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Impacts of City Life on Nutrition: Evidence from Resettlement Lotteries in China*

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Abstract

Urban environments are thought to mitigate hunger issues, by offering improved access to markets and income opportunities. Yet this idea is hard to test empirically, because where people reside is partly the result of self-selection. This study leverages a resettlement program in China to provide the first quasi-experimental estimate of city life on food consumption and nutrition among low-income households. Lottery-determined timing of resettlement enables causal inference. A comparison of village-to-village vs. village-to-town resettlement additionally helps identify the role of urban environments. Empirics are based on a 3-year panel of over 1000 households, and a range of variations on difference-in-differences methodologies and matching procedures. We find that those who were resettled to towns significantly increased both food consumption and diet variety, shifted towards more valued staples, and consumed more macro- and micronutrients. Diet quality mostly improved, but we also found signs of over-consumption, notably for processed foods and carbohydrates. Our results stand in sharp contrast to recent literature that finds little or no effect of living environments on food consumption and posits that nutrition outcomes primarily demand-driven even among the poor. Instead, we reveal a significant impact of urban environments in shaping diets and bolster the notion that supply-side channels do matter.

1 Introduction

Hunger issues tend to be less severe in urban areas. Cities are home to 56% of the global population, but most of the food-insecure, and especially the extremely food-insecure, live in rural areas (World Bank, 2018; Ahmed et al., 2007). Child outcomes are particularly skewed: two thirds of stunted children are rural (DIPR, 2020). These observations contribute to the common notion that urban environments help mitigate issues of hunger and malnutrition, notably through easier access to markets (Katz, 2013; Ruel et al., 2017). Paciorek et al. (2013) estimated that 9%-15% of improvements in child height and weight over the period 1985-2011 were attributable to urbanization. However, such conclusions are not without caveats: between the emergence of slums (Hussain and Lunven, 1987), hidden hunger (Gödecke et al., 2018), and econometric issues due to selection or confounding factors (Zezza et al., 2011), the question of whether moving to cities can improve the nutritional outcomes of the poor is far from settled. Conversely, urban lifestyles are also often blamed for issues of overweight and obesity. Studies show that obesity is worse in urban areas (Black et al., 2013), including in low-income areas of developing countries (Neuman et al., 2013), but again evidence of causal links remains elusive (Eid et al., 2008).

The current situation is thus characterized by persistent under-nutrition and growing over-nutrition – the "double burden" of malnutrition – over a backdrop of rapid urbanization which evidently affects these dynamics but in ways that are poorly understood (UN, 2020). Given this context, the need to understand whether, why, and how urban environments affect what we eat is as critical as ever. In this article, we study a unique lottery re-housing program in China to provide elements of answers to these questions.

Estimating the relationship between urban living and food consumption presents a host of empirical challenges. Cross-sectional comparisons of people living in different environments can only highlight correlations (Frank et al., 2004). Studies of rural-urban migrants can show that they suffer less from food insecurity, but self-selection issues cast doubt on any causal interpretation of such results (Eid et al., 2008; McKenzie and Rapoport, 2010; Zezza et al., 2011). To empirically disentangle these effects requires a setting where variation in rural-vs-urban living is determined exogenously, and preferably at random – such opportunities are few and far between. Our work leverages one such opportunity by studying China' s Poverty Alleviation Resettlement (PAR) program.

The PAR is a recently-completed (2015-2020) program which, as part of China's poverty-eradication campaign, resettled about 10 million rural poor households around the country into newly constructed settlements (NDRC, 2014). Two features enable us to use this program for the purpose of studying the impact of urban living on nutrition. First, the timing of resettlement was determined by lottery, which provides the randomness necessary to estimates causal impacts. Second, only some households were resettled to urban areas (small towns), while others were resettled within rural areas (villages), providing the perfect counterfactual. We collected three rounds of panel data from over 1,000 households spanning 8 provinces and 4 years (2016-2019). We estimate treatment effects using a range of variations on difference-in-difference methods. We account for the effect of time- and space-invariant confounders with household and time fixed-effects (two-way fixed effects), and ensure baseline sample balance with matching methods based on LASSO predictions and propensity score matching (PSM).

Overall, we find very strong and significant impacts of relocation on nutrition for those who were relocated to towns, but very limited impacts on those who were relocated to villages. Urban-relocators ate significantly more meat, vegetables, and other non-staples. They diversified their diet, and increased overall intake of most macro- and micro-nutrients. Diet quality results are mostly positive, though we do see evidence of excessive intake of carbohydrates. Further analysis of pathways suggest that these effects are more likely to be driven by market access rather than by income effects.

These results further our understanding of the rural-urban nutrition gap in several ways. First, we provide the first quasi-experimental empirical assessment of this gap. Previous literature is mostly limited to international comparisons or changes in urbanization rates over time as sources of variation (Fox and Heaton, 2012; Van de Poel et al., 2007; Liu et al., 2013; Ervin and Bubak, 2019). In contrast, our methodology is most similar to the studies of the Moving To Opportunity program (Katz et al., 2001; Chetty et al., 2016; Kling et al., 2010) and other public initiatives in which housing was randomly assigned (Chyn, 2018). Previous studies have used such programs to study neighborhood effects on education, incomes, and other economic outcomes, but our paper seems to be the first to address nutrition. The PAR program setting is perhaps as close as researchers can get to a random allocation of households to homes, and thus offers an opportunity for uniquely strong empirics.

Second, we confirm the strong positive impact of urban areas on nutrition and the potential role of urbanization in the fight against hunger. This result parallels some existing findings (Ruel et al., 2017; Fan et al., 2017; Fan and Rue, 2015; Smith et al., 2006) but stands in contrast to others (Faye et al., 2011; Smith et al., 2006; Hut, 2020; Colozza and Avendano, 2019). At the same time, our results reveal signs of excess nutrition, which echoes the literature on worsening overweight among the urban poor in the global south (Hawkes et al., 2017; Dinsa et al., 2012; Popkin, 1999), and highlights the potential role of urbanization in the growing obesity epidemic.

Third, we contribute to debate over neighborhood effects and the role of market access on food consumption (Hilmers et al., 2012). While better access to supermarkets has previously been linked to better nutrition in U.S. urban areas (Larson et al., 2009; **?**), recent findings have cast doubt on the role of neighborhood effects, suggesting nutritional inequality was mostly explained by differences in demand rather than access (Allcott et al., 2019; Alviola et al., 2013; Smith and Morton, 2009; Pearson et al., 2005). In our context, supply does appear to matter.

Overall, insights from this work bear policy relevance not only for the specific case of China's PAR program and poverty-eradication efforts, but also more broadly in the areas of food security, urban planning, and public health.

The remainder of this paper is organized as follows. Section 2 provides the policy background and data sources. Section 3 introduces our empirical strategy and summary statistics. Results are presented in Section 4; Section 5 discusses and concludes.

2 Background and Data

2.1 Program Design and Implementation

The PAR program was a part of China’ s poverty-eradication campaign launched in 2016 and completed in December 2020. It aimed to ensure that basic living standards were met for all households in China, with a focus on housing amenities (clean water, electricity, etc.) and access to public services (health and education). The program targeted about 9.8 million households (NDRC, 2014), identified as the most vulnerable households in the most impoverished rural communities around the country. These households were offered the option to leave their former dwellings and be rehoused into government-provided settlements. Participation was voluntary, but since the new homes featured dramatically improved living conditions, the vast majority of targeted households accepted the relocation offer (Lo and Wang, 2018). All relocations were completed by the end of 2020.

Selection of households into the program was decentralized, but coordinated nationally. PAR was deployed in all counties with high levels of poverty, the majority of which lie in the country's non-coastal provinces. The program targeted only households officially eligible for government assistance due to low-income status, which in 2014 meant yearly incomes below 2,736 CNY per capita (CPAD, 2014). Local administrations were charged with selecting recipients from among those households, following a system of quotas. This process was monitored and cross-validated by the National Bureau of Statistics, and recipient rosters were made public to ensure transparency and prevent corruption (CPAD, 2014).[1] Virtually all eligible households accepted the resettlement offer.

Program roll-out was gradual, following the gradual construction of settlements. All participant households were provided with a new home at some point during the 2015-2020 period, but not at the same time. To ensure fairness, local authorities would implement lotteries: those who won

[1] A concurrent vigorous anti-corruption campaign by the central government strongly encouraged the denunciation of corrupt local officials, such that concerns over corruption in the selection process are minimal. Regardless, this would not impact our identification strategy as our sample includes only recipients.

earlier would be able to move sooner, while others would have to wait until the next lottery. This feature is what allows us to compare resettled and not-yet-resettled households in a causal inference framework (more on this later). Again, the lotteries were closely monitored for transparency and held publicly, suggesting winners were indeed chosen at random.

The new homes provided by PAR all meet predefined requirements in terms of amenities (electricity, water, etc.) and surface (25 square meters per person). Recipients own their new home, but under two conditions: they must give up ownership of their previous residence (which gets demolished), and they cannot sell, rent, nor otherwise sublease the new home. These conditions ensure that (1) all recipients in our data actually live in their new home after resettlement, and (2) the intervention is purely a housing transfer, not an income transfer – both of which bolster our identification strategy.

While all new homes meet similar standards in terms of amenities, the program distinguishes two types of settlements: rural and urban. The rural settlements are typically located in "central" villages (where rural administrations reside), while the "urban" settlements are on the outskirts of small towns (usually county seats). We will refer to them as "Resettled in villages" and "Resettled in towns" , respectively, with the understanding that the latter are county-level towns, not large cities. Implementation is decentralized to the county level, such that no recipient is ever resettled outside of their own county. However, those who are relocated to town settlements are likely to experience more dramatic changes in terms of environment, including in terms of market access.

2.2 A three-year panel survey

Our data consist of three rounds of panel data collected from 16 counties in 8 provinces and spanning 4 years (2016-2019). These 8 provinces (Gansu, Guangxi, Guizhou, Hubei, Hunan, Sichuan, Shanxi, Yunnan) were selected to account for relocation plans and regional heterogeneity. Together they account for 73.6% of the total population relocated over the span of the program at the end of 2020 [2]. In each province, we selected 2 counties and 2-3 townships in each county,

[2] According to data from Poverty Alleviation Office of the State Council, 2020, Beijing.

based on PAR-eligible population and geographical characteristics (to ensure variability accross time, space, and geographical features). In each township 3 villages were randomly selected, then 8-10 low-income households were selected at random from administrative rosters for interview. All of the surveyed households were eligible for PAR, but the program had not yet been announced and respondents were unaware of its existence at the time of the first round (July and August 2016, prior to the launch of PAR). The survey collected information on basic demographics, living conditions, income, consumption, employment, and more. A first follow-up survey took place one year after the baseline, between July and August 2017, then a second follow-up two years later (three years after baseline) in April and May 2019. Most households in the sample were re-settled during the study period (to homes across 106 settlement communities), and following survey rounds tracked them to their new PAR-provided housing. We removed 27 households with missing information on daily calorie intakes or household income. The final panel consists of 1025 households from 251 villages, followed over three rounds of survey. Relocations started soon after the survey baseline. Table 1 shows the resettlement schedule in our sample, by province. Of the 1025 households, 28.8% had relocated by the time they were re-interviewed in 2017, and 82.9% had relocated by 2019. Of those who were resettled, 34.6% were resettled to small towns, and 65.4% within rural areas, either within their village or to a village nearby. Though resettlement type varies from province to province in our sample, there were both town and village relocations in all but Yunnan and Guangxi.

3 Empirical Strategy and Summary Statistics

3.1 Estimation Methodology

The core of our econometric estimation strategy is a two-way fixed-effects (TWFE) specification, meaning a variant of difference-in-differences that controls for both household fixed-effects and year fixed-effects . Letting Y_{it} be an outcome of interest for household i in survey round t (food and nutrition variables or measures of market access), we estimate the following equation:

$$Y_{it} = \mu_i + T_t + \beta_1 Village_{it} + \beta_2 Town_{it} + \boldsymbol{\gamma Z} + \epsilon_{it} \tag{1}$$

where μ_i is the fixed effect for household i and T_t are survey-round dummies. $Village_{it}$ is a dummy variable with $Village_{it} = 1$ after a household has been relocated to a village. $Town_{it}$ is a similar dummy for relocation to towns. The relocation being irreversible, both dummies remain at 1 in periods following the initial relocation. The coefficients of interest are β_1 and β_2, which give the average treatment effect of PAR relocation. We include 21 additional time-varying controls, denoted by $Z_{i,t}$, such as household demographics, assets, and more (details to follow). ϵ_{it} represents the random errors, clustered at the household level.

The underlying assumption of a difference-in-differences specification is that, conditional on controls, households would have exhibited similar trends in the outcome variables in the absence of the PAR program. This is less credible if the households we are comparing have very different characteristics. Because the timing of relocation is determined by lottery, we can reasonably expect that our treatment and control groups were determined truly at random and are on average comparable. Nevertheless, as a robustness check we also run the specification from equation (1) in a restricted sample of pairwise-matched treatment and control households. This is performed through radius matching, with the radius set to 0.005 and propensity scores based on a LASSO regression of relocation on the Z covariates.

3.2 Variable Selection and Summary Statistics

We consider three main types of outcome variables. First, variables measuring the consumption of various food items including staple foods like rice or maize and non-staple food like vegetable, meat, or processed snacks (17 food items in total). We use those outcomes independently (expressed in grams) as left-hand side variables in some of our regressions, or combined as food diversity scores. Second, we convert food consumption into nutrient intake variables. Table 2 provides the detail of that conversion. We compute per capita intakes of calories, Carbohydrates, protein, fat, calcium, vitamin A, vitamin C, thiamin and riboflavin. Table 3 provides a comparison between measures of baseline-year food intake in our sample and Dietary Reference Intakes (DRIs) from the Institute of Medicine (IOM) which indicates the mixed, balanced diet (Katz and Meller, 2014). In our regressions, we use absolute measures of nutrient intake, as well as relative measures expressed as divergence scores away from the DRIs. Third, in some specifications we use measures capturing households' access to food and food markets, including market distance, frequency going to market, production diversity and household total income per capita. Table 4, Table 5 and Table 6 reports summary statistics for all variables used in our regressions, for each round of survey as well as overall. The following paragraphs detail how all these variables were sourced.

3.2.1 Food consumption variables.

Our survey recorded quantities of different food items consumed by families in a two-week recall. Consumption includes not only quantities that were purchased at store or shops, but also the farm-produced quantities eaten at home which were calculated from production and sales (netting out livestock feed). Only 3.5% of households had consumed any food away from home, with an average expenditure is CNY 4.2 in two weeks, suggesting food away from home is negligible and can be ignored. Per capita food consumption was computed using only family members currently living in the home, converted to adult-equivalents, and excluding members who had migrated away for work. The average food consumption in the sample is shown in the rightmost column of Table 2.

3.2.2 Nutrient intake variable.

We decompose food quantities into intakes of macro- and micro-nutrients. Macro-nutrients (calories, carbohydrates, proteins and fat) are needed in large quantities, and their intake measures the basic nutritional status and food sufficiency. Micro-nutrients (in our data: Calcium, Vitamin A, Vitamin C, Thiamin, Riboflavin) are required in small amounts but are essential for the body to function.[3] Their intake is a more subtle measure of nutritional adequacy, as a diet can be suffi-

[3]Micronutrients tend to be essential for specific dimensions of health. For example, Vitamin A helps with build up the immune system and improve eyesight; Thiamin can promote infant intelligence development;

cient in quantity by deficient in micro-nutrients, also called "hidden hunger" (Larson et al., 2009). Following Huang et al. (2017) and Setayeshgar et al. (2017), we decompose food consumption to nutritional intake according to China Food Composition Table (2018) (CCDC, 2009). Table 2 shows decomposition factors, which we apply to calculate per capita daily nutrient intake.

We use nutrient divergence values to explore changes in diet for households that were relocated through PAR. Each nutrient has a recommended range, such that quantity itself is not an adequate measure of nutritional quality. We compute the absolute divergence (percent) between nutrient intake and recommended intake levels specified in Dietary Reference Intakes 2013 (DRIs 2013). DRIs are age-specific: the recommend ranges used for this paper is based on optimal ranges for males and females aged 16-60.

Based on these data and measurement from Zhou et al. (2020) , we can compute nutrient divergence scores (DS) as follows:

$$N_{itk} = \sum_{f=1}^{17} w_{fk} C_{itf} \tag{2}$$

$$DS_{itk} = \frac{|N_{itk} - R_k|}{R_k} \times 100\% \tag{3}$$

where C_{itf} is the daily per capita intake of food category f for household i in survey round t. N_{itk} is the daily per capita intake of nutrient k for household i in survey round t. w_{fk} is the conversion weight for food category f and nutrient k. DS_{itk} is the divergence index of nutrient k for household i in survey round t, computed as the percent divergence (in absolute value) between the average daily nutrient intake N_itk and corresponding recommendation R_k in the DRIs. Since R_k are daily recommended intake intervals, we compute divergences from the nearest point in the interval: when $N_{itk} < min(R_k), R_k = min(R_k)$, when $N_{itk} > max(R_k), R_k = max(R_k)$, and when $min(R_k) < N_{itk} < min(R_k), DS_{itk} = 0$. This ensures the divergence score is a conservative measure.

The range of DS is $[0, +\infty)$, such that a smaller DS index indicates better diet quality. When

Riboflavin helps against inflammation in the mouth, lips, tongue and skin (Jha et al., 2009).

DS approaches 0, the respondent' s diet is consistent with DRI intake standards. Importantly, DS captures both over- and under-nutrition.

Table 3 compares the DRIs and the daily per capita intake in our sample in the baseline year. Among macronutrients, daily per capita intakes of calories, protein and fat all appear within range, but carbohydrates significantly exceed the recommended intake (311g against 120g). Among micro-nutrients, only Thiamin consumption falls within the recommended range. Calcium, Vitamin A and Riboflavin intakes at baseline are all significantly below their DRIs, while Vitamin C intake is significantly above. Overall, this suggests an issue of diet quality, with sufficient caloric intake, excess carbohydrates, and insufficient micro-nutrient intake.

3.2.3 Food environment variables

We choose four variables to measure household access to food and food markets. The first is distance to markets, which captures convenience and accessibility according to Huang and Tian (2019), particularly for fresh foods. We consider either the nearest open-air free market for rural households or the nearest supermarket or grocery store for households that were relocated to towns. The second variable is frequency to market. Even if markets are close-by, households may not frequent them –particularly if they are unfamiliar with their new surroundings after relocation. We use the frequency to market to capture this behavior. The survey asked respondents how many times any of the family members went to the market to buy fresh food in the past month, which we converted to a yearly figure. The third variable is total yearly per capita household total income, to capture food affordability. It includes wage income, operating net income from businesses, rental income and transfer income. Last, we measure own-production diversity from farms or home-gardens, as home production can influence the food availability, diversity, and dietary intake for rural households (Sibhatu et al., 2015; Huang and Tian, 2019). We thus observe the changes of production diversity after relocation.

3.2.4 Independent and control variables

The main independent variables capture treatment status: relocation to villages and relocation to towns, both expressed as dummy variables. The control group is comprised of all households who have not relocated (yet). The treatment groups are households that have relocated to villages or towns. We use the group that relocated to towns to capture the influence of an urban environment and city life on household nutrition. Because the timing of relocation is determined by lottery, assignment to treatment or control group is random, such that our estimates of impact of relocating to villages or to towns have a causal interpretation. While the assignment to village- or town-settlements is not deliberately randomized, village-relocators still provide a good benchmark when compared to town-relocators. Control variables include household demographics and characteristics, all summarized in Table 5 and Table 6.

3.3 Balance Tests and Matching

Before running regressions, we test the statistical differences between our three groups at baseline, in order to make sure that they have similar food consumption and nutrient intake patterns. We do not have multiple pre-treatment data rounds, such that we cannot test the parallel trends which underpin difference-in-differences estimation. Nevertheless, similarity at baseline can provide some reassurance that treatment and control groups are on comparable trends. We first compare the three groups in the full dataset, then in a subset selected using a matching procedure. The results are shown in Table 7 and Figure 1. We use four main categories of variables we believe may influence participation in the PAR program and the relocation time to estimate the propensity score: 1) Household demographics (household size, average age of members, proportion of children, elderly, or women, etc.); 2) Human capital (education, self-reported health, etc.); 3) Household resources (income per capita, farm size, number of assets, water source, housing materials, etc.); 4) Access to services and infrastructure (such as the distance to paved roads, banking centers, village committee, etc.). The full list of variables and their description are provided in Table 6. The left panel of Table 7 reports baseline means of household characteristics for the three groups in the full sample. Asterisks indicate statistically significant differences compared to the not-yet-relocated group. Table 7 shows that before matching, a number of variables show statistically significant differences between households in the treated groups compared to the controls: 14 variables out of 25 show significant differences for the village relocators, and 13 out of 25 for the town relocators. This lack of balance could cast doubt on the validity of our results, therefore throughout the paper we present not only results using the full sample, but also results in a subset selected by propensity score matching (PSM) with scores based on a LASSO regression. In all our regressions, PSM-lasso results and full-sample results are overwhelmingly similar in terms of significance and magnitude. To select the subset, we first run a LASSO regression of the treatment dummy on all control variables and the several variables have been selected and the random error has been estimated. We then compare the control variables in the groups using PSM methods with radius matching and the p-scores are equal to the predicted error coefficients of lasso regression. In this paper, we have estimated twice using LASSO regressions to get two predictions. Once for the relocated to towns vs controls using non-relocated and relocated to towns samples. Once for relocated to villages vs controls using non-relocated and relocated to villages samples. And then, we do the two propensity score matching separately using the three samples. Finally, the three samples (non-relocated, relocated to towns and relocated to villages) have been screened. The number of households in the sample was reduced from 1025 to 901 (meaning total observations reduced from 3075 to 2703). Figure 1 presents the kernel densities before and after matching for different two groups. It shows that the distribution of propensity scores in the PSM-lasso sample are nearly identical for treated and control households. The right panel of Table 7 shows that many of the baseline differences are eliminated once we restrict to the PSM-lasso subsample, though some remain significant. For instance, distance to road and life satisfaction, building materials, distance to village committee and house surface all show significant differences for village-relocators. Yet overall the differences between treated and control households were greatly reduced been reduced, and these significant differences are not large and likely not related to household nutrient intakes. After matching and screening, we mainly remove non participating households that are too dissimilar to participating households to be appropriate comparators, and drop a few participating households that differ too much from any non-participating households. We estimate the effects using the matched households with positive weight. The fixed effects will eliminate both observed and unobserved time-invariant differences among households, and the assumption of a common underlying trend in the absence of the PAR program needs to be satisfied. So that it is likely to be more credible using the screened samples after PSM with lasso regression.

4 Results and Discussion

4.1 Impacts on Food Consumption and Diversity

Table 8 presents estimates of the average impact of relocation on food consumption and food variety. We show the results using the full sample in rows 1-2, and the results using the PSM-lasso matched sample in rows 3-4. All specifications control for household fixed-effects, year fixed-effects, and all the covariates listed in Table 6, but we only display key parameters in the interest of space. Coefficients should be interpreted as the impact of a given type of resettlement (to villages or to towns) relative to control (not-yet-resettled) households. We assume that the lottery-determined relocation timing allows a causal interpretation, though caveats apply. In the text, we will report the magnitudes from PSM-lasso results, which are likely to be more trustworthy.

The first key insight from the table is that several of the coefficients of interest do appear significant: households who were resettled into new homes did indeed alter their consumption patterns for certain foods, compared to their not-yet-resettled counterparts. Some coefficients are positive, others negative, and we examine those patterns in more detail below.

The second key insight comes from comparing households resettled within villages to those resettled to a town. Those who were resettled to towns altered their food intake patterns much more significantly than those who remained in the rural sector. Results for households resettled in villages only show two significant coefficients (maize and pork), whereas town-relocators show significant coefficients for all but one food category. In addition, the magnitudes of coefficients are much larger for those who were relocated to towns. These regressions all control for income, all our covariates, any time-invariant household characteristics, as well as year effects, such that they are likely to be reflecting the impact of the treatment. It appears being relocated to a town has a much more dramatic impact on food consumption, as predicted by our theoretical framework.

Looking at food categories reveals several distinguishable patterns. First, town-relocators shifted their intake of staples toward those regarded as better-tasting and higher status. Their daily maize consumption per capita decreased by 65.6 g, while rice and potato intakes increased by 67.5 g and 41.1 g, respectively. In contrast, village-relocation led to a much smaller decrease in maize consumption (-16.5 g), and other staples did not increase significantly.

Second, households that were relocated to towns significantly increased non-staple food intake, including pork, fish, fruits, vegetables and snacks. Daily per capita vegetables intake increased by 70.0 g for households that relocated to towns, and fruits by 9.5 g. Consumption of pork increased by 15.6 g per capita, and fish consumption has increased by 2.8g per capita. An increase in vegetable, fruit, meat, and fish intakes is usually thought of as an improvement in diet quality. In contrast, village-relocators only increased their consumption of pork significantly by 11.1 g per capita, with no significant change for other non-staple foods. Most of these non-staple food items are usually regarded as relatively healthy (fruits and vegetables, meats, fish).

Third, the consumption of snacks also increased significantly for town-relocators. Snacks include processed foods regarded as unhealthy such as sweets, cakes, chips and so on, with abundant carbohydrates and fats. Per capita consumption increased by 3.5 g, which represents a 120% increase from the mean at baseline, the largest relative increase in the table.

The last column of Table 6 presents results on food variety. Compared to households that did not relocate, town-relocators increased their food variety score significantly by 0.66, meaning the average household added 0.66 to their weekly count of food types after relocation. In contrast, the impact is not significant for households that were relocated to villages.

Overall, the table shows that poor households who were relocated to towns significantly increased consumption of both healthy and unhealthy non-staple foods, and increased diet diversity. These results are consistent with a number of previous findings. Kato and McKinney (2015) show that underprivileged households value and consume healthy foods if given access to them. Several studies have shown positive associations between food accessibility or market access and household diet diversity (Braha et al., 2017; Herzfeld et al., 2014; Koppmair et al., 2017).

4.2 Impacts on Nutrition

We further explore the impact of relocation on the low-income households' nutrition level. Nutrient conversions are shown above in Table 2. Table 9 presents the results of regressions with nutrient intakes on the left-hand side. Again, we show both full-sample and PSM-lasso results, with overwhelmingly similar results (the only difference in significance appears for fat intake).

Again, the effect of PAR resettlement is much more dramatic for town-relocators than village-relocators. From the results shown in row 3-4, we see that all nutrient intakes increased significantly for households relocated to towns, and none for those relocated to villages.

For households relocated to towns, intakes of macronutrients (calorie, carbohydrate, protein and fat) and intakes of micronutrients (calcium, vitamin A, vitamin C, thiamin and riboflavin) both increased significantly for households that were resettled to towns. Under 1% significance level, the calorie and carbohydrate intakes of households that relocated to towns rose by 329.5 kcal and 52.5 g per capita per day. The daily intake of protein has increased by 7.3 g per capita, and the daily intake of fat has increased by 8.05 g per capita for households that relocated to towns. Daily per capita intakes of calcium, vitamin A, riboflavin, vitamin C and thiamin all increased significantly for households that relocated to towns (by 39.2 mg, 55.2 g, 0.085 mg, 23.7 mg, and 0.22 mg, respectively). Based on Table 3, the intakes of the calcium, vitamin A, and riboflavin were all below the recommended intake at baseline. Thus the increase of such micronutrient intakes likely helped improve nutritional status in households that were relocated to towns. The findings of this study are consistent with other research which found that urban slum condition and environment impact children's nutritional health Goudet et al. (2017). In contrast, nutritional intake of households relocated to villages seems not to have improved significantly compared to the households that did not relocate.

We further examine these questions of nutritional quality using divergence scores, with results presented in Table 10. A lower divergence score indicates a better diet, meaning that negative coefficients denote an improvement in nutritional intakes. These results provide a more nuanced picture of the impact of relocation on nutrition.

Households that relocated to towns have significantly decreased their micronutrient divergence for calcium, vitamin A and riboflavin, with nutrient intakes much closer to the recommend range, indicating more balanced diets. Divergence scores for calcium, vitamin A, and riboflavin decreased by 3.8 percentage points, 6.5 percentage points, and 7.2 percentage points respectively. However, their divergence scores for carbohydrate and fat intakes significantly increased, suggesting excessive intake and worse diets. The carbohydrate divergence increased by 38.3 percentage points and fat divergence increased by 5.5 percentage points, suggesting the overconsumption of carbohydrate is more dramatically beyond the recommended range. Vitamin C divergence also increased significantly, suggesting optimal quantities are more than met, though significance is weak. Meanwhile, results for households who were resettled within villages show limited impact: improvements in protein and thiamin intakes when using the full sample, but no significant coefficients using the PSM-lasso sample.

On balance, these results show that being resettled to towns dramatically impacted household nutrition, with a strong positive increase in daily intakes of all macro- and micro-nutrients. However, these results are not clear-cut in terms of diet quality post-relocation: several micro-nutrient intakes are closer to optimal, but carbohydrate and fat intakes are further away. This suggests that relocation to towns increases access to healthy foods but also facilitates excess nutrition. The results are in accordance with the findings showing excess caloric intake, rather than insufficient calorie expenditures, is responsible for much of the rising obesity trends after Americans moved to cities (Cutler et al., 2007; Downs et al., 2009).

4.3 Heterogeneity Analysis

Household demographics and intra-household decisions are among the characteristics affect nutritional intake (along with a variety of economic and non-economic factors not considered here). In the following analysis, we test whether PAR resettlement impacts may have been heterogeneous for households with different characteristics along three dimensions: the presence of children under 16 (Figure 2), whether a woman is in charge of food purchases for the household, and the average age of household members. In each case, we run the same regressions as previously, but adding an interaction term between the treatment variable and the household characteristic of interest.

This section still needs to be completed

4.4 Possible Impact Channels

Our theoretical model identifies two main impact channels for how resettlement impacts food purchases and diets: changes in access to markets, and changes in home-production. In addition, household income may be affected, which will also shifts demand. Table 11 presents the results of resettlement on market accessibility, market utilization, agricultural production and household income level. The table shows results using both the total sample (observations = 3075) and the PSM-lasso sample (observations = 2703), with very similar results.

First, relocating to towns has a statistically negative impact on the distance to market and a significantly positive effect on the frequency to market. Average distance to market was shortened by 8.16km for town-relocators in the matched sample, from a baseline of 11.71 km. Impacts are more muted for those relocated to villages (-2.4km in the full sample, not significant in the matched sample). The yearly frequency to market significantly increased by 75.23 person-times for those who were relocated to towns, relative to a baseline of only 19.45 person-times. No significant effect was found for those moved to villages. This indicates that a large improvement of market accessibility and market utilization for households that relocated to towns.

Second, compared to the households that relocated to towns, the households that relocated to villages significantly increased their production diversity and total income. After relocating to villages, the household’ s total production diversity increased by 0.53 production items using the screened samples. Total income per capita significantly increased by 1293.18 CNY for households that relocated to villages, which is almost the half of the mean at baseline. These results likely reflect improved environments in the “central” villages compared to recipients previous location.

Meanwhile, relocating to towns had no significant effect on either of these variables.

On the whole, the households that were relocated to towns experience much greater changes in the market environment than those relocated to villages, without significantly altering their incomes. This suggests that the large impacts on food and nutrition we see among town-relocators are likely due supply effects.

4.5 Caveats

A first caveat is that while the timing of resettlement was determined at random, the selection into rural PAR and urban PAR was not. Rather, it was determined by geographical location and resettlement plans at the province and county level. The comparison between town resettlement and village resettlement may thus be picking up some time-varying geographic variation that did not wash out with fixed effects. Similarly, town resettlements tended to start later than village resettlements on average, suggesting the potential for time-related confounders. However, this would only affect the comparison of town and village resettlments, not the validity of each estimation taken individually, so it does not threaten our main conclusion that resettlement to urban areas had substantial impacts on food consumption.

A second possible worry is the potential for anticipation effects. Households may be starting to change their food consumption behavior as soon as they know that they will eventually get resettled. For instance, they might neglect their vegetable garden in the knowledge they have to abandon it eventually, and start relying more on store-purchased foods. However, this type of anticipation effect would more likely lead to lead to attenuation bias, rather than the results we see.

An additional concern is that we may be mis-attributing the increase in food consumption to the urban market environment. For instance, it could be that moving to the PAR settlements brings changes in the cooking environment, such as the use of gas, access to refrigeration, etc. However, since the village and town settlements are all designed to meet similar standards, we would not likely see such differences in impacts if this was purely driven by kitchen amenities. Nevertheless, we cannot exclude that such alternative pathways play a part in explaining our results. Additional work would be needed to further disentangle all the mechanisms involved.

5 Conclusions

This work leveraged a unique lottery re-housing program in China to examine the impact of the living environment on nutrition. Low-income households living in relatively remote rural areas were resettled into new housing at various locations, some in villages and others in small towns. All households were eventually resettled, but as timing was lottery-determined, comparing resettled to not-yet-resettled households arguably yields causal impact estimates free from selection biases. Using a three-year panel, a range of two-way fixed effects specifications, as well as matching methods, we estimate impact of resettlement to different areas on food and nutrition.

Results show that while being resettled to villages led to a slight increase in meat consumption and improvement in protein intake, being resettled to towns led to much more dramatic impacts. Town-relocators increased their food consumption accross all tracked categories, reducing only maize consumption (a staple usually regarded as less-preferred). Their food variety increased significantly by 0.75 items per week. Their macro- and micro-nutrient intakes increased across all tracked items. Simultaneously, market access and utilisation sharply increase, which echoes previous studies that find correlations between poor food access and poverty (LeClair and Aksan, 2014) or low-quality diets (Rose et al., 2010).

From the perspective of hunger-alleviation, these results are encouraging. The resettlement program targeted some of China's most vulnerable populations as part of campaign to eradicate extreme poverty; increased food consumption likely participates to greater food-security for the beneficiaries. At the same time, we found that *increased* nutrition only translated to *improved* nutrition by some measures: intake of Calcium, Vitamin A, and Riboflavin got closer to optimum, suggesting better micro-nutrient intake. However, Carbohydrate intake diverged further from optimum, as did (though weakly) Fat and Vitamin C. These latter results suggest over-nutrition, and highlight the simultaneous challenges posed by malnutrition's "double-burden".

Putting normative considerations aside, our results provide evidence of a strong impact of urban environments on food consumption and nutrition. Because our estimates are arguably free from selection bias, they suggest that the rural-urban nutrition gap documented extensively in the literature (Fan and Rue, 2015; Chen, 2016; Huang and Tian, 2019) is not due to intrinsic differences in populations or preferences, but indeed environmentally driven. Further, our results shed light on the mechanism behind this gap: it appears not to be driven by incomes or job opportunities, but indeed by market access. This finding is in sharp contrast with situations where nutrition gaps between different urban neighborhoods were found to be almost entirely demand-driven (Fitzpatrick et al., 2019; Allcott et al., 2019). In our context, supply side factors appear to be the key constraints.

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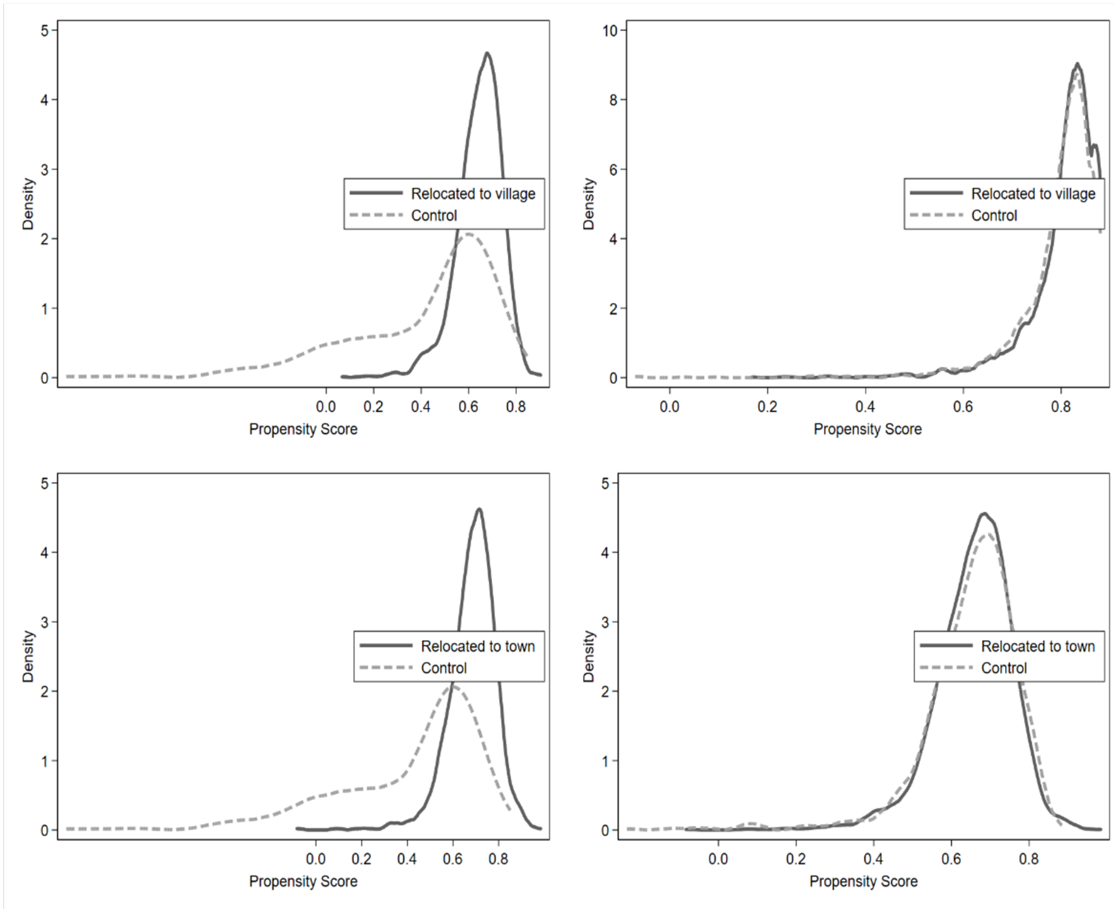
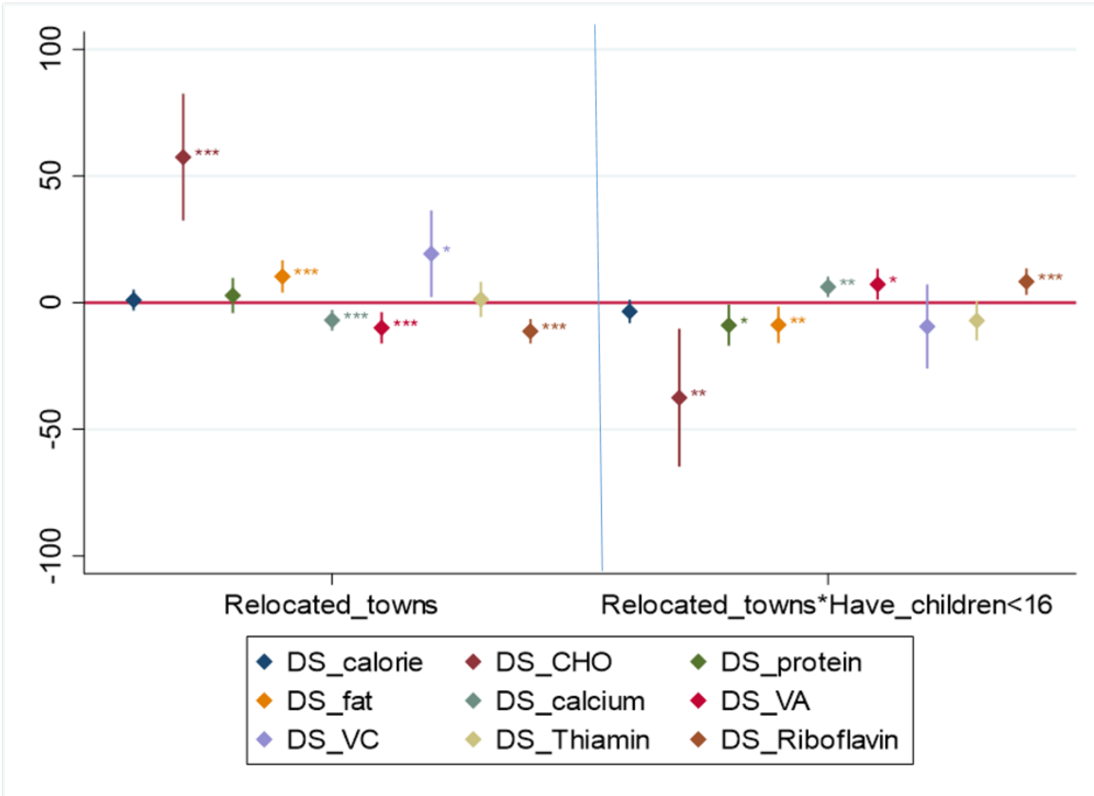
6 Figures and Tables

6.1 Figures



Notes:

Fig. 1: Kernel Density Before (left) and After (right) Matching for households relocated to Villages (above) or Towns (below)



Notes:

Fig. 2: Effects of relocating to towns with interaction (have children <16)

6.2 Tables

Table 1: Descriptive statistics for PAR lottery winner vs. control group - group mean at baseline

Province	2016	2017			2019		
	Sample size (pre-resettlement)	Not yet resettled	Resettled to towns	Resettled to villages	Not yet resettled	Resettled to towns	Resettled to villages
Yunnan	141	90	0	51	16	0	125
Sichuan	144	71	0	73	1	1	140
Guangxi	107	106	1	0	3	104	0
Hubei	119	73	0	46	7	4	108
Hunan	138	133	0	5	32	63	43
Gansu	150	136	7	7	80	16	54
Guizhou	101	51	48	2	6	92	3
Shanxi	125	70	6	49	30	12	83
Total	1025	730	62	233	175	294	556

Table 2: Nutrient Content per 100g and Mean Food Consumption

Food	Calorie (kcal)	Carbohydrate (g)	Protein (g)	Fat (g)	Calcium (mg)	Vitamin A(g)	Vitamin C(mg)	Thiamin (mg)	Riboflavin (mg)	Average consumption per capita(g)
Rice	346	77.9	7.9	0.9	8	0	0	0.15	0.04	258.82
Flour	359	75.2	12.4	1.7	28	0	0	0.2	0.06	70.57
Maize	112	22.8	4	1.2	0	0	16	0	0	58.05
Grain	337	74.7	9.3	2.3	47	20	0	0.28	0.16	2.83
Potato	81	17.2	2.6	0.2	7	6	14	0.1	0.02	178.59
Beans	390	34.2	35	16	191	220	0	0.41	0.2	25.9
Animal oil	897	0.2	0	99.6	0	27	0	0.02	0.03	15.17
Vegetable oil	900	0	0	100	10	0	0	0	0.09	30.92
Vegetables	20	3.2	1.6	0.2	57	80	37.5	0.05	0.04	271.29
Pork	395	2.4	13.2	37	6	18	0	0.22	0.16	61.99
Beef	164	2	19.45	9.15	14.5	14.5	0	0.045	0.14	0.41
Poultry	167	1.3	19.3	9.4	9	48	0	0.05	0.09	6.15
Fish	103	1.6	16.6	3.3	58	11	0	0.05	0.07	2.34
Eggs	144	2.8	13.3	8.8	56	234	0	0.11	0.27	21.75
Dairy	54	3.4	3	3.2	104	24	1	0.03	0.14	9.81
Fruits	53	13.5	0.4	0.2	4	50	3	0.02	0.02	17.28
Snack	432	67.1	4.9	12.3	29	0	0	0.06	0.01	2.91

Table 3: Nutritional intakes at baseline vs. Dietary Reference Intakes

Variables	Observation	Average of sample at baseline	99% Conf. Interval	Dietary reference intakes
Calorie(kcal)	1025	2149.25	(2092.09, 2206.41)	1750-3200
Carbohydrate(g)	1025	311.828	(302.3, 321.36)***	120
Protein(g)	1025	58.952	(57.22, 60.69)	55-75
Fat(g)	1025	67.774	(65.43, 70.11)	39-107
Calcium (mg)	1025	271.407	(262.07, 280.75)***	1000-1300
Vitamin A(g)	1025	332.736	(320.29, 345.18)***	700-900
Vitamin C(mg)	1025	143.521	(138.16, 148.88)***	65-90
Thiamin(mg)	1025	1.107	(1.07, 1.14)	1.0-1.2
Riboflavin(mg)	1025	0.503	(0.49, 0.52)***	1.0-1.3

Table 4: Dependent Variable Definitions and Summary Statistics by Survey Round

Variable		Explanation	2016	2017	2019
Dependent variables					
Nutrient Intake	Calorie	Calories per capita daily intake (kcal)	2149.25	2413.179	2500.709
	Carbohydrate	Carbohydrate per capita daily intake (g)	311.828	347.054	316.603
	Protein	Protein per capita daily intake (g)	58.952	67.816	71.397
	Fat	Fat per capita daily intake (g)	67.774	79.771	98.019
	Calcium	Calcium per capita daily intake (mg)	271.407	302.614	311.409
	Vitamin A	Vitamin A per capita daily intake (ug)	143.521	143.51	122.892
	Vitamin C	Vitamin C per capita daily intake (mg)	332.735	377.83	386.959
	Thiamin	Thiamin per capita daily intake (mg)	1.107	1.26	1.253
	Riboflavin	Riboflavin per capita daily intake (mg)	0.503	0.599	0.655
Divergence Score	Calorie	Direct deviation between actual intake and recommended intake	13.308	11.586	11.779
	Carbohydrate		164.918	191.301	166.738
	Protein		23.055	24.373	26.827
	Fat		11.11	14.347	19.431
	Calcium		72.899	69.799	69.015
	Vitamin A		80.823	83.312	63.372
	Vitamin C		53.763	50.293	47.978
	Thiamin		30.258	33.077	30.93
	Riboflavin		50.352	43.398	38.797
Potential Impact Pathways	Distance to market	The distance to market (km)	11.713	9.604	8.795
	Frequency to market	How many times did they go to market last year	19.446	22.058	56.433
	Production diversity	The number of crop and livestock species produced on a farm	4.566	4.316	3.541
	Total income	Total net income per capita in a year (yuan)	2839.058	4200.047	5708.456

Table 5: Core Independent and Heterogeneity Variable Definitions and Summary Statistics by Survey Round

Variable	Explanation	2016	2017	2019
Core Independent variables				
Resettled to towns	Household was moved to a PAR settlement in a town. (Yes=1, No =0)	0.001	0.06	0.287
Resettled to villages	Household was moved to a PAR settlement in a village. (Yes=1, No=0)	0.013	0.227	0.542
Control variables				
Children	Whether have children under 16 years old in family. (Yes=1; No=0)	0.466	0.464	0.442
Woman decision	Whether women are responsible for food purchase. (Yes =1; No = 0)	0.506	0.506	0.506
Young family	Average members' age under 40. (Yes=1; No=0)	0.482	0.478	0.433

Table 6: Control Variable Definitions and Summary Statistics by Survey Round

Variable	Explanation	2016	2017	2019
Household size	How many people eat at home during this two weeks	2.895	3.02	2.635
Dependency ratio	Children and old people' s proportion in the family	0.398	0.393	0.405
Woman proportion	Woman' s proportion in the family	0.447	0.448	0.445
Average age	The average age of the whole family members	42.191	42.762	43.803
Healthy people proportion	Proportion with health people in the family	0.558	0.589	0.7
Education proportion	The number of people who receive education over 9 years / household number	0.213	0.247	0.277
Total income	Total net income per capita in a year (yuan)	2839.058	4200.047	5708.456
Road distance	The distance to the road (km)	2.09	1.253	0.398
Farm size	Farming land area (mu)	5.923	6.998	6.651
Labor proportion	Proportion of healthy labor (16-60 years old) in the family	0.406	0.458	0.466
House construction	House construction (0=no house, 1=Civil structure, 2=brick and wood, 3=brick and concrete, 4=thatch house, 5=wood house)	1.491	0.944	2.58
Social capital	How many friends do they have	27.902	19.201	39.802
Distance to village committee	The distance to the village government (km)	14.947	13.75	10.909
Off-farm worker proportion	Proportion of non agricultural employment in family	0.209	0.275	0.301
Family loans	How much money did the family borrow last year	9122.888	12325.11	5337.951
Finance situation	How many financial institutions around the home	2.111	1.845	2.092
Household total expenditure	Household total expenditure per capita	4288.454	4292.179	4854.167
Life satisfaction	Grading for living satisfaction, 1-7, the higher score, the more satisfied	3.189	4.103	5.35
Phone	Whether connecting phone at home, 1=yes; 0=no	0.943	0.956	0.976
Network	Whether connecting network at home, 1=yes; 0=no	0.106	0.197	0.255
Water	Whether having tap water at home, 1=yes; 0=no	0.526	0.682	0.868
Energy utilization	Household energy consumption per capita in a year(standard coal)	424.057	389.65	344.571
Asset ownership	The number of durable consumer goods in family	7.534	.	.
House area	House area (square meter)	81.671	.	.
Relocation knowledge	Relocation knowledge (1=Understand very well, 2=know little, 3=Not at all)	1.685	.	.

Table 7: Balance Tests

Selected variables	Full sample			PSM with Lasso		
	No resettlement	Resettled to towns	Resettled to villages	No resettled	Resettled to towns	Resettled to villages
Household size	3.029	3.102	2.743**	2.951	3.103	2.722
Dependency ratio	0.375	0.390	0.410	0.409	0.400	0.411
Woman proportion	0.463	0.452	0.440	0.464	0.448	0.440
Average age	41.526	39.528*	43.808**	42.942	40.057**	43.837
Healthy people proportion	0.553	0.608*	0.534	0.511	0.589**	0.531
Education proportion	0.274	0.227**	0.187***	0.211	0.220	0.187
Total income	3486.817	2422.621***	2855.380*	2960.167	2459.836	2852.782
Road distance	2.541	2.335	1.819***	3.026	2.376*	1.823***
Farm size	15.586	3.496***	4.165***	4.340	3.468**	3.945
Labor proportion	0.410	0.442	0.386	0.353	0.420*	0.384
House construction	1.337	2.041***	1.248	1.559	1.790	1.245***
Social capital	7239.771	5959.354	5969.119	5039.804	5879.762	5996.399
Distance to village committee	14.189	16.738**	14.238	18.522	16.796	14.199***
Off-farm worker proportion	0.197	0.223	0.205	0.193	0.221	0.205
Family loans	11292.000	9971.803	7991.277*	7187.255	9820.079	7746.161
Finance situation	1.680	2.129**	2.237***	2.049	2.000	2.249
Household total expenditure	4467.132	4071.638	4346.863	3826.733	4076.707	4348.407
Life satisfaction	3.149	2.714***	3.453***	2.982	2.765	3.452***
Phone	0.960	0.959	0.930	0.961	0.956	0.929
Network	0.143	0.133	0.081**	0.118	0.131	0.080
Water	0.434	0.585***	0.523**	0.461	0.560*	0.525
Energy utilization	496.122	384.619**	422.229**	447.023	372.864	421.029
Asset ownership	8.783	7.823***	6.987***	7.500	7.817	6.931
House area	84.190	83.097	80.125	90.402	84.284	80.282**
Relocation knowledge	1.794	1.687**	1.649***	1.706	1.683	1.647
Sample size	175	294	556	102	252	547

Table 8: Impacts on Food Consumption and Diversity

	(1) Rice	(2) Maize	(3) Potato	(4) Vegetables	(5) Pork	(6) Poultry	(7) Fish	(8) Fruits	(9) Snack	(10) Food variety
Mean at baseline	258.82	58.05	178.59	271.29	61.99	6.15	2.34	17.28	2.91	6.784
TWFE(Sample: 3075)										
Resettled to towns	71.715***	-87.690***	33.116*	51.127***	12.063**	4.307*	2.706**	13.078***	3.007*	0.754***
	(13.501)	(11.498)	(17.378)	(18.358)	(5.413)	(2.257)	(1.175)	(4.978)	(1.677)	(0.200)
Resettled to villages	8.286	-27.310***	-17.058	1.582	9.132*	-2.772	0.455	2.244	-0.102	0.196
	(12.832)	(9.347)	(18.138)	(18.416)	(4.773)	(1.866)	(1.034)	(4.294)	(1.951)	(0.189)
PSM-lasso TWFE (Sample: 2703)										
Resettled to towns	67.497***	-65.586***	41.055**	69.999***	15.560***	4.342	2.786**	9.485*	3.463*	0.656***
	(15.304)	(12.117)	(20.056)	(20.827)	(6.016)	(2.640)	(1.329)	(5.210)	(2.058)	(0.229)
Resettled to villages	4.682	-16.496*	-10.695	15.485	11.139**	-3.100	0.194	-0.232	0.521	0.139
	(14.130)	(9.845)	(19.402)	(19.898)	(5.165)	(2.071)	(1.153)	(4.600)	(2.267)	(0.205)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 9: Impacts on Nutritional Intake

Nutrient Intakes	Calorie (kcal)	Carbohydrate (g)	Protein (g)	Fat (g)	Calcium (mg)	Vitamin A (g)	Vitamin C (mg)	Thiamin T (mg)	Riboflavin (mg)
Mean at baseline	2149.25	311.828	58.952	67.774	271.407	143.521	332.735	1.107	0.503
TWFE (Sample: 3075)									
Resettled to towns	275.773***	43.639***	5.459*	6.286	32.937*	43.293*	13.691*	0.195***	0.070***
	(88.185)	(13.765)	(3.198)	(4.293)	(17.798)	(23.758)	(7.902)	(0.051)	(0.027)
Resettled to villages	-61.465	-14.020	-4.151	1.570	-11.570	-25.694	-6.929	-0.040	-0.026
	(82.355)	(13.039)	(3.062)	(4.107)	(18.103)	(24.723)	(7.938)	(0.050)	(0.027)
PSM-lasso TWFE (Sample: 2703)									
Resettled to towns	329.537***	52.518***	7.303**	8.030*	39.207*	55.195**	23.728***	0.215***	0.085***
	(98.809)	(15.209)	(3.573)	(4.782)	(20.485)	(27.445)	(9.059)	(0.058)	(0.030)
Resettled to villages	-18.053	-4.122	-2.404	2.079	-4.828	-13.126	0.280	-0.014	-0.012
	(88.559)	(13.657)	(3.279)	(4.443)	(19.750)	(27.319)	(8.607)	(0.054)	(0.029)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 10: Impacts on Nutrition Divergence Scores

Divergence Score of Nutrients	Calorie (%)	Carbohydrate (%)	Protein (%)	Fat (%)	Calcium (%)	Vitamin A (%)	Vitamin C (%)	Thiamin (%)	Riboflavin (%)
Mean at baseline	13.308	164.918	23.055	11.11	72.899	80.823	53.763	30.258	50.352
Two-Way Fixed-Effects (Sample: 3075)									
Resettled to towns	-5.280***	29.042***	-7.307**	0.942	-3.164*	-5.291*	6.396	-8.864***	-6.873***
	(1.994)	(11.140)	(3.159)	(2.878)	(1.748)	(2.730)	(7.088)	(3.189)	(2.163)
Resettled to villages	-1.635	-12.347	-6.465**	-3.675	1.195	3.348	-8.027	-6.010**	2.804
	(1.870)	(10.568)	(2.945)	(2.667)	(1.777)	(2.794)	(6.772)	(3.021)	(2.136)
Two-Way Fixed-Effects with PSM(Sample: 2703)									
Resettled to towns	-1.033	38.312***	-2.182	5.487*	-3.750*	-6.521**	14.465*	-2.747	-7.186***
	(2.150)	(12.336)	(3.536)	(3.164)	(2.004)	(3.070)	(8.076)	(3.520)	(2.407)
Resettled to villages	1.211	-2.947	-2.948	-0.790	0.543	1.717	-3.509	-1.853	2.190
	(1.963)	(11.059)	(3.116)	(2.858)	(1.936)	(3.016)	(7.293)	(3.190)	(2.313)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 11: Impacts on Potential Impact Pathways

Living Condition Variables	(1) Distance to market (km)	(2) Frequency to market (person-times)	(3) Production diversity (type)	(4) Total income (CNY)
Mean at baseline	11.71	19.45	4.57	2839.06
Fix-Effect (Sample: 3075)				
Relocating to towns	-9.960***	77.752***	-0.085	420.991
	(0.917)	(7.971)	(0.162)	(531.396)
Relocating to villages	-2.422***	-3.590	0.506***	1416.585***
	(0.756)	(3.524)	(0.131)	(441.264)
PSM-Fix-Effect (Sample: 2703)				
Relocating to towns	-8.158***	75.228***	-0.072	177.765
	(0.938)	(8.667)	(0.177)	(591.066)
Relocating to villages	-0.991	-2.815	0.532***	1293.176***
	(0.714)	(3.929)	(0.135)	(499.085)
Control Variables	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Household FE	Y	Y	Y	Y