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Women as breadwinners: A multifaceted relocation program and women's labour market outcomes

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ABSTRACT

This paper exploits the staggered timing of relocations across eligible households to examine its impact on female's labour market outcomes, under China's Poverty Alleviation Relocation Program (PARP). Utilizing four waves of household panel data that retrospectively record individuals' off-farm employment histories from 2011 to 2021, we find that relocation significantly increases the likelihood of off-farm employment among working-age women. However, it has limited effects on their annual working months, monthly wages, and annual earnings once being off-farm employed. Furthermore, the program's impact on men's off-farm employment is modest compared to that for women, suggesting that although PARP is designed to be gender-neutral, it has generated more favorable labour market effects for women than for men. Heterogeneity analysis further reveals that the increase in women's off-farm employment is more pronounced among those with lower educational attainment, those who are married, those with resident children, as well as those relocated to urban or collective sites. We also provide suggestive evidence that improved time allocation and reshaped social networks may be mechanisms encouraging women to step out of the home.

1. Introduction

Exploring effective ways to empower vulnerable and poor women in the long term has emerged as one of the most salient development issues worldwide (Duflo, 2012; UN, 2022; World Bank, 2024). The roots of female poverty are intricate, stemming from various factors such as women's limited access to markets, education and healthcare (Dupas and Jain, 2024; Keat, 2018), unequal inheritance rights to land and other assets (Bhalotra et al., 2020; Deininger et al., 2013), as well as labour market barriers and entrenched cultural norms (Doepke et al., 2012; Fogli and Veldkamp, 2011). In light of this, a growing number of policy interventions have been implemented to address multiple barriers encountered by women in diverse contexts.[1] However, the empirical results have been disparate, with many interventions yielding neither significant nor persistent effects. One plausible explanation is that these interventions often target one particular constraint, rather than employing the "big push" strategies that provide a battery of supportive measures (Angelucci et al., 2023; Bandiera et al., 2020; Banerjee et al., 2015; Maldonado, 2024).

This paper examines the impact of a large-scale poverty alleviation relocation program (PARP) in China on women's labour market outcomes – which is not only a crucial determinant of women's economic empowerment (Duflo, 2012), but also has important implications for gender wage differentials, marriage and fertility behaviors (Jensen, 2012), and aggregate productivity and welfare (Erosa et al., 2022). The primary objective of PARP was to lift the poor out of poverty through relocation, effectively addressing the multidimensional challenges faced by poor women and their households. Between 2016 and 2020, the Chinese government relocated over 9.6 million impoverished individuals from inhospitable areas to new settlements with improved infrastructure and job opportunities across approximately 1,400 counties in 22 provinces (Chen et al., 2025; Ding et al., 2024). While the central government outlined an overarching relocation plan, county-level governments retained the discretion to determine the

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[1] Representative interventions aimed at empowering women include programs related to education (Keat, 2018), skill training (Bandiera et al., 2020), microcredit (Kochar et al., 2022), asset transfer (Bandiera et al., 2017; Balboni et al., 2022), and the provision of direct job opportunities for women (Jensen, 2012).

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specific timing and locations of resettlements based on local conditions and resources. The plausibly exogenous variation in the timing of relocations for targeted households, therefore, enables the implementation of a staggered Difference-in-Differences (DID) identification strategy to investigate the causal effect of relocation on women's labour market outcomes in relocated households.

We draw upon a comprehensive longitudinal household-level dataset gathered through four survey waves spanning the period between 2011 and 2021. A distinctive feature of the dataset is the granular employment history module for household members who engaged in wage-earning activities, enabling us to trace changes in individual employment dynamics over a span of up to 11 years. Notably, all surveyed households were *eligible* for relocation and had ultimately underwent relocation by the survey endline. This helps mitigate selection bias concerning households' decisions on whether to relocate—a pervasive identification challenge in evaluating the causal effects of relocation programs (Bazzi et al., 2016; Nakamura et al., 2021). However, the absence of a pure control group (i.e., households that had never relocated) means that our staggered DID design is essentially a within-treatment group analysis, comparing households who relocated earlier with those waiting to participate in the program.

Our findings reveal that PARP has a significant, positive and economically meaningful impact on the labour market outcomes for working-age women at the *extensive* margin. Our preferred estimates suggest that compared to women who have not yet relocated, women in relocated households are significantly more likely to engage in off-farm employment by approximately 5.9 percentage points, or equivalently, a noteworthy 36.6 percent increase relative to the sample mean of the not-yet-relocated group. Extending our analysis to the *intensive* margin, we find that PARP significantly increases women's annual working months by about 0.5 months (15 days). We further investigate the impacts of PARP on monthly wage and annual earnings. While our results indicate that PARP significantly enhances women's monthly wage and annual earnings under the unconditional scenarios, these effects become insignificantly negative when conditioned on women who are employed. This implies that the positive impacts of relocation on women's labour market outcomes primarily operate on the *extensive* margin. We replicate these analyses for working-age men. The results show that the impacts of PARP on all of men's labour market outcomes (i.e. off-farm employment status, annual working months, monthly wage and annual earnings) are statistically insignificant under the most saturated specifications. Our examination of gender-differential effects reinforces the conclusion that, although the relocation program is gender-neutral by design, it has more pronounced impacts on women's labour market outcomes than on men's.

A causal interpretation of the observed labour market effects hinges on the assumption that, in the absence of the relocation policy, the outcomes of the relocated and not-yet-relocated groups would have followed similar time trends. Our event-study estimates provide compelling visual evidence, indicating that the estimated coefficients for all events one year before relocation are statistically indistinguishable from zero, thereby supporting the validity of the parallel trend assumption. To further solidify our results, we undertake a series of robustness checks to address potential issues such as heterogeneous treatment effects due to the staggered timing of relocations (Sun and Abraham, 2021), selection bias related to the *relative* timing of household relocation and other potential threats to our causal identification. The results of all these analyses consistently support our initial findings and reinforce the reliability of our main results.

We then delve deeper into the data to understand how PARP disproportionately affects women's likelihood of engaging in off-farm employment. Our exploration suggests that optimized time allocation and reshaped social networks are likely two key mechanisms driving the increase in women's off-farm employment. First, we find that households experienced significant improvements in dwelling conditions, having better access to tap water, stable electricity, flush toilets, and trash services. They also acquired more labour-saving consumer durables, such as electric cookers, washing machines, refrigerators and air conditioners. In addition, relocated households gained improved access to various public amenities. These combined improvements, both inside and outside the home, help save women's time spent on home production and childcare (Dinkelman and Ngai, 2022; Franklin, 2020; Greenwood et al., 2005). Our heterogeneous analysis further resonates the time allocation argument, showing that the effects on women's off-farm employment are more salient among married individuals and households with resident children.[2] Second, the results reveal that women are more likely to receive job referrals from friends and relatives after relocation, consistent with the well-established literature revealing the significance of social networks in providing information about job opportunities (Barwick et al., 2023; Dustmann et al., 2015; Meng and Xue, 2020; Munshi, 2003). Finally, we discuss the human capital mechanisms. However, the estimated results suggest that skill training and improved health status might play a secondary role in boosting women's off-farm employment.

This paper first contributes to the literature on the impacts of state-led relocation programs. Adopting analogous relocation policies to tackle development challenges is prevalent in many developing countries. However, existing evidence has predominantly focused on evaluating the effects on agricultural productivity and social integration (Gebresilasse, 2024; Mueller et al., 2014; Tang et al., 2022). For instance, Bazzi et al. (2016) revealed that Indonesia's Transmigration Program increased rice productivity in villages that received migrants from regions with more similar agroclimatic conditions one to two decades later. In a related study, Bazzi et al. (2019) delved into the long-term consequences of intergroup contact on national integration within the same program, revealing greater integration in fractionalized communities with many small groups and decreased integration in polarized communities with a few large groups. Shifting focus to China, a growing body of literature has explored the effects of the PARP on household income and labour reallocation, with relatively less attention paid to its consequences concerning women and the demographic heterogeneity of labour market outcomes (Qiu et al., 2024; Zhang et al., 2023). A notable exception is Ding et al. (2024), who find that PARP significantly enhanced married women's relative decision-making power within households. While this study confirmed that changes in married women's relative wage income was a key driver of household decision-making dynamics, it was constrained by the use of only two waves of household panel data, limiting a detailed exploration of women's labour market outcomes. The extended periods of individual employment history data from 2011 to 2021 enable us to close this research gap.

Second, our study is closely linked to the broader literature examining the determinants of female labour supply. Studies exploring the determinants is immense, including women's human capital improvement such as educational attainment (Goldin, 2006), psychological attributes such as risk preferences and attitudes towards competition and negotiation (Bertrand, 2011), labour demand shocks such as the expansion of the service sector (Blau and Kahn, 2017), technological advancements such as oral contraceptives, electrification and automation (Anelli et al., 2021; Autor et al., 2024; Bailey, 2006; Goldin and Katz, 2002), institutional changes such as reforms related to property rights and divorce laws (Doepke et al., 2012; Huang et al., 2023), as well as cultural factors such as gender identity and gender norms (Bertrand et al., 2015; Fernández, 2013). However, these studies have largely

[2] Our survey data also include detailed individual time-use information on specific tasks such as grocery shopping and cooking, and firewood collection, although not comprehensive across all types of housework. Using these data, we provide suggestive evidence that relocation significantly reduces women's time spend on these activities. We further discuss this in the mechanism section (please see Appendix Table A12).

neglected the crucial impact of changes in neighborhood quality on female labour supply.[3] To the best of our knowledge, we are the first to systematically examine the impacts of substantial changes in living conditions on women's labour market outcomes under the context of China's large-scale relocation program.[4] Specifically, our paper provides novel evidence that improved living conditions might play a key role in shaping women's labour market trajectories by saving their time in home production and child-rearing, aligning with Becker's (1965) time allocation theory. Moreover, we provide suggestive evidence that reshaped social networks may also play a role in boosting women's off-farm employment.

The rest of this study proceeds as follows. Section 2 provides the background of China's poverty alleviation relocation program. Section 3 describes our survey, data and summary statistics. Section 4 outlines our empirical strategy. Section 5 presents our main results of the effects of PARP on women's labour market outcomes, probes the robustness of our results and explores the heterogeneity among different subgroups. Section 6 sheds light on the potential mechanisms underlying the effect of the relocation program and the final section concludes.

2. Background: China's poverty alleviation relocation program

On the eve of China's Targeted Poverty Alleviation (TPA) strategy in 2013, the remaining pockets of poverty were predominantly concentrated in remote and mountainous areas. These regions were generally characterized by harsh natural conditions, frequent natural disasters, and challenging living conditions. The poor living conditions appear to be a "Great Curse" for people living there due to the scarcity of economic resources and opportunities, worsening their subsistence situations and trapping them in these areas for generations. Recognizing the severe "poverty traps" faced by the disadvantaged in these areas, the Chinese government launched a new-round Poverty Alleviation Relocation Program (PARP), which became the flagship initiative among the *Five Measures for Poverty Elimination*.[5] The program aimed to systematically relocate over 9.6 million impoverished individuals to better locations between 2016 and 2020. By the end of 2020, approximately 600 billion RMB (≈ 87 billion US dollars) had been invested in PARP and around 35,000 new resettlements have been constructed. Meanwhile, all program participants were successfully resettled into new homes equipped with basic infrastructure and public services.

Natural villages (or villager groups) served as the basic unit for determining the relocation regions within each county. Following the guideline outlined in the *13th Five-Year Plan for Poverty Alleviation Relocation*, the chosen areas generally met at least one of the following conditions: 1) Poor production and living conditions, such as limited access to land and water resources; 2) Fragile ecological environments; 3) Frequent geological disasters or prevalence of endemic diseases; 4) Designation as restricted development zones, ecological protection zones, or other functionally constrained areas; 5) Remote locations with severely underdeveloped infrastructure and public services; 6) Other reasons, such as highly scattered living patterns. Once the natural villages or villager groups were selected, township governments will submit the list of planned relocation sites to the county-level Leading Group Office of Poverty Alleviation and Development for approval and subsequent implementation.

Within the approved relocation regions in each county, local governments proceeded to identify the targeted households, which were primarily identified poor households (IPHs) registered in the National Poverty Alleviation and Development Information System (NPADIS) since 2013.[6] These households typically lived in adobe huts with thatched roofs or stone houses, often lacking access to running water, stable electricity and sanitary toilets. However, non-IPH households could also participate through the "Accompanying Relocation" policy. The final list of program participants was a joint decision of eligible households and multiple levels of government: households first applied for program participation, and then the village committee verified their eligibility before submitting relocation applications to the Leading Group Office of Poverty Alleviation and Development (LGOPAD) in the county. Notably, households could withdraw their applications even after approval with full exemption (Zhang et al., 2023). In other words, PARP only relocated eligible households that voluntarily opted for relocation.[7]

A merit of PARP was the arguably exogenous timing of relocation for program participants. County-level governments designed and executed relocation plans, and the timing of relocation was largely determined by the construction process of different resettlements. For collectively relocated households, the locations of the resettlements were also selected by local governments, implying that beneficiaries had no say over where they could move.[8] As suggested by the national guidelines of PARP, it was preferable to build resettlements in places with convenient transportation and complete infrastructure and public service facilities (such as central villages, town centers, or industrial parks), taking local land availability, landscape, and other factors into consideration.

Furthermore, for collectively relocated households, the housing allocation process was largely random. Local governments allocated units to housing applicants whenever new housing projects were developed. Typically, for households of the same size, housing units were randomly allocated by lotteries (Qiu et al., 2024). The quality of new houses conformed to strict standards and was strictly supervised by local governments. The size of the housing units was capped at 25 m^2 per

[3] An extensive body of literature underscores that improvements in neighborhoods yield substantial positive effects on adult labour supply and happiness (Cattaneo et al., 2009; Field, 2007; Franklin, 2020), and also have profound impacts on intergenerational outcomes (Chetty et al., 2016; Chyn, 2018; Galiani et al., 2017). Yet, most studies examining the effects of neighborhood exposure have largely overlooked the gender dimension.

[4] Existing literature investigating the impacts of living conditions on individual labour supply has so far largely focused on urban slum upgrading programs, with limited exploration of relocation programs for rural households (Franklin, 2020).

[5] The *Five Measures for Poverty Elimination* could be found in a white paper titled Poverty Alleviation: China's Experience and Contribution, which was released by the State Council Information Office of the PRC. (Available at: http://www.china.org.cn/english/china_key_words/2021-01/12/content_77106208.html)

[6] To improve the targeting of poverty alleviation, the Chinese central government developed the NPADIS database to monitor the poverty dynamics of the IPHs. In the meanwhile, the central government established the village first secretary system, wherein these village first secretaries are tasked with routinely updating the poverty status of all households within the database (He and Wang, 2017). The poverty status recorded in the database is categorized into three groups: not poor, poor (currently enjoying the policy) and out of poverty (no longer enjoying the policy).

[7] From a policy-making perspective, the PARP was oriented to be voluntary, as stated in the national guideline of PARP: "voluntary to move, all who should be relocated should move" (in Chinese: *qun zhong zi yuan, ying ban jin ban*). However, in practice, the relocation process may involve both voluntary and involuntary elements. Local governments had incentives to encourage relocation in light of performance evaluations and the potential to generate surplus construction land. As a result, some eligible households might have been somehow involuntary to relocate. We thank an anonymous reviewer for raising this important point.

[8] Collective relocation refers to public housing relocation, in which relocated households move into designated resettlement sites selected by the local government. Under this type of relocation, the government is responsible for constructing public housing, infrastructure, and providing public services in these sites. In contrast, dispersed relocation refers to housing voucher relocation, where households are free to choose the location of their new home (outside their original natural village), and receive a subsidy after purchasing or building it. In our sample, about 78.7% of relocated households opted for collective relocation.

person. The housing units were uniformly five or six stories, typically with one or two bedrooms, one bathroom, one kitchen and one living room, connected to tap water and electricity in the home. Notably, beneficiaries could receive a new house only by giving up their previous homesteads, which were reclaimed by the government with a compensation of 30 Yuan/m^2 (Zhang et al., 2023). This condition is crucial for our identification, ensuring that households who completed relocation were almost surely living in their new houses, rather than merely owning them.[9]

3. Data

3.1. Survey and data

The dataset used in this study comes from a longitudinal survey of rural poor households, conducted by the Renmin University of China. The primary objective of the survey was to evaluate the impact of the PARP on the welfare of relocated households. The baseline survey was conducted in 2016, followed by three subsequent waves in 2017, 2019, and 2021. A total of 2,185 households were interviewed at baseline, and 2030 were successfully re-interviewed in the 2021 endline survey, yielding an overall attrition rate of approximately 7 %.

A stratified random sampling strategy was employed to select sample households. First, eight provinces with the largest populations slated for relocation—Hubei, Hunan, Guangxi, Sichuan, Guizhou, Yunnan, Shaanxi, and Gansu—were selected. Within each province, two major participating counties were chosen based on the scale of relocation and their geographical representativeness.[10] Second, within each county, two or three participating townships were randomly chosen using a complete official list of the townships provided by the county governments. Third, within each selected township, three administrative villages were randomly selected from the list of eligible villages offered by the township government. Finally, twenty households participating in the relocation program were randomly selected using village household rosters. Notably, all sampled households in the baseline survey were included in the relocation plan, ensuring comparable external conditions and household characteristics across the sample.

As depicted in Fig. 1, the resulting sixteen counties are geographically representative of China's poor regions. Table 1 further compares the socio-economic characteristics of sampled counties in 2015 (i.e., before the PARP) with other national poor counties (NPCs) in China to indicate the representativeness of the sampled counties. The findings show that, across most socio-economic variables, the mean differences between the sampled counties and the rest of NPCs are statistically insignificant or only marginally significant at the 10 % level, except for fiscal expenditure *per capita*.

The survey was collected at three levels: origin villager groups, resettlement communities, and households. In the baseline survey of origin villager groups, village cadres were asked to report the three main reasons their villager group was included in the relocation program. As Appendix Fig. A1 depicts, approximately 77 % of villager groups indicate remote geographic location as the primary reason for relocation, while 46 % pointed to poor natural conditions—such as lack of water and arable land, or location in alpine regions. About 36 % of villager groups mentioned fragile ecological environments, and 30 % referred to frequent natural disasters or endemic diseases. These reported prevailing reasons closely align with the selection criteria for relocation regions described in Section 2. Additionally, the villager group questionnaire also collected information on natural, economic, and demographic characteristics, facilitating us to examine the determinants of households' relocation timing at the villager-group level.

The household questionnaire included modules that enumerated household demographics, household income and expenditures, business activities, contracted land, livelihood assets, housing conditions, and other information. Specifically, the employment history module has two significant advantages. One merit is its retrospective nature which allows us to reconstruct labour market trajectories for each individual from 2011 to 2021 using four waves of survey data.[11] The long panel structure not only allows us to control for individual and year fixed effects and flexibly capture village-group-specific time-varying unobservables, but also facilitates testing the parallel trends assumption. Another merit was that our panel data provides comprehensive coverage of individual off-farm employment. Appendix Fig. A2 provides an example of the original employment module from the 2017 household survey questionnaire. As shown, the module includes detailed information on the number of working months per year, monthly wage, and granular data on the locations, occupations, sources of off-farm employment, and labour contracts. We define an individual's annual off-farm employment status based on the number of working months, assigning a value of one if the individual worked any months in a given year and zero otherwise. Furthermore, we construct a measure of annual earnings, defining it as the product of monthly wage and the number of working months. The rich employment information enables us to disentangle the effects of price (monthly wage) and quantity—both at the *extensive* margin (whether the individual engaged in off-farm work) and the *intensive* margin (how many months he/she worked).

Another crucial facet of our household survey was its comprehensive coverage of the household's relocation experience, encompassing the timing of relocation, types of relocation (collective or dispersed), and attributes of relocation (urban or rural). Fig. 2 illustrates the staggered inclusion of households into the relocation programs, with the relocation years ranging from 2015 to 2020. Among the eligible households, approximately two-thirds moved during 2017 and 2018, with almost all households (98.6 %) completing relocation in 2019. At the end of 2020, all eligible households had successfully relocated.

3.2. Sample

We implemented several restrictions to form the sample for this paper. First, households benefiting from similar poverty alleviation policies aimed at improving living conditions, such as the renovation program for dilapidated houses (*Wei Fang Gai Zao*), scenic countryside development, and original residence reconstruction, were excluded. Moreover, households initially assessed as eligible but subsequently deemed ineligible during PARP's follow-up inspections were excluded. Second, to examine women's labour market outcomes, we restricted the sample to working-age women aged 22 to 60.[12] After removing

[9] The ownership of new houses in resettlements belongs to the relocated households. Local governments will issue real estate rights certificates to these relocated households in accordance with regulations. However, to avoid the risk of these households falling back into poverty, the new houses cannot be rented out, sold, subleased, used as collateral, or financially profited within 20 years after relocation (Qiu et al., 2024).

[10] Column 1 of Appendix Table A1 presents the scale of the relocated population in each sampled county at the end of the relocation program, ranging from 9,700 in Wuding County to 62,800 in Ziyang County.

[11] The household survey not only collected individual's employment data in the year preceding the survey year but also all previous years since the last survey. In particular, the 2016 wave gathered information on individuals' employment history from 2011 to 2015, the 2017 wave documented individuals' employment history for 2016, the 2019 wave compiled individuals' employment history for 2017 and 2018, and the 2021 wave collected individuals' employment history from 2019 to 2021.

[12] We also restrict the sample to working-age women aged 15 to 65, in line with the international standards where ages 15 and older are generally considered the working-age population (ILO, 2023). The estimated coefficients on the *Relocate* variable remain almost unchanged across all dependent variables. The results are available upon request.

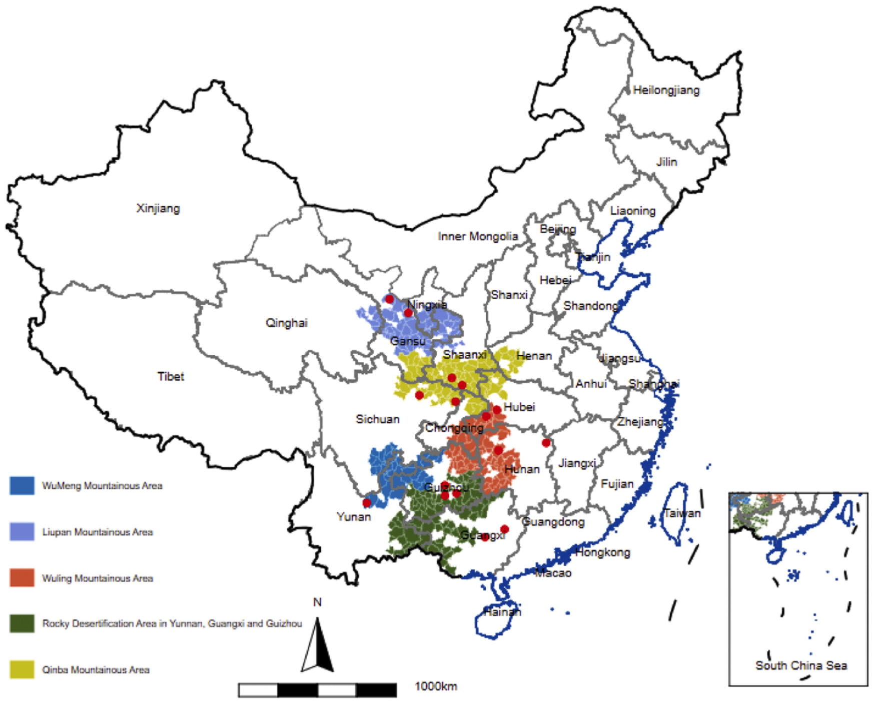

Fig. 1. Geographical distribution of sampled counties.
Notes: The regions shaded in different colors represent five contiguous areas of extreme poverty designated in 2012, while the red circles represent the 16 sampled counties.

observations with incomplete information on labour market outcomes, we create an unbalanced panel containing all prime-aged female individuals with at least two years of employment data. This panel includes 12,254 female-year observations spanning the years 2011 to 2021, corresponding to 1,963 unique female individuals. Among them, 580 female individuals are observed every year from 2011 to 2021. In our main analysis, we utilize the full unbalanced panel data to maximize the statistical power, but also perform robustness checks using the balanced panel.

Given the unbalanced nature of the individual panel data, we further examine attrition at the individual level. Specifically, we define an individual as attrited if she or he was not surveyed in the endline survey, equal to one for attrition and zero otherwise. We then determine whether attrition status is systematically related to baseline individual and household characteristics for sampled individuals aged 22 to 60. Column 1 of Appendix Table A2 show that attritors and non-attritors are generally well balanced across most baseline characteristics, with the exception of individual's gender and health status. More importantly, the attrition status is not significantly associated with individuals' baseline off-farm employment status or their household's relocation timing, suggesting that attrition is unlikely to introduce bias to the results.[13]

3.3. Descriptive statistics

Table 2 presents the years covered (column 1) and descriptive statistics (columns 2–4) for the variables used in our study. Specifically, the labour market outcomes of interest include: each woman's off-farm employment status, out-migration status,[14] annual working months, monthly wage, annual earnings, whether she signed a labour contract, whether she created business, agricultural work status and overall work status.[15] The primary explanatory variable is a dummy variable indicating whether the household has already been relocated in a specific year. Control variables include: 1) individual's age, ethnicity, educational attainment and marital status; 2) the number of children within households; 3) respondent's age, gender and educational attainment.

As depicted in Table 2, among females between 2011 and 2021, approximately one quarter (24.7 %) of observations indicated that they engaged in off-farm work in a given year. However, the average out-migration rate was only 15 %, suggesting that roughly 61 % of employed women chose to work outside their home county. Fig. 3 depicts the evolving dynamics of women's off-farm employment and out-migration rates between 2011 and 2021. The proportion of females engaged in off-farm employment saw a notable increase from 6.6 % in 2011 to 43.4 % in 2021, peaking at 44 % in 2020. Similarly, the proportion of females working outside their home county gradually rose from 4.4 % in 2011 to 23.4 % in 2021.

We then turn to the summary statistics on other outcomes of off-farm employment. The average duration of off-farm employment was around 2.3 months per year. The average monthly wage was only around 603 Yuan, much lower than the lowest tier of the monthly minimum wage in 2020.[16] Annual earnings from off-farm work, on average, were

[13] In Columns 2-3 of Appendix Table A2, we further examine whether the relocation timing is associated with predetermined individual and household characteristics for non-attritors and attritors, respectively. We construct a binary variable, *Early Relocation*, indicating whether a household relocated in or before 2017, and regress it on a set of predetermined characteristics. The results reveal no significant differences in baseline characteristics between early- and late-relocated groups for both non-attritors and attritors.

[14] Since relocation is akin to migration, it is necessary to define out-migration clearly in our context. Here, out-migration is defined as someone leaving their home county, regardless of whether they have been relocated or not.

[15] Data on individuals' labour contract, business creation and agricultural status were not collected consistently each year between 2011 and 2021. Overall work status is defined as whether an individual engaged in either farming or off-farm employment in a given year.

[16] The lowest tier of China's monthly minimum wage in 2020 was 1,180 Yuan. Data on monthly minimum wage in 2020 was available at: http://www.mohrss.gov.cn/SYrlzyhshbzb/laodongguanxi_/fwyd/202004/t20200426_366507.html

Table 1
Representativeness of sampled counties.

Variables	Sampled Counties (1)	Other NPCs (2)	Difference (3)=(2)-(1)
Population density (10,000 Person/ km^2)	0.018	0.018	0.000
	(0.007)	(0.022)	(0.002)
Share of GDP in the primary industry (%)	24.02	23.81	−0.204
	(6.956)	(10.87)	(1.780)
Share of GDP in the secondary industry (%)	38.55	36.89	−1.665
	(13.55)	(14.67)	(3.426)
GDP *per capita* (Yuan)	20,566	22,903	2337
	(7504)	(13,260)	(1933)
Fiscal expenditure *per capita* (Yuan)	5716	9861	4145***
	(1346)	(7361)	(423.9)
Deposit *per capita* (Yuan)	13,877	15,255	1379
	(4554)	(8426)	(1213)
Household size (Persons)	4.490	4.659	0.168
	(0.516)	(0.986)	(0.134)
Housing area (m^2)	125.6	122.4	−3.167
	(23.84)	(45.42)	(6.170)
Age (Years)	36.05	34.65	−1.402*
	(2.969)	(3.807)	(0.754)
Proportion of males (%)	0.525	0.514	−0.011*
	(0.020)	(0.030)	(0.005)
Proportion of married (%)	0.703	0.701	−0.003
	(0.035)	(0.072)	(0.009)
Educational attainment (Years)	7.942	7.580	−0.362*
	(0.669)	(1.423)	(0.175)
Observations	16	816	

Notes: This table compares socio-economic variables of Sampled Counties measured in 2015 with other National Poor Counties (NPCs) in China. The data of the first six variables comes from the County Statistical Yearbook of China. The remaining variables are calculated from the 2015 1 % National Population Sample Survey of China. Colum 3 reports the results of Welch's *t*-test for equality of means. Standard deviations (columns 1 and 2) and standard errors (column 3) are reported in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

approximately 5636 Yuan. Across all years for which labour contract data is available (2015, 2018–2021), about 13.6 % of individual observations revealed that they worked under a labour contract, aligning with existing literature that highlights the high prevalence of informal work among women in developing countries, which often falls outside the purview of labour regulations and policies (Jayachandran, 2021; Katzkowicz et al., 2021). Moreover, very few females ran a business, accounting for only 1.1 % of observations.

Table 2 also unveils some noteworthy characteristics of the sampled women and their households. The average age among sampled women was approximately 41 years old. The proportion of sampled women identified as ethnic minorities was approximately 24 %, around 8 percentage point higher than the proportion of female minorities (16.4 %) in the eight sampled provinces in 2020.[17] This indicates the notably greater diversity among the relocated population. Sampled women attained about 5.2 years of education on average, roughly equivalent to completing primary school under China's compulsory education system. At the time of the survey, about 83 % of women were married. The average number of children per family was slightly less than one. In terms of the respondent characteristics, the average age was about 51 years old, and about 64 % of them were male. The average educational attainment was about 5 years.

4. Empirical strategy

We leverage the staggered rollout of relocation across households to investigate the impact of PARP on individual's labour market outcomes. The basic estimation equation is the following:

$$Y_{ihvt} = \alpha + \beta Relocate_{hv,t-1} + \delta_i + \mu_t + \varepsilon_{ihvt} \tag{1}$$

where Y_{ihvt} denotes a set of labour market outcomes for individual i residing in household h of origin village v in year t, including off-farm employment status, out-migration status, annual working months, the natural logarithm of monthly wage and annual earnings, and other outcomes. The key explanatory variable, $Relocate_{hv,t-1}$, is a binary indicator equal to one if household h in origin village v has relocated to the new destination in year t-1, and zero otherwise.[18] The specification includes individual fixed effects (δ_i) to control for time-invariant characteristics at the individual level and above that may be correlated with households' relocation timing and the individual's labour market outcomes, and year fixed effects (μ_t) to absorb macroeconomic shocks and other time-varying factors common across origin villages, such as the COVID-19 pandemic and the subsequent recession. Standard errors are clustered at the villager-group level to account for within-villager-group correlation over time and across individuals.

In Appendix Table A3, we further examine whether the timing of household relocation is predicted by pre-determined characteristics of origin villager groups and households.[19] The results show that only a few factors exhibit statistically significant coefficients, and the R^2 values across specifications are low. This suggests that baseline characteristics explain only a small share of the variation in relocation timing, leaving considerable idiosyncratic variation that can be exploited for identification. Despite of this, our preferred specification further includes villager-group-by-year fixed effects (μ_{vt}) to flexibly account for villager group-specific time-varying unobservables that may simultaneously influence both relocation timing and women's labour market outcomes.

The validity of our DID identification depends on the parallel trend assumption that the differences in labour market outcomes between the relocated and not-yet-relocated group would be constant in the absence of relocation. The parallel trend assumption might be violated if households that relocated in different years demonstrate a different development trajectory. To investigate this possibility, we conduct an event study on the impact of relocation to examine pre-relocation trends. The empirical model is specified as:

$$Y_{ihvt} = \alpha + \sum_{k=-4,k\neq-1}^{3} \beta_k Relocate_{hv,t_0+k} + \delta_i + \mu_t + \varepsilon_{ihvt} \tag{2}$$

where Y_{ihvt} are still labour market outcomes for individual i residing in household h of origin village v in year t. $Relocate_{hv,t_0+k}$ denotes a set of

[17] The proportion of female minorities in the eight sampled provinces in 2020 was calculated based on the data from *China Statistical Yearbook 2021*. The calculation of the proportion of female minorities was based on the total number of female minorities, because data on the number of working-age female minorities was unavailable.

[18] Given that many households completed relocation late in the year, we define treatment status based on the year after relocation and estimate its causal effect on women's labour market outcomes.

[19] As discussed earlier, the construction of the resettlements should take into account many factors. For instance, PARP may be carried out earlier in more disadvantaged regions and regions that suffered more severe natural disasters. Furthermore, the demographic structures of origin villages could also affect the rollout of relocation. If these potential characteristics of villages and regions are associated with differential trends in the outcome variables, the key parameter of interest, β, might be biased. Therefore, we generate two outcome variables to examine whether the household's relocation timing was determined by a range of baseline characteristics both at the villager group and household level. Columns 1-3 of Appendix Table A3 report results using a binary outcome indicating whether a household relocated in or before 2017; while Columns 4-6 use another binary outcome indicating whether the household relocated in the year of the first batch of relocations in its county. Across specifications, we find that both outcomes are associated with only a few baseline characteristics. We thank an anonymous reviewer for suggesting this analysis.

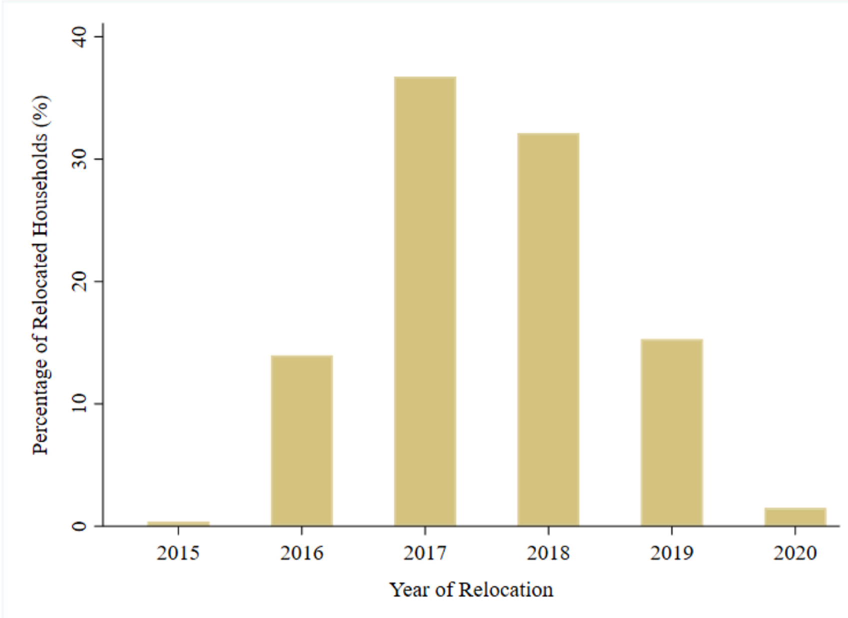

Fig. 2. Relocation rollout across relocated households.

Table 2
Summary statistics.

Variables	Years covered (1)	N (2)	Mean (3)	S.D. (4)
Dependent Variables				
Off-farm employment status (1=Engaged, 0 otherwise)	2011–2021	12,254	0.247	0.431
Out-migration (1=Worked outside home county, 0 otherwise)	2011–2021	12,254	0.150	0.357
Working months (Number)	2011–2021	12,254	2.296	4.297
Monthly wage (Yuan)	2011–2021	12,254	603.0	1299
Annual earnings (Yuan)	2011–2021	12,254	5636	13,044
Labour contract (1=Signed a labour contract, 0 otherwise)	2015, 2018–2021	5,986	0.136	0.343
Business creation (1=Ran business, 0 otherwise)	2016, 2018	3,458	0.011	0.106
Agricultural work status (1=Engaged, 0 otherwise)	2015, 2016,2018,2020	4,333	0.486	0.486
Overall work status (1=Engaged, 0 otherwise)	2015, 2016,2018,2020	4,343	0.411	0.411
Independent variable of interest				
Relocate (1=Yes, 0=No)	2011–2021	12,254	0.339	0.473
Characteristics of the female individual, household and respondent				
Age of the woman (Years)	2011–2021	12,254	40.97	11.20
Ethnicity of the woman (1=*Han*, 0=Minority)	2011–2021	12,254	0.754	0.431
Educational attainment of the woman (Years)	2011–2021	12,254	5.210	4.376
Marital status of the woman (1=Married, 0=Others)	2011–2021	12,254	0.834	0.373
Number of children (Number)	2011–2021	12,254	0.922	1.008
Age of the respondent (Years)	2011–2021	12,254	50.78	11.57
Gender of the respondent (1=Male, 0=Female)	2011–2021	12,254	0.649	0.477
Educational attainment of the respondent (Years)	2011–2021	12,254	5.096	3.643
Number of unique females		1,963		
Number of females covering 2011–2021		549		

Notes: Each observation is a female-year individual. The data are unbalanced and span the years 2011 to 2021.

dummy variables indicating the years relative to the relocation year t_0 of household h. Specifically, for all $k > 0$, it equals one if household h relocated k years after relocation. We treat the group for which $k = -1$ as the benchmark, so it is omitted from the model. Hence, β_k captures the differential effect between the treatment group k years after relocation and the benchmark group one year before relocation. To avoid imprecise estimation due to small sample sizes in periods far from the relocation year, we aggregate all years that are four or more years before relocation into period -4 (i.e., $k = -4$ refers to $t \leq t_0 - 4$), and all years that are three or more years after relocation into period 3 (i.e., $k = 3$ refers to $t \geq t_0 + 3$).

5. Results

5.1. Main results on the extensive margin: off-farm employment status

We begin by investigating how the impact of PARP on women's off-farm employment status varies under different sets of fixed effects. As shown in Appendix Table A4, the estimated coefficient on the *Relocate* variable becomes larger and more statistically significant when replacing township fixed effects (column 1) with villager group fixed effects (column 2). Column 3 further includes resettlement fixed effects to account for time-invariant unobservables specific to each resettlement site that may confound women's off-farm employment (Carrillo et al., 2023). For instance, the proximity of each resettlement site to nearby markets may vary, indicating different job opportunities available for women. The estimated effect remains robust in both magnitude and statistical significance. Column 4 includes individual and year fixed effects, with the estimated coefficient remaining statistically significant at the 1 % level. Notably, individual fixed effects represent the most granular level that can be controlled, meaning that all time-invariant confounders at both the villager group and resettlement levels are absorbed by the individual fixed effects. These results imply that there are substantial idiosyncratic variations in the timing of household relocation even accounting for all time-invariant location-specific confounders. This finding aligns with our earlier analysis, which shows that the observable baseline characteristics at the villager group and household level have limited power in predicting sampled households' relocation timing. This provides

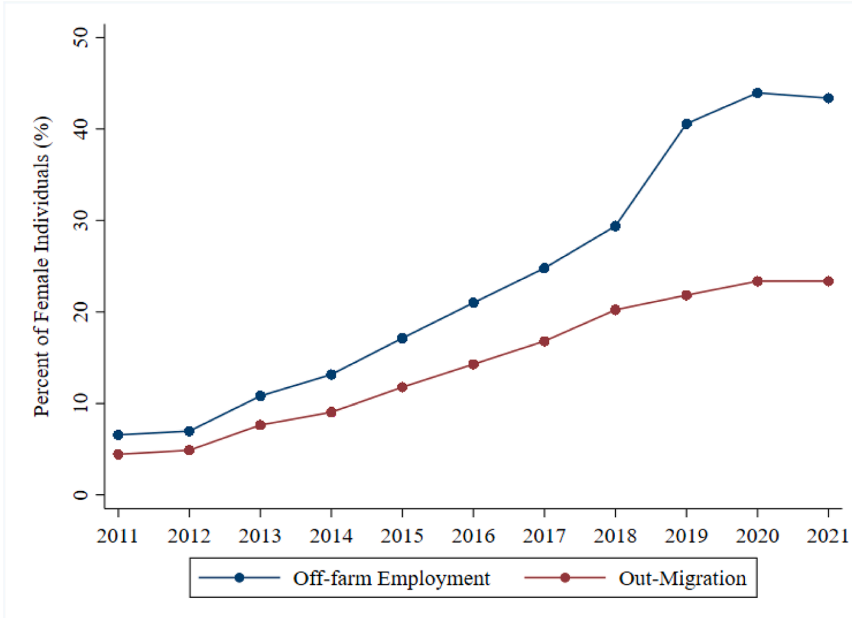

Fig. 3. Percentage of female individuals engaged in off-farm work and out-migration.
Notes: The blue line shows changes in the percentage of female individuals engaged in off-farm employment between 2011 and 2021, while the red line shows changes in the percentage of female individuals who worked outside the home county.

justification for using individual and year fixed effects as the baseline specification in the subsequent analyses.

Columns 1–3 of Table 3 present the estimated impacts of relocation on women's likelihood of engaging in off-farm employment. Column 1 controls for respondents' characteristics, as well as individual and year fixed effects. The estimated coefficient on the *Relocate* variable is positive and statistically significant at the 1 % level. Column 2 further includes individual demographics interacted with year fixed effects to capture the possibility that different demographic subgroups were on divergent off-farm employment trajectories prior to relocation. The magnitude of the estimated coefficient on the *Relocate* variable increases slightly and the statistical significance remains at the 1 % level. Column 3 is our preferred specification, which additionally incorporates villager-group-by year fixed effects to flexibly account for villager group-specific time-varying unobservables that may drive part of the correlation between relocation timing and women's labour market outcomes. The estimated coefficient on the *Relocate* variable remains statistically significant at the 5 % level. Specifically, the estimate in column 3 is quantitatively sizable, implying that compared to women still awaiting relocation, relocated women are 5.9 percentage points more likely to engage in off-farm employment, equivalent to roughly 36.6 percent of the average off-farm employment rate among the not-yet-relocated group.[20]

Fig. 4(a) illustrates the event study estimates for the impact of relocation on the probability of women's off-farm employment, using the model specified in Eq. (2). The estimates confirm a notable increase in the probability of off-farm employment for women whose households relocated to new destinations. Interestingly, we find that the significant positive effect of relocation on women's off-farm employment only becomes apparent one year after relocation, indicating that there might be an adjustment period for female individuals to adapt to the new environment. Subsequently, the effect of relocation on women's off-farm employment amplifies as the duration of relocation increases. Moreover, the pre-relocation trends appear parallel, with the estimated coefficients for each period before relocation hovering around zero and showing no tendency towards improving or deteriorating off-farm employment. This parallel trend before relocation helps mitigate potential anticipation effects (Roth et al., 2023), where individuals might adjust their labour supply before relocation in response to the policy. Overall, the event study estimates enhance the credibility of our DID strategy.

We now turn to examine the impacts on men's off-farm employment status, employing the same estimation strategy applied for women. Columns 4–6 of Table 3 report the corresponding results for men. The estimated coefficients are also positive across columns, but the magnitude for men is always substantially smaller (in absolute terms) than for women. Furthermore, in Column 6, which further accounts for villager-group-by year fixed effects, the estimated coefficient on the *Relocate* variable declines substantially and is no longer statistically significant. It corresponds to less than 1/2 of the effect size on women. This suggests that, although men are also affected by PARP, the impact on the likelihood of off-farm employment is gender-biased and affects women substantially more. Fig. 4(b) presents event study estimates on men's likelihood of off-farm employment. The pre-relocation trends appear parallel, enhancing the credibility of the estimated results for male individuals.

Further comparing the magnitudes of the estimated coefficients (Column 3 vs. Column 6 of Table 3), we find that the impact of relocation on off-farm employment is larger for women. We formally assess the gender-differentiated effects on off-farm employment status, pooling the male and female samples. Specifically, an interaction term between *Relocate* and a *Female* dummy variable is additionally included in our baseline regression. To address potential confounding from differing labour market trends across genders, we further incorporate gender-specific linear time trends. The gender-differentiated effects on off-farm employment, reported in column 1 of Appendix Table A5, show that the interaction term is positive and statistically significant at the 5 % level, confirming that relocation has a

[20] In addition to changes in residential location, the relocation process often involves significant accompanying measures. For instance, local governments are obliged to implement supportive initiatives for relocated households, including providing jobs in poverty alleviation workshops, offering skilling training, and improving infrastructure around resettlement areas. We interpret our findings as capturing the overall impact of the relocation program, inclusive of these bundled interventions. We thank an anonymous reviewer for raising this point.

Table 3
Effects of relocation on individual's probability of off-farm employment.

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Relocate	0.052***	0.055***	0.059**	0.039**	0.041**	0.023
	(0.018)	(0.018)	(0.027)	(0.018)	(0.019)	(0.024)
Mean of the control group	0.161	0.161	0.161	0.419	0.419	0.419
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Demographics-by-year FE	N	Y	Y	N	Y	Y
Villager group-by-year FE	N	N	Y	N	N	Y
R^2	0.554	0.566	0.662	0.552	0.565	0.656
Observations	12,254	12,237	11,929	15,208	15,205	14,909

Notes: Each observation is an individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to individuals aged 22–60 in each year. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects. Columns 2 and 5 additionally control for individual demographics (ethnicity and years of schooling) interacted with year fixed effects. Columns 3 and 6 further add villager group-by-year fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

more pronounced effect on women's off-farm employment than on men's. This is particularly intriguing, since PARP is a gender-neutral policy that targets poor households, yet it produces female-favored off-farm employment effects. One possible explanation is that PARP influenced household labour reallocation decisions, increasing women's availability to participate in the labour market as living conditions improved (Ding et al., 2024). Furthermore, the average off-farm employment rate is already high for men; in contrast, it is much lower for women (42 % for men not yet relocated vs. 16 % for women not yet relocated), indicating greater potential for women to increase their participation along the extensive margin of employment.

5.2. Main results on annual working months, monthly wage and annual earnings

Next, we explore whether PARP impacts the number of months individuals work per year – an important measure of individual labour supply at the *intensive* margin. The results are presented in Columns 1–2 of Table 4, with Panel A reporting estimates for women and Panel B for men. Column 1 in both panels controls for individual and year fixed effects, while Column 2 additionally includes villager-group-by year fixed effects and interactions between individual demographics and year fixed effects. For women, the estimated coefficient on the *Relocate* variable is positive and statistically significant in both columns; while for men, it loses statistical significance in Column 2. Specifically, our preferred specification in Panel A, Column 2 suggests that PARP increases women's annual labour supply by approximately 0.5 months (15 days) on average.[21] In contrast, Panel B, Column 2, indicates that relocation raises men's working months by about 0.3 months (9 days) per year.

Furthermore, the interaction term in Column 2 of Appendix Table A5 is positive but statistically insignificant, suggesting no significant gender-differential effect of PARP on working months. Figs. 4(c) and 4 (d) illustrate the event study estimates for women's and men's working months, respectively. Consistent with the dynamic effects observed in women's off-farm employment, we find that the positive and statistically significant effect on women's working months emerges primarily in periods beyond one year after relocation.

We further examine whether relocation could impact individual's monthly wages. Columns 3–4 of Table 4 present the relocation effect when the dependent variable is the natural logarithm of monthly wage, with Panel A displaying results for women and Panel B for men. In Panel A, the estimated coefficient on the *Relocate* variable is consistently positive and statistically significant in both columns, indicating that women's monthly wage increases by about 37 % after relocation (Column 4). However, in Panel B, the estimated coefficient on the *Relocate* variable loses significance when villager-group-by year fixed effects and year-by-demographics fixed effects are additionally controlled for, suggesting that the effect of relocation on men's monthly wage is statistically marginal. The interaction term in Column 3 of Appendix Table A5 is significantly positive at the 5 % level, suggesting that PARP has a more pronounced effect on women's monthly wages.

Columns 5–6 of Table 4 report the effect of relocation on individual's annual earnings. Again, in Panel A, the estimated coefficient on the *Relocate* variable is statistically significant and positive in both columns, implying that relocation increases women's annual earnings by 48 % (Column 6). In Panel B, consistent with the patterns observed for men's working months and monthly wages, the impact of relocation on men's annual earnings becomes statistically insignificant, and its magnitude declines substantially under the most saturated specification. This comparison is further supported by the interaction term in Column 4 of Appendix Table A5, which suggests that relocation has a more pronounced effect on women's annual earnings. The event study estimates for individual's monthly wage and annual earnings, shown in Figs. 4(e)-4(h), mirror the patterns observed for off-farm employment in Figs. 4(a) and 4(b), revealing that the effect of relocation on monthly wage and annual earnings follows a development trajectory that increases gradually as the duration of relocation exceeds.

Table 5 further explores the sources of the increase in individual's working months, monthly wages, and annual earnings, using the most saturated specifications across all columns. Conditioning on individuals being off-farm employed, we observe that the impact on women's working months becomes statistically insignificant. This indicates that the variation in women's working months is primarily driven by the *extensive* margin—i.e., more women entering off-farm employment—rather than by increasing the duration of work among those already employed. For monthly wages, the estimates turn negative for both employed women and men, suggesting that the sudden influx of labour following relocation exerts downward pressure on local wages almost equally for men and women. However, the moderate magnitude of

[21] The reported monthly wage variable exhibits a clear bunching pattern at multiples of 500 and 1,000. However, this type of measurement error is unlikely to bias our estimates, provided it is uncorrelated with the key independent variable. Empirically, we find that the probability of reporting monthly wage at multiples of 500 or 1000 is not significantly associated with the *Relocate* variable of interest. We thank an anonymous reviewer for suggesting this discussion.

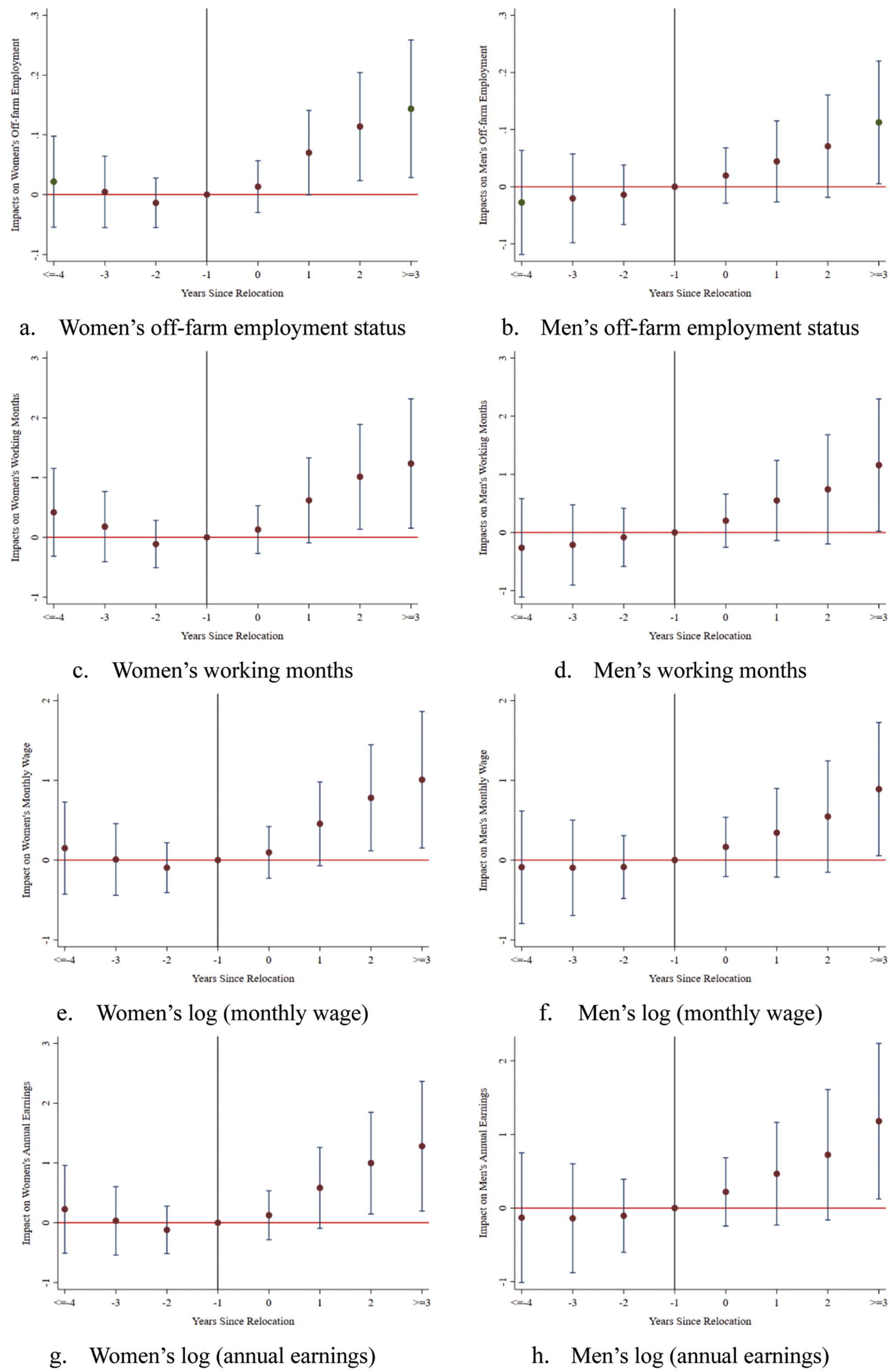

Fig. 4. Event-study estimates for individual's labour market outcomes.
Notes: The eight sub-figures plot estimated coefficients and 90 % confidence intervals from an event-study analysis using Eq. (2). The key explanatory variables are a set of event-time dummies indicating years relative to the year of household's relocation. All models include respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager group-by-year fixed effects. Standard errors are clustered at the villager group level.

Table 4
Effects of relocation on working months, monthly wage and annual earnings.

	Working Months		Log (Monthly Wage)		Log (Annual Earnings)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Women						
Relocate	0.587***	0.535**	0.385***	0.374*	0.508***	0.480*
	(0.179)	(0.265)	(0.135)	(0.200)	(0.174)	(0.256)
Mean of the control group	1.466	1.466	1.199	1.199	1.533	1.533
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Additional Interactive FE	N	Y	N	Y	N	Y
R^2	0.569	0.674	0.566	0.670	0.571	0.675
Observations	12,254	11,929	12,254	11,929	12,254	11,929
Panel B. Men						
Relocate	0.719***	0.324	0.277**	0.177	0.403**	0.242
	(0.197)	(0.245)	(0.140)	(0.188)	(0.178)	(0.238)
Mean of the control group	3.552	3.552	3.195	3.195	4.027	4.027
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Additional Interactive FE	N	Y	N	Y	N	Y
R^2	0.558	0.666	0.568	0.671	0.574	0.677
Observations	15,208	14,909	15,208	14,909	15,208	14,909

Notes: Each observation is an individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to individuals aged 22–60 in each year. Monthly wage and annual earnings are both winsorized at the 99th percentile. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects. Columns 2, 4 and 6 in both panels additionally control for individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager group-by-year fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

the effect on monthly wage suggests that the general equilibrium effect of the labour supply shock on the local labour market remains limited.[22] Moreover, the estimated impacts on annual earnings also become negative, although statistically insignificant, implying that the positive effects on unconditional annual earnings are primarily driven by individuals who changed their labour participation decision (i.e. whether to participate in off-farm work).

5.3. Other labour market outcomes

The probability of out-migration. As households relocate to more advantaged locations with improved transportation, the mobility barriers for individuals may decrease, thus facilitating their migration behaviors (Asher and Novosad, 2020; Lagakos, 2020). The results reported in Columns 1–3 of Appendix Table A6 support this claim, showing that the estimated coefficient on the *Relocate* variable is statistically significant across all specifications. This suggests that, beyond local opportunities, PARP also boosts women's off-farm employment outside their home counties. However, the estimated coefficients in Columns 4–6 of Appendix Table A6 are small in magnitude, suggesting that relocation has no significant impacts on men's migration behavior. This can be explained by the result that we only observe moderate increase in men's probability of engaging in off-farm employment following relocation, as shown in Column 6 of Table 3.

The quality of off-farm employment. We evaluate the quality and stability of the off-farm employment for either gender by examining whether they signed a labour contract in a specific year. The first two columns of Appendix Table A7 present the impact of relocation on the probability of signing labour contracts for female and male individuals, respectively. We observe that the estimated coefficients on the *Relocate* variable are negative and statistically insignificant for both columns, indicating that relocation does not improve the stability of off-farm work irrespective of gender. This is likely due to the predominance of informal sector employment among the sampled individuals, which falls outside the scope of many labour regulations and policies (Katzkowicz et al., 2021).

Entrepreneurship. A parallel question about off-farm employment in informal sectors is self-employment, or business creation - an important measure of entrepreneurship. As pointed out in the national guidelines

Table 5
Effects on working months, monthly wage and annual earnings for the employed.

	Working Months		Log (Monthly Wage)		Log (Annual Earnings)	
	Women (1)	Men (2)	Women (3)	Men (4)	Women (5)	Men (6)
Relocate	−0.065	0.131	−0.065	−0.056*	−0.053	−0.055
	(0.319)	(0.179)	(0.057)	(0.029)	(0.089)	(0.040)
Mean of the control group	9.506	8.540	7.560	7.687	9.717	9.699
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Additional Interactive FE	Y	Y	Y	Y	Y	Y
R^2	0.822	0.727	0.901	0.801	0.877	0.804
Observations	2,186	7,135	2,176	7,101	2,176	7,101

Notes: Each observation is an individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to individuals aged 22–60 in each year. Monthly wage and annual earnings are both winsorized at the 99th percentile. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager group-by-year fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

[22] Appendix Table A1 reports the proportion of relocated population and workers in the sixteen sampled counties. On average, the relocated population accounts for approximately 5.8% of the total population, while relocated workers aged 16–59 represent about 6.1% of the total workforce. This relatively small labour supply shock induced by relocation is consistent with the moderate decline observed in monthly wages for both genders. Furthermore, we calculate the share of the relocated population by gender. The results show that relocated females account for approximately 5.5% of the county's total female population, while the corresponding share for males is about 6.2%. These similar shares align with the comparable magnitude of the impact on monthly wages for both genders.

of PARP, the relocated population is encouraged to start businesses through avenues such as rural e-commerce, leisure agriculture, folk arts, and rural tourism. Financial institutions are also incentivized to furnish business guarantee loans to foster entrepreneurial activities. Therefore, we examine whether there is an increase in entrepreneurship activities after relocation, leveraging two waves of data recording information on private business activities at the individual level. Columns 3–4 of Appendix Table A7 present the impact of relocation on business creation for either gender. The estimated coefficients on the *Relocate* variable are small in magnitude and statistically insignificant in both columns, indicating no evidence that relocation positively affects entrepreneurial activities for either gender.[23]

5.4. Robustness checks

The results so far show that relocation significantly increases the likelihood of women engaging in off-farm employment, with the employment effect primarily driven by the *extensive* margin. Furthermore, the impact of relocation on women's off-farm employment is more pronounced than that on men's. Therefore, the remainder of the paper will focus on women's off-farm employment status. Before unpacking the underlying mechanisms, we provide several robustness checks to enhance the credibility of our findings on women's off-farm employment status.

Alternative estimators considering treatment effect heterogeneity. Recent literature shows that when the timing of entry into treatment varies across cohorts, the classic TWFE DID estimator could be biased due to heterogeneous treatment effects across periods and cohorts (Callaway and SantAnna, 2021). To alleviate this concern, we employ the interaction weighted estimator developed by Sun and Abraham (2021) to examine whether our main results are robust to these alternative estimators. The estimated coefficients on the *Relocate* variable shown in Appendix Table A8 are comparable in both magnitude and statistical significance to the corresponding results presented in Tables 3 and 4. This mitigates concerns regarding potential estimation bias that may arise due to the staggered timing of relocation across sampled households.

Restricting to collectively relocated individuals. One remaining concern is that there could be a selection in the *relative* timing of relocation, although all sampled households were relocated by the survey endline. For instance, households who have a greater attachment to the origin villages may postpone their relocation, while those who have a comparative advantage in off-farm employment are more inclined to relocate earlier (Luke and Munshi, 2011; Nakamura et al., 2021). As discussed in Section 2, the timing of collective relocation is largely determined by the construction process of resettlement communities, while the timing (and location) of dispersed relocation could be chosen by households themselves. This policy design implies that the timing of collective relocation is arguably more exogenous to households and women in particular (Ding et al., 2024; Zhang et al., 2023). We therefore narrow the focus on female individuals from collectively relocated households to address potential selection bias in the relative timing of relocation. The results are reported in Appendix Table A9, using specifications consistent with Eq. (1) across all dependent variables. Column 1 presents the estimates for women's off-farm employment. Reassuringly, the estimated coefficients on the *Relocate* variable are comparable to the corresponding results in Tables 3 and 4.

Placebo test using randomly assigned relocation years. To further ensure that our main results are not driven by unobserved confounders, we conduct a permutation test that reshuffles a relocation year to each household. Specifically, we randomly select a year from 2011 to 2021 as the "placebo" relocation year for each household and repeat this procedure 500 times. The estimation specification employed for this placebo test is identical to that used in Column 3 of Table 3. The estimated coefficients in these placebo regressions are visualized in Appendix Fig. A3, illustrating that the majority of the estimated coefficients are concentrated around zero and significantly skewed to the left of the true coefficient estimate. Furthermore, most p-values are greater than 0.1, indicating that most of the estimated coefficients obtained under the "placebo" years are statistically insignificant. This placebo test further strengthens the robustness of our main results.

Restricting to balanced panel. The unbalanced nature of the individual panel data may introduce potential bias to our main results. To assess the severity of such estimation bias, we focus on individuals who were surveyed in every year from 2011 to 2021, resulting in 6,029 female-year observations from 549 female individuals. The estimated results are reported in Appendix Table A10. For women's off-farm employment status, the estimated coefficient on the *Relocate* variable in Column 1 is slightly larger than that in Column 3 of Table 3 (0.059). Similarly, the estimated coefficients are larger than those in the corresponding columns of Tables 4 when the dependent variable is working months, monthly wage or annual earnings. Therefore, any bias resulting from the unbalanced nature of the dataset is more likely to *underestimate* our main findings within the context of our study. That is, the results in Columns 1–3 of Table 3 and Panel A of Table 4 present the lower bound of our finding.

Robustness check considering sample selection bias. The unbalanced nature of our individual panel data is likely to induce a standard sample truncation problem (Wooldridge, 2010). Specifically, individuals with recorded off-farm employment data for each year from 2011 to 2021 differ systematically in many unobserved aspects from those without complete data. To address this, we recover the unbalanced individual panel to balanced ones and employ a two-step Heckman model. First, we estimate a probit model using the recovered full sample of female individuals with and without observed off-farm employment data. The dependent variable is a binary indicator equal to one if an individual's off-farm employment information is recorded in a given year, and zero otherwise. The independent variables include individual and household characteristics, village and year fixed effects, and the proportion of migrants in the origin village which serves as the excluded variable. Second, we include the calculated Inverse Mills Ratio (IMR) from the first step into the employment equation using individuals with observed off-farm employment data to correct for the potential selection bias. Columns 1 and 2 of Appendix Table A11 report the results of the second and first stages, respectively. We find that the IMR is statistically insignificant, alleviating our concern about the sample selection bias. Furthermore, the magnitude of the estimated coefficient on the *Relocate* variable remains comparable to that in Column 3 of Table 3, with the significance level increased to 1 % level.

5.5. Heterogeneity analyses

In this subsection, we further investigate the heterogeneous effects of relocation on women's off-farm employment across different subgroups. Specifically, we incorporate the interaction terms between the *Relocate* variable and a range of baseline demographics or relocation types in the baseline regressions.

Heterogeneous effects by educational attainment. Previous studies have highlighted the crucial role of education in determining individuals' labour supply and earning differentials, particularly following the human capital revolution (Deming, 2022; Gunderson and Oreopoulos, 2020). Therefore, we sought to investigate whether female individuals with higher levels of education derived greater benefits from PARP by

[23] In Appendix Table A7, we also examine the impact of relocation on the probability of agricultural work (Columns 5-6) and on overall employment status (Columns 7-8). We find suggestive evidence of a decline in both outcomes following relocation for either gender, though the estimates are not statistically significant. Given the limited number of waves available for these outcomes and the lack of pre-2015 baseline data, the results in Appendix Table A7 should be interpreted as suggestive and approached with caution.

interacting the *Relocate* variable with a dummy variable for low education. Column 1 of Table 6 reports the differential effects of relocation by women's baseline educational attainment. The estimated coefficient on the interaction term between *Relocate* and the low education dummy is significantly positive at the 10 % level, suggesting that relocation has a more pronounced effect on off-farm employment for women with lower education. This finding may reflect that a substantial portion of the supportive measures supplementing PARP are means-tested, prioritizing assistance for those who are disadvantaged in the off-farm labour market.

Heterogeneous effects by home production burdens. As discussed above, poor living conditions could place particular burdens on women's time use. If so, we would expect the effect of relocation on women's off-farm employment to be more pronounced among those who bear more housework. We explore this potential heterogeneity from two perspectives: marital status and the presence of resident children in the household, motivated by the stylized fact that married women typically shoulder more housework than their unmarried counterparts, and that women in rural China generally bear the majority of childcare (Connelly et al., 2018). First, we include an interaction term between *Relocate* and a dummy variable indicating whether the woman was married at baseline in the regression. The result is reported in Column 2 of Table 6, suggesting that the effects on women's propensity to engage in off-farm employment are concentrated among those who are married. Next, we include an interaction term between *Relocate* and a dummy variable indicating whether the household has any resident children. Column 3 of Table 6 presents the corresponding heterogeneous effect. The estimated coefficient on the interaction term is significantly positive, suggesting that relocation leads to a greater increase in off-farm employment for women in households with resident children. Taken together, these results align with our prediction that relocation has more pronounced effects on women with heavier housework burdens, stimulating us to further explore the mechanism of time allocation in Section 6.

Table 6
Heterogeneous analysis on women's off-farm employment.

	Women's Off-Farm Employment Status				
	(1)	(2)	(3)	(4)	(5)
Relocate	0.028	−0.023	0.003	0.029	−0.011
	(0.023)	(0.032)	(0.023)	(0.020)	(0.030)
Relocate × Low Education	0.049*				
	(0.026)				
Relocate × Married		0.094***			
		(0.032)			
Relocate × Has Children			0.085***		
			(0.025)		
Relocate × Urban				0.058*	
				(0.031)	
Relocate × Collective					0.081***
					(0.031)
Mean of the control group	0.162	0.162	0.162	0.162	0.162
R^2	0.554	0.555	0.556	0.554	0.555
Observations	12,254	12,254	12,254	12,254	12,254

Notes: Each observation is a female individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to female individuals aged 22–60 in each year. The dependent variable is a binary indicator equal to one if the female individual particiapted in off-farm employment in a given year. All models control for respondents' characteristics (age, gender, and years of schooling), as well as individual and year fixed effects. All covariates used in constructing the interaction terms in columns 1–3 are baseline characteristics. In column 1, low education is an indicator equal to one if the female individual had fewer than six years of schooling at baseline survey. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Heterogeneous effects by relocation types. We explore two main heterogeneity analyses based on relocation types. The first dimension compares women's off-farm employment outcomes between urban and rural relocated households. Figs. 5(a) and 5(b) illustrate changes in household's access to diverse institutions and public services before and after relocation for the urban and rural relocated groups, respectively. It clearly shows that both groups experience reduced distances to all institutions post-relocation; however, the urban relocated group notably enjoys much better access to these institutions (especially a sharp decline in proximity to the nearest county). This suggests that women in urban relocated households are more likely to benefit from active local labour markets and convenient public services, indicating that urban relocation may have a more substantial positive effect on women's off-farm employment compared to rural relocation. This conjecture is further confirmed in Column 4 of Table 5, where the estimated coefficient on the interaction term between *Relocate* and a dummy variable for urban relocation type is significantly positive. Additionally, we examine another dimension of heterogeneity—collective vs. dispersed relocation—by including an interaction term between *Relocate* and a dummy for collective relocation. The estimated coefficient on this interaction term, presented in Column 5 of Table 5, indicates that relocation has a more pronounced effect for women in collectively relocated households.

6. Further discussion: potential mechanisms

In this section, we propose three suggestive mechanisms through which PARP could enhance women's off-farm employment. First, we explore the time allocation channel, wherein improved dwelling conditions, increased labour-saving consumer durables, and better access to public services may jointly liberate women's time from home production, consequently allowing for greater participation in the labour market. Moreover, relocation may alter households' landholding and thus change their labour reallocation between agricultural and non-agricultural sectors. The second potential mechanism is the social network channel, which argues that changes in social networks due to relocation may impact individuals' sources of information regarding employment opportunities. Third, we examine the human capital channel, positing that women may receive more skill training and their health status may be enhanced after relocation, both are factors that could improve their labour productivity.

6.1. Time allocation

We begin by examining how relocation affects households' dwelling conditions and access to labour-saving consumer durables. Panel A of Table 7 reports the effects of relocation on dwelling conditions, showing that PARP significantly improves households' access to tap water, stable electricity, flush toilets, and trash service (Columns 1–4). These improvements have been recognized in the literature as significant time-saving technologies for women working in the home (Devoto et al., 2012; Dinkelman, 2011; Franklin, 2020). Furthermore, Column 5 implies that PARP significantly elevates self-reported housing quality. By moving into secure and high-quality housing, households likely reduce time spent on house repairs and maintenance, thus potentially freeing up time for labour market participation.[24]

Panel B of Table 7 further presents that the number of labour-saving consumer durables, including electric cookers, washing machines,

[24] Anecdotal evidence suggests that households in remote and mountainous areas often have to repair or rebuild homes due to natural disasters and accidents such as flooding, landslides and fires. A stunning example illustrating the destruction of houses, farmland, and disruptions in power and communication due to a severe flood that occurred a PARP county can be found in: https://www.gov.cn/gzdt/2010-07/28/content_1665513.htm

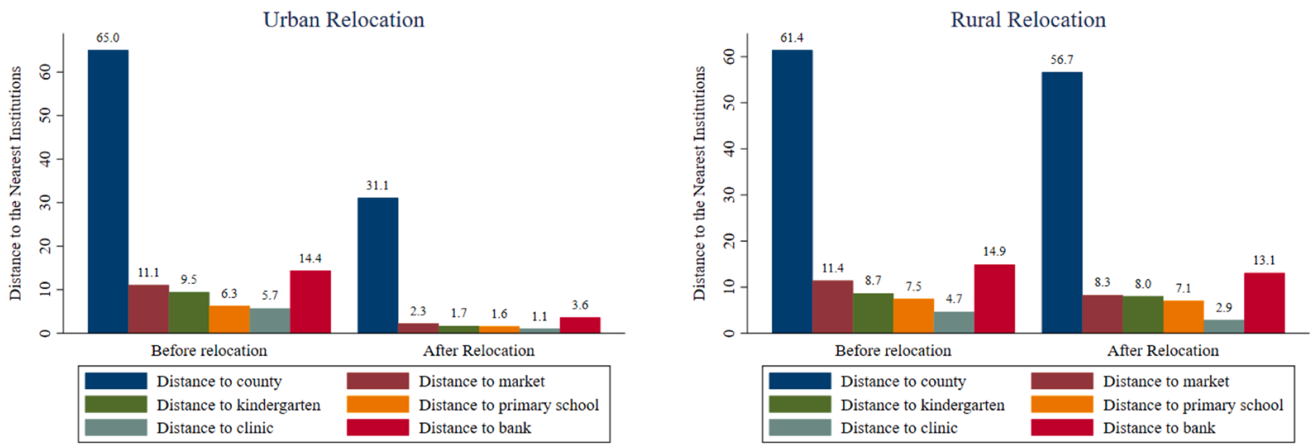

Fig. 5. Changes in distance to various institutions by relocation attribute.
Notes: The left figure highlights the average minimum distance to various institutions and public services before and after relocation for urban relocated households, while the right figure shows the same for rural relocated households. The values displayed on each bar represent the mean value of the minimum distance to various institutions and public services within each respective group.

Table 7
Effects of relocation on household dwelling conditions and durable goods.

Panel A. Dwelling Conditions	Tap water (1)	Stable electricity (2)	Flush toilet (3)	Trash service (4)	House quality (5)
Relocate	0.307***	0.050***	0.749***	0.533***	1.905***
	(0.036)	(0.018)	(0.034)	(0.041)	(0.075)
Mean of the control group	0.550	0.947	0.053	0.125	1.808
R^2	0.667	0.547	0.891	0.789	0.853
Observations	3,905	3,284	3,280	3,283	3,190
Panel B. Stock of the Durable Goods	TV (6)	Refrigerator and air conditioner (7)	Washing machine (8)	Electric cooker (9)	Car (10)
Relocate	0.115***	0.068*	0.176***	0.157**	0.009
	(0.033)	(0.035)	(0.033)	(0.063)	(0.012)
Mean of the control group	0.893	0.370	0.473	0.898	0.007
R^2	0.536	0.669	0.633	0.701	0.452
Observations	4,204	4,204	4,204	3,117	4,204

Notes: Each observation is a household-year. The data used in this table span the years 2015, 2016, 2018, and 2020. In panel A, the dependent variables in columns 1–4 are binary indicators for whether the household has access to tap water, stable electricity, flush toilets, and trash collection services, respectively. The dependent variable in column 5 is a categorical variable indicating the current level of housing quality, coded as follows: 1=badly damaged, 2=generally damaged, 3=basically intact, 4=intact. In Panel B, the dependent variables represent the stock of the corresponding durable goods at the end of each survey year. All models control for respondents' characteristics (age, gender, and years of schooling), household fixed effects, year fixed effects, and villager group-specific linear time trends. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

refrigerators and air conditioners, increased significantly after relocation. These appliances are well-known to reduce the time spent on onerous household chores such as food preparation, laundry and cleaning (Greenwood et al., 2005). Interestingly, Column 6 indicates that the number of televisions also rises significantly after relocation, possibly reflecting the consumption pattern among low-income households that prioritize leisure over basic necessities (Banerjee and Duflo, 2011). Moreover, Column 7 doesn't show any evidence that relocation significantly impacts car ownership, likely because cars remain prohibitively expensive for most relocated households.

Subsequently, we explore how relocation changes the neighborhood quality by examining changes in the proximity to various amenities and public services. The findings are reported in Table 8, showing that households enjoy improved access to all types of institutions, including the nearest committee, market, government, county seat, banks, schools, clinics and hospitals. Notably, improvements in access to the nearest kindergarten are particularly pronounced (Column 6), suggesting a substantial reduction in the time mothers spend on childcare-related travel (Bauernschuster and Schlotter, 2015). In addition, we observe that PARP has a substantial effect on reducing the round-trip time to the nearest market, likely saving women's time on grocery shopping (Column 2).[25]

Beyond housing and neighborhood improvements, landholding status may also influence women's time allocation.[26] Columns 1–2 of Table 9 show that relocation does not substantially affect total landholdings: the estimated coefficients on the *Relocate* variable are statistically insignificant for both total contracted land and total farmland.[27] However, Column 4 reveals a modest but significant increase in farmland within resettlements post-relocation. Yet, this newly allocated farmland remains limited in size—on average, only 0.23 *Mu* compared to 7.77 *Mu* in origin villages. Meanwhile, the farmland in origin villages remains largely intact (Column 3), indicating that local governments adopted a conservative land policy that allowed relocated households to retain their original farmland. Nevertheless, relocated households are less opt to continue cultivation because of the increased travel distance to original farmland. Consistently, Columns 5 and 6 show that the

[25] We also notice that households were quite far away from the county seat before relocation, with an average distance of 61 km. After relocation, the round-trip time to the nearest county seat both decreased by approximately 23% (Column 4). This may suggest that the increased off-farm employment rate for female individuals after relocation could be attributed, at least in part, to more job opportunities as a result of closer proximity to the county seat.

[26] In 1998, Chinese farmers were legally granted 30-year land use contracts. In 2013, China launched a new round of land-rights reform, extending these land use contracts for an additional 30 years (Chari et al., 2021). However, land ownership always remains with the village collective.

[27] We also examine the impact of relocation on the total contracted area of other land types (including woodland, grassland, and wasteland). Similarly, there are no significant changes in the total area of these land types after relocation.

Table 8
Effects of relocation on round trip time to various institutions.

	Committee (1)	Market (2)	Government (3)	County (4)	Bank (5)
Relocate	−0.478***	−0.608***	−0.309***	−0.234***	−0.307***
	(0.091)	(0.088)	(0.070)	(0.080)	(0.073)
Mean of the control group	3.910	4.446	4.665	5.401	4.633
R^2	0.672	0.709	0.683	0.652	0.704
Observations	4,198	4,198	4,198	4,196	4,194
	Kindergarten (6)	Primary school (7)	Middle school (8)	Clinic (9)	Hospital (10)
Relocate	−0.440***	−0.364***	−0.246***	−0.553***	−0.291***
	(0.091)	(0.077)	(0.075)	(0.088)	(0.075)
Mean of the control group	4.069	4.145	4.635	4.000	4.615
R^2	0.724	0.704	0.685	0.687	0.614
Observations	3,086	4,197	4,192	4,198	4,198

Notes: Each observation is a household-year. The data used in this table span the years 2015, 2016, 2018, and 2020. The dependent variables are the logarithm of the round-trip time to the nearest institution. Data on round-trip time to the nearest kindergarten were only collected in 2016, 2018, and 2020. All models control for respondents' characteristics (age, gender, and years of schooling), household fixed effects, year fixed effects, and villager group-specific linear time trends. Robust standard errors clustered at the villager level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

proportion of abandoned farmland rose by about 4 % after relocation, with larger effects among households relocated to urban areas. Thus, the reduced access to arable land in new resettlements and the constraints on commuting to origin villages likely restrict individual's agricultural engagement, thereby pushing them towards off-farm jobs.[28]

Furthermore, while not comprehensive across all types of housework, our data does include detailed individual time-use information on specific tasks such as grocery shopping and cooking, and firewood collection. The estimated results, presented in Appendix Table A12, reveal significant reductions in the time women spent on grocery shopping and cooking (Column 1) and on collecting firewood (Column 3). These unpaid domestic tasks are highly time-consuming and primarily performed by women in impoverished areas, often preventing them from participating in the labour market. Taken together, although the above evidence is suggestive, the results consistently suggest that PARP may alter women's time allocation and facilitate their participation in the labour market.

6.2. Social networks

Extensive literature highlights the crucial role of social networks in facilitating rural migrants finding non-agricultural jobs (Imbert et al., 2022; Kinnan et al., 2018; Munshi, 2011). Our sample data confirms the prevalence of social networks among the sampled female individuals: nearly 70 % of employed women found off-farm jobs through themselves, friends or relatives. Nevertheless, relocation might weaken their traditional network at the origin, leading to increased isolation from origin networks and a reduction in informal insurance (Barnhardt et al., 2017; Luke and Munshi, 2011; Meng and Xue, 2020; Munshi and Rosenzweig, 2016). At the same time, the establishment of new social networks in new destinations may offer fresh job referrals for the relocated women. Therefore, the impact of social network reconfiguration on women's participation in off-farm employment remains ambiguous and requires empirical investigation.

We utilize five years of data (2016 and 2018–2021) documenting off-farm job sources to examine whether individual's sources off-farm jobs have changed after relocation. Panel A of Table 10 reports the results for women. The estimated coefficient on the *Relocate* variable in Column 1 is positive and statistically significant, suggesting that the likelihood of women being referred to jobs by friends or relatives increased post-relocation. Furthermore, the results in Column 5 of Panel A indicate that relocated women became more likely to engage in part-time employment. This pattern may indicate the ongoing tensions between caregiving responsibilities and labour market participation: For women seeking off-farm employment but constrained by care duties and household chores, long and inflexible working hours associated with full-time "greedy" positions may be untenable (Goldin, 2021). As a result, part-time jobs may serve as a second-best option when working hours are constrained. Finally, we find that there is no discernible evidence revealing a significant change in the likelihood of women being provided jobs by local governments, firms or advertising and intermediary agents after relocation.

Panel B of Table 10 presents the results for male individuals. In contrast to the findings for females, Column 1 of Panel B indicates no significant positive impact of relocation on the likelihood of men being referred to jobs by friends or relatives. This result may be driven by two factors: on the one hand, traditional social networks in origin villages are often male-dominated and patriarchal, suggesting that men may suffer greater losses in social ties after relocation than women; on the other hand, in the absence of support from traditional networks, women may be more capable of establishing new social connections in the destinations, thereby enhancing their adaptation to the new environment and job search outcomes relative to men.

6.3. Human capital accumulation

Cognitive and non-cognitive skills are crucial elements of human capital and their impacts on various economic outcomes are extensively studied (Deming, 2022). In the context of PARP, local governments have initiated a range of training programs to promote employment among the relocated population. Given that all sampled working-age women have completed their education, we are curious about whether PARP could foster women's participation in skill training programs and whether PARP could improve their health status.[29]

First, we employ four years of data recording household members engaged in any skill training programs to investigate the impact of PARP

[28] The results in columns 5-6 of Appendix Table A6 show that relocation reduces relocated individuals' participation in agricultural work, further providing supportive evidence that limited access to farmland in resettlements may force individuals to seek off-farm jobs. We thank an anonymous reviewer for pointing out this.

[29] A burgeoning literature has underscored the important role of subjective well-being in explaining worker's performance and productivity (Srivastava et al., 2018; Sule et al., 2023). However, using household data from the 2018 and 2020 waves, we do not find any significant effects of relocation on the overall well-being of female respondents.

Table 9
Effects of relocation on land reallocation.

	Total land	Farmland	Farmland in origin villages	Farmland in resettlements	Prop. of abandoned farmland (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Relocate	−0.014	0.010	0.006	0.100***	4.094*	0.712
	(0.069)	(0.043)	(0.046)	(0.028)	(2.083)	(2.115)
Relocate × Urban						9.005***
						(3.408)
Mean of dep. var. (level)	33.05	8.007	7.772	0.234	13.35	13.35
R^2	0.683	0.710	0.697	0.592	0.521	0.523
Observations	4,535	4,535	4,535	4,535	4,306	4,306

Notes: Each observation is a household-year. The data used in this table span the years 2015, 2016, 2018, and 2020. The dependent variables in columns 1–4 are the inverse hyperbolic sine (IHS) transformations of the total land area or farmland area, while the dependent variable in column 5 represents the proportion of abandoned farmland relative to total farmland. All models control for respondents' characteristics (age, gender, and years of schooling), household fixed effects, year fixed effects, and villager group-specific linear time trends. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table 10
Effects of relocation on individual's sources of off-farm jobs.

	Friend Referral (1)	Government Provided (2)	Firm Provided (3)	Advertising or Intermediary (4)	Part-time jobs (5)
Panel A. Women					
Relocate	0.050***	−0.004	−0.014	0.002	0.018**
	(0.016)	(0.007)	(0.014)	(0.011)	(0.008)
R^2	0.698	0.647	0.406	0.334	0.511
Observations	5,844	5,844	5,844	5,844	5,844
Panel B. Men					
Relocate	0.011	0.004	−0.022	0.014	0.017*
	(0.018)	(0.008)	(0.017)	(0.010)	(0.010)
R^2	0.698	0.556	0.522	0.311	0.500
Observations	6,968	6,968	6,968	6,968	6,968

Notes: Each observation is an individual-year. The data span the years 2016 and 2018–2021. The sample is restricted to individuals aged 22–60 in each year. The dependent variables are binary variables indicating whether the individual obtained off-farm jobs through specific channels. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, as well as villager-group specific linear trends. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

on individual's skill training. As reported in Columns 1 and 2 of Appendix Table A13, the estimated coefficients on the *Relocate* variable are positive for both genders, but small in magnitude and statistically insignificant. This suggests that there is no strong evidence of an increase in skill training for individuals post-relocation.

Second, given that relocation improved households' access to healthcare facilities, individuals' physical health status may have potentially improved as a result. However, the estimated results presented in Columns 3 and 4 of Appendix Table A13 is insignificantly negative, ruling out the possibility of physical health serving as a mediator. Taken together, the estimated results provide suggestive evidence that the improvement in women's off-farm employment following relocation is *less* likely driven by an enhancement in human capital accumulation.

7. Conclusions

This paper draws on eleven years of individual employment data to investigate the impact of China's large-scale Poverty Alleviation Relocation Program (PARP) on women's labour market outcomes, capitalizing on exogenous variation in relocation timing across eligible households. Our findings show that PARP had different consequences for female and male individuals. For women, relocation significantly increased the likelihood of participating in off-farm employment, especially among those with lower educational attainment, those who are married, those with resident children, and those relocated to urban or collective sites. While we also observe positive effects on other labour outcomes for women—such as the number of working months per year, monthly wages, and annual earnings—these gains become statistically insignificant once we condition on employment status. This suggests that the program's primary impact on women's labour market outcomes operates through the *extensive* margin, by enabling more women to enter off-farm work. In contrast to women, the program's effects on men's labour market outcomes are relatively modest. This indicates that, despite being gender-neutral by design, PARP has produced more favorable labour market outcomes for women, contributing to reducing gender gaps in labour market outcomes.

These findings have some parallels to the relocation programs in other developing countries. Many international initiatives highlight that women often represent one of the most vulnerable subgroups in relocated or displaced populations, and may face worsened labour market prospects if gender-sensitive support mechanisms are absent—especially in contexts shaped by restrictive gender norms (Bauloz et al., 2024; Duflo, 2012). Our analysis demonstrates that even a gender-neutral relocation program in China can meaningfully enhance women's economic outcomes through multifaceted interventions. As governments in the Global South increasingly turn to relocation as a feasible strategy to reduce poverty and achieve other development goals (such as mitigate the adverse effects of climate change and excessive population growth), lessons from China's PARP may offer a practical and effective path for advancing multiple Sustainable Development Goals.

CRediT authorship contribution statement

Yawen Ding: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiaobing Wang:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Alan de Brauw:** Writing – review & editing, Methodology, Investigation. **Huanguang Qiu:** Supervision, Resources, Funding acquisition.

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Appendix

Tables A1, A8

Table A1
Proportion of relocated population and workers in sampled counties.

Province	County	Relocated population (1)	Total Population (2)	Prop. of relocated population (3)	Relocated workers (4)	Total Workers (5)	Prop. of relocated workers (6)
Shaanxi	Ziyang	6.28	26.10	24.07	3.71	15.13	24.52
Shaanxi	Xixiang	1.69	32.15	5.26	0.99	18.47	5.36
Gansu	Jingyuan	1.82	37.31	4.89	1.18	22.67	5.21
Gansu	Gulang	2.53	25.02	10.11	1.67	15.22	10.99
Hubei	Jianshi	4.87	41.16	11.84	3.03	24.87	12.17
Hubei	Zigui	1.09	30.96	3.51	0.66	18.07	3.67
Hunan	Pingjiang	3.38	95.11	3.56	2.07	56.55	3.65
Hunan	Yuanling	1.70	51.01	3.34	1.07	29.24	3.65
Guangxi	Tianyang	2.50	30.88	8.10	1.53	18.57	8.26
Guangxi	Duan	4.56	53.81	8.47	2.70	29.47	9.15
Sichuan	Jiange	4.13	42.39	9.75	2.57	23.93	10.72
Sichuan	Xuanhan	3.89	95.41	4.07	2.28	54.84	4.16
Guizhou	Weining	3.74	128.01	2.92	2.53	77.75	3.25
Guizhou	Shuicheng	4.53	74.64	6.07	2.74	44.40	6.17
Yunnan	Xuanwei	5.23	118.98	4.39	3.46	72.99	4.74
Yunnan	Wuding	0.97	23.91	4.06	0.64	15.48	4.16
Total		52.92	906.8	5.84	32.82	537.7	6.10

Notes: The unit of the number of relocated (total) population (workers) is 10 thousand, and the unit of the proportion of relocated population (workers) is %. Relocated population refers to the total number of relocated population between 2016 and 2020 and total population denotes the resident population in 2020. Relocated workers refer to relocated population aged 16–59, while total workers denote population aged 15–59 calculated by aggregating the population in each age range. Data on the relocated population and relocated workers aged 16–59 was obtained from the National Poverty Alleviation Information System, which was established by the State Council Leading Group Office of Poverty Alleviation and Development. Data on the total population and total workers aged 15–59 was drawn from the Tabulation on 2020 China Population Census by County.

Table A2
Attrition test at the individual level.

	Attrition status (1)	Non-attritors: Early relocation (2)	Attritors: Early relocation (3)
Age	−0.000	−0.001	0.001
	(0.001)	(0.001)	(0.002)
Female	0.026*	−0.012	0.002
	(0.015)	(0.012)	(0.025)
Years of education	−0.004	−0.004	0.006
	(0.003)	(0.003)	(0.006)
Minor ethnicity	−0.058	0.040	0.095*
	(0.042)	(0.052)	(0.055)
Married	−0.013	−0.000	−0.061
	(0.024)	(0.020)	(0.046)
Health status	0.047**	0.006	−0.059
	(0.019)	(0.015)	(0.039)
Family size	0.013	0.002	0.017
	(0.010)	(0.009)	(0.026)
Off-farm employment	0.025	−0.009	−0.034
	(0.018)	(0.016)	(0.032)
Year of relocation	−0.032	–	–
	(0.021)	–	–
R^2	0.228	0.709	0.815
Observations	2,428	2,013	378

Notes: Each observation is an individual. The sample is restricted to individuals aged 22–60 in the baseline survey year (2015). All regressions control for villager group fixed effects. The dependent variable in Column 1 is a binary indicator equal to one if the individual surveyed at baseline was not surveyed at endline. In Columns 2 and 3, the dependent variable is a binary indicator equal to one if the household in which the sampled individual resides relocated in or before 2017, and zero otherwise. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A3
Determinants of household relocation timing.

	Whether Early Relocation			Whether the 1st Round of Relocation		
	(1)	(2)	(3)	(4)	(5)	(6)
Hills	−0.045	−0.184	0.043*	0.016	−0.096	0.052
	(0.124)	(0.156)	(0.025)	(0.077)	(0.115)	(0.048)
Plateau	−0.010	0.175	–	0.258	0.215	–
	(0.445)	(0.454)	–	(0.263)	(0.232)	–
Log (Altitude)	0.000***	0.000***	−0.000***	0.000**	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (Disaster Loss)	0.001	−0.001	0.007	−0.000	−0.000	0.002
	(0.008)	(0.007)	(0.006)	(0.004)	(0.003)	(0.004)
Prop. of IPHs	−0.001	−0.001	0.002	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prop. of CCPs	0.005	0.013	−0.007	0.010	0.011	0.015**
	(0.015)	(0.015)	(0.013)	(0.009)	(0.008)	(0.008)
Prop. of ethnic minorities	−0.000	−0.002**	0.001	0.000	−0.001**	−0.001
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Prop. of households with the most common surname	−0.000	−0.000	−0.000	0.000	−0.000	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prop. of households holding religious beliefs	0.002	0.002	0.002*	0.000	−0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prop. of households with access to electricity	−0.004***	−0.004**	0.003**	0.001	−0.000	−0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Prop. of households with access to safe water	0.000	0.001	−0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Household Size	−0.025	−0.022	−0.010	0.001	−0.005	−0.003
	(0.018)	(0.016)	(0.013)	(0.010)	(0.009)	(0.009)
Num. of Children	0.037*	0.034*	0.018	0.001	0.009	0.006
	(0.021)	(0.019)	(0.019)	(0.011)	(0.010)	(0.010)
Log (Total Expenditure)	−0.011	0.001	0.008	0.010	−0.003	−0.016
	(0.030)	(0.024)	(0.020)	(0.017)	(0.016)	(0.017)
Log (Farmland)	−0.061	−0.003	−0.017	−0.018	0.013	0.029
	(0.038)	(0.035)	(0.029)	(0.018)	(0.018)	(0.020)
County fixed effects	N	Y	N	N	Y	N
Village fixed effects	N	N	Y	N	N	Y
R^2	0.039	0.206	0.542	0.038	0.210	0.409
Observations	1,167	1,167	1,160	1,167	1,167	1,160

Notes: The dependent variable in columns 1–3 is a binary indicator equal to one if the household relocated in or before 2017, while the dependent variable in columns 4–6 is a binary indicator equal to one if the household relocated in the first year of relocation implementation in its county. All explanatory variables are pre-determined villager-group and household characteristics, including: 1) Natural conditions of the villager group: terrain type (with mountainous terrain as the reference group), altitude and the log of total losses from natural disasters; 2) Baseline demographic characteristics of the villager group: the proportion of identified poor households (IPHs), the proportion of households with Chinese Communist Party (CCP) membership, the proportion of ethnic minorities, the proportion of households with the most common surname, and the proportion of religious households; 3) Initial economic conditions of the villager group: the proportion of households with access to electricity and to safe water; 4) Baseline household characteristics: household size, number of children, the log of total household expenditure, and the log of total farmland area in the origin village. Standard errors clustered at the villager group level are reported in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A4
Effects of relocation on women's off-farm employment status.

	Women's Off-farm Employment Status			
	(1)	(2)	(3)	(4)
Relocate	0.046**	0.052***	0.049***	0.052***
	(0.020)	(0.019)	(0.019)	(0.018)
Mean of the control group	0.161	0.161	0.161	0.161
Year FE	Y	Y	Y	Y
Township FE	Y	N	N	N
Villager-group FE	N	Y	Y	N
Resettlement FE	N	N	Y	N
Individual FE	N	N	N	Y
R^2	0.137	0.189	0.214	0.554
Observations	12,365	12,364	12,290	12,254

Notes: Each observation is an individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to female individuals aged 22–60 in each year. All models control for respondents' characteristics (age, gender, and years of schooling) and year fixed effects. Column 1 additionally includes township fixed effects. Column 2 adds villager-group fixed effects. Column 3 incorporates both villager-group and resettlement fixed effects. Column 4 further includes individual fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A5
Gender-differential effects.

	Off-farm employment (1)	Working months (2)	Log (monthly wage) (3)	Log (annual earnings) (4)
Relocate	0.015	0.294	0.103	0.156
	(0.020)	(0.212)	(0.153)	(0.195)
Relocate × Female	0.049**	0.190	0.321**	0.370*
	(0.021)	(0.207)	(0.159)	(0.203)
Mean of the control group	0.306	2.646	2.320	2.935
R^2	0.651	0.655	0.663	0.668
Observations	27,372	27,372	27,372	27,372

Notes: Each observation is an individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to female individuals aged 22–60 in each year. Monthly wage and annual earnings are both winsorized at the 99th percentile. All models control for respondents' characteristics (age, gender, and years of schooling), individual and year fixed effects, interactions between individual demographics (ethnicity and years of schooling) and year fixed effects, villager group-by-year fixed effects, and gender-specific linear time trends. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A6
Effects of relocation on individual's probability of out-migration.

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
Relocate	0.025*	0.028**	0.042**	0.012	0.014	0.003
	(0.013)	(0.013)	(0.020)	(0.016)	(0.016)	(0.022)
Mean of the control group	0.107	0.107	0.107	0.286	0.286	0.286
Individual FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Demographics-by-year FE	N	Y	Y	N	Y	Y
Villager group-by-year FE	N	N	Y	N	N	Y
R^2	0.591	0.605	0.681	0.595	0.607	0.690
Observations	12,254	12,237	11,929	15,208	15,205	14,909

Notes: Each observation is an individual-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to individuals aged 22–60 in each year. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects. Columns 2 and 5 additionally control for individual demographics (ethnicity and years of schooling) interacted with year fixed effects. Columns 3 and 6 further add villager group-by-year fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A7
Effects of relocation on other labour market outcomes.

	Sign Labour Contracts		Business Creation		Agriculture Work		Overall Work Status	
	Women (1)	Men (2)	Women (3)	Men (4)	Women (5)	Men (6)	Women (7)	Men (8)
Relocate	−0.095	−0.046	−0.002	0.009	−0.069	−0.024	−0.047	−0.006
	(0.086)	(0.051)	(0.016)	(0.020)	(0.055)	(0.047)	(0.048)	(0.026)
Mean of the control group	0.152	0.110	0.009	0.023	0.737	0.775	0.809	0.905
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Additional Interactive FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.915	0.792	0.641	0.671	0.692	0.671	0.628	0.590
Observations	1,261	3,789	1,730	2,168	3,852	5,013	3,863	5,019

Notes: Each observation is an individual-year. The sample is restricted to individuals aged 22–60 in each year. The dependent variable in columns 1–2 indicates whether the individual signed any labour contracts, with data available for 2015 and 2018–2021. The dependent variable in columns 3–4 denotes whether the individual engaged in any business activity, with data only available for 2016 and 2018. The dependent variables in columns 5–6 and columns 7–8 represent whether the individual participated in agricultural work and employment in any sector, respectively, with data available for 2015, 2016, 2018 and 2020. All regressions control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager group-by-year fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A8
Heterogeneity-robust estimators.

	Off-farm employment (1)	Working months (2)	Log(Monthly wage) (3)	Log(Annual earnings) (4)
Relocate	0.047**	0.565**	0.329*	0.440**
	(0.023)	(0.227)	(0.174)	(0.223)
R^2	0.594	0.619	0.599	0.606
Observations	9556	9556	9556	9556

Notes: Each observation is a female-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to female individuals aged 22–60 in each year. The results are estimated under the interaction-weighted method of Sun and Abraham (2021), using the last-treated units as the control group. Monthly wage and annual earnings are both winsorized at the 99th percentile. All models control for respondents' characteristics (age, gender and years of schooling), individual fixed effects, year fixed effects, as well as villager group-specific linear time trends. Robust standard errors clustered at the village group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A9
Robustness check - restrict to collective-relocated subsample.

	Off-farm employment (1)	Working months (2)	Log (Monthly wage) (3)	Log (Annual earnings) (4)
Relocate	0.050**	0.555***	0.368**	0.482**
	(0.020)	(0.194)	(0.147)	(0.188)
Mean of the control group	0.155	1.427	1.158	1.485
R^2	0.608	0.625	0.618	0.623
Observations	10,119	10,119	10,119	10,119

Notes: Each observation is a female-year. The data are unbalanced and span the years 2011 to 2021. The sample is restricted to female individuals aged 22–60 in each year and their households that chose collective relocation. Monthly wage and annual earnings are both winsorized at the 99th percentile. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager group-specific linear time trends. Robust standard errors clustered at the villager group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A10
Robustness check – restrict to balanced panel of female individuals.

	Off-farm employment (1)	Working months (2)	Log (Monthly wage) (3)	Log (Annual earnings) (4)
Relocate	0.065**	0.734***	0.436**	0.580**
	(0.028)	(0.271)	(0.210)	(0.268)
Mean of the control group	0.140	1.202	1.037	1.317
R^2	0.547	0.553	0.555	0.561
Number of unique individuals	549	549	549	549
Observations	6,029	6,029	6,029	6,029

Notes: Each observation is a female-year. The data are balanced and span the years 2011 to 2021, covering 549 unique female individuals. The sample is restricted to female individuals aged 22–60 in each year. Monthly wage and annual earnings are both winsorized at the 99th percentile. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager group-specific linear time trends. Robust standard errors clustered at the village group level appear in parentheses (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Table A11
Sample selection bias on women's off-farm employment.

	Second Stage (1)	First Stage (2)
Relocate	0.050***	
	(0.015)	
Age	-0.006***	−0.001
	(0.000)	(0.001)
Educational attainment	0.006***	-0.029***
	(0.002)	(0.003)
Marital status	-0.136***	0.626***
	(0.048)	(0.026)
Family Size	0.004	-0.081***
	(0.006)	(0.009)
N. of children	-0.015**	0.057***
	(0.006)	(0.013)
Prop. of migrants	–	-0.004**
	–	(0.002)
IMR	−0.188	–
	(0.130)	–
Village FE	Y	Y
Year FE	Y	Y
Num. of female individuals	1804	1804
Num. of observations	19,844	19,844

Notes: Each observation is a female-year. The data is balanced and ranges from 2011 to 2021. The sample is restricted to individuals aged 22–60 in each year. Robust standard errors appear in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A12
Effects of relocation on individual's time use in housework.

	Time spent on grocery shopping & cooking		Time spent on collecting firewood	
	Women (1)	Men (2)	Women (3)	Men (4)
Relocate	-2.514***	−0.296	-1.317***	-1.211***
	(0.504)	(0.246)	(0.262)	(0.232)
Mean of the control group	8.648	1.834	2.282	2.410
R^2	0.731	0.681	0.626	0.619
Observations	1,792	2,212	1,796	2,212

Notes: Each observation is an individual-year. The data used in this table cover the years 2016 and 2018. The sample is restricted to individuals aged 22–60 in each year. The dependent variables in columns 1–2 measure the number of hours spent on grocery shopping and cooking per week, while the dependent variables in columns 3–4 denote the hours spent collecting firewood per trip. All models control for respondents' characteristics (age, gender and years of schooling) and individual fixed effects. Robust standard errors clustered at the villager group level appear in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A13
Effects of relocation on individual's human capital.

	Skill Training		Physical Health	
	Women (1)	Men (2)	Women (3)	Men (4)
Relocate	0.009	0.018	−0.015	−0.013
	(0.014)	(0.017)	(0.025)	(0.021)
Mean of the control group	0.068	0.132	0.627	0.693
R^2	0.609	0.610	0.658	0.644
Observations	4,900	5,787	4,249	5,250

Notes: Each observation is an individual-year. The sample is restricted to individuals aged 22–60 in each year. The dependent variables in columns 1–2 indicate whether the individual received any skill training in a given year, with data available for 2017, 2018, 2020, and 2021. The dependent variables in columns 3–4 indicate whether the individual was in good health in a given year, with data available for 2015, 2016, 2018, and 2020. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, and villager group-specific linear time trends. Robust standard errors clustered at the villager group level appear in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

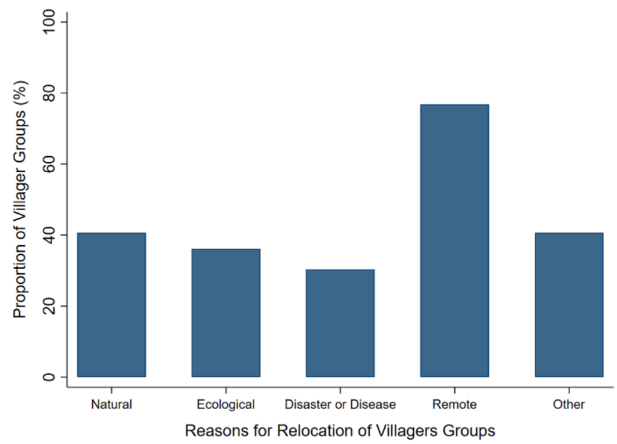

Fig. A1. Reasons for relocation of sampled villager groups.

In 2016, the wages earned by all persons in Form A (for those who have been employed for ⩾ 10 days or have a permanent occupation during the year, one member can fill in more than one type, and the income includes cash income and various income in kind).

	A14	A15	A16	A17	A18		A19	A20	A21	A22	A23
										If you didn't live at home	
	Engaged in the industry	Engaged in the type of work	Duration of work	Average monthly income	Place of work		How much money was given to the family in 2016?	In 2016, the total value of the money and material support given to the member by the family	Did you live at home in 2016?	What was the top reasons for working outside the home (single choice).	The average number of times your family contacted the member each month in 2016
Perosnal code	**Industry code**	**Job code**	Month	RMB	Work location code	Work area code	Yuan	Yuan	**1 Yes 2 No**	**Reason code**	times/month

Industry Code:
1. Government civil servants, public institutions, village cadres or group leaders 2. Planting 3. Forestry 4. Animal husbandry 5. Sideline 6. Fishery 7. Extractive Industry 8. Manufacturing 9. Production and Supply of Electricity, Gas and Water
10. Construction 11. Transportation, Warehousing and Posts and Telecommunications 12. Wholesale and Retail Trade, Catering 13. Finance and

Job Code:
1. Unit management, 2. Professional and technical personnel, 3. Equipment operators or front-line production employees, 4. Office clerks or clerks, 5. Tertiary service personnel, 6. Workshop or production line management, 7. Others

Reason codes:
1. There is no job or employment in the place of residence, 2. The salary in the place of residence is low, 3. The natural environment of the place of residence is poor, 4. It is affected by other migrant workers in the village, 5. Provide better education for children
6 Marital issues (including divorce) 7 Others (please specify)

Work Location Code:
1 village, 2 villages, 3 counties, other villages, 4 other counties, other counties, 5 other provinces, 6 foreign countries

Work Area Code:
11 Beijing, 12 Tianjin, 13 Hebei, 14 Shanxi, 15 Inner Mongolia, 21 Liaoning, 22 Jilin, 23 Heilongjiang, 31 Shanghai, 32 Jiangsu 33 Zhejiang, 34 Anhui, 35 Fujian, 36 Jiangxi, 37 Shandong, 41 Henan, 42 Hubei, 43 Hunan, 44 Guangdong, 45 Guangxi, 46 Hainan 50 Chongqing 51 Sichuan 52 Guizhou 53 Yunnan 54 Tibet 61 Shaanxi 62 Gansu 63 Qinghai 64 Ningxia 65 Xinjiang 71 Taiwan 81 Hong Kong 82 Macau 99 Abroad

Fig. A2. The employment module of the 2017 household survey questionnaire.
Notes: The image of this employment module can be found in the Appendix of Chen et al. (2025). Readers interested in our survey refer to Chen et al. (2025), which includes portions of the questionnaire modules from the 2016, 2017 and 2019 waves.

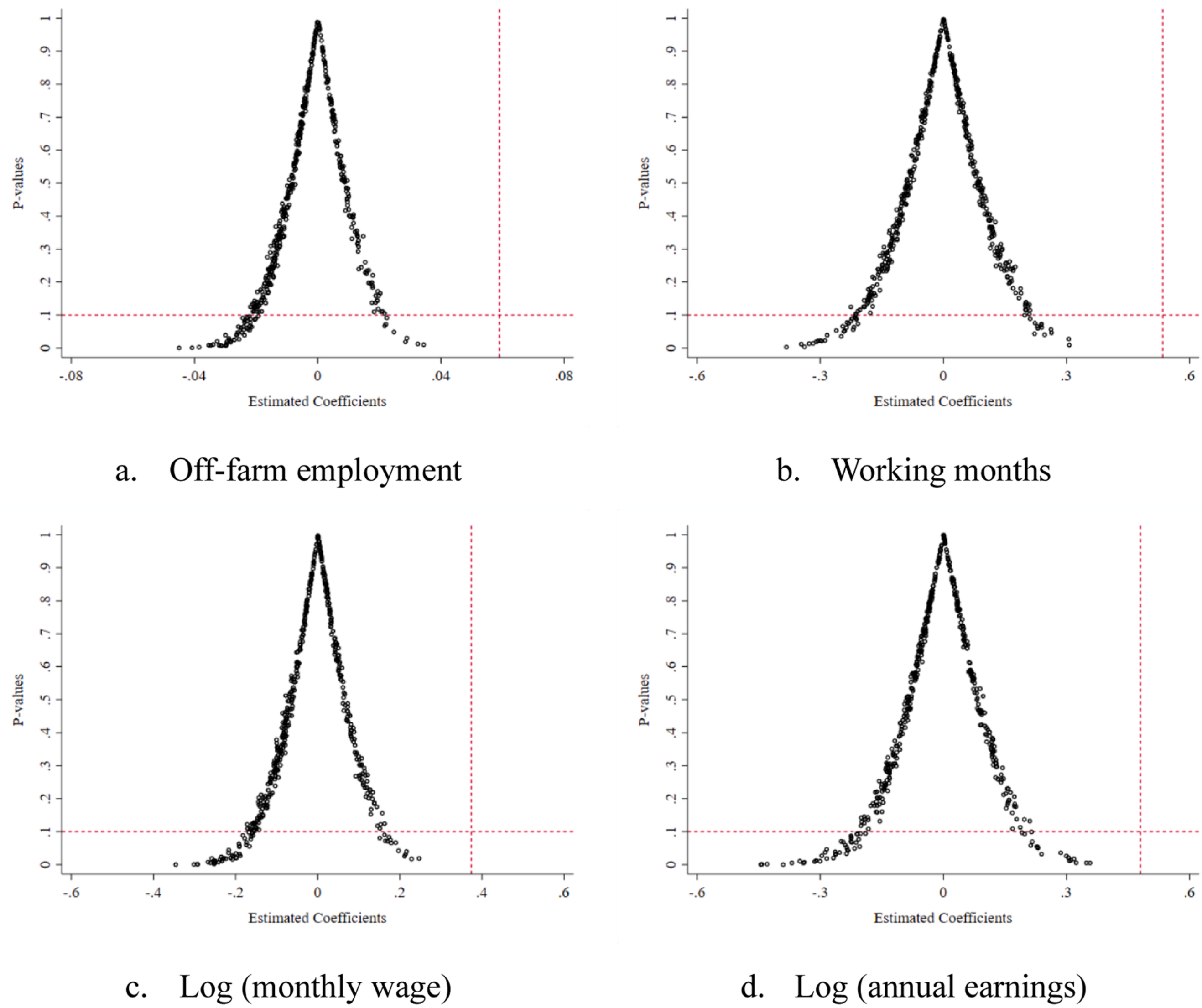

Fig. A3. Placebo test using randomly assigned relocation year.
Notes: Figures a-d depict the estimated coefficients and corresponding p-values from estimating the effect of the "placebo" relocation year on the probability of women's off-farm employment, working months per year, the logarithm of monthly wage and the logarithm of annual earnings, respectively. All models control for respondents' characteristics (age, gender and years of schooling), individual and year fixed effects, individual demographics (ethnicity and years of schooling) interacted with year fixed effects, as well as villager-group specific linear time trends. We randomly select a year from the period of 2011–2020 as the "placebo" relocation year for each household and repeat this random sampling procedure 500 times. The vertical red dashed lines in figures a-d represent the true estimated coefficients in column 3 of Table 3, column 2 of Panel A in Table 4, column 4 of Panel A in Table 4 and column 6 of Panel A in Table 4, respectively. Standard errors are clustered at the villager group level.

Data availability

Data will be made available on request.

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