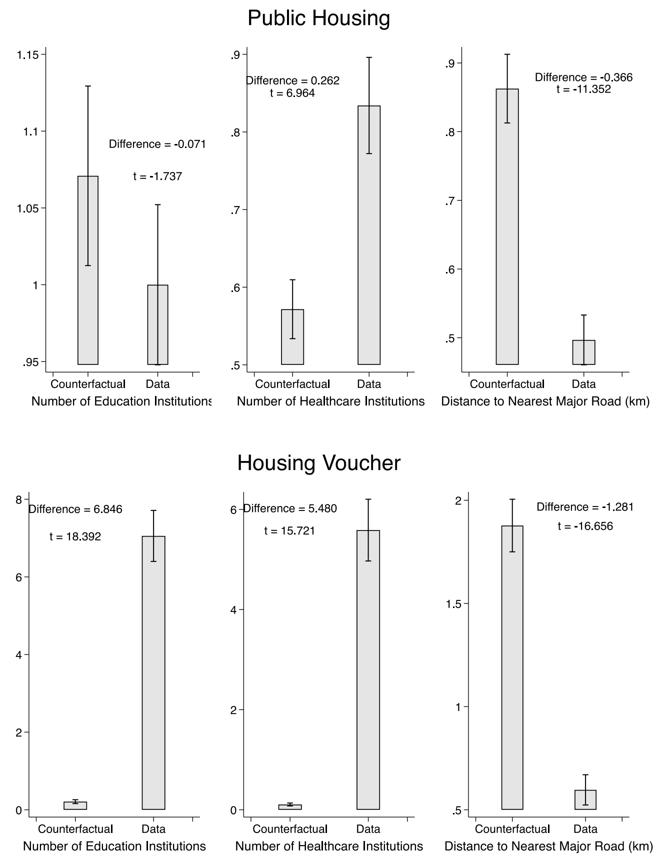


Fig. 6. Amenities of locations in public housing and housing voucher groups.
Notes: The above panel highlights the findings for the public housing group, while the bottom panel shows the outcomes for the housing voucher group. Figures on the left indicate the average number of educational institutions within a one-kilometer radius around the residence after relocation and the centroid of the village of origin. Figures in the middle show the average number of medical institutions within one kilometer around the residence after the relocation and the centroid of the village of origin. Figures on the right show the average minimum distance from the residence after relocation and the centroid of the village of origin to the nearest main roads in the county. Capped vertical lines specify the 95% confidence interval of the mean values, and the differences and corresponding t-statistics are stated in the figure.

we add two DID-type interactions into the regression to estimate the effects of the two different treatments as shown in Eq. (3).

$$\ln Y_{ht} = \beta_0 + \lambda^p \cdot APRP_{public,ht} + \lambda^v \cdot APRP_{voucher,ht} + \sum_{j=1}^{k} \beta_j X_{j,ht} + \alpha_h + \gamma_t + u_{ht} \tag{3}$$

where $APRP_{public,ht}$ is the interaction of the dummy variable D_t, which equals one if time $t \geq t_{h0}$, zero otherwise, and t_{h0} is the year wherein household h relocated. The dummy variable $Public\ housing_h$ equals one if household h participated in the public housing group and zero otherwise. $APRP_{voucher,ht}$ is the interaction of a dummy variable D_t and the dummy variable $Housing\ voucher_h$, which equals one if household h participated in the housing voucher group and zero otherwise. Hence, coefficient λ^p captures the ATT of public housing and coefficient λ^v captures the ATT of housing voucher.

We estimate the relative ATT based on inverse probability weighting with multiple treatment groups (Hirano et al., 2003; Wooldridge, 2010) and summarize the results in Table 4. Columns (1) and (2) show that public housing significantly increased per capita income and wages, while housing vouchers had no such effect. Column (3) conveys that neither relocation type had a significant effect on agricultural and business income. Columns (4) and (5) show that housing vouchers

[29] Education institutions include nursery schools, kindergartens, primary schools, middle schools, high schools, and vocational schools. Healthcare institutions include clinics, hospitals, Centers for Disease Control, and nursing homes.

Table 4
Treatment effect of different types of relocation on different income sources.

VARIABLES	(1) Log(per capita income)	(2) Log(per capita wage)	(3) Log(per capita operational income)	(4) Log(per capita property income)	(5) Log(per capita transfer)
$APRP_{public,ht}$	0.115***	0.218***	0.0484	0.247	0.0596*
	(0.0217)	(0.0492)	(0.104)	(0.180)	(0.0360)
$APRP_{voucher,ht}$	0.0429	−0.00495	0.0473	0.457***	0.0694
	(0.0268)	(0.0689)	(0.123)	(0.161)	(0.0543)
Observations	58,039	57,780	57,619	57,122	58,047
Number of unique_id	11,738	11,736	11,734	11,734	11,738
Adjusted R-squared	0.697	0.271	0.059	0.496	0.270
Balanced	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y
Relative ATT (Public vs Voucher)	0.0723***	0.223***	0.00102	−0.210	−0.00975
$p-$ value (Public vs Voucher)	0.00853	0.00580	0.994	0.354	0.881

Notes: Controls are selected for each dependent variable with LASSO, and robust standard errors in parentheses are clustered at the village level. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

significantly increased property income and that public housing significantly increased transfer income, respectively. Comparing the effects of the two relocation types, we can see in the bottom two rows that only the effects on per capita wage and per capita income are significantly different ($p < 0.01$). This notion attests to our conjecture that public housing relocation has a larger positive impact on wage income and net income compared to housing voucher relocation. Additionally, the finding that offering housing vouchers cannot improve aggregate economic outcomes, measured by per capita income, and labor market outcomes, measured by wage income, is consistent with previous results in Jacob and Ludwig (2012) and Barnhardt et al. (2017). In Appendix E.4, we conduct an event study for each relocation type, and the findings are consistent with the DID results here.

We are curious why housing vouchers have no positive impact on wage income, given that they have improved access to main roads and more job opportunities in the county center compared to before the relocation. We propose two potential explanations. The first one is the income effect of the housing voucher, which is that the housing voucher provides a negative incentive to participate in the labor market because of its cash transfer nature. The other is the disruption and isolation effect of the housing voucher relocation wherein households move out of their home township and suffer a loss of social interactions with others in their original communities. Detailed discussions are provided in Appendix E.4.3.

5.2.2. Heterogeneity in labor competitiveness

Based on our conceptual framework, we hypothesize that individuals with comparative advantage in the non-agricultural sector benefit more from the APRP. We consider three variables to find empirical counterparts to the potential income in the non-agricultural sector: gender, working experience, and health conditions. We generate three dummies: whether one is male, whether one has working experience in the last year, and whether one is healthy (i.e., no serious illnesses, no chronic diseases, and no disabilities). We assume that male workers have higher potential income than females for two reasons. The first reason is the potential discrimination in the labor market, and the other is that females take on the main household responsibilities in China, such as taking care of the elderly and young children. We also assume that experienced and healthy workers should have higher potential income in the labor market.

We investigate the effects of the APRP on different sub-groups defined by the dummies mentioned above using Eq. (4). In Eq. (4), $Month_{it}$ is the number of months of work of individual i in year t; public housing and housing voucher groups are indicated by $APRP_{public,it}$ and $APRP_{voucher,it}$; $X_{j,it}$ stands for individual-level control variables including age, gender, level of education, capacity for work, health condition, and social insurance participation; φ_i is individual fixed effects; γ_t is time fixed effects; u_{it} is the error term.[30]

$$Month_{it} = \beta_0 + \lambda^c \cdot APRP_{public,it} + \lambda^d \cdot APRP_{voucher,it} + \sum_{j=1}^{k} \beta_j X_{j,it} + \varphi_i + \gamma_t + u_{it} \tag{4}$$

We compare the differences in coefficients across different sub-samples in Fig. 7. Notably, public housing significantly increased the working time only for those who are relatively more competitive in the labor market. However, housing vouchers had no significant positive effect on any sub-group, which is consistent with the findings in the previous subsection.

These results are consistent with the Roy-model-based framework wherein the income increase facilitated by the switch across sectors depends on comparative advantage in the non-agricultural sector. They also provide a new perspective for understanding the results in previous literature. Following the line of the competition model discussed by Jencks and Mayer (1990), offering more opportunities would not make workers more competitive if they were disadvantaged due to family care responsibilities or poor health. Instead, this strategy would help those who were competitive but constrained by limited opportunities.

Field (2007) and Franklin (2020) documented significant positive effects of housing assistance programs on female labor supply. The present study is in line with theirs, such that both pieces of literature emphasize the importance of removing barriers in increasing labor supply. In our study, however, further migration to places outside Xin County is important for earning a wage. Women may lack the motivation to migrate if they need to take care of family members left behind. Besides, they may be constrained by limited job opportunities if most positions available are related to manufacturing or construction. Nevertheless, when local job opportunities are available in poverty alleviation workshops around public housing communities, female members of the labor force living in those communities increase labor supply significantly as shown in Table E10.[31]

[30] In Appendix E.4, we report the dynamic panel data model results by including a lagged dependent variable $Month_{i,t-1}$ in the regression because the working status of an individual affects their working status in the next year. As indicated in Fig. 7, the difference of dependent variables may be correlated with one's consistent characteristics, like gender. Thus, System-GMM may not be appropriate, and the model is estimated by a Difference-GMM method.

[31] We thank the reviewer for a discussion on this point.

Fig. 7. Comparisons of coefficients across sub-samples.
Notes: Estimation results of Eq. (4). Each dot specifies the point estimation of the treatment effect of APRP via relocation type, and each vertical line with a cap signifies the 95% confidence interval of the treatment effect. Samples are all restricted to working-age adults (i.e., 25192 individuals), and the left part of the figure compares the female (42.3%) and male IPH members (57.7%). The middle part compares the IPH members who did not work (48.2% of the observations) and those who worked in the previous year (51.8%). The right part compares the IPH members who were unhealthy (i.e., with a disability, serious illness, or chronic disease; 19.4%) and those who were healthy. Control variables include age and its squared term, individual education level, health condition, labor force status, whether a student, whether a Dibao/Wubao recipient, and area of woodland owned by the household. Robust standard errors are clustered at the village level.

5.3. Mechanisms

To complete the argument that our conceptual framework in Section 4 provides insightful predictions of the effects of the APRP, we need to show that the increase in income and labor market outcomes are indeed induced by a reduction in switching cost m. We utilize the exogenous variations in the switching cost reduction, which arises due to the fact that participating households in the same public housing community are from different origin villages. Hence, the level of switching costs across sectors, along with other confounding factors (e.g., peer composition), are held equal after relocation. The variation of reduction in switching cost comes solely from the switching cost in the origin villages before relocation. We argue that such variation is exogenous to households because self-relocation across villages is very rare among poor households. Any effect of origin switching cost on individual-level unobserved characteristics is eliminated by comparing participants and non-participants in the same village. Thus, we can identify how reductions in switching costs determine the program's treatment effect.

As discussed above, the switching cost is multifaceted, and several variables are considered that potentially capture the pre-treatment switching cost. First, we consider the average income of IPHs and the average proportion of wage to total income. Based on the large agricultural productivity gap in China (Adamopoulos et al., 2022a), the average income is expected to be higher in places with more IPHs working in the non-agricultural sector. Furthermore, based on our conceptual framework, a higher proportion of wage to total income is only possible with a lower switching cost when IPHs are heavily constrained by credit constraints, despite the distribution of comparative advantage. Second, transportation conditions measured by Terrain Ruggedness Index and average slope are considered.

We exclude households in the housing voucher group in this part of the empirical analysis as the empirical strategy only applies to the public housing group. The empirical model is stated in Eq. (5):

$$\ln Y_{ht} = \beta_0 + \lambda^* \cdot APRP_{public,ht} + \psi \cdot APRP_{public,ht} \times m_h^0 + \sum_{j=1}^{k} \beta_j X_{j,ht} + \alpha_h + \gamma_t + u_{ht} \tag{5}$$

where m_h^0 denotes the original switching cost measured in 2014, capturing the inverse of the reduction in switching cost. Hence, a negative ψ indicates that switching cost reduction across sectors does have a significant impact on the treatment effect of APRP on household income.

Estimation results are exhibited in Fig. 8. Consistent with our predictions, households that came from villages with lower average income, a lower average proportion of wage on total income, and worse transportation conditions benefit significantly more from the APRP. From these findings, we conclude that households that were initially trapped in the agricultural sector and lacked non-agricultural job opportunities are more likely to benefit from the program.

Further, we test whether the information friction of finding non-agricultural jobs accounts for a major part of the switching cost. We exploit the exogenous policy variation of access to poverty alleviation workshops as discussed in Section 2. We hypothesize that if information friction is an important type of switching cost, offering extra job opportunities in nearby workshops will improve the treatment effect on the program's economic outcomes. As depicted in Table E10, there is no significant interaction effect on per capita income or wage income of access to poverty alleviation workshops. Therefore, we exclude information friction as a critical component of the switching cost.

Although the empirical design in Eq. (5) excludes the effect of exposure to neighbors in towns that are typically paid higher and more educated, it is interesting to see if moving to a community with high income generates a larger positive impact on the treated. As we can only access IPHs' income data, we assume villages with a higher average income of IPHs also have higher average income in general. We simultaneously add two interaction terms of $APRP_{public,ht}$ and the average income of IPHs in the destination village in 2014, as well as in 2017, into Eq. (5). Outcomes in Table E11 prove that, although households do benefit more from the APRP in villages with a higher average income of IPHs, the impact comes from a larger treatment effect on transfer income but not wage income.

As in Section 5.1, we control for the effect of the housing renovation program. Results show that the housing renovation program, which improves housing quality but does not change the households' location, has no impact on economic outcomes, suggesting that improved housing quality is not a crucial mechanism.

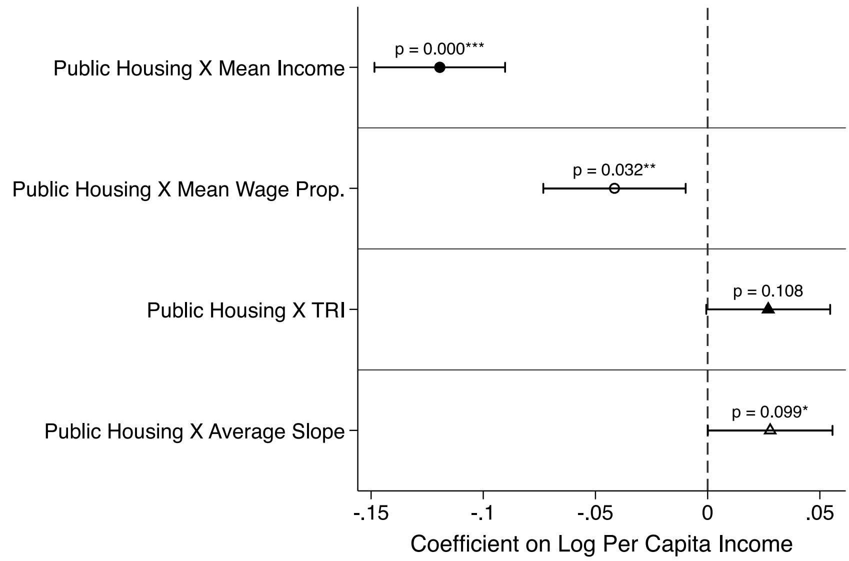


Fig. 8. Reduction in switching cost and ATT.
Notes: Each mark highlights the coefficient of the interaction term calculated in a separate regression. Capped solid lines indicate the 90 percent confidence interval, and the *p*-value of each coefficient is shown. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

6. Cost–benefit analysis

The cost–benefit analysis of APRP not only provides suggestive evidence regarding the extent of credit constraints faced by impoverished households but also provides direct policy implications for the government. Based on data availability, we conduct a back-of-the-envelope calculation to compare the fiscal expenditure of the program and the increase in household lifetime income induced by the program.

We conduct the cost–benefit analysis under different growth scenarios and assumptions of the treatment effect for the following considerations. Given that the treatment effect is estimated with a DID method, the increase in income is relative to the lifetime income of the counterfactual situation. Additionally, the medium- to long-term effect of the APRP may not be the same as the short-term effect estimated in this paper.

The basic idea of our calculation is summarized in Eq. (6).

$$\text{Net Benefit} = \underbrace{\sum_{y=2014}^{2018}\left[I_y - \left(\frac{1}{1+\delta}\right)^{y-2016} g_c^{y-2016} I_{2016}\right]}_{\text{benefit within the data period}} + \underbrace{\left\{\sum_{t=1}^{T}\left(\frac{1}{1+\delta}\right)^{t}\left[\lambda_t g^t I_{2018}\right]\right\}}_{\text{benefit on life-cycle income}} - \underbrace{(1+\tau)C}_{\text{cost of the program}} \tag{6}$$

where

$T = 43, \quad \delta = 0.03, \quad \tau = 0.3, \quad C = 60000$
λ_t : treatment effect at period t
g_c : 1 + average growth rate of control group in 2014–2018
g : 1 + counterfactual growth rate
I_y : per capita income of the treatment group at year y within data period

The explicit and implicit assumptions embedded in this calculation are listed as follows. (1) An individual earns income for 43 years (from the age of 18 years to 60 years). (2) The discount rate is 3%, and (3) the marginal cost of public funds is 0.3 (Finkelstein and Hendren, 2020).

The three parts on the right-hand side of Eq. (6) are listed as follows. (1) The benefit within the data period. We compute the counterfactual per capita income of households in the treatment group utilizing the control group's average annual growth rate from 2014 to 2018. All monetary values are in 2016 Yuan, and the gap between the actual income in the data and the counterfactual income is the benefit of the APRP within the data period. (2) The benefit of life-cycle per capita income. It is calculated as the discounted sum of the product of treatment effect λ_t and counterfactual income under a specific assumption of counterfactual real growth rate for the treatment group. (3) The cost of APRP. This cost is normalized to 78,000 Yuan based on the per capita expenditure of 60,000 Yuan set by the central government, times an excess burden factor of 1.3 (i.e., one plus the marginal cost of public funds stated above).

The long-term potential benefit provided to the next generations may exceed the benefit given to adult participants. As illustrated in previous literature, the benefit of relocation on young children is considerable (e.g., the intention-to-treat effect on wage income is about 14.41% in Chetty et al., 2016, and 16% in Chyn, 2018). However, rural households may eventually catch up with those who relocated in the long run. Thus, we consider three scenarios of treatment effect λ_t: (1) constant $\lambda_t = 0.0961$ as the baseline estimation in Table 3, (2) λ_t is increasing linearly to 15% in 40 years, and (3) λ_t is decreasing linearly to zero in 40 years. Results are summarized in Fig. 9. Under the first scenario, the benefit will exceed the cost of the program when the counterfactual real growth rate reaches 6.45% annually. This growth rate is quite steep but may be achievable for a rapidly growing country like China.[32]

We did not consider the redistribution effect of the program, which potentially can be considerable because the APRP targets impoverished households. Non-pecuniary benefits and costs are not considered in this cost–benefit analysis; thus, the result is likely to underestimate the APRP's net benefit and should not be regarded as a welfare analysis.

The broad implication is that the returns to relocation are higher than the costs for many participating households, suggesting that a considerable number of households are trapped in rural poverty, and

[32] In 2019, the real growth rate of per capita income for rural households in China was 6.2%, and the growth rate for rural households in poor areas was 8.0%. Sources: http://www.stats.gov.cn/english/PressRelease/202001/t20200119_1723719.html, http://www.stats.gov.cn/english/PressRelease/202002/t20200203_1724909.html. Last accessed: Aug 7, 2022.

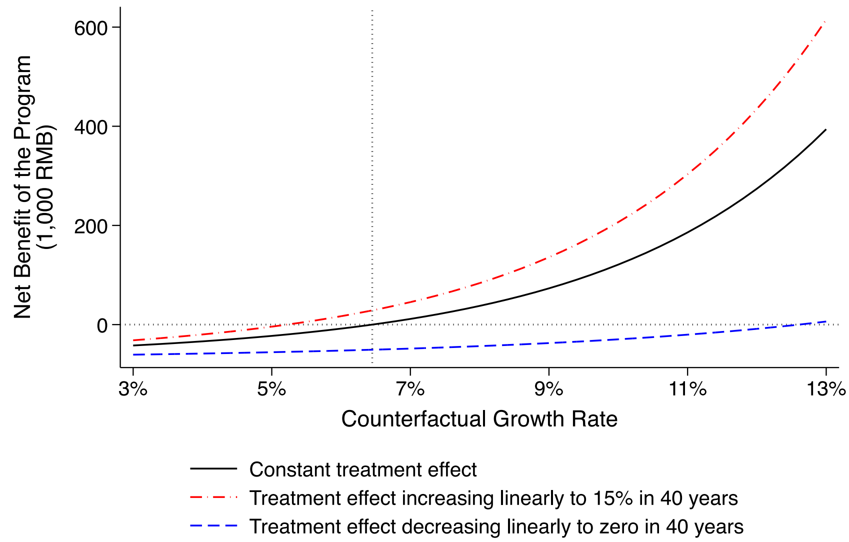


Fig. 9. Net benefit of the program and counterfactual growth rate.
Notes: This figure relays the net benefit of the APRP throughout a participant's life cycle under various scenarios of treatment effect, and different counterfactual growth rate. The vertical dotted line outlines a counterfactual growth rate of 6.45%.

policy interventions akin to the APRP could be a feasible choice for the government to help these households.[33]

7. Conclusion and implications

In 2020, China announced victory against poverty by successfully eliminating extreme poverty, lifting 98.99 million impoverished people out of poverty. However, less is known about the wisdom of poverty reduction in China.

To fill in the gap, this study assesses the effects of a large-scale anti-poverty relocation program in rural China and explores the underlying mechanisms. The relocation brought many changes to the treated households regarding surrounding socio-economic conditions, even though the relocation distance was very short (i.e., less than 15 kilometers on average). The relocation program improves households' access to non-agricultural job opportunities significantly. From this perspective, we incorporate a Roy-model-based conceptual framework with comparative advantage in sectors, switching costs, and compensating differential in amenities, to understand the effects of the program.

The conceptual framework sheds light on the potential existence of labor misallocation across the agricultural and non-agricultural sectors in rural China due to switching costs across sectors. Mobility barriers across sectors exist even in a "local" context. Based on the conceptual framework, the APRP generates a positive impact on participants' economic outcomes by decreasing switching costs across sectors and bringing a net benefit to the economy when credit constraints are prevalent among participants.

A fine-scale administrative dataset covering the impoverished population in Xin County is used, and a DID method, along with other empirical strategies, is employed to provide empirical support to our framework. The APRP contributes to poverty alleviation by increasing household income and improving the labor supply. We find that public housing relocation improved the labor supply of those with higher potential income in the non-agricultural sector significantly. For households who received housing vouchers, they relocated to places with better access to educational resources, consistent with the fact that there are more young children in these households. As gain in educational resources partially compensates for the wage difference, the treatment effects on economic outcomes are smaller for the housing voucher group. Finally, we provide evidence that when households are highly trapped in the agricultural sector, they will benefit more from the program, consistent with our framework that switching cost across sectors distorts the labor market.

By comparing the fiscal expenditure of the APRP to the increase in lifetime income, our back-of-the-envelope calculation indicates that the APRP generates a net benefit to the economy when the counterfactual per capita income growth rate exceeds 6.45%. As the effect of relocation varies across relocation types and household characteristics, governments may improve the relocation's cost-effectiveness by improving the targeting accuracy. Comparing the relocation policy that targets specific households to other policies that generally improve access to the labor market by reducing the transportation cost (e.g., paving roads), we would like to emphasize that our treatment effect estimation comes from a DID method where both the treated and the control witnessed large-scale road construction during the sample period. The DID estimate captures excess improvement in economic outcomes while controlling for other programs. For ultra-poor households without access to vehicles, like the IPHs in our study, the effect of building roads could be limited. Finally, connecting roads for remote households that are spatially isolated could be expensive. A baseline implication is that relocation policy can prove to be a feasible choice for the government, especially for targeting ultra-poor households trapped in remote rural areas.

There are more research topics worthy of addressing in the future when the data become available. First, the APRP is a component of a systemic poverty alleviation campaign. It is worth comparing the effects and efficiency across different programs to determine the most efficient combination of poverty alleviation programs. Second, we study only the short-term impact of the APRP in Xin County because of data availability. When long-term data and information on more regions become available, further investigation is merited to fully understand

[33] Households are either trapped because of the unawareness of the returns of relocation, or information barriers in the housing market prevent them from moving to towns, or financial constraints that stop them from moving. Given that participating households did follow the sorting pattern predicted by our conceptual framework, they are likely aware of the returns to relocation and the situation in the housing market. Therefore, financial constraints should be the most pronounced barrier to these households. We thank the reviewer for the discussion on this point.

the effects of such relocation policies in other regions and future generations.

CRediT authorship contribution statement

Li Zhang: Conceptualization, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Lunyu Xie:** Methodology, Investigation, Resources, Writing – original draft, Writing – review & editing, Project administration. **Xinye Zheng:** Investigation, Resources, Supervision, Funding acquisition.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.jdeveco.2022.102945.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2022.102945.

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