A Mixed Blessing: The Unintended Consequences of Social Welfare Policies on Child Development

Chao Liang[1], Susu Wang[1], Yongkun Yin[2], and Jie Zou[2]

[1]Center for Economic Research, Shandong University

[2]School of Economics, Shandong University

February 28, 2026

Abstract

This paper examines the unintended consequences of China's Nutrition Improvement Program (NIP) on rural household migration and the incidence of left-behind children. Although the program aims to improve child nutrition, its benefits are tied to children's residence in their home counties. Using a joint migration model, we demonstrate that non-portable, child-targeted subsidies can encourage parents to migrate without their children. Exploiting the program's staggered rollout in a difference-in-differences framework, we find that the NIP increased the probability that rural children are left behind by 17%. Mechanism analyses indicate that free school meals reduce child-rearing costs and caregiving constraints in rural areas, thereby facilitating parental migration without children. While the program improves the physical development of disadvantaged children, the induced parental absence significantly harms their children's mental health. These findings highlight the distortionary effects of non-portable welfare policies during urbanization.

1 Introduction

To break the intergenerational cycle of poverty, the Chinese government has implemented a series of targeted welfare policies aimed at enhancing the human capital of rural children. These interventions focus on critical stages of child development, including the "Two Exemptions and One Subsidy" program for basic education, the Nutrition Improvement Program (Free School Meals) for physical health, and specialized educational and medical assistance for children under the Targeted Poverty Alleviation framework.

While these initiatives have substantially improved the well-being of rural children by directly subsidizing the costs of child-rearing, they are characterized by a common institutional feature: non-portability. Because these public resources—such as meal subsidies and educational grants—are predominantly place-based and managed by local institutions at the registered place of residence, beneficiary children must remain in their home villages to access them. In the context of rapid urbanization, this institutional design creates a micro-level distortion in household migration decisions. When remaining in the rural origin becomes a prerequisite for receiving substantial child-specific benefits, rational households are more likely to opt for a strategy where children are left behind while parents migrate. Consequently, public investments intended to support child development may inadvertently institutionalize parental separation.

This policy-induced "left-behind" status leads to a potential trade-off in the accumulation of child human capital. On one hand, programs like the NIP directly improve a child's physical health (physical capital). On the other hand, the resulting parental absence may significantly undermine psychological well-being and cognitive development (psychological capital). Empirical literature suggests that the negative externalities of parental absence are often profound and irreversible. If the nutritional gains from welfare programs are offset by the loss of parental care, the marginal contribution of such policies to overall child welfare will be diminished. Evaluating the spillovers of these targeted child benefits on migration patterns is therefore central to assessing their comprehensive net impact.

To identify the impact of the aforementioned institutional constraints on household migration decisions, this paper exploits the implementation of the Nutrition Improvement Program (NIP) in rural China since 2011 as a quasi-natural experiment. As a major public initiative covering over 20 million rural students in compulsory education, the NIP represents a substantial central government investment designed to bolster the nutritional status of rural children through free school meals. Theoretically, we construct a joint migration model to derive how households weigh the place-based policy benefits in rural areas against the social costs of family migration. Empirically, we utilize data from the China Family Panel Studies (CFPS) and the China Household Income Project (CHIP), employing a Difference-in-Differences (DID) framework to identify the causal effect of the NIP on the status of left-behind children.

The empirical results demonstrate that the implementation of the NIP significantly altered the labor allocation and living arrangements of rural households. Specifically, the program led to a more than 17% increase in the probability of rural children being left behind. Mechanism analysis reveals that this effect operates through two primary channels. First, the program significantly reduced the direct financial burden of rural schooling, creating a "staying effect" that incentivized children to remain in their villages. Second, the institutionalization of meal provision eased the household care burden and enhanced the feasibility of intergenerational care by grandparents, thereby facilitating parental migration. While the NIP improved the physical development of children from low-socioeconomic status families in the long run, the resulting parental absence imposed a significant negative shock on children's mental health outcomes.

Our findings suggest a pressing need for a redesign of the child welfare architecture. To minimize the social costs of urbanization, policymakers should transition from place-based subsidies toward portable welfare models, ensuring that public services are dynamically aligned with the movement of children. Furthermore, this issue is of global relevance. In many developing nations undergoing rapid urbanization, targeted interventions for children often face similar institutional barriers. This study provides critical empirical evidence for balancing the provision of specialized welfare with the maintenance of family integrity in a global context.

This study builds upon three distinct strands of literature, making corresponding marginal contributions to each field.

The first strand of literature investigates the determinants of left-behind children. In many developing countries, most notably China, a vast body of research has documented the adverse short- and long-term consequences of parental absence on children's academic performance, health outcomes, and psychological well-being (Wang et al., 2023; Zhao et al., 2014; Seror, 2022; Zhang et al., 2014; Zheng et al., 2022; Fan et al., 2021; Cameron et al., 2022).

Regarding the determinants of left-behind children, the extant literature generally posits that the phenomenon stems from the migration decisions of rural labor, who are attracted by superior employment opportunities in urban (Clemens and Tiongson, 2017; Bai et al., 2018; Wilson, 2021). However, access to urban welfare amenities, such as public schooling and healthcare, is typically restricted to local residents. Under the constraints of China's rigid Hukou (household registration) system, rural migrants face substantial institutional barriers and high costs when attempting to relocate with their children (Chen and Feng, 2013; Kuhn and Shen, 2015; Wang et al., 2019; Tom; Hao et al., 2020; Jin and Zhang, 2023; Sieg et al., 2023; Bosker et al., 2012). Consequently, the prevalence of left-behind children is primarily interpreted as a result of resistance at the urban destination.

While the existing literature on left-behind children focuses heavily on these destination-side factors, the role of pull factors at the place of origin remains largely unexplored. This paper constitutes the first attempt to understand the phenomenon of left-behind children through the lens of origin-based child development policies and the associated costs of local schooling. Our research aligns with the broader labor migration literature, which suggests that the attractiveness of the home region significantly shapes migration decisions (Farnham and Sevak, 2006). For instance, higher-quality natural endowments and superior public service provision in rural areas are known to reduce the propensity of labor to out-migrate (Wilson, 2021; Rupasingha et al., 2015; Dustmann and Okatenko, 2014). Qiu et al. (2024) has found that improved residential environments act as a deterrent to migration, while secure rural land tenure systems also discourage mobility by ensuring the protection of household land rights (Chen, 2017; Chari et al., 2021; Ngai et al., 2019; Adamopoulos and Restuccia, 2020; Adamopoulos et al., 2024). Collectively, these studies underscore that the place of origin exerts a distinct pull on rural residents; as this pull intensifies, the incentive to migrate diminishes.

However, our study departs from the existing research on origin-side pull factors in one critical dimension. While the aforementioned factors typically provide incentives for the entire household to remain local, we demonstrate that when a pull factor is child-specific—or if welfare policies are targeted exclusively at children—it may not reduce, and could potentially even increase, the parents' propensity to migrate. By lowering the cost of child-rearing at the place of origin without providing equivalent incentives for adults to stay, such policies may inadvertently lead to a higher incidence of left-behind children. Our finding is consistent with the work of (Havnes and Mogstad, 2011), which suggests that an increase in child-targeted subsidies can lead to an expansion of parental labor supply. In this context, the local welfare policy acts as a subsidy that relaxes the household's budget constraint and reduces the shadow cost of parental absence, thereby facilitating rather than hindering parental migration.

The second strand of literature relates to the free meals. The free meals has a long history, and consequently, there is a substantial body of economic literature examining it. Most studies focus on the impact of the NIP on children's health and academic performance. It has been shown to significantly reduce the incidence of hunger, malnutrition, obesity, and metabolic syndrome (Bhattacharya et al., 2006; Afridi, 2010; Hoynes et al., 2016; Anderson et al., 2018).The majority of the literature finds that the NIP significantly boosts student achievement and also improves student attendance rates (Belot and James, 2011; Chakraborty and Jayaraman, 2019; Aurino et al., 2023). The literature generally finds that early childhood health status influences human capital accumulation throughout the life course (Case and Paxson, 2008); consequently, many studies also focus on the long-term effects of the NIP. Lundborg et al. (2021) found that Sweden's school lunch NIP increased the lifetime income of beneficiary children by 3%; Similarly, Hoynes et al. (2016)found that access to food stamps during childhood can improve women's economic status in the long run. Regarding the impact of China's NIP, existing literature mainly focuses on children's cognitive abilities and health outcomes (Fang and Zhu, 2022), academic performance (Duan et al.), maternal labor supply decisions (Fang and Zhu, 2022), and the quantity and distribution of household education investment (Wang and Cheng, 2022).

In contrast to the aforementioned studies, this paper is the first to focus on the impact of the region-oriented Free NIP on children's left-behind behavior. We reveal that this non-portable NIP child welfare policy has unintentionally led to an increase in the phenomenon of left-behind children. Although the NIP improves children's physical health, it has potential adverse effects on their mental health; this is the first time the literature has explored the possible negative impacts of the NIP. The associated policy implications are clear: in the future, developing countries should expand the coverage of the NIP to ensure that migrant families can still enjoy the Free NIP after moving to destination areas, thereby reducing the distortion of the NIP on intra-household decisions regarding left-behind children.

The third strand of literature evaluates the effectiveness of place-based policies. Most existing studies focus on location-specific policies aimed at economic development, such as enterprise subsidies and tax incentives, exploring their impacts on resource allocation, firm entry, and regional growth (Kline, 2010; Busso et al., 2013; Kline and Moretti, 2014; Ehrlich and Seidel, 2018; Hasan et al., 2021).

However, place-based policies in practice encompass not only subsidies for firms but also a wide range of social welfare programs, such as the Minimum Living Guarantee and the Nutritious Lunch Program in China. A defining characteristic of these policies is their inportability; local residents lose access to these benefits once they migrate out of the designated region. Despite their prevalence, place-based welfare policies have received relatively little academic attention. Baseler et al. (2025)found that the non-portability of food stamps in India restricts labor mobility from rural to urban areas. Imbert and Papp (2020a) and Imbert and Papp (2020b) documented that the implementation of the National Rural Employment Guarantee Act (NREGA) in rural India similarly reduced out-migration.

While the existing literature on place-based policies focuses heavily on the migration-deterrent effects for adult labor, our findings suggest a different mechanism when the beneficiaries are children. Unlike adults, children do not have independent agency in migration decisions. We find that the impact of non-portable welfare varies significantly across family members. For the direct beneficiaries—the children—the welfare policy creates a strong child-locking effect that anchors them in the place of origin. For the parents, however, the benefits provided by local welfare are insufficient to offset the urban wage premium. Furthermore, by reducing the cost of child-rearing in the home region, these policies inadvertently increase the incentive for parents to migrate without their children. Consequently, the non-portability of such welfare programs leads to the unintended consequence of an increase in the incidence of left-behind children.

The remainder of this paper is organized as follows. Section 2 provides the institutional background, focusing on the welfare policies for rural children and the implementation of the Nutrition Improvement Program (NIP). Section 3 develops the theoretical framework, utilizing a joint migration model to analyze the mechanisms through which non-portable welfare influences household decisions. Section 4 describes the research design and data sources. Section 5 presents the empirical results, including robustness checks and mechanism analyses. Finally, Section 6 concludes the paper with a discussion of the findings and policy implications.

2 Institutional Background

Over the past two decades, the Chinese government has implemented a series of targeted interventions to foster human capital accumulation among rural children and narrow the persistent urban-rural divide. These social protection measures span several critical dimensions, including the "Two Exemptions and One Subsidy" policy, which eliminated tuition and fees for compulsory education, as well as specialized educational and medical assistance under the Targeted Poverty Alleviation framework. However, despite these comprehensive efforts, nutritional deficiencies remained a significant barrier to the early development of rural children.

By 2010, the stunting rate among rural students stood at 12%, while the underweight rate exceeded 9%. This nutritional crisis was further exacerbated by the "School Consolidation" policy (2001–2010), which closed numerous small rural schools to centralize resources in larger townships, resulting in significantly longer commutes for students. Consequently, by 2010, over 30 million rural students lived on campus, and even non-boarding students faced severe challenges in accessing midday meals, prompting the State Council to launch the Nutrition Improvement Program (NIP) in the fall semester of 2011 to address "student hunger" and bolster the physical well-being of the rural compulsory education cohort.

A defining institutional feature of the NIP is its design as a place-based welfare program characterized by strict non-portability. Under this program, the central government provides a daily nutritional subsidy—initially set at 3 RMB per student and subsequently increased to 5 RMB, totaling approximately 1,000 RMB per academic year—which is distributed exclusively through institutionalized school canteens in the students' registered rural districts. From an economic perspective, this arrangement creates a profound linkage between the receipt of welfare and the child's physical presence in the local rural educational system.

Unlike portable cash transfers that follow a family to their urban migration destination, the NIP subsidy is "locked" within the origin's administrative boundaries. For a migrant household, the opportunity cost of bringing a child to an urban area thus includes the forfeiture of these significant nutritional benefits, thereby creating a distorted financial incentive that encourages parents to leave their children behind in the home village to retain access to the state-provided meals.

Furthermore, the implementation of the NIP followed a dual-track system consisting of Central Pilots and Local Pilots, exhibiting substantial heterogeneity in funding stability and implementation quality. As of 2020, the program covered 1,631 counties nationwide, including 726 designated Central Pilot counties where subsidies are primarily financed through stable, direct central government transfers. Figure 1 illustrates the geographical scope and the specific timing of the implementation across these central pilot counties.

In these Central Pilots, the policy focuses on standardized, cafeteria-based hot meals supported by dedicated central grants for infrastructure, whereas Local Pilots often rely on the varying fiscal capacities of provincial and county governments, frequently resulting in lower-quality and more flexible support such as "Egg and Milk" snacks. Given that Central Pilots offer a more robust and uniform policy shock with minimal local funding pressure, they provide a cleaner quasi-natural experiment for identifying the causal impact of institutionalized welfare on migration behavior. Therefore, this study focuses its empirical identification on the implementation of these central government interventions to evaluate how rural households adjust their labor allocation and residential arrangements in response to such place-based child welfare.

3 Theoretical Framework

In this section, we develop a model to study how the School Nutrition Improvement Program influences household migration decisions. In the model, rural parents decide whether to migrate to urban areas for work and, if they do, whether to take their child with them. Wages differ between rural and urban labor markets, and parents are heterogeneous in their human capital, with higher-ability parents benefiting more from urban employment. Children accumulate human capital through schooling, which also differs between rural and urban areas. Children are heterogeneous in their initial human capital, and higher-ability children benefit more from urban schooling. When parents migrate but leave their child in rural areas, the household incurs a separation disutility. Therefore, migration decisions depend on parental and child human capital, schooling costs in each location, and the separation disutility. The School Nutrition Improvement Program reduces rural schooling costs and mitigates the separation disutility, thereby affecting household migration choices.

3.1 Environment

We consider households originating from rural areas. For simplicity, assume that each household consists of two parents and one child. Parents decide whether to migrate to urban areas for work and, conditional on migration, whether to bring their child with them. Let l^p denote the parents' work location and l^k the child's schooling location. Let r and u represent rural and urban areas, respectively, and then $l^p, l^k \in \{r, u\}$.

Parents are heterogeneous in their human capital $H \in [0, \bar{H}]$. Labor income depends on both human capital and location:

$$I_{l^p}(H) = A_{l^p} + B_{l^p} H, \quad l^p \in \{r, u\}.$$

We assume $A_r > A_u > 0$ and $B_u > B_r > 0$, implying that low-human-capital parents earn more in rural areas, while high-human-capital parents earn more in urban areas.

Children accumulate human capital through schooling, and they are heterogeneous in their initial human capital $h \in [0, \bar{h}]$. A child's final human capital depends on her initial human capital and the schooling location:

$$h'_{l^k}(h) = a_{l^k} + b_{l^k} h, \quad l^k \in \{r, u\}.$$

We assume $a_r > a_u > 0$ and $b_u > b_r > 0$, so that rural schools yield higher human capital for low-ability children, while urban schools yield higher human capital for high-ability children.

Let C_r and C_u denote the costs of schooling in rural and urban areas, respectively. We assume that schooling is more costly in urban areas than in rural areas: $C_u > C_r$. In addition, we assume $A_u > C_u$, so that all parents can afford urban education.

Households derive utility from consumption and the child's human capital. Consumption equals parental income net of schooling costs. When parents work in urban areas while their child remains in rural areas, the household incurs a fixed separation disutility, denoted by $\log(V)$ with $V > 1$. This disutility reflects several factors, including psychological costs arising from family separation and the reliance on external caregivers (e.g., grandparents), whose care quality may be inferior to parental care and can adversely affect the child's physical and mental health.

Given parental and child human capital, household utility depends on the joint location choice (l^p, l^k) and is given by:

$$U(l^p, l^k) = \log[I_{l^p}(H) - C_{l^k}] + \alpha \log\left[h'_{l^k}(h)\right] - \mathbf{I}(l^p \neq l^k)\log(V),$$

where $\mathbf{I}(\cdot)$ is an indicator function that equals one if the parents' and child's locations differ and zero otherwise. Parents choose (l^p, l^k) to maximize household utility.

3.2 Location Choice

Parents have three feasible location choices: staying together in rural areas (r, r), migrating alone and leaving the child in rural areas (u, r), or migrating together with the child (u, u). The optimal choice depends on the parents' human capital H and the child's human capital h. We characterize household migration decisions by deriving three cutoff conditions.

First, a household is indifferent between (r, r) and (u, r) if

$$H^* = \frac{V(A_r - C_r) - (A_u - C_r)}{B_u - VB_r}. \tag{M1}$$

Households with $H < H^*$ prefer (r, r), while those with $H > H^*$ prefer (u, r).[1] Thus, conditional on the child remaining in rural areas, parents migrate to urban areas if their human capital is sufficiently high. In Figure 3, this cutoff is represented by a vertical line in the (H, h) space.

Second, a household is indifferent between (u, r) and (u, u) if

$$\frac{a_u + b_u h^*}{a_r + b_r h^*} = \frac{1}{V}\left(\frac{A_u + B_u H^* - C_r}{A_u + B_u H^* - C_u}\right)^{\frac{1}{\alpha}}. \tag{M2}$$

This condition defines a downward-sloping curve in the (H, h) space, as shown in Figure 3.[2] Households below the curve prefer (u, r), while those above the curve prefer (u, u). In other words, conditional on parental migration, parents take the child to urban areas if the child's human

[1] To have an interior solution, we assume that $B_u > VB_r$.

[2] See Appendix A for the proof of the negative slope.

capital is sufficiently high.

Third, a household is indifferent between (u,u) and (r,r) if

$$\frac{a_u + b_u h^*}{a_r + b_r h^*} = (\frac{A_r + B_r H^* - C_r}{A_u + B_u H^* - C_u})^{\frac{1}{\alpha}}. \tag{M3}$$

This condition also defines a downward-sloping curve in the (H,h) space, as shown in Figure 3.[3] Households in the upper-right region prefer (u,u), while those in the lower-left region prefer (r,r). In other words, households with high-ability parents and high-ability children fully migrate to urban areas, whereas households with low-ability parents and low-ability children remain in rural areas.

In summary, equations (M1)–(M3) partition the (H,h) space into regions in which different location choices are optimal for different households.

3.3 School Nutrition Improvement Program

We now incorporate the School Nutrition Improvement Program into the model. This program mainly affects household decisions through two channels. First, it provides subsidized meals in rural schools, thereby reducing the cost of rural schooling, C_r. Second, it offers an alternative form of childcare in rural areas during school hours. This improves the quality of care and reduces the disutility of leaving the child behind, as reflected by a lower V.

For expositional convenience, we assume that the program operates with a continuous intensity S, such that

$$\frac{dC_r}{dS} < 0 \quad \text{and} \quad \frac{dV}{dS} < 0.$$

We analyze how the program affects household migration decisions by examining how the cutoff conditions shift in response to changes in S.

We first consider the trade-off between (r,r) and (u,r), i.e., whether parents migrate to urban

[3]See Appendix A for the proof of the negative slope.

areas while the child remains in rural areas. Differentiating Equation (M1) with respect to S yields

$$\frac{dH^*}{dS} = \underbrace{\frac{(A_r - C_r)B_u - (A_u - C_r)B_r}{(B_u - VB_r)^2}\frac{dV}{dS}}_{<0} + \underbrace{\frac{1-V}{B_u - VB_r}\frac{dC_r}{dS}}_{>0} \gtreqless 0. \tag{D1}$$

The first term is negative. Improved care quality in rural areas lowers the separation costs, increasing parents' incentives to migrate while leaving their child behind. The second term is positive. Lower rural schooling costs increase consumption, reducing the marginal utility gains from higher urban returns to human capital and dampening migration incentives. Therefore, the net effect on H^* is ambiguous. If the reduction in separation disutility dominates, the cutoff H^* decreases, and the M1 line shifts leftward.

Next, we consider the trade-off between (u,r) and (u,u), i.e., whether the parents take the child with them, conditional on the parents moving to urban areas. Holding H^* fixed and differentiating equation (M2) with respect to S yields

$$\frac{dh^*}{dS} = \underbrace{-\frac{1}{\alpha V^\alpha}\Gamma_U^{1-\alpha}\frac{a_R b_U - a_U b_R}{(b_U - b_R\Gamma_U)^2}\frac{1}{A_U + B_U H^* - C_U}\frac{dC_R}{dS}}_{>0} \underbrace{-\frac{1}{V}\Gamma_U\frac{a_R b_U - a_U b_R}{(b_U - b_R\Gamma_U)^2}\frac{dV}{dS}}_{>0} > 0, \tag{D2}$$

where $\Gamma_u \equiv \frac{1}{V}(\frac{A_u + B_u H^* - C_r}{A_u + B_u H^* - C_u})^{\frac{1}{\alpha}} > 0$.

Both terms of (D2) are positive. A reduction in rural schooling costs makes it more attractive for migrant parents to leave their child in rural areas. In addition, lower separation disutility further strengthens this incentive. Consequently, the M2 curve shifts upward as S increases.ir child in rural areas. This implies that the M2 curve shifts upward when S increases.

Finally, we examine the trade-off between (u,u) and (r,r), i.e., whether the parents and child migrate together to urban areas or remain together in rural areas. Holding H^* fixed and differentiating equation (M3) with respect to S yields

$$\frac{dh^*}{dS} = -\frac{1}{\alpha}\Gamma_r^{1-\alpha}\frac{a_r b_u - a_u b_r}{(b_u - b_r\Gamma_r)^2}\frac{1}{A_u + B_u H^* - C_u}\frac{dC_r}{dS} > 0. \tag{D3}$$

where $\Gamma_r \equiv (\frac{A_r + B_r H^* - C_r}{A_u + B_u H^* - C_u})^{\frac{1}{\alpha}} > 0$.

The positive sign of (D3) implies that the M3 curve shifts upward when S increases. Lower costs in rural schools make rural education more attractive. To avoid separation and its associated disutility, parents are also more likely to stay in rural areas with their child.

Figure 4 illustrates the resulting changes in household choices. The purple region corresponds to households that would stay together in rural areas in the absence of the program but choose (u,r) after its introduction. The yellow region represents households that would migrate together (u,u) without the program but switch to (u,r) with the program. The cyan region represents households that would migrate together but instead remain in rural areas after the program. Newly left-behind children induced by the policy are those in the purple and yellow regions. Notably, households in the yellow region tend to have high-ability parents, while those in the purple region tend to have low-ability children. In other words, policy-induced left-behind children are more likely to come from in households with high parental human capital or low child human capital.

We summarize the analytical results in the following proposition.

Proposition*: Assume that household utility is increasing and concave in consumption and child human capital, and that the School Nutrition Improvement Program reduces rural schooling costs and separation disutility. If, in parents' location choice, the effect of reduced separation disutility dominates the effect of lower rural schooling costs, then an increase in program intensity increases the likelihood that parents migrate without their child. Moreover, this increase is concentrated among households with high-ability parents and low-ability children.*

4 Research Design and Data

4.1 Research Design

To examine how transfer payment policies favoring underdeveloped regions affect population migration based on the pilot of the Nutrition Improvement Plan (NIP), this study adopts a Difference-in-Differences (DID) identification strategy. The NIP is implemented at the county level, and this policy primarily alters the cost of schooling in the home region for children in the compulsory education stage. If the nutrition meal plan indeed distorts family migration decisions by changing the opportunity cost of accompanying school-age children, thereby increasing the proportion of left-behind children, then the migration behavior of school-age children in other regions not implementing the nutrition meal plan should not be affected by the policy. This serves as the basis for constructing the DID model. Here, pilot counties are treated as the treatment group, and other counties as the control group to construct the DID model.

$$Left_{ijt} = \alpha_0 + \alpha_1 Treat_j \cdot Post_t + \delta X_{ijt} + \mu_j + \tau_t + \varepsilon_{ijt} \tag{1}$$

We use the left-behind status of children from urban and rural families as the dependent variable, and construct a DID model based on whether the region is a pilot area and whether it is after the policy implementation to examine the impact of the NIP on children's left-behind behavior. The regression controls for individual and parental characteristics, including individual gender, age, and the years of education of both parents. The regression progressively controls for fixed effects at the county, community (village/neighborhood), family, and even individual levels to capture unobservable factors that do not vary with time across these dimensions. It also controls for survey year fixed effects to capture time trends such as overall economic development. Since the implementation of the NIP is at the county level, all regression standard errors in the subsequent text are clustered at the county level.

In addition, since the nutrition improvement plan only targets children in the compulsory education stage in rural areas of contiguous destitute regions, and children in other regions as well as urban areas cannot enjoy the benefits of the nutrition meals, nor are non-compulsory education stage children within the target scope of the policy, we can also study the left-behind phenomenon of urban school-age children and rural non-school-age children as a counterfactual analysis. If no significant impact of the nutrition meal plan is found on the probability of urban children and rural non-school-age children becoming left-behind children, it can be confirmed that the nutrition meal plan, which targets specific regions and populations, distorts family migration decisions, thereby causing children to be left behind.

4.2 Data Introduction

This paper conducts research based on the China Family Panel Studies (CFPS) data. The CFPS is implemented by the Institute of Social Science Survey (ISSS) at Peking University. CFPS focuses on the economic and non-economic welfare of Chinese residents, covering many research topics such as economic activities, educational outcomes, family relationships and family dynamics, population migration, and health. It is a national, large-scale, multidisciplinary social tracking survey project. CFPS aims to reflect the changes in China's society, economy, population, education, and health by collecting data at the individual, family, and community levels, providing a data foundation for academic research and public policy analysis. The CFPS sample covers 25 provinces/municipalities/autonomous regions, with a target sample size of 16,000 households, and the survey subjects include all family members in the sample households. CFPS conducted initial and follow-up test surveys in Beijing, Shanghai, and Guangdong in 2008 and 2009, and officially launched the survey in 2010. All baseline family members defined in the 2010 baseline survey and their future biological/adopted children serve as CFPS gene members and become permanent tracking objects; therefore, this data can be used to study children's left-behind and migration behaviors.

We selected 0-15-year-old minors as observation subjects and constructed a binary variable indicating whether the individual is a left-behind child in 2010, 2012, 2014, 2016, 2018, and 2020. The specific process is as follows: First, based on whether the parents live in the household and whether the mother lives in the household in the surveys over the years, we construct the migration information of the father and mother; second, the situation where either the father or the mother is away from home is defined as a left-behind child. Based on this definition, we calculate the proportion of left-behind children in the CFPS survey over the years. As shown in Table 1, it can be found that the proportion of left-behind children was 17.7% in 2010, after which it began to rise, remaining basically stable at around 30% between 2012 and 2018. However, it declined in 2020, which may be related to the difficulty for a large number of floating population to go out after returning to their hometowns under the impact of the pandemic. Unlike urban and rural areas, the probability that rural children are left behind over the years is higher than that of urban families. On average, one out of three children in rural areas is a left-behind child, while approximately one out of five children in urban areas is a left-behind child. This value is basically consistent with the calculations based on the data from the Seventh National Census, reflecting the reliability of the CFPS survey.

Table 2 further provides descriptive statistics of the CFPS data, where Panel A displays the descriptive statistics for the 2010-2020 CFPS data distinguishing between the treatment group and the control group regions. It can be found that, because the contiguous destitute areas implementing the NIP are relatively poor, the probabilities of fathers and mothers going out are significantly higher, and the probability of children being left behind is 33.3%, which is also higher than the 23.7% in the control group regions. The difference between the two groups of regions can also be seen from the hukou status; only 7.3% of children in the treatment group regions hold a non-agricultural hukou, while the proportion of children in the control group regions holding a non-agricultural hukou is as high as 23.7%. The years of education of parents of children in the control group regions are also far lower than those in the control group regions; the former are 4.5 years and 4.7 years respectively, while the latter reach 9.2 years and 8.5 years respectively. Panel B further displays the status of children being left behind and parents going out in rural areas before the implementation of the NIP. It can be found that before the policy implementation, the probability of children being left behind in the treatment group regions was 24.8%, and in the control group regions was 22.3%; the difference between the two is very small. The difference in the probability of their parents going out is also not large, which indicates that the implementation of the NIP itself does not have a very obvious relationship with the proportion of left-behind children. However, in rural areas after the policy implementation, Panel C shows that the probability of children being left behind in the treatment group regions rose to 38.1%, while in the control group regions it was 30.9%; the former began to be significantly higher than the latter. From the perspective of parents going out, the proportions of fathers and mothers of children in rural treatment group regions going out were 32.4% and 24.2% respectively, while the proportions of parents of children in rural control group regions going out were lower, at 26.9% and 20% respectively.

5 Empirical Results

5.1 Baseline Results

This section examines whether the implementation of the Free Nutrition Improvement Program (NIP) leads to an increase in the number of left-behind children. Table 3 presents the regression results based on Equation1.

Using the CFPS sample of children aged 0–15, Column (1) controls for county and survey year fixed effects, as well as individual characteristics (gender, age) and parental education levels. We found that the implementation of the NIP increased the probability of children aged 0–15 becoming left-behind by 4.51 percentage points.

However, Column (1) only controls for county and year fixed effects, which leaves room for unobserved heterogeneity to bias the results. In Column (2), we added village fixed effects to address potential village-level heterogeneity. We found that the probability of becoming left-behind increased by 3.98 percentage points in NIP-implemented regions.

Even after controlling for village fixed effects, changes in household migration behavior before and after the NIP could still introduce sample selection bias. Column (3) incorporates household fixed effects. This specification not only absorbs time-invariant household characteristics but also accounts for selection effects driven by household migration. Under this specification, the NIP increased the probability of being left-behind by 8.36 percentage points.

Finally, we remained concerned about individual heterogeneity. For instance, the sample structure might shift due to individual migration, or parents in non-NIP regions might possess unobserved preferences (e.g., higher education levels leading to a stronger preference for living with children). To mitigate these potential sample selection and preference issues, Column (4) controls for individual fixed effects. This effectively captures unobserved parental preferences and relies solely on within-individual variation for identification. We found that the probability of being left-behind significantly increased by 7.5 percentage points.

It is important to clarify the mechanics behind these results. Since the CFPS data is based on the place of usual residence, the observed increase in the left-behind ratio could stem from an increase in the numerator, a decrease in the denominator, or differential growth rates (e.g., migrant children returning to their hometowns to become left-behind children, or changes in household migration patterns). We address two specific concerns regarding identification.

First, when controlling for community fixed effects, samples migrating within the county are excluded. We do not define children as "left-behind" if their parents migrate within the same county, as this allows for frequent home visits. Second, estimations with household or individual fixed effects require the observed unit to appear in at least two survey waves. Consequently, sample structural changes caused by permanent migration are absorbed, and the estimates capture the local average treatment effect on the remaining population.

Based on these considerations, we use the county fixed effects specification as our benchmark for the subsequent analysis. Regarding economic magnitude, the average proportion of left-behind children aged 0–15 in the CFPS data is 26.1%. Our estimates suggest that the NIP increased the scale of left-behind children by over 17.3% (0.0451/0.261). This indicates that place-based transfer payment policies have a non-negligible impact on expanding the population of left-behind children.

5.2 Identification Strategy

The baseline difference-in-differences (DID) estimation suggests that the Free Nutrition Improvement Program (NIP) led to an increase in the number of left-behind children. In this section, we further validate this causal relationship. As noted earlier, the NIP is a place-based transfer payment policy targeted specifically at "rural students in the compulsory education stage" in underdeveloped regions. We exploit these two eligibility constraints—"rural status" and "schooling stage"—to refine our identification strategy.

First, we examine the urban-rural divide. Since the NIP targets only rural areas, the left-behind status of children in urban areas should theoretically remain unaffected. Table 4 reports the results, Columns (2) and (3) report the results for urban and rural subsamples, respectively. Consistent with our hypothesis, the coefficient for the urban sample in Column (2) is statistically insignificant, indicating that the probability of urban children becoming left-behind is unrelated to the implementation of the NIP in surrounding rural areas. In contrast, Column (3) shows a significant positive impact on rural children aged 0–15; the probability of becoming left-behind increased by 6.16 percentage points following the policy implementation.

Second, we distinguish between different schooling stages within the rural sample. We classify rural children into two groups: preschool-age children and compulsory-education-age children. The corresponding results are presented in Columns (4) and (5). For preschool children (Column 4), who are ineligible for the NIP, the policy had no significant effect on their left-behind status. Conversely, for children of compulsory education age (Column 5), the NIP significantly increased the probability of becoming left-behind.

In summary, by exploiting variations across urban-rural status and schooling stages, we provide robust evidence for the causal effect of the NIP on the increase of left-behind children in rural areas.

5.3 Placebo Test: Evidence from Local Pilot Programs

As discussed in the background section, China's NIP comprises two categories: central pilot counties and local pilot counties. They differ in three key aspects.

First, funding sources differ. The central government fully funds the meals in central pilot regions. In contrast, the costs for local pilot counties are primarily borne by local governments (provincial, municipal, and county levels). Consequently, dietary standards in some local pilot regions are lower than the central standards. For instance, in Hebei Province, the subsidy in local pilot counties remained at 2.5 RMB per student per day (for 200 days a year) prior to the fall semester of 2020.

Second, the mode of provision differs. For central pilot regions, the central government not only covers food costs but also uses specific transfer payments to support cafeteria construction, thereby improving on-campus dining conditions. Conversely, local pilot counties often rely on "egg-and-milk" programs provided as snacks between classes, lacking robust infrastructure for full cafeteria meals.

Third, implementation rules differ. The central pilot adopts a "one-size-fits-all" approach, where all rural students in compulsory education within pilot counties receive free meals. In contrast, local pilots allow for flexibility to enhance fund efficiency. For example, some local pilots implement a targeted NIP based on household income data, charging fees to families who are not registered as impoverished households. These structural differences lead to heterogeneous impacts on human capital accumulation.

This paper focuses on the unintended consequences of the uniform, place-based central pilot policy on the left-behind status of children. We exploit the local pilot programs to conduct a placebo test. Table 5 reports the results.

In Column (1), we excluded regions implementing local pilots from the control group. We found that the central pilot still led to a significant increase in the probability of children becoming left-behind. In Column (2), we excluded central pilot regions to examine only the impact of local pilots. We found that local NIP implementation did not significantly increase the number of left-behind children. This non-result may be attributed to lower financial input, lack of cafeteria facilities, and the targeted nature of some local programs.

Finally, in Column (3),* we included both central and local pilots in the specification. We found that the impact of the central pilot remained significant, whereas the local pilot showed no significant effect. These findings further indicate that, compared to flexible local policies, the centralized, "one-size-fits-all," place-based welfare policy is more likely to trigger unintended consequences such as the increase in left-behind children.

5.4 Robustness Checks

5.4.1 Ruling out the Influence of the Boarding School System

The central government initially implemented the NIP in contiguous destitute areas. Coinciding with the NIP, these regions also saw the establishment of numerous boarding schools due to the "School Consolidation Policy" and the "Boarding School Construction Project in Central and Western China". The availability of boarding schools could reduce the burden of childcare on families, potentially encouraging parents to migrate and increasing the number of left-behind children. Therefore, in this section, we rule out the confounding influence of the boarding school system.

The CFPS surveys from 2010 to 2020 include questions regarding students' boarding status. Based on these surveys, we constructed two indicators: (1) whether the child boards at school, and (2) whether the child attends a boarding school.[4]

Columns (1) to (3) of Table 6 use the full sample of school-age children aged 15 and under in both urban and rural areas. Column (1) shows that the implementation of the NIP had no statistically significant effect on whether a child boards at school. Furthermore, in Columns (2) and (3), we controlled for Boarding Status and Boarding School Type, respectively. We found that while boarding children indeed have a higher probability of being left-behind (Column 2), the estimated impact of the NIP on the left-behind status remains robust and significant.

Columns (4) to (6) restrict the sample to rural children aged 15 and under in the compulsory education stage. Consistent with the full sample results, the NIP did not increase the probability

[4]The boarding-related questions are asked only for children who are already enrolled in school. Specifically, the survey includes two items: “Does the school the child attends offer boarding?” and “Does the child board at school?”

of boarding for this specific group. Moreover, after controlling for boarding-related variables, the positive effect of the NIP on the probability of being left-behind remains robust.

These findings suggest that the increase in left-behind children driven by the NIP is not a byproduct of the boarding school system, thereby validating the robustness of our baseline results.

5.4.2 Evidence from CHIP Data

The CFPS survey was initiated in 2010, providing only one wave of data prior to the implementation of the NIP in 2011. This limitation prevents us from formally testing the parallel trend assumption—a prerequisite for the validity of our difference-in-differences (DID) design—using the baseline sample.

To address this concern, we employ data from the China Household Income Project (CHIP), which conducts surveys at intervals of approximately five to six years.[5] Compared to the CFPS, the primary advantage of the CHIP dataset is the availability of multiple pre-policy observation periods, enabling us to examine pre-treatment trends between the treatment and control groups. However, the CHIP dataset has a limitation: it is not longitudinal (panel) data. Consequently, we cannot track specific changes in the migration status of individual children or parents across waves. Therefore, we retain the CFPS dataset for our baseline regressions and mechanism analyses.

To minimize the confounding effects of unobserved factors over long time horizons, we restricted our sample to the rural surveys of CHIP 2002, 2007, 2013, and 2018. This approach allows us to verify the robustness of our previous findings while simultaneously conducting a pre-policy parallel trend test.

Due to changes in survey design across waves, the specific questions used to identify left-behind children vary slightly. We harmonized the definitions as follows: First, in CHIP 2002, we identified children based on their relationship to the household head. A child is defined as left-behind if they reside locally while one or both parents (the respondent or their spouse) are engaged

[5] To track the dynamics of income distribution in China, the China Household Income Project (CHIP) has conducted six rounds of household surveys in 1989, 1996, 2003, 2008, 2014, and 2018. These surveys collected income and expenditure information for 1988, 1995, 2002, 2007, 2013, and 2018, respectively, along with a rich set of household- and individual-level characteristics. The corresponding datasets are commonly labeled CHIP1988, CHIP1995, CHIP2002, CHIP2007, CHIP2013, and CHIP2018. All six rounds were jointly organized by Chinese and international researchers and implemented with the assistance of the National Bureau of Statistics (NBS). Based on these household surveys, the resulting database—known internationally as "CHIPS"—has been widely regarded as one of the most authoritative foundational data sources for research on income distribution and labor markets in China.

in migrant work or business outside the locality. Second, in CHIP 2007, based on questions regarding the child's "primary residence" and "primary caregiver," we defined a child as left-behind if they lived locally but did not reside with both parents. Third, in CHIP 2013, the identification strategy follows that of CHIP 2002. We identified children based on household rosters and determined their left-behind status based on whether the respondent and their spouse were migrant workers. Fourth, in CHIP 2018, the survey explicitly asked, "Who does the child primarily live with?" We defined children living with both parents as non-left-behind, while classifying all others as left-behind. A potential measurement issue in the 2018 wave arises from the response option "boarding at school." Classifying boarding students as left-behind would be inaccurate if their parents are actually residing at home. However, within our restricted sample of children aged 0–15, this subgroup accounts for a negligible share of observations. We verified that either excluding these observations or reclassifying them as non-left-behind does not qualitatively alter the results presented in this section.

We pooled data from CHIP 2002, 2007, 2013, and 2018 to construct a pseudo-panel dataset, which we then matched with the NIP coverage data at the county level. Using pilot counties as the treatment group and non-pilot counties as the control group, we conducted a difference-in-differences regression controlling for county and year fixed effects. The results are reported in Table 7.

Column (1), based on the sample of children aged 0–15, indicates that the NIP increased the probability of being left-behind by 20 percentage points. Columns (2) and (3) distinguish between different age groups. We found that the NIP had a statistically significant positive effect only on children aged 7–15 (the compulsory education stage), whereas it had no significant impact on preschool children. This finding is consistent with the results in Table 4, further validating the robustness of our conclusions.

Notably, the estimated magnitude of the effect using CHIP data is larger than that observed in the CFPS analysis. This discrepancy can be attributed to two primary reasons: First, as noted in the definitions, the baseline proportion of left-behind children in the CHIP dataset is higher than in the CFPS dataset. This difference may stem from variations in the rural sampling scope or the specific definitions of "left-behind" employed by the two surveys. Second, the survey designs differ fundamentally. The CFPS is a longitudinal tracking survey, where subsequent waves follow the initial sample. In contrast, the CHIP employs repeated cross-sectional sampling for each wave. Consequently, the two datasets may differ in their representativeness across survey years.

Given that the CHIP dataset spans multiple periods before and after the policy implementation, we estimate the following event study specification to examine the pre-treatment parallel trends:

$$Y_{ijt} = \alpha_0 + \sum_{k \neq 2007} \beta_k Policy_{jkt} + X \cdot \theta + \mu_j + \tau_t + \varepsilon_{ijt} \tag{2}$$

We use 2007 as the reference year. The results of the event study are plotted in Figure 5.Figure 5a presents the estimates for children aged 7–15 (compulsory education stage). We observed no significant pre-existing trend differences in the probability of being left-behind between the treatment and control groups prior to the policy implementation. However, following the introduction of the NIP, the probability for the treatment group began to rise significantly relative to the control group.In contrast, Figure 5b reports the results for preschool children aged 0–6. We found no significant divergence in the probability of being left-behind between the treatment and control groups, either before or after the policy intervention.Collectively, these findings validate the parallel trend assumption—the core prerequisite of the DID design—thereby reinforcing the reliability of our baseline estimates.

5.5 Mechanism Analysis

The NIP provides dietary subsidies to rural students in compulsory education. Initially set at 3 RMB per student per day (calculated based on 200 school days per year), the subsidy standard was raised to 4 RMB in late 2014 and further increased to 5 RMB in 2021. The direct consequence of this subsidy is a reduction in the financial burden of education for rural households. Furthermore, as part of the central pilot implementation, the central government allocated specific funds through the "Renovation Project for Weak Rural Compulsory Education Schools" to support the construction of school cafeterias and improve dining conditions in the central and western regions. The provision of on-campus dining services generates an indirect effect: it alleviates the time burden associated with daily commutes. Specifically, parents or guardians are no longer required to pick up children for lunch, thereby significantly reducing the intensity of childcare responsibilities. In the following sections, we explore these mechanisms from two perspectives: parental childcare burden (time cost) and household financial burden (monetary cost). We examine how these distinct channels influence parental migration decisions and child migration decisions, respectively.

5.5.1 The Financial Burden Channel

We first examine the impact of the NIP on household financial burden using data from the China Household Finance Survey (CHFS).

Data Constraints and Variable Construction: Inconsistencies in the CHFS survey design pose a challenge for measuring educational food expenditures consistently over time. Specifically, the survey did not inquire about food expenditures in 2010[6]; it began collecting this data in 2012, but from 2016 onwards, it merged food expenses with transportation and accommodation costs. Consequently, we cannot directly construct a continuous time series for the amount of food expenditure.

To address this limitation, we adopted an alternative approach by constructing a binary dummy variable indicating whether a household incurred any educational food expenditure (1 = Yes, 0 = No). Under the plausible assumption that no region implemented the NIP in 2010, we constructed a panel dataset covering three waves (2010, 2012, and 2014) to examine the policy's effect on the extensive margin of food spending.

Empirical Results: Column (1) of Table 8 reports the results. We found that the implementation of the NIP reduced the probability of households paying for school meals by 10.5 percentage points. The fact that the probability did not drop to zero suggests that the daily subsidy of 3–4 RMB often fails to fully cover the actual cost of meals, requiring some families to continue bearing a portion of the expense.

Furthermore, we examined the impact on the total educational expenditure of the household. As shown in Column (2) of Table 8, the NIP led to an average reduction of 679 RMB in annual educational spending per child. This magnitude is remarkably consistent with the ex-ante calculation of the subsidy benefits (approximately 600–800 RMB per year, based on a daily subsidy of 3–4 RMB for 200 school days).

The NIP specifically targets children with rural hukou who attend school in their place of

[6]Of course, some provinces—such as Shaanxi and Fujian—implemented "egg-and-milk" programs or local meal-subsidy schemes. Excluding these observations does not materially change our results, and our conclusions remain robust.

registration. This reduction in the cost of raising children at the origin (home county) alters the relative costs of migration. Consequently, parents may be more inclined to leave their children in their hometowns rather than migrating with them.

We leverage the longitudinal nature of the CFPS dataset to track individual migration behaviors over time. We constructed a binary variable for individual migration (1 = migrated, 0 = otherwise) by comparing the county codes of an individual's residence across consecutive survey waves. Table 8 presents the results regarding the impact of the NIP on child migration behaviors.

Column (1) indicates that, overall, the NIP had a significant inhibitory effect on child migration. Specifically, the implementation of the policy reduced the probability of child migration by 0.85 percentage points.

Columns (2) and (3) further examine the heterogeneous responses across households of different socioeconomic statuses. We found that the inhibitory effect on child migration was significantly more pronounced among lower-class households. These families are likely more sensitive to the financial burden of education, making them more responsive to the subsidies provided by the NIP.

5.5.2 The Childcare Burden Perspective

In this section, we examine whether the convenience of on-campus dining provided by the NIP reduced the childcare burden on families, thereby facilitating the migration of parents (the primary caregivers) and ultimately increasing the probability of children being left behind.

Commuting Costs as a Proxy for Childcare Burden: The CFPS survey (2010, 2012, and 2014 waves) records "transportation expenditures related to education." We use this indicator as a proxy for the daily commuting pressure associated with school runs. Column (1) of Table 9 presents the DID results. We found that following the implementation of the NIP, the annual commuting expenditure for children's schooling decreased by approximately 43 RMB.

Substitution of Caregiving Responsibility: Column (2) further examines whether this reduction in daily commuting pressure relieved parents of their immediate guardianship duties. We found that the probability of children being cared for by grandparents increased by 7 percentage points after the policy implementation. This implies a significant shift in caregiving arrangements, where parental responsibilities were effectively substituted by intergenerational care.

Impact on Parental Migration: Columns (3) to (5) investigate parental migration behaviors.

The results indicate that the reduction in childcare burden significantly increased the probability of mothers—typically the primary suppliers of daily care—migrating for work. It also raised the probability of both parents migrating simultaneously.

Magnitude Consistency Check: It is worth noting that the magnitude of the increase in maternal migration probability, combined with the magnitude of the decrease in child migration probability (discussed previously), aligns closely with the 4.5 percentage point increase in the probability of children being left-behind observed in our baseline regression. This quantitative consistency reinforces the validity of our mechanism.

Comparison with Literature: Furthermore, our findings are consistent with Fang & Zhu (2022), who documented that free school meal programs improve the labor market performance of women by releasing them from household constraints.

5.6 Heterogeneity Analysis

In this section, we examine the heterogeneous effects of the place-based transfer payment policy on the left-behind status of children. Table 10 reports the results.

Gender Heterogeneity: First, we investigate the heterogeneity across gender. After controlling for county and year fixed effects, Columns (1) and (2) indicate that the implementation of the NIP significantly increased the probability of girls becoming left-behind, whereas it had no statistically significant impact on boys. This finding is likely driven by traditional son preference. It is consistent with Gao et al. (2023), who documented that migrant families are more inclined to bring sons with them while leaving daughters in their hometowns.

Parental Education Heterogeneity: Next, we stratify the sample by parental education level (high school or above vs. below high school) in Columns (3) and (4). We found that the NIP significantly increased the probability of being left-behind for children of parents with higher educational attainment. While the effect is also significant for parents with lower education, the magnitude is notably smaller.

This disparity may be attributed to the higher opportunity cost of childcare for better-educated parents. When the provision of free school meals releases them from household caregiving duties, these parents are more likely to migrate for work (given their higher potential earnings), thereby increasing the probability of their children being left behind.

6 Discussion

The original intention of the NIP was to improve the health status of children in backward areas. This section extends the discussion to the impact of the NIP on children's mental health and physical health development.

6.1 The Impact of the NIP on Children's Mental Health

Parental migration increases children's depression levels due to the inability to provide empathetic companionship. This section further examines the impact of the NIP on children's mental health. We measure children's mental health levels using relevant indicators in the CFPS questionnaire. Specifically, the Kessler Psychological Distress Scale (K6) was used in the 2010 and 2014 CFPS surveys, and the Center for Epidemiologic Studies Depression Scale (CES-D) was used in the 2012, 2016, 2018, and 2020 CFPS surveys. The CES-D scale is used to measure an individual's depression level. The scale has various forms; the CESD20 with 20 items was used in the 2012 survey, and it was gradually simplified to CESD8 in 2016 and subsequent years, but the CFPS data still provided a comparable score CESD20sc.[7] To avoid potential problems caused by dimension differences, we uniformly standardize the CESD total score to obtain an indicator reflecting children's mental health with a mean of 0 and a standard deviation of 1; a higher score indicates a worse mental health condition of the individual.

To reflect the potential long-term mental health changes brought about by the NIP, we conduct an examination based on the sample aged 15-18. Based on the CESD index constructed above, we use whether the local district/county implemented the NIP during the individual's primary and middle school years as the core explanatory variable, i.e., adopting a Cohort Difference-in-Differences (Cohort-DID) method for examination. The results are shown in Table 12. It can be found that in Column 1, when urban and rural samples are put together and district/county and birth

[7] References include the China Family Panel Studies 2010 Integrated Variables (2): Education Level & Depression Scale, the China Family Panel Studies 2012 Mental Health Scale, the China Family Panel Studies 2016 Database Introduction and Data Cleaning Report, the China Family Panel Studies 2018 Database Introduction and Data Cleaning Report, and the China Family Panel Studies 2020 Database Introduction and Data Cleaning Report.

year fixed effects are controlled, the mental health condition of children who have experienced the NIP becomes worse, with the CESD score increasing by 0.142 standard deviations. When Column 2 further controls for community fixed effects, the effect of the nutrition improvement plan causing children's mental health to deteriorate is further strengthened, reaching 0.183 standard deviations. Columns 3 and 4 distinguish between urban and rural samples for examination. It can be found that this effect of causing adolescents' mental health to deteriorate is mainly concentrated in the rural sample, while the impact on the urban sample is not significant, and the coefficient is obviously closer to 0. Columns 4 and 5 use whether one feels depressed as the dependent variable. It can be found that the probability of feeling depressed among adolescents affected by the NIP rises by 21.9%. The examination in this section indicates that the NIP, which leads to more left-behind children, has caused worse mental health conditions for children.

6.2 The Impact of the NIP on Children's Health Development

The original intention of the NIP in the compulsory education stage is to improve the health status of children in the rural compulsory education stage and promote their healthy physical growth. This section examines whether the NIP has achieved its original intention, that is, whether it has improved the physical development status of rural children. In the long run, children with different enrollment years (or birth years) have different lengths of time experiencing the NIP, and their physical health development levels will inevitably differ. Here, we construct the exposure duration of the NIP for examination. The specific indicator is as follows:

$$Exposure_{ijc} = \begin{cases} 0 & \text{if } birthyear_{ijc} + 15 < policyyear_j \\ \frac{birthyear_{ijc}+15-policyyear_j}{9} & \text{if } birthyear_{ijc} + 7 < policyyear_j \leq birthyear_{ijc} + 15 \\ 1 & \text{if } birthyear_{ijc} + 7 \geq policyyear_j \end{cases} \tag{3}$$

The indicator $Exposure_{ijc}$ represents the proportion of time that individual i born in year c in region j was exposed to the NIP during the compulsory education stage. Its maximum value is 1, indicating that individual i enjoyed the NIP throughout the entire compulsory education stage; its minimum value is 0, representing that individual j had already completed compulsory education when the NIP was implemented, and thus would not be affected. We construct the following cross-sectional DID regression model (Cohort-DID) based on the exposure indicator $Exposure_{ijc}$ to examine the impact of the nutrition improvement plan on long-term development.

$$Y_{ijc} = \alpha_0 + \alpha_1 Exposure_{ijc} + X \cdot \theta + \mu_j + \tau_c + \varepsilon_{ijc} \tag{4}$$

The main indicators reflecting children's health development in CFPS data are weight and height. To examine the long-term impact of the NIP, we here use the height and weight of the interviewed adolescents after completing the compulsory education stage (15 years old and after) as dependent variables for examination, which can reflect the impact of the individual receiving the NIP on long-term physical development. The regression controls for district/county fixed effects and individual birth year fixed effects. The coefficient α_1 reflects the impact of an individual's complete exposure to the NIP on their physical development. The results are shown in Table 13. Columns 1 to 6 conduct the examination based on the rural area sample. Columns 1 and 2 examine the average impact of the NIP on the physical development of rural children, finding that their height increased by 2 centimeters on average, but there was no significant change in weight. Columns 3 to 6 examine the heterogeneous effects of the policy on families of different strata. It can be found that for families with relatively low parental education levels, the NIP has a significant promoting effect on children's weight gain and height growth, reflecting the obvious positive effect of the NIP on the physical development of children from families at the bottom of society. Regardless of whether the heterogeneity examination is based on the father's or mother's education level, the conclusions are consistent. In addition, Columns 7 and 8 further conduct an examination based on the urban sample as a placebo test. It can be found that for the urban area sample, the core regression coefficients are not significant, indicating that the NIP targeting rural areas has not promoted significant improvements in development indicators such as weight and height for urban children.

6.3 Welfare Discussion

According to the aforementioned research, the region-oriented NIP, while achieving certain policy goals, also brings potential welfare losses. This section distinguishes between different types of families to conduct a corresponding welfare discussion.

First, for those children who would choose to stay in their hometown regardless, the NIP brings certain welfare improvements. In reality, there is always a segment of families who, due to land, information, caring for the elderly, or other reasons, choose to stay in their hometown; parents do not go out to work, and children stay locally to study. From the CFPS data, in districts and counties implementing the NIP, the proportion of rural children left behind in 2018 was 41.1%, with 34% of fathers and 25.6% of mothers leaving their children to go out for work, which means that nearly 59% of children are still not left-behind children. From the perspective of family income, the per capita net income of left-behind children's families reaches 8,859 yuan due to parents going out to work, while the per capita income of families where neither parent goes out is lower, approximately 7,572 yuan. For these families of children who choose to stay in their hometown regardless, due to their lower income levels, the marginal effect of the reduced family burden brought by the NIP will be larger, and the children's nutritional status will also be well improved, thereby promoting their growth and development. For these lower-income families, the NIP will not increase the probability of their children becoming left-behind children, so the improvement in child welfare is the greatest. For those families where the father or mother would choose to go out to work regardless, their children's left-behind decision will also not be affected by the policy, but since the income of such families is slightly higher, the free nutrition meals will also improve the welfare of such children, but the magnitude may be smaller than that of the former type of family.

Secondly, for those families who would always take their children with them when going out, that is, those children who always choose to flow out of their hometown, the NIP will not affect their migration decisions. Since the free nutrition meals only target children in the compulsory education stage studying in their place of household registration, these migrant children will not be covered by the policy in the inflow area, and thus their welfare will not change as a result.

Finally, for those children who are marginally affected by the policy and become left-behind children, their welfare changes are uncertain. According to the previous results, more than 17% of left-behind children belong to this type, yet their welfare changes are uncertain. First, these children became left-behind children because of the implementation of the NIP, and their mental health status may be impaired as a result; but at the same time, their health status and physical growth and development will be improved due to the free nutrition meals. Second, the parents of these children were able to go out to work after the nutrition improvement plan, which will bring growth in family income and may also indirectly improve the level of child welfare.

In summary, this paper does not simply believe that the region-oriented NIP brings good or bad effects, but rather emphasizes its differential impacts on different families. For those groups who became left-behind children because of the implementation of the NIP, special attention should be paid to the negative shocks to them. If we can, like developed countries such as Europe and the United States, implement a nutrition improvement plan for children nationwide, rather than distinguishing by region, household registration, or other identities, and at the same time provide free meals or corresponding subsidies based on family income levels, transforming region-oriented welfare policies into people-based welfare policies, then this distortion effect will be readily solved.

7 Conclusion

This paper investigates the unintended consequences of China's Nutrition Improvement Program (NIP) on household migration decisions and the prevalence of left-behind children. By constructing a theoretical model of joint household migration, we illustrate how place-based and non-portable welfare policies distort labor allocation by altering the relative costs of child-rearing. Empirically, we utilize data from the China Family Panel Studies (CFPS) and the China Household Income Project (CHIP), employing a Difference-in-Differences (DID) framework to identify the causal impact of the program.

Our findings demonstrate that the NIP significantly reshaped the residential arrangements of rural households. The empirical results reveal that the program led to a more than 17% increase in the probability of rural children being left behind. Mechanism analysis suggests that this effect operates through two primary channels: first, the program substantially reduced the financial burden of rural schooling, creating a potent "child-locking effect" that anchored children in their home villages to retain access to benefits. Second, the institutionalization of meal provision eased the household care burden and enhanced the feasibility of intergenerational care by grandparents, thereby lowering the opportunity cost of parental migration and facilitating asymmetrical labor movement. While the NIP improved the physical development of children from low-socioeconomic status families in the long run, the resulting parental absence imposed a significant negative shock on children's mental health.

Based on these findings, we propose the following policy recommendations. First, the public welfare architecture must transition from a place-based to a portable model. Policymakers should redesign welfare schemes to ensure that targeted subsidies, such as free school meals, "follow the person." Ensuring that the children of rural migrants can access equivalent nutritional support in urban destinations is crucial to eliminating the institutional incentives for household fragmentation. Second, mental health interventions for left-behind children should be strengthened. Rural welfare investments should incorporate psychological counseling and family support services to offset the adverse effects of parental separation. Finally, this study holds global relevance. In developing nations undergoing rapid urbanization, governments must carefully account for potential distortions in family integrity when designing targeted interventions for children. Enhancing material well-being should not come at the expense of the family unit's role as the core vessel for human capital accumulation.

References

Jianxin Wang, Caiyun Yuan, Qian Zhang, and Daniel Houser. Parents' absence harms norm obedience of girls more than boys. *Journal of Economic Behavior Organization*, 214:17–29, 10 2023. ISSN 0167-2681. doi: 10.1016/J.JEBO.2023.07.037.

Qiran Zhao, Xiaohua Yu, Xiaobing Wang, and Thomas Glauben. The impact of parental migration on children's school performance in rural china. *China Economic Review*, 31:43–54, 12 2014. ISSN 1043-951X. doi: 10.1016/J.CHIECO.2014.07.013.

Avner Seror. Child development in parent-child interactions. *https://doi.org/10.1086/720398*, 130: 2462–2499, 9 2022. ISSN 1537534X. doi: 10.1086/720398.

Hongliang Zhang, Jere R. Behrman, C. Simon Fan, Xiangdong Wei, and Junsen Zhang. Does parental absence reduce cognitive achievements? evidence from rural china. *Journal of Development Economics*, 111:181–195, 11 2014. ISSN 0304-3878. doi: 10.1016/J.JDEVECO.2014.09.004.

Xiaodong Zheng, Zuyi Fang, Yajun Wang, and Xiangming Fang. When left-behind children become adults and parents: The long-term human capital consequences of parental absence in china. *China Economic Review*, 74:101821, 8 2022. ISSN 1043-951X. doi: 10.1016/J.CHIECO.2022.101821.

Yi Fan, Junjian Yi, and Junsen Zhang. Rising intergenerational income persistence in china. *American Economic Journal: Economic Policy*, 13:202–30, 2021. ISSN 1945-7731. doi: 10.1257/POL.20170097.

Lisa Cameron, Xin Meng, and Dandan Zhang. Does being "left–behind" in childhood lead to criminality in adulthood? evidence from data on rural-urban migrants and prison inmates in china. *Journal of Economic Behavior Organization*, 202:675–693, 10 2022. ISSN 0167-2681. doi: 10.1016/J.JEBO.2022.08.017. URL `https://www.sciencedirect.com/science/article/abs/pii/S0167268122002918`.

Michael A. Clemens and Erwin R. Tiongson. Split decisions: Household finance when a policy discontinuity allocates overseas work. *The Review of Economics and Statistics*, 99:531–543, 7 2017. ISSN 0034-6535. URL `https://dx.doi.org/10.1162/REST_a_00657`.

Yu Bai, Linxiu Zhang, Chengfang Liu, Yaojiang Shi, Di Mo, and Scott Rozelle. Effect of parental migration on the academic performance of left behind children in north western china. *Journal of Development Studies*, 54:1154–1170, 7 2018. ISSN 17439140.

Riley Wilson. Moving to jobs: The role of information in migration decisions. *https://doi.org/10.1086/713008*, 39:1083–1128, 10 2021. ISSN 0734306X. doi: 10.1086/713008. URL `/doi/pdf/10.1086/713008`.

Yuanyuan Chen and Shuaizhang Feng. Access to public schools and the education of migrant children in china. *China Economic Review*, 26:75–88, 2013. ISSN 1043951X. doi: 10.1016/J.CHIECO.2013.04.007.

Peter Kuhn and Kailing Shen. Do employers prefer migrant workers? evidence from a chinese job board. *Journal of Labor Economics*, 4:22–, 11 2015. ISSN 2193-8997.

doi: 10.1186/S40172-015-0038-0. URL https://link.springer.com/article/10.1186/s40172-015-0038-0.

Chunchao Wang, Chenglei Zhang, Jinlan Ni, Haifeng Zhang, and Junsen Zhang. Family migration in china: Do migrant children affect parental settlement intention? *Journal of Comparative Economics*, 47:416–428, 6 2019. ISSN 0147-5967. doi: 10.1016/J.JCE.2019.01.002.

Tongtong Hao, Ruiqi Sun, Trevor Tombe, and Xiaodong Zhu. The effect of migration policy on growth, structural change, and regional inequality in china. *Journal of Monetary Economics*, 113:112–134, 8 2020. ISSN 03043932. doi: 10.1016/J.JMONECO.2020.03.003.

Zhangfeng Jin and Junsen Zhang. Access to local citizenship and internal migration in a developing country: Evidence from a hukou reform in china. *Journal of Comparative Economics*, 51:181–215, 3 2023. ISSN 0147-5967. doi: 10.1016/J.JCE.2022.08.004.

Holger Sieg, Chamna Yoon, and Jipeng Zhang. The impact of local fiscal and migration policies on human capital accumulation and inequality in china. *International Economic Review*, 64:57–93, 2 2023. ISSN 14682354. doi: 10.1111/IERE.12597;REQUESTEDJOURNAL:JOURNAL:14682354;WGROUP:STRING:PUBLICATION.

Maarten Bosker, Steven Brakman, Harry Garretsen, and Marc Schramm. Relaxing hukou: Increased labor mobility and china's economic geography. *Journal of Urban Economics*, 72:252–266, 9 2012. ISSN 0094-1190. doi: 10.1016/J.JUE.2012.06.002. URL https://www.sciencedirect.com/science/article/abs/pii/S0094119012000411.

Martin Farnham and Purvi Sevak. State fiscal institutions and empty-nest migration: Are tiebout voters hobbled? *Journal of Public Economics*, 90:407–427, 2 2006. ISSN 0047-2727. doi: 10.1016/J.JPUBECO.2005.07.005. URL https://www.sciencedirect.com/science/article/abs/pii/S0047272705001313.

Anil Rupasingha, Yongzheng Liu, and Mark Partridge. Rural bound: Determinants of metro to non-metro migration in the united states. *American Journal of Agricultural*

Economics, 97:680–700, 4 2015. ISSN 1467-8276. doi: 10.1093/AJAE/AAU113. URL /doi/pdf/10.1093/ajae/aau113https://onlinelibrary.wiley.com/doi/abs/10.1093/ajae/aau113https://onlinelibrary.wiley.com/doi/10.1093/ajae/aau113.

Christian Dustmann and Anna Okatenko. Out-migration, wealth constraints, and the quality of local amenities. *Journal of Development Economics*, 110:52–63, 9 2014. ISSN 0304-3878. doi: 10.1016/J.JDEVECO.2014.05.008. URL https://www.sciencedirect.com/science/article/abs/pii/S030438781400073X.

Huanguang Qiu, Junqiao Hong, Xiangrui Wang, and Mateusz Filipski. Home sweet home: Impacts of living conditions on worker migration with evidence from randomized resettlement in china. *Journal of Economic Behavior Organization*, 220:558–583, 4 2024. ISSN 0167-2681. doi: 10.1016/J.JEBO.2024.02.030. URL https://www.sciencedirect.com/science/article/abs/pii/S0167268124000684.

Chaoran Chen. Untitled land, occupational choice, and agricultural productivity. *American Economic Journal: Macroeconomics*, 9:91–121, 2017. ISSN 1945-7707. doi: 10.1257/MAC.20140171.

Amalavoyal Chari, Elaine M. Liu, Shing Yi Wang, and Yongxiang Wang. Property rights, land misallocation, and agricultural efficiency in china. *Review of Economic Studies*, 88:1831–1862, 2021. ISSN 1467937X. doi: 10.1093/RESTUD/RDAA072.

L. Rachel Ngai, Christopher A. Pissarides, and Jin Wang. China's mobility barriers and employment allocations. *Journal of the European Economic Association*, 17:1617–1653, 10 2019. ISSN 15424774. doi: 10.1093/JEEA/JVY035.

Tasso Adamopoulos and Diego Restuccia. Land reform and productivity: A quantitative analysis with micro data. *American Economic Journal: Macroeconomics*, 12:1–39, 7 2020. ISSN 1945-7707. doi: 10.1257/MAC.20150222.

Tasso Adamopoulos, Loren Brandt, Chaoran Chen, Diego Restuccia, and Xiaoyun Wei. Land security and mobility frictions. *The Quarterly Journal of Economics*, 139:1941–1987, 7 2024.

ISSN 0033-5533. doi: 10.1093/QJE/QJAE010. URL https://dx.doi.org/10.1093/qje/qjae010.

Tarjei Havnes and Magne Mogstad. No child left behind: Subsidized child care and children's long-run outcomes. *American Economic Journal: Economic Policy*, 3:97–129, 5 2011. ISSN 1945-7731. doi: 10.1257/POL.3.2.97.

Jayanta Bhattacharya, Janet Currie, and Steven J. Haider. Breakfast of champions? the school breakfast program and the nutrition of children and families. *The Journal of Human Resources*, 41(3):445–466, 2006. ISSN 0022166X. URL http://www.jstor.org/stable/40057265.

Farzana Afridi. Child welfare programs and child nutrition: Evidence from a mandated school meal program in india. *Journal of Development Economics*, 92(2):152–165, 2010. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2009.02.002. URL https://www.sciencedirect.com/science/article/pii/S0304387809000169.

Hilary Hoynes, Diane Whitmore Schanzenbach, and Douglas Almond. Long-run impacts of childhood access to the safety net. *American Economic Review*, 106(4):903–34, April 2016. doi: 10.1257/aer.20130375. URL https://www.aeaweb.org/articles?id=10.1257/aer.20130375.

Michael L. Anderson, Justin Gallagher, and Elizabeth Ramirez Ritchie. School meal quality and academic performance. *Journal of Public Economics*, 168:81–93, 2018. ISSN 0047-2727. doi: https://doi.org/10.1016/j.jpubeco.2018.09.013. URL https://www.sciencedirect.com/science/article/pii/S0047272718301816.

Michèle Belot and Jonathan James. Healthy school meals and educational outcomes. *Journal of Health Economics*, 30(3):489–504, 2011. ISSN 0167-6296. doi: https://doi.org/10.1016/j.jhealeco.2011.02.003. URL https://www.sciencedirect.com/science/article/pii/S0167629611000270.

Tanika Chakraborty and Rajshri Jayaraman. School feeding and learning achievement: Evidence from india's midday meal program. *Journal of Development Economics*, 139:249–265,

2019. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2018.10.011. URL https://www.sciencedirect.com/science/article/pii/S0304387818305145.

Elisabetta Aurino, Aulo Gelli, Clement Adamba, Isaac Osei-Akoto, and Harold Alderman. Food for thought? *Journal of Human Resources*, 58(1):74–111, 2023. ISSN 0022-166X. doi: 10.3368/jhr.58.3.1019-10515R1. URL https://jhr.uwpress.org/content/58/1/74.

Anne Case and Christina Paxson. Stature and status: Height, ability, and labor market outcomes. *Journal of Political Economy*, 116(3):499–532, 2008. ISSN 00223808, 1537534X. URL http://www.jstor.org/stable/10.1086/589524.

Petter Lundborg, Dan-Olof Rooth, and Jesper Alex-Petersen. Long-term effects of childhood nutrition: Evidence from a school lunch reform. *The Review of Economic Studies*, 89(2):876–908, 05 2021. ISSN 0034-6527. doi: 10.1093/restud/rdab028. URL https://doi.org/10.1093/restud/rdab028.

Guanfu Fang and Ying Zhu. Long-term impacts of school nutrition: Evidence from china's school meal reform. *World Development*, 153:105854, 2022. ISSN 0305-750X. doi: https://doi.org/10.1016/j.worlddev.2022.105854. URL https://www.sciencedirect.com/science/article/pii/S0305750X22000444.

Xueyi Duan, Yinhe Liang, and Xiaobo Peng. Free school meals and cognitive ability: Evidence from China's student nutrition improvement plan. 33(7):1480–1502. ISSN 1099-1050 1057-9230. doi: 10.1002/hec.4824.

Haining Wang and Zhiming Cheng. Kids eat free: School feeding and family spending on education. *Journal of Economic Behavior Organization*, 193:196–212, 2022. ISSN 0167-2681. doi: https://doi.org/10.1016/j.jebo.2021.11.023. URL https://www.sciencedirect.com/science/article/pii/S0167268121004960.

Patrick Kline. Place based policies, heterogeneity, and agglomeration. *American Economic Review*, 100:383–87, 5 2010. ISSN 0002-8282. doi: 10.1257/AER.100.2.383.

Matias Busso, Jesse Gregory, and Patrick Kline. Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review*, 103:897–947, 4 2013. ISSN 0002-8282. doi: 10.1257/AER.103.2.897.

Patrick Kline and Enrico Moretti. Local economic development, agglomeration economies, and the big push: 100 years of evidence from the tennessee valley authority. *The Quarterly Journal of Economics*, 129:275–331, 2 2014. ISSN 0033-5533. doi: 10.1093/QJE/QJT034. URL https://dx.doi.org/10.1093/qje/qjt034.

Maximilian V. Ehrlich and Tobias Seidel. The persistent effects of place-based policy: Evidence from the west-german zonenrandgebiet. *American Economic Journal: Economic Policy*, 10: 344–74, 11 2018. ISSN 1945-7731. doi: 10.1257/POL.20160395.

Rana Hasan, Yi Jiang, and Radine Michelle Rafols. Place-based preferential tax policy and industrial development: Evidence from india's program on industrially backward districts. *Journal of Development Economics*, 150:102621, 5 2021. ISSN 0304-3878. doi: 10.1016/J.JDEVECO.2020.102621. URL https://www.sciencedirect.com/science/article/abs/pii/S0304387820301966.

Travis Baseler, Ambar Narayan, Odyssia Ng, and Sutirtha Sinha Roy. Social welfare portability and migration: Evidence from india's public distribution system. *American Economic Journal: Economic Policy*, 17:135–64, 11 2025. ISSN 1945-7731. doi: 10.1257/POL.20240183.

Clément Imbert and John Papp. Short-term migration, rural public works, and urban labor markets: Evidence from india. *Journal of the European Economic Association*, 18:927–963, 4 2020a. ISSN 1542-4766. doi: 10.1093/JEEA/JVZ009. URL https://dx.doi.org/10.1093/jeea/jvz009.

Clément Imbert and John Papp. Costs and benefits of rural-urban migration: Evidence from india. *Journal of Development Economics*, 146:102473, 9 2020b. ISSN 0304-3878. doi: 10.1016/J.JDEVECO.2020.102473. URL https://www.sciencedirect.com/science/article/abs/pii/S0304387820300481.

Figure 1: The implementation scope of the free meals

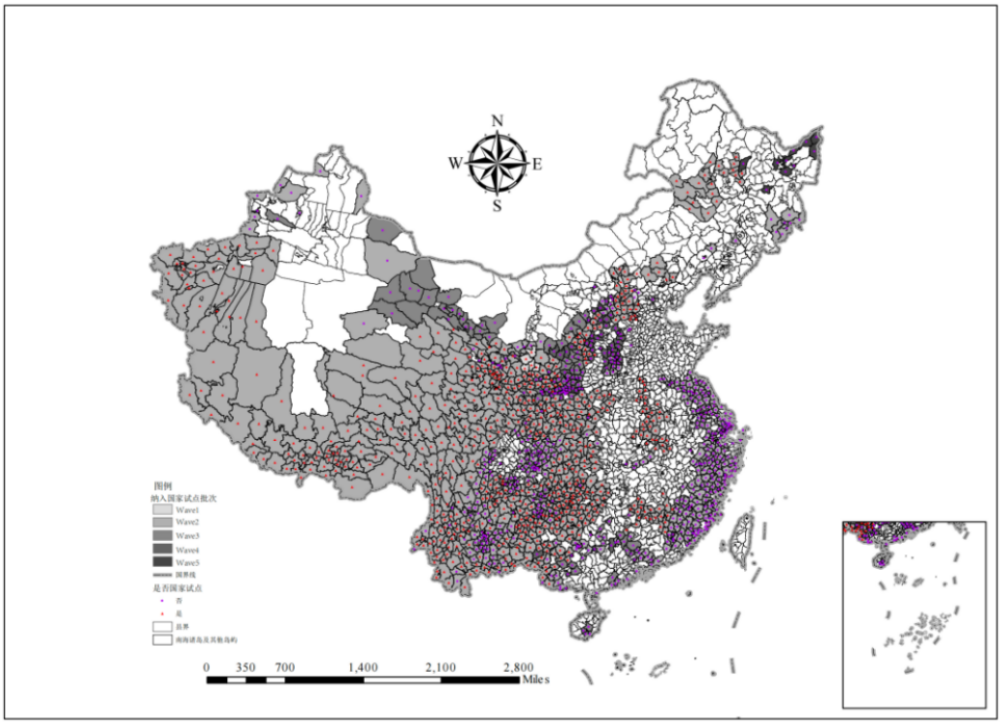
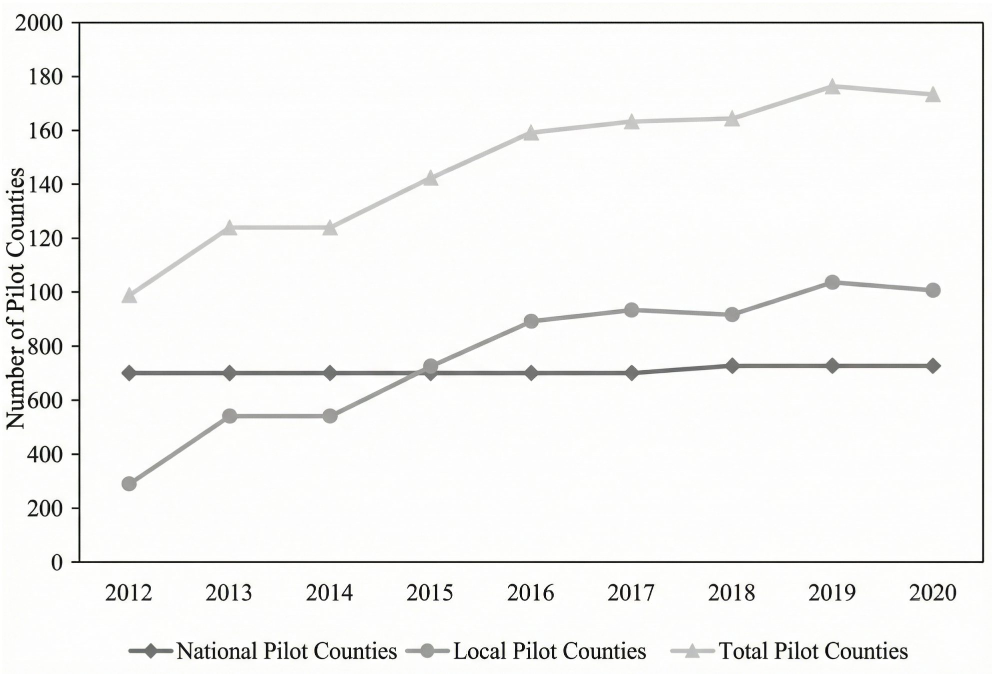


Figure 2: Number of NIP Pilot Counties



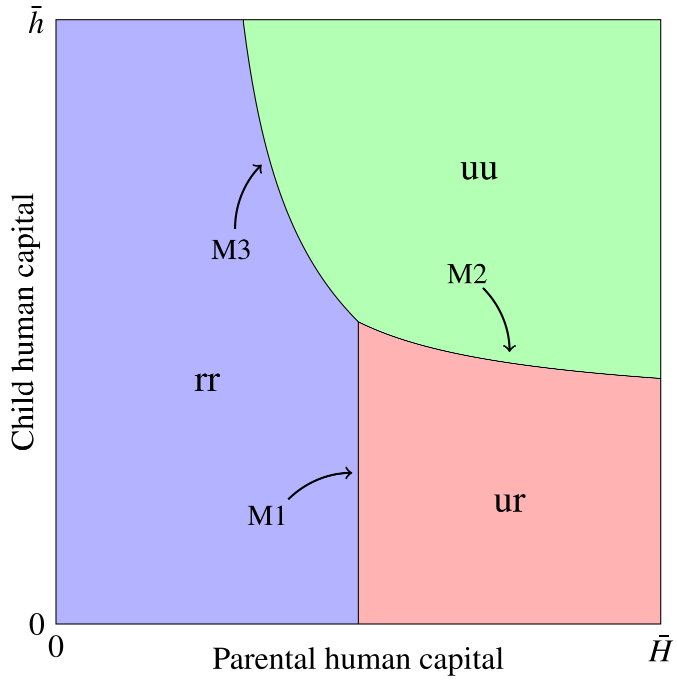


Figure 3: Parents and Children's Location Choices

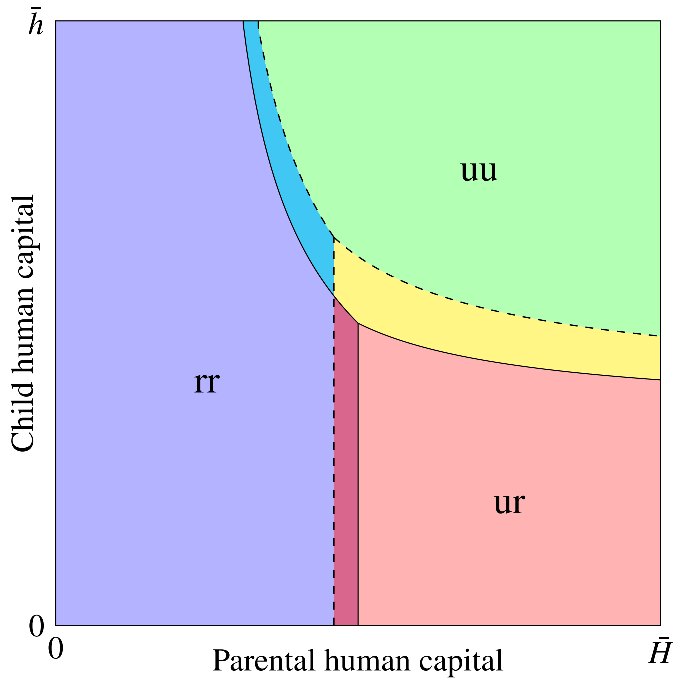
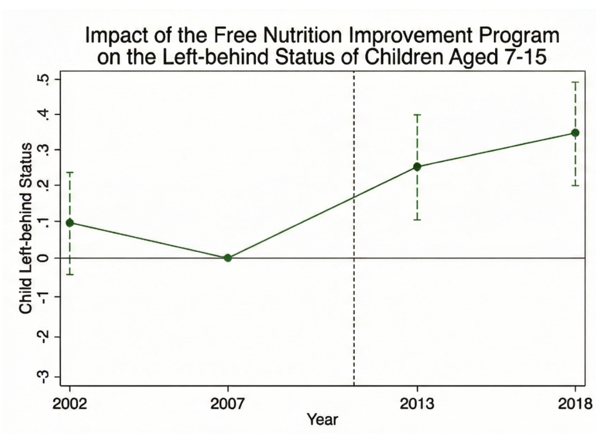


Figure 4: Parents and Children's Location Choices After the NIP

Figure 5: Results from Event-Study Regressions

(a) Evidence from School-Age Children



(b) Evidence from Preschool Children

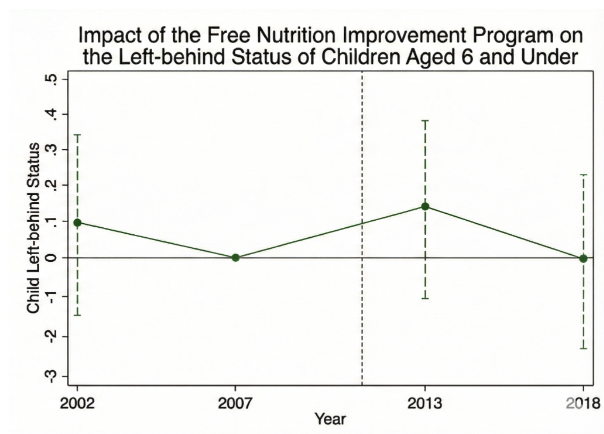


Table 1: Proportion of Left-behind Children in CFPS

Region / Sample	2010	2012	2014	2016	2018	2020
Overall	0.177	0.308	0.306	0.273	0.292	0.266
Rural	0.226	0.342	0.359	0.327	0.348	0.306
Urban	0.093	0.198	0.223	0.192	0.213	0.217

Table 2: Descriptive Statistics

	Treatment			Control		
	N	Mean	SD	N	Mean	SD
			Panel A: 2010-2020 Full Sample			
Left-behind child	12885	.333	.471	33634	.237	.425
Father migrated	12531	.289	.453	32618	.208	.406
Mother migrated	12502	.204	.403	32736	.144	.351
Birth year	12885	2007.092	5.644	33634	2007.201	5.527
Gender (male=1)	12882	.534	.499	33632	.528	.499
Non-agri Hukou	12625	.073	.26	33010	.237	.425
Father's edu (yrs)	12534	6.6	4.457	32767	9.166	3.699
Mother's edu (yrs)	12513	5.213	4.711	32801	8.528	4.126
			Panel B: Pre-policy Rural Sample			
Left-behind child	1944	.248	.432	3509	.223	.416
Father migrated	1795	.239	.427	3197	.219	.414
Mother migrated	1781	.12	.325	3173	.114	.318
			Panel C: Post-policy Rural Sample			
Left-behind child	8200	.381	.486	15388	.309	.462
Father migrated	8071	.324	.468	15159	.269	.443
Mother migrated	8028	.242	.428	15134	.2	.4

Table 3: Impact of Free Meals on Left-behind Status

	(1)	(2)	(3)	(4)
Samples	Urban & Rural Children Aged 0–15			
Outcome	Left-behind (1=Yes)			
Free Meals	0.0451**	0.0398*	0.0836***	0.0750***
	(0.0222)	(0.0241)	(0.0239)	(0.0253)
Gender	0.00171	0.00340	-0.000427	-0.0566**
	(0.00494)	(0.00494)	(0.00424)	(0.0248)
Age	0.000695	0.000838	0.00148*	0.0223**
	(0.000644)	(0.000686)	(0.000777)	(0.0112)
Father's edu	0.000339	0.00348***	-0.00351*	-0.00652***
	(0.00117)	(0.00130)	(0.00205)	(0.00250)
Mother's edu	-0.00102	0.00304***	-0.000593	-0.00295
	(0.00110)	(0.000977)	(0.00191)	(0.00206)
Observations	46,827	44,395	45,087	42,772
R-squared	0.123	0.214	0.536	0.587
County FE	Yes	No	No	No
Village FE	No	Yes	No	No
Family FE	No	No	Yes	No
Individual FE	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Results by Region and School Age

Samples	(1) All Aged 0–15	(2) Urban Aged 0–15	(3) Rural Aged 0–15	(4) Rural Kindergarten	(5) Rural Compulsory	(6) Rural Primary	(7) Rural Junior High
Outcome	Left-behind (1=Yes)						
Free Meals	0.0451**	0.00325	0.0616**	0.0257	0.0645**	0.0560*	0.0805*
	(0.0222)	(0.0386)	(0.0280)	(0.0708)	(0.0320)	(0.0334)	(0.0438)
Gender	0.00171	0.00190	0.00620	0.00337	-0.00357	0.00661	-0.0300**
	(0.00494)	(0.00675)	(0.00680)	(0.0116)	(0.0110)	(0.0121)	(0.0151)
Age	0.000695	0.00381***	-0.000235	0.000680*	-0.00682***	-0.00747***	-0.00373
	(0.000644)	(0.000708)	(0.000889)	(0.00378)	(0.00147)	(0.00202)	(0.00661)
Father's edu	0.000339	-0.00328**	0.00526***	0.00362	0.00597***	0.00649***	0.00482
	(0.00117)	(0.00157)	(0.00158)	(0.00287)	(0.00201)	(0.00218)	(0.00298)
Mother's edu	-0.00102	-0.000850	0.00298**	0.00368	0.00175	0.00237	0.000807
	(0.00110)	(0.00140)	(0.0143)	(0.00241)	(0.00174)	(0.00189)	(0.00256)
Observations	46,827	17,908	28,279	5,350	14,248	10,646	3,593
R-squared	0.123	0.127	0.126	0.148	0.133	0.137	0.154
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions control for the child's gender and age, as well as the years of schooling of the father and mother.

Table 5: Falsification Test: Local Pilot Policies

	(1)	(2)	(3)
Samples	All Aged 0–15	All Aged 0–15	All Aged 0–15
Outcomes		Left-behind (1=Yes)	
Central Pilot	0.0745***		0.0714***
	(0.0269)		(0.0259)
Local Pilot		-0.0211	-0.0170
		(0.0211)	(0.0209)
Observations	34,420	31,522	42,772
R-squared	0.587	0.599	0.587
Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All regressions control for the child's gender and age, as well as the years of schooling of the father and mother.

Table 6: Robustness Check: Excluding the Impact of Boarding

	(1)	(2)	(3)	(4)	(5)	(6)
Samples	Urban Children Aged 0–15 in School			Rural Children Aged 0–15 in Compulsory Education		
Outcomes	Boarding	Left-behind		Boarding	Left-behind	
Free Meals	0.0174	0.0470*	0.0538**	0.0144	0.0630**	0.0703**
	(0.0226)	(0.0266)	(0.0268)	(0.0280)	(0.0316)	(0.0311)
Boarding		0.0167*			0.0178	
		(0.00971)			(0.0123)	
Boarding Availability			0.00223			0.00399
			(0.00813)			(0.0110)
Observations	29029	29029	27760	14012	14012	13202
R-squared	0.274	0.114	0.112	0.319	0.130	0.130
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions control for the child's gender and age, as well as the years of schooling of the father and mother.

Table 7: Robustness Check: Investigation Based on CHIP Data

	(1)	(2)	(3)
Samples		Rural	
	Aged 0–15	Aged 7–15	Aged 0–6
Outcomes		Left-behind (1=Yes)	
Free Meals	0.203***	0.246***	0.118
	(0.047)	(0.043)	(0.088)
Gender	-0.002	-0.005	0.005
	(0.006)	(0.007)	(0.013)
Ethnicity (Han Ethnicity=1)	0.015	0.038	-0.051
	(0.029)	(0.033)	(0.042)
Age	-0.006***	-0.009***	-0.003
	(0.001)	(0.002)	(0.004)
Number of Children in the Household	-0.017***	-0.010**	-0.025***
	(0.005)	(0.005)	(0.008)
Observations	18,195	13,619	4,542
R-squared	0.235	0.227	0.324
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Mechanism Analysis: Financial Burden

Outcomes	(1) Has meal costs	(2) Total edu spending	(3)	(4) Child migration	(5)
Free meals	-0.105***	-678.5***	-0.00850*	-0.0158***	-0.0184***
	(0.0375)	(116.4)	(0.00330)	(0.00401)	(0.00473)
Free meals × Father's edu				0.00108**	
				(0.000449)	
Free meals × Mother's edu					0.00186***
					(0.000715)
Observations	23,023	22,739	46,827	46,827	46,827
R-squared	0.291	0.265	0.562	0.562	0.562
Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions control for the child's gender and age, as well as the years of schooling of the father and mother.

Table 9: Mechanism Analysis: Care Burden

Outcome	(1) Commuting expenses	(2) Cared by grandparents	(3) Father migrated	(4) Mother migrated	(5) Both migrated
Free Meals	-43.16***	0.0695***	0.0346	0.0325**	0.0221**
	(12.50)	(0.0181)	(0.0217)	(0.0131)	(0.0108)
Observations	22,095	36,909	46,521	46,521	46,521
R-squared	0.133	0.078	0.115	0.105	0.099
Controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions control for the child's gender and age, as well as the years of schooling of the father and mother.

Table 10: Heterogeneity

	(1)	(2)	(3)	(4)
Samples	Girl	Boy	Parents high edu	Parents low edu
Outcomes	Left-behind (1=Yes)			
Free Meals	0.0977***	0.0396	0.136**	0.0567*
	(0.0355)	(0.0372)	(0.0643)	(0.0327)
Observations	6,714	7,527	2,165	12,079
R-squared	0.148	0.147	0.220	0.142
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All regressions control for the child's gender and age, as well as the years of schooling of the father and mother.

Table 11: Impact of Regional Policies on Urbanization

Sample	(1) Overall	(2) Urban	(3) Rural	(4) Init. Urban	(5) Init. Rural	(6) Init. Non-agri	(7) Init. Agri
Outcome	Non-agricultural Hukou Status (1=Yes)						
Free Meals	-0.00913	-0.000598	-0.0158**	0.0157	-0.0151**	-0.00175	-0.0278***
	(0.00882)	(0.0433)	(0.00621)	(0.0275)	(0.00684)	(0.0269)	(0.00649)
Gender	0.00677	0.00438	0.00408	-0.000709	0.00812***	8.72e-06	-0.000480
	(0.00469)	(0.00882)	(0.00287)	(0.00978)	(0.00296)	(0.00600)	(0.00300)
Age	0.00601***	0.00906***	0.000423	0.00747***	0.000336	0.000411	0.000414
	(0.000772)	(0.00112)	(0.000337)	(0.00133)	(0.000394)	(0.000900)	(0.000284)
Father's edu	0.0158***	0.0195***	0.00507***	0.0182***	0.00513***	0.00134	0.000953**
	(0.00145)	(0.00253)	(0.000731)	(0.00301)	(0.000767)	(0.00108)	(0.000469)
Mother's edu	0.0186***	0.0229***	0.00559***	0.0202***	0.00543***	0.00386**	0.00144***
	(0.00142)	(0.00210)	(0.000693)	(0.00253)	(0.000740)	(0.00174)	(0.000426)
Observations	40,113	14,201	25,560	11,087	22,620	4,375	21,268
R-squared	0.459	0.541	0.192	0.581	0.218	0.214	0.118
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. (1) The NIP incentivizes children to retain non-agricultural Hukou status. (2) Welfare policies targeted at underdeveloped rural areas appear to induce a counter-urbanization effect.

Table 12: The Impact on Children's Mental Health

	(1)	(2)	(3)	(4)	(5)	(6)
Samples	Urban	Urban	Urban	Rural	Urban	Rural
			Aged 15-18			
Outcome	Standardized CESD Score				Low Emotion	
Free Meals	0.142*	0.183**	0.0789	0.164*	0.0865	0.219***
	(0.0739)	(0.0915)	(0.159)	(0.0888)	(0.106)	(0.0816)
Observations	7,424	7,090	2,939	4,412	2,939	4,412
R-squared	0.066	0.165	0.100	0.083	0.086	0.065
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Village FE		Yes				
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.In the regression analysis, control variables including the education level of both fathers and mothers, individual Hukou, gender, and family size have been accounted for.

Table 13: The Impact on Physical Development of Teenagers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Samples				Rural				Urban
Outcomes	Weight	Height	Weight	Height	Weight	Height	Weight	Height
Free Meals	1.106	2.028*	5.843*	5.891***	3.978*	3.855***	-0.796	-0.431
	(2.179)	(1.075)	(3.010)	(1.508)	(2.362)	(1.372)	(2.777)	(0.934)
Free meals * Father's edu			-0.771**	-0.628***				
			(0.362)	(0.166)				
Free meals * Mother's edu					-0.688**	-0.440***		
					(0.298)	(0.168)		
Observations	3,222	3,280	3,222	3,280	3,222	3,280	2,153	2,177
R-squared	0.270	0.388	0.271	0.392	0.271	0.390	0.357	0.558
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The numbers in parentheses are robust standard errors clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.In the regression analysis, control variables including the education level of both fathers and mothers, individual Hukou, gender, and family size have been accounted for.

Table 14: Discussion on Welfare

Child Type	**Family Type**	**Welfare Change**
Children staying home	Parents stay home with child	Maximum gain
	Parents migrate while child stays	Significant gain
Migrating children	Parents migrate with child	No change
Marginaly affected	Policy-induced left-behind status	Welfare gain or loss