Nutrition and Child Development: Evidence from the Student Nutrition Improvement Program

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Abstract

School feeding programs, providing reduced-price or entirely free meals to eligible students, are prevalent globally. Prior research has primarily focused on their impact on children's physical health and cognitive skills. This paper presents the first evaluation of school feeding programs on noncognitive and behavioral outcomes among school-aged children. Noncognitive and behavioral skills hold an equally crucial role alongside cognitive skills in human capital formation. This paper investigates the impact of a school feeding program on child development, leveraging the staggered implementation of the program across counties in China. Our findings reveal significant enhancements in physical health, cognitive development, noncognitive and behavioral aspects among children exposed to the program. Specifically, we observe a notable increase of 0.210 standard deviations in the rated importance of effort to future achievement, an important measure of noncognitive outcomes. In terms of behavioral outcomes, there are substantial improvements, with learning behavior, social competence, and autonomy indices experiencing increase of 0.359, 0.315, and 0.528 standard deviations, respectively. Heterogeneous analyses underscore that these effects are more pronounced among marginalized groups, particularly girls and children with mothers possessing lower levels of education. The mechanisms driving these positive impacts include enhanced parental income, improved nutrition intake, increased monetary investment in children, and the adoption of more engaged parenting styles and interactive family dynamics. Furthermore, our cost and benefit analysis reveals that the additional benefits stemming from improved noncognitive and behavioral outcomes constitute approximately 48.9% of the program's overall benefits, suggesting that prior studies may have underestimated the benefits of school feeding programs.

JEL Classification: I18; I24; I38; H42; H53

Keywords: School Feeding Programs, Child Development, Noncognitive Outcomes, Behavioral Outcomes, Parenting Styles

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§For their helpful comments, we thank Clément de Chaisemartin, Naijia Guo, Kelsey Jack, Jacob Moscona, participants in the 2023 Asian Meeting of Econometric Society at Tsinghua University, and seminar participants at The Chinese University of Hong Kong, Shenzhen.

1 Introduction

The food crisis remains a significant global concern, particularly affecting school-aged children. In 2020, 349 million people in 79 countries, including 153 million children and young individuals, faced the threat of starvation (World Food Programme, 2022). The impact of this crisis on children is particularly severe, given that early adverse nutrition experiences have been linked to stunted growth (Gørgens et al., 2012), lower income (Chen and Zhou, 2007), depression, overweight issues, challenges in daily activities, and late-life cognitive impairments (Cui et al., 2020). School feeding programs, which are universally acknowledged as the most extensive safety net, offer an opportunity to enhance the well-being of children impacted by the food crisis. In 2022, these programs assisted around 418 million children in 176 countries by subsidizing school meals (World Food Programme, 2022). Therefore, policymakers need to have a comprehensive understanding of the benefits of such large-scale programs. Previous research has largely focused on children's physical health and find that school feeding programs increase the height of these children (Lundborg et al., 2022) and reduced the prevalence of obesity among this group (Holford and Rabe, 2022) by addressing malnutrition and improving food security (Afridi, 2010; Gundersen et al., 2012; Marcus and Yewell, 2022). An expanding body of research also highlights the positive impacts of these programs on the cognitive skills of children (Frisvold, 2015; Anderson et al., 2018; Chakraborty and Jayaraman, 2019) by reducing their school absenteeism (Belot and James, 2011). However, the effects of school feeding programs on children's noncognitive and behavioral outcomes, which are critical to human capital development, have been supported by little evidence thus far. Failing to account for these impacts may result in underestimating the overall benefits of the programs.

Noncognitive abilities, including self-esteem, beliefs, personality traits and preferences, are as critical as cognitive abilities (Cunha et al., 2010; Lindqvist and Vestman, 2011; Heckman and Kautz, 2012; Edin et al., 2022) due to their profound influence on educational and labor market outcomes (Heckman et al., 2006; Heckman et al., 2013) and their intergenerational persistence in educational achievements and income gap (Blanden et al., 2007; Grönqvist et al., 2017).[1][2]

[1] Lindqvist and Vestman (2011) differentiate noncognitive ability from the capacity for abstract problem solving and conventional human capital metrics, such as training and experience.

[2] Noncognitive attributes are known by various terms, including soft skills, personality traits, noncognitive

Behavioral pattern is another crucial factor influencing labor market performance. Misbehavior of children contributes to elevated dropout rates, diminished employment prospects, and reduced earnings (Cairns et al., 1989; Bowles et al., 2001; Le et al., 2005). Favorable conduct not only causally enables access to success but also mitigates coordination costs among workers, thereby leading to efficient production (Deming, 2017).

We try to fill in the gap by examining the effects of the Student Nutrition Improvement Program (SNIP) in China on the noncognitive and behavioral outcomes of school-aged children. Drawing inspiration from school feeding programs conducted in other countries, the Ministry of Education in China announced the SNIP in a few pilot counties in 2009 and launched the program at a national scale in a stepwise manner starting from the academic year 2011. In rural regions, each student enrolled in compulsory education received an annual meal subsidy of CNY 600 (USD 95), which is around 23.4% of rural households' per capita annual expenditure on food, at the beginning of the program.[3] In essence, the SNIP stands out as an extensive and impactful program in China. By 2020, the program has covered approximately 40.61 million students, accounting for 27.1% of all students enrolled in compulsory education and 42.4% of compulsory students from rural areas (Ministry of Education, China, 2020). By 2021, the central government has cumulatively allocated CNY 1,967 billion (USD 312 billion) to students' nutrition subsidies (Central Government, China, 2021). These subsidies were directly allocated to schools based on their number of students, in order to enhance the quality of meals and the environment of canteens. To evaluate the impacts of these programs on child development outcomes, we adopt the difference-in-differences estimators of intertemporal treatment effects proposed by De Chaisemartin and d'Haultfoeuille (2022). By leveraging longitudinal data from the China Family Panel Studies datasets from 2010 to 2020, we estimate the average treatment effect, including instantaneous and dynamic effects, over exposed children in eligible cohorts.

We organize our findings into three parts. First, we investigate the effect of a school feeding program on children's health and cognitive outcomes, and find that this program has significantly increased the *height* of children by 4.533 *cm* on average. We also observe a substantial 6.5% decrease in the likelihood of *hospitalization* among exposed children and marked improvements

skills, noncognitive abilities, characters, and socioemotional skills (Heckman and Kautz, 2012).

[3] In 2012, rural households in China had a per capita annual expenditure on food of approximately CNY 2,563 (USD 406.83) in 2012 (Yuan et al., 2019).

in their key health indicators. Specifically, we find that rates of *stunting* (a critical measure of malnutrition and growth impairment), *obesity*, and *overweight* among exposed children, significantly reduce by 6.5%, 6.5%, and 8.9%, respectively, as a result of the SNIP.[4] In terms of cognitive outcomes, the SNIP has a particularly striking impact on children's *cognitive test index* and self-rated *academic performance* which increase by 0.115 and 0.391 standard deviations, respectively.[5] The children participating in the program not only experience objective improvements in cognitive skills but also demonstrate an enhanced sense of confidence and self-efficacy in their academic pursuits.

Second, our findings underscore a significant change in children's beliefs, which constitute a substantial aspect of their noncognitive skills. In our design, we specifically focus on beliefs regarding the importance of effort versus luck for individual's future achievement. The nuanced perspectives on effort versus luck are significant determinants of economic success (Piketty, 1995), perceptions of fairness (Alesina and Angeletos, 2005), and government redistribution (Giuliano and Spilimbergo, 2014). We find that the school feeding program increasingly places greater emphasis on the role of *effort*, showcasing a significant increase of 0.210 standard deviations. Meanwhile, the rated *importance of luck* to future achievement decreases by 0.095 standard deviations.[6]

Third, we use the *learning behavior index*, and three-dimensional *positive behavior scales* to measure behavioral outcomes. The *learning behavior index* captures the self-evaluations of studying habits, while the three-dimension *positive behavior scale* created by Polit (1998) assesses the favorable aspects of children's lives, including their *social competence*, *compliance*, and *autonomy*. In the context of this study, *social competence* refers to one's ability to interact effectively with peers, become well-regarded, demonstrate generosity and thoughtfulness, and be aware of others' emotions and perspectives. *Compliance*, not refers to obedience but pertains to adhering to expectations without continual supervision. An individual with high *autonomy* is generally self-reliant, and is capable of undertaking tasks independently. Our examination unveils a positive shift toward a better *learning behavior index* by 0.359 standard deviations,

[4]We do not find any impact on *depression index*.

[5]The *cognitive test index* evaluates arithmetic and reading abilities based on standardized math and word tests in surveys.

[6]We do not find any significant change on *Rosenberg self-esteem index*.

while for the three-dimension *positive behavior scale*, we find that the treated children exhibit significant improvements in their *social competence* and *autonomy* skills by 0.315 and 0.528 standard deviations, respectively.

We also shed light on the heterogeneous effects of the SNIP across gender and parents' education levels. For instance, disadvantaged segments of the population, especially girls and children born to mothers with lower levels of education, emerge as the primary beneficiaries of the program. Nonetheless, we do not observe significant differences among children born to fathers with different education levels. This targeted benefit represents a crucial stride toward mitigating disparities in children's access to essential nutrition and its profound effects on their overall development. Meanwhile, we find no significant disparities in the effects of the SNIP across different time of initial program exposure. In other words, the effects on those children exposed to the program at primary- or middle-school age show no significant differences.

To investigate the mechanisms, we have developed a conceptual framework that illustrates the pathways through which the nutrition subsidy, akin to an unearned positive "income shock", exerts its influence. First, this "income shock" prompts the household decision-maker to reevaluate her/his allocation of resources, including parental labor supply and income, monetary and time investment on children. This reallocation process directly impacts the nutrition intake, monetary investment, and time devoted to the child, thus collectively shaping the overall quantity of investment directed toward the child's development. Second, the change in the family's financial condition necessitates a reevaluation of the expected returns from monetary and time investment in children (Cunha, 2014; Kiessling, 2021), thus leading to shifts in parenting styles and family dynamics. The changing expectations then influence the process by which nutrition intakes, time and monetary investment are combined to produce child development outcomes (Li et al., 2023).

We then categorize these potential channels into three parts, (i) parental labor supply and income, (ii) nutrition intake, monetary and time investment, and (iii) parenting styles and family dynamics. First, our subsequent analyses reveal that the SNIP triggers an increase in the extensive margin of parental labor supply, specifically a 6.8% increase in labor force participation rates, which underscores the influence of school feeding programs on parental workforce engagement. Meanwhile, the intensive margin, such as *monthly hours worked*, shows an insignificant increase of 15.023 hours. Moreover, the increase in extensive margin translates to a significant 14.5% increase in average *annual income* for parents, denoting a substantial positive economic impact.

Second, we focus on quantity of investment, which includes nutrition intake, allocation of monetary and time resources to children. The likelihood of incorporating protein-rich foods, such as *eggs and dairy*, into family diets is estimated to increase by 9.7%. This dietary shift is accompanied by a significant 32.3% reduction in *annual food expenses*, which is indicative of a partial crowding-out effect, consistent with prior research (Long, 1991; Holford and Rabe, 2022; Marcus and Yewell, 2022). This reduction in household food expenditure also leads to a notable 21.8% increase in *annual education expenses*, whereas *medical expenses* remain largely unchanged. Furthermore, parents' *tutoring hours* marginally increases by 0.346 hours per week.

Third, we treat effectiveness, which depends on parenting styles and family dynamics, as another underlying mechanism. The SNIP has a palpable influence on parenting styles. Parents tend to adopt a more authoritative approach, that exhibits high responsiveness and demandingness in interactions with their children. This shift is marked by a significant 32.1% increase in the proportion of *authoritative* parents. Meanwhile, the percentage of *uninvolved* parents, who exhibit a more detached approach to child rearing, significantly decreases by around 25.6%. We also observe 0.536 times decrease in disputes between children and parents and 0.455 times reduction in quarrels between mothers and fathers, thus attesting to the program's positive role in fostering a harmonious family environment. The attitudes of parents regarding their children's homework also show an improvement. Specifically, parents express a greater willingness to be involved in reviewing and assisting with their children's schoolwork as marked by a notable 0.133 standard deviations increase.

Based on above estimates and the method proposed by Hendren and Sprung-Keyser (2020), we conduct a cost and benefit analysis of the SNIP. Using 2011 as the base year, costs include a nutrition subsidy of approximately CNY 5,833 (USD 926) over a 9-year period, while benefits include increased consumption tax, reduced obesity-related expenses, and future income tax through enhanced physical, cognitive, noncognitive, and behavioral improvements. The estimated net benefit to the government over the program's duration is CNY 49,720 (USD 7,892), thus emphasizing a favorable long-term outcome relative to immediate costs. Specifically, the increased income tax from enhanced physical and cognitive outcomes is approximately CNY 27,770 (USD 4,408), while that from improved noncognitive and behavioral outcomes is around 27,176 (USD 4,314). These results underscore that the benefits of school feeding programs can be underestimated when their impacts on noncognitive and behavioral outcomes are not adequately considered.

Our article makes three contributions to the literature. First, it adds to the large literature on the impacts of school feeding programs on child development outcomes, including nutrition (Afridi, 2010; Gundersen et al., 2012), physical health (Millimet et al., 2010; Abouk and Adams, 2022; Holford and Rabe, 2022; Lundborg et al., 2022), cognitive abilities (Belot and James, 2011; McEwan, 2013; Frisvold, 2015; Anderson et al., 2018; Chakraborty and Jayaraman, 2019) and labor market outcomes (Bütikofer et al., 2018; Lundborg et al., 2022). Our study is the first to examine the effects of school feeding programs on noncognitive and behavioral outcomes, utilizing the recent multiple difference-in-differences methods developed by De Chaisemartin and d'Haultfoeuille (2022).[7] We find that children exposed to the school feeding program tend to place a higher value on effort as a crucial factor for their future success. They also exhibit improvements in their learning behaviors, social competence, and autonomy. This expanded perspective allows us to explore the role of beliefs and behaviors as potential pathways leading to long-term improvements in labor market outcomes. As stated in the cost and benefit analysis, such perspective underscores the considerable economic importance of noncognitive and behavioral development in the context of such initiatives. Our comprehensive analysis stands out as the first to reveal the multifaceted benefits of school feeding programs, spanning from physical health to cognitive, noncognitive, and behavioral outcomes, in a developing country. These positive outcomes serve as a resounding testament to these programs' effectiveness in fostering holistic development among school-aged children, and this broader view enhances our understanding of the comprehensive effects of early-life interventions in long-term consequences on human capital development.

Second, our study is the first to examine the effects of school feeding programs on the inter-

[7] The school feeding programs mentioned in previous literature have been implemented with staggered adoption designs, however, their estimators are mostly derived from two-way fixed effect model. In this case, their estimators may be contaminated by substantial negative weights stemming from the inclusion of early-treated groups (Goodman-Bacon, 2021).

action between exposed children and their parents, i.e., parenting styles and family dynamics. Previous research of family income and child development often focuses on the quantity of production inputs (including child-centered goods and time inputs), rather than the production process or the quality margin of family investment on children (Del Boca et al., 2014; Francesconi and Heckman, 2016; Attanasio et al., 2020a; Attanasio et al., 2020b; Attanasio et al., 2022). Not until recent years the economic studies have started to incorporate parenting styles in the analysis of child development (Doepke et al., 2019). We contribute to these studies by examining the effect of a school feeding program on parenting styles (responsiveness and demandingness from parents) and family dynamics (intra-household conflicts and whether parents engage in checking their children's homework), and find that the program fosters greater involvement in parenting styles, reduces family conflicts, and enhances interactions related to schoolwork.

Third, our study contributes to the literature analyzing the impacts of welfare programs on household expenditures. A large body of literature has explored how welfare programs, including cash transfers, in-kind transfers, and pensions, stimulate individual's consumption decision (Hoynes and Schanzenbach, 2009; Haushofer and Shapiro, 2016; Armand et al., 2020; Huang and Zhang, 2021). With regard to the effect of school feeding programs on household food expenses, Long (1991) finds that every dollar benefit from the National School Lunch Program in the United States corresponds to a 61-cent decrease in household food expenditures. Marcus and Yewell (2022) discover that eligibility to the Community Eligibility Provision in the United States can reduce monthly food purchases by approximately USD 11. Holford and Rabe (2022) point out a significant decrease in family expenditures on supermarket food and eating out as a result of the Universal Infant Free School Meals program in the United Kingdom. Moreover, these three school feeding programs were initiated in developed countries, and our study reveals the crowding-out effect in developing countries, which is more substantial than that in developed countries. Such disparity may be explained by the deficiency in nutrition knowledge among parents with lower levels of education. Upon examining the heterogeneous effects, we find that those households with mothers having lower educational attainment exhibit a perfect crowding-out effect. In contrast, those with mothers having higher levels of education do not manifest any discernible crowding-out effect.

The remainder of this paper is structured as follows. Section 2 provides an overview of the

SNIP in China and a conceptual framework. Section 3 describes the data, sample, variables, and econometric model. Section 4 presents the baseline results, dynamic effects, magnitude comparison and heterogeneous effects. Section 5 explores the potential mechanisms of child development outcomes. Section 6 discusses the crowding effect and cost-benefit analysis of the program. Section 7 concludes the paper.

2 Background and Conceptual Framework

2.1 Nutrition and Health Status of Children in Rural China

Infants and children in rural China are notably lacking in their consumption of dairy and animal-source foods, such as meat, eggs, or bean products (Shi et al., 2010). Despite significant improvements in nutrition intake among Chinese residents since 1982, there have been ongoing challenges with nutrition intake in rural areas, resulting in growth-and health-related issues (Hui et al., 2011). As of 2002, the overall stunting rate for children under 5 in China is 14.3%, with a higher rate of 17.3% in rural areas and a lower rate of 4.9% in urban areas (Li et al., 2005). In extremely impoverished areas of China, the stunting rate was even around 40% in 2000 (Zhao and Glewwe, 2010).[8] The inappropriate nutritional enhancement process in these areas also occasionally leads to a disproportional increase in weight relative to height. This phenomenon, often referred to as "stunted obesity", highlights the importance of prioritizing the enhancement of dietary quality apart from ensuring sufficient energy intake (Zhang et al., 2018). In 1985, the Chinese Student Physical Fitness and Health Survey indicated that the prevalence of overweight and obesity among rural boys and girls aged between 7 and 18 years was only 0.5% and 1.6%, respectively. However, by 2000, these rates increased to 5.9% and 4.6%, respectively, signaling the emergence of childhood obesity as a nationwide trend, hence reiterating the importance of enriched nutritional content in diets to effectively foster height and weight growth in a coordinated manner. Moreover, malnutrition can lead to fatality, extending beyond growth-related concerns, contributing to 22% of deaths among Chinese children under the age of 5 in 2000. (National Institute for Nutrition and Health, China, 2012). Especially in

[8]Stunting serves as a more cumulative indicator of malnutrition compared to underweight (De Brauw and Mu, 2011).

poverty regions, the mortality rate of children suffering from severe illnesses was approximately 54%, which is about 8 times higher than that of urban children (National Health Commission, China, 2012).

2.2 Student Nutrition Improvement Program

To improve the nutritional conditions for rural children, the SNIP was initiated during the fall semester of 2009 in pilot counties within Shanxi Province. Following the success of these trials, the Ministry of Education gradually expanded the program nationwide in different waves from fall semester of 2011. Figure 1 provides an overview of the years in which the nutrition program was adopted in different counties across China. Certain counties located in impoverished regions were prioritized in the implementation of the nutrition policy, and we control this predefined criterion in our econometric model. Under this program, every eligible student, i.e., students in rural regions under compulsory education, received a nutrition subsidy of CNY 3 (USD 0.48) per school day, and the total subsidy was calculated based on 200 school days per year. The subsidy amount was increased to CNY 4 (USD 0.63) per school day in 2014 and further raised to CNY 5 (USD 0.79) per school day in 2021. These subsidies were distributed directly to pilot schools with the intention of improving their meal quality and enhancing the surrounding environment of their canteens. The SNIP encompasses three primary feeding modes, namely, meals provided by school canteens, enterprises, and family, among which the first two were the most popular among students, accounting for 99.8% in 2021 (Ministry of Education, China, 2022).

Initially, the program was introduced in select pilot regions in 2011, benefiting around 26 million students across 680 counties and cities. The central government allocated substantial funding that exceeds CNY 16 billion (USD 2.54 billion) annually to provide dietary subsidies to rural students undergoing compulsory education (Ministry of Education, China, 2011). By May 2020, the program had been implemented in 1,762 counties across 29 provinces throughout China, encompassing 145,700 rural compulsory education schools. From 2011 to 2020, the central government invested CNY 147.2 billion (USD 23.37 billion) into the program. By then, the program had approximately 40.61 million student beneficiaries, accounting for 27.08% of students undergoing compulsory education and 42.4% of compulsory students from rural areas (Ministry of Education, China, 2020).

The Ministry of Education in China appointed committee members to oversee the implementation of the SNIP in 2015 (Ministry of Education, China, 2015), including supervisors from the Ministry of Education, relevant experts, representatives from the National People's Congress, and members of democratic parties. These members established 9 panels to assess the current status of school meals in 18 provinces and randomly selected 144 compulsory education schools in impoverished areas. Since then, the SNIP has actively received public scrutiny via different forms of media, such as newspapers, internet, radio, and television. As required, each primary and secondary school has established notice boards where they disclose information about their menus, recipes, and meal prices. These notice boards are subject to supervision by students, parents, teachers, and members of the committee.[9]

In 2018, the Ministry of Education reinforced its supervision over the SNIP (Ministry of Education, China, 2018, 2019). Specifically, the supervision committee issued a notice stipulating that concerned administrative departments, in conjunction with the finance, development and reform, and auditing departments, were to immediately conduct a comprehensive investigation and to establish hotlines and mailboxes for reporting issues about schools and catering companies. This notice signals that local authorities should pay close attention to those regions and schools that have received strong feedback from the public and check for potential issues, such as misappropriation, arrears, or misallocation of nutrition subsidies. In cases where individuals neglect their responsibilities in ensuring school food safety, fail to fulfill their duties, or contribute to significant food safety incidents or negative societal impacts, the relevant officers will be rigorously held accountable. Those who are found guilty of dereliction of duty that leads to criminal consequences will be legally prosecuted.

[9] Local authorities supplement the salaries of staff in school canteens. For instance, Guizhou allocates over CNY 6 billion (USD 952 million) annually to provide more than 40,000 cafeteria staff, whose salaries and insurance benefits are included in county-level financial budgets. Pilot cities in Yunnan collectively invest CNY 270 million (USD 42.86 million) annually to allocate service staff to over 25,000 schools. These authorities have also established a mechanism to guarantee operational funds for cafeterias. For example, Chongqing incorporates the operational funds for school cafeterias in 14 pilot counties into its municipal budget to provide subsidies to all schools within the scope based on a per capita standard of CNY 80 (USD 12.70) per year. Ningxia allocates CNY 16.18 million (USD 2.57 million) in subsidies for public expenses for schools implementing the SNIP, thus increasing its per capita public expenses by CNY 60 (USD 9.52) for pilot schools.

2.3 Conceptual Framework

Insights from the literature indicate that similar in-kind transfers can have substantial impacts on a range of outcomes in children, including the health, cognitive, noncognitive, and behavioral domains. This phenomenon can be attributed to several compelling and interrelated factors that merit further exploration. First, the unearned "income shock" triggers a fundamental reevaluation by the household decision maker regarding her/his allocation of resources, including labor supply, monetary and time investment in children (Hoynes, 1993; Lefebvre and Merrigan, 2008; Attanasio and Lechene, 2014; Fitzsimons et al., 2016). Collectively, these adjustments play a pivotal role in determining child development (Blau, 1999; Weinberg, 2001; Akee et al., 2010). The unearned "income shock" also prompts a reevaluation of the anticipated returns from monetary and time investment (Cunha, 2014). This reassessment, in turn, leads to changes in parenting styles and family dynamics. These factors are acknowledged as central determinants of the effectiveness in shaping children's noncognitive and behavioral outcomes (Jenkins, 1968; Jenkins et al., 1989; Darling and Steinberg, 1993; Crosnoe et al., 2002; Dooley and Stewart, 2007; Aaron and Dallaire, 2010). In this strand of literature, "effectiveness" pertains to the extent to which the quantity of investment ultimately translates to effective investment that profoundly influence children's future development. In sum, the multifaceted impacts of school feeding programs which belongs to in-kind transfers on children's cognitive, noncognitive, and behavioral outcomes is a complex interplay of factors related to budget constraint relaxation, changes in parental labor supply, and the dynamics of family life. Understanding these intricate relationships is crucial for policymakers and researchers to improve the well-being and future prospects of children.

We develop a conceptual framework as a more intuitive interpretation of the potential channels discussed above. For simplicity, we adopt a conventional approach often found in the literature, where we assume a single parent and a single child only span two periods ($t = 1, 2$) and the child lives independently from the parent in the second stage (Cunha and Heckman, 2007; Cunha et al., 2010; Heckman and Mosso, 2014). In the context of this framework, the individual taking on the role of the household decision-maker is represented as a single parent.

The process of child development θ_{t+1} can be characterized as:

$$\theta_{t+1} = A \cdot H_t(\theta_t, Food_t^{Total}(S), e_X \cdot X_t, e_T \cdot T_t) \tag{1}$$

where θ_t is a vector of physical and mental health, cognitive skills, noncognitive and behavioral outcomes, reflecting child development in period t. A denotes productivity and H_t is a production function, that is twice continuously differentiable and increasing in all inputs; $Food_t^{Total}(S) = Food_t^{Paid} + \frac{S}{\bar{p}_t}$ denotes the child's nutrition intake in period t, which depends on food paid for the child by the parent ($Food_t^{Paid}$), nutrition subsidy (S) and food price level at period t ($\bar{p}_t$); X_t and T_t represent the monetary and time investment in the child, respectively, while $e_X = f(P, F)$ and $e_T = g(P, F)$ show the effectiveness of monetary and time inputs (Abrams and Kaslow, 1976; Royle et al., 2004; Cunha, 2014), which can be positively determined by parenting styles P and family dynamics F. The technology of skill formation H_t is characterized by the following CES production function:

$$H_t = \{\alpha \cdot \theta_t^{\rho} + (1-\alpha) \cdot \{\beta \cdot [\mu \cdot Food_{Total,t}^{\sigma} + (1-\mu) \cdot (e_X \cdot X_t)^{\sigma}]^{\frac{\gamma}{\sigma}} + (1-\beta) \cdot (e_T \cdot T_t)^{\gamma}\}^{\frac{\rho}{\gamma}}\}^{\frac{\nu}{\rho}} \tag{2}$$

where α is a constant relative factor share between different factors, ρ, σ and γ determine the constant elasticity of substitution between different inputs, and ν measures the degree of homogeneity of the production function.

The household decision maker intends to maximize her/his value function, which depends on the child's utilities U_t in both periods and the child's value function $CV(\cdot)$ in the second stage:

$$PV = \mathbb{E}[U_1(C_1, L_1, P, F) + U_2(C_2, L_2) + \delta \cdot CV(\theta_2, B)] \tag{3}$$

where δ indicates the altruism of the parent to the child's future well-being (Laferrère and Wolff, 2006). The child's value function $CV(\cdot)$ depends on her/his development in second stage θ_2 and wealth transfer B from the parent with $\frac{\partial CV(\cdot)}{\partial \theta_2} > 0$ and $\frac{\partial CV(\cdot)}{\partial B} > 0$. We assume that the parent's utility $U_t(\cdot)$ is positively associated with consumption C_t and leisure time L_t ($\phi_1, \phi_2 > 0$). Given that the parent needs to involve care and patience in order to demonstrate a more engaged parenting style and interacted family dynamics, we categorize them as cost in the following ($\phi_3, \phi_4 > 0$).

$$U_t = \phi_1 \ln C_t + \phi_2 \ln L_t - \phi_3 P \cdot [t=1] - \phi_4 F \cdot [t=1] \tag{4}$$

The parent is limited by the minimum nutrition requirement in the first stage and by monetary and time budget constraints in both periods:

$$Food_1^{Paid} \geq 0 \tag{5}$$

$$C_1 + \bar{p_1} \cdot Food_1^{Paid} + X_1 + \frac{D}{1+r} \leq w_1 N_1 \tag{6}$$

$$C_2 + B \leq w_2 N_2 + D \tag{7}$$

$$L_t + T_t \cdot [t=1] + N_t = 1 \ for \ t = 1, 2 \tag{8}$$

where r refers to the risk-free rate, δ denotes the discount factor, D reflects the deposit in period 1, w_t and N_t indicate income and labor supply in period t, respectively. We then combine the two monetary constraints and substitute $\bar{p_1} \cdot Food_1^{Paid}$ with $\bar{p_1} \cdot Food_1^{Total}(S) - S$, then the monetary budget restriction will be $C_1 + \bar{p_1} \cdot Food_1^{Total}(S) + X_1 + \frac{C_2}{1+r} + \frac{B}{1+r} \leq w_1 N_1 + \frac{w_2 N_2}{1+r} + S$. With the new budget constraint, the nutrition subsidy can be interpreted as a in-kind transfer equivalently, thus incurring reevaluation of resources within the household.[10]

In the context of this established framework, the parent chooses the way to rear the child (i.e., monetary and time inputs, parenting styles and family dynamics) optimally given the above constraints. The nutrition subsidy (S) can be viewed as an in-kind transfer that possesses the capacity to enhance a child's nutrition intake ($Food_t^{Total}$) without imposing constraints on the family budget. As illustrated in Figure 2, the subsidy (S) can influence a child's health, cognitive abilities, noncognitive and behavioral outcomes through several potential channels. First, this subsidy prompts the household decision-maker to reallocate resources within the household, thus impacting monetary distribution (consumption C_t, monetary investment X_t and wealth transfer B) and time allocation (leisure time L_t and labor time N_t). This reallocation essentially determines the quantity of investment on the child, including financial resources

[10]See Slesnick (1996).

and time inputs, which are vital in shaping the child development outcomes. Second, the effectiveness of monetary and time inputs (e_X and e_T) are unknown to parent when she/he makes the investment decision in period 1. Based on her/his experience, environment and information, the parent form beliefs and expectations about effectiveness of investment on the child ($\mathbb{E}[e_X]$ and $\mathbb{E}[e_T]$). As proposed by Cunha (2014) and Kiessling (2021), the relaxation of the budget constraint can lead to changes in the household decision-maker's perception of effectiveness, which can significantly influence household decisions regarding parenting styles (P) and family dynamics (F). In essence, the nutrition subsidy (S) impacts not only the quantity of investment but also the quality margin of the investment, thereby shaping child development outcomes. In Section 5, we employ econometric methods to empirically investigate the role of these mechanisms in shaping child development outcomes.

3 Data and Empirical Strategy

3.1 Data and Sample

The dataset is sourced from China Family Panel Studies (CFPS), a nationally representative longitudinal survey conducted among individuals, families, and communities in China (Xie and Hu, 2014). Initiated by Peking University in 2010, this survey encompasses 25 provinces, sampling from approximately 94.5% of China's population, and conducts across six waves (2010, 2012, 2014, 2016, 2018, and 2020). As a result, the CFPS dataset is representative of the entire Chinese population (Zhang et al., 2017; Wang et al., 2019; Cao et al., 2022; Deng et al., 2022; Huang and Liu, 2023). CFPS offers a wealth of information, including the economic circumstances, demographic details, educational background, family dynamics, health metrics, and perspectives of the respondents. The CFPS questionnaire is divided into four main sections, namely, community, family, adults, and children, including individual attributes (such as gender, date of birth, education level, marital status, occupation, family composition, and income level), preferences (such as hobbies, leisure activities), viewpoints (regarding social status, wealth, relationships, and corruption), and family income and expenditure breakdowns.

We consolidate the datasets from the 6 survey waves and focus on children within the targeted cohorts, those born between September 1995 and August 2013 and live in rural regions. This range encompasses all school-aged children that can be affected by the school feeding program, covering children of 6 to 14 years old from the first policy year in 2009 up to the final survey year in 2020. Our final sample size comprises 26,968 children, with 16,231 children from the never-treated group. Within this final sample, we observe a diverse distribution across survey waves, allowing us to capture potential variations in the program's impacts over time. Specifically, we have 5,038 children in 2010; 5,132 children in 2012; 4,745 children in 2014; 4,416 children in 2016; 4,026 children in 2018; and 3,611 children in 2020.

To explore possible mechanisms, we analyze parental outcomes, particularly parental labor supply and income, directly with the parents sample. To ensure that our analysis remains tightly aligned with the program's intended beneficiaries, we include those parents who are surveyed in rural regions and have at least one child eligible for the SNIP. Among 41,098 parents, 17,378 observations come from the never-treated group, thus forming the basis for our comparative analysis. Within this parents sample, we observe a diverse representation across survey waves. Specifically, our sample includes 6,932 parents in 2010; 8,548 individuals in 2012; 7,753 observations in 2014; 8,017 individuals in 2016; 4,580 observations in 2018; and 5,268 observations in 2020.

3.2 Variables

For child development outcomes, we examine those prominently discussed in the child development literature and are available in CFPS data sets, including children's health conditions, cognitive and noncognitive outcomes, and behavior scales. The definitions of each outcome can be found in Table 1a—Table 1e, and the age range of respondents for each question utilized in our analysis is provided in Table A1a and Table A1b.

Measure of Health Status. CFPS includes questions on both physical and mental health status. We create the first physical health measure *hospitalization* which is assigned a value of 1 if the respondent was hospitalized in a given year due to illness or injury and 0 otherwise.[11] Our second physical health measure is the *height* in Centimeter measured by interviewers at survey.

[11] As the response to this question reflects the physical health status in one year before the survey year, we adjust the time variable when using *hospitalization* as the dependent variable, by replacing it with last year. This adjustment ensures that the time variable aligns appropriately with the lag in reporting for the *hospitalization* variable.

We also define four binary variables *stunting*, *obesity*, *overweight*, and *underweight*, according to the measured height, weight and the children's growth standards established by the World Health Organization (WHO) in 2007.[12] The detailed definition for each indicator can be found in Table A1a.[13] As robustness checks, we alternatively construct indicators for obesity, overweight and underweight using other growth standards from International Obesity Task Force (IOTF), National Health Commission of the People's Republic of China and Ministry of Education of the People's Republic of China. Details can be found in Table A4d.

Our measure of mental health is constructed using the 6-item Kessler Psychologtical Distress Scale (K6) and the 20-item/8-item Center for Epidemiologic Studies Depression Scale (CES-D). The K6 and CES-D are both widely used screening instrument for nonspecific psychological distress in large health surveys, such as the National Health Interview Survey and the National Household Survey on Drug Abuse, and has been validated and used in more than 30 countries, including China. In Table A1b, we list the questions used in these three questionnaires. Respondents are asked to rate the frequency of each statement about mental states experienced over the previous month or week. To construct an index of depression, we sum up the item scores and standardize the summed value by sample mean and variance within each wave. A higher value on the *depression index* indicates poorer mental health.

Measure of Cognitive Outcomes. Three sets of questions, as listed in Table 1c, can be directly linked to children's cognition development. Firstly, we include two measures of school performance, the first one is a binary variable *dropout* which takes a value of 1 if the observation dropped out before completing high school and 0 otherwise, the second is *absence* which records the frequency of children's school absence in the last month. Secondly, the CFPS presents respondents with two sets of cognitive tests to assess their cognition development. While cognitive set A consists of verbal problems and mathematical questions and was used in the 2010, 2014, and 2018 waves, cognitive set B contains word recall and number series tests, and it was used in the 2012, 2016, and 2020 waves. Using this information, we construct a *cognitive test index* by

[12]Source: https://www.who.int/tools/child-growth-standards.

[13]For individuals aged between 10 and 18 years, the category *underweight* is undefined because weight-for-age reference data are unavailable for this age range (World Health Organization, 2007). Notably, this indicator does not differentiate between height and body mass during a period when many children undergo the pubertal growth spurt, which can lead to the appearance of excess weight (by weight-for-age) due to increased height than body fat.

taking a simple average of z scores for the arithmetic (math & number series) and verbal (word & memory) test scores. A higher value of the index corresponds to higher cognition development. Finally, respondents were asked to rate their academic performance from 1 to 5, ranging from "extremely unsatisfied" to "extremely satisfied". We standardize this self-rated value as one additional subjective indicator (*academic performance*) for cognitive outcomes.

Measure of Noncognitive Outcomes. Our first measure of noncognitive outcomes gauges beliefs of the perceived importance of two contributing factors, namely, effort and luck, in determining success.[14] These variables, which are widely adopted in scholarly discourse, serve as key indicators of belief and have been proven to exert significant influence on economic success (Piketty, 1995), perceptions of fairness (Alesina and Angeletos, 2005), and attitudes toward government redistribution (Giuliano and Spilimbergo, 2014). The CFPS questions pertaining to beliefs are detailed in Table 1d. Higher values in the self-rated responses signify a stronger alignment with the respective beliefs. To facilitate the comparative analysis, we standardize the two belief outcomes within each wave of the survey using sample mean and variance. The second measure of noncognitive outcomes included is *Rosenberg self-esteem index* (Rosenberg, 1965), which has been extensively used in the existing economic literature and has been shown to strongly affect labor market outcomes and social performance in adulthood (e.g., Groves, 2005; Heckman et al., 2006). The set of questions related to *Rosenberg Self-esteem Index* are listed in Table 1d. The 10 questions are closely link to how the respondents evaluate themselves, asking respondents to rated each one from 1 to 5, spanning from "totally disagree" to "totally agree". We sum up the self-reported value of each item and then take the average to create the *Rosenberg self-esteem index*, with higher *Rosenberg self-esteem index* indicating higher degree of approval toward him/herself.[15]

[14]Piketty (1995) proposes a theoretical framework which posits that shocks can influence individual beliefs about luck and effort.

[15]The CFPS also include modules related to the other two widely used noncognitive skill measures, i.e., the Nowicki-Strickland locus of control for children and Big Five traits. However, questions related to Nowicki-Strickland locus of control for children are available for respondents aged 13 and 15 in wave 2010, and for those aged between 10 and 21 without historical records in waves 2014 and 2018. Respondents who were 15 years old in wave 2010 had already graduated from middle school, and thus, they were not eligible to the SNIP and not included in the children's sample. Consequently, the number of eligible children before the policy implementation may be extremely small, posing challenges in testing the effect of the SNIP on this measure. Similarly, questions related to Big Five Traits are only applicable to individuals aged above 15 in wave 2018. As a result, the lack of pre-treatment records for Big Five Traits hinders our ability to investigate the impact of the SNIP on this measure.

Measure of Behavioral Outcomes. We employ a methodology in line with that proposed by Kling et al. (2007) to formulate *learning behavior index*, which is meticulously constructed from responses to six survey questions as outlined in Table 1e. These questions delve into various aspects, such as hardworking, effective time management, and concentration, thus providing a comprehensive self-assessment over studying habits. *Learning behavior index* serves as a robust metric to gauge the effectiveness and diligence of the respondents in their learning endeavors. A higher index corresponds to a more proficient and dedicated approach toward academic pursuits, contributing to overall academic performance and cognitive development. This metric is also instrumental in our endeavor to understand the intricate interplay between learning behavior and educational outcomes. In addition, we construct the positive behavior scale using the assessment on children's behavior from their parents, and we follow the framework outlined by Quint et al. (1997), Polit (1998), and Epps et al. (2005) to divide this scale into three dimensions, namely, social competence, compliance, and autonomy.[16] Specifically, *social competence index* assesses an individual's ability to overcome challenges and interact with others, including the factors of interpersonal skills, empathy, and popularity. Instead of merely measuring obedience, *Compliance index* reflects a child's capacity to meet expectations and fulfill responsibilities with minimal ongoing oversight or guidance from others. *Autonomy index* captures the extent to which a child can independently solve problems and make decisions without external assistance.[17]

We provide detailed descriptive statistics for the children and parents sample in Table 2a and Table 2b, respectively. These two tables are structured to offer a comprehensive view of the key indicators before and after treatment. Columns 1—3 present the means, standard deviations, and number of observations for the pre-treatment period, Columns 4—6 mirror this format for the post-treatment period, and Column 7 highlights the difference in means before and after treatment.

3.3 Research Design

To investigate the effects of SNIP on child development outcomes, we explore the staggered implementation of program across counties in the academic years 2011 through 2019 in

[16]Refer to Appendix Table 1e for a complete list of questions corresponding to each index.

[17]In a manner consistent with the approach outlined by Kling et al. (2007), we construct all three indices for the positive behavior scale.

a difference-in-differences (DID) framework. Appendix Table A2 lists the sampling counties, the corresponding academic year in which SNIP was rolled out. Recent studies have illustrated that standard two-way-fixed-effect (TWFE) estimators can be biased in the presence of heterogeneous treatment effects in DID framework (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2022). To address such bias, we use the method proposed by De Chaisemartin and d'Haultfoeuille (2022) to estimate the DID_l estimator allowing for dynamic effects when the treatment is binary and the design is staggered. Specifically, we estimate the following event study model:

$$Y_{ict} = \alpha + \sum_{l \geq L, l \neq -1}^{U} \beta^l D^l_{c,t} + \lambda_c + \lambda_t + Z_c \times \lambda_t + X'_{ict}\gamma + \epsilon_{ict}. \tag{9}$$

The dependent variable Y_{ict} is the development outcome for child i who is living in county c and surveyed in period t.[18] The event study indicators $D^l_{c,t}$ are treatment of interests which indicate different periods before and after the program implementation; i.e., $D^l_{c,t} \equiv I\{t = t^*_c + l\}$, where t^*_c denotes the year when county c implemented the SNIP, L and U are the largest numbers of periods tested before and after t^*_c. And $D^l_{c,t} = 1$ if $t - t^*_c = l$, and 0 otherwise for $-L \leq l \leq U$ and $l \neq -1$. We bin our event study indicators at $U = 3$ and $L = -3$, use the period immediately before the launch of SNIP as the reference group ($l = -1$) and calculate the coefficients for all other periods relative to the base.

The DID_l method provides dynamic estimators (β^l for $l \geq 0$) and placebo estimators (β^l for $l < 0$). When $l \geq 0$, the coefficient β^0 captures contemporaneous treatment effects and estimates β^l compute dynamic treatment effects on outcome Y_{ict}, l periods after the program implementation.[19] The identification of those β^l hinges on the assumption of parallel trends between the first-time switchers and the not-yet treated control groups. As proposed by De Chaisemartin and d'Haultfoeuille (2022), the placebo pre-treatment coefficients (β^l for $l < 0$), which compare first-time switchers' and not-yet switchers' outcome evolution before first-time switchers' treatment changes, directly offers a test of the pre-treatment trend. If the common trend assumption is satisfied, then we cannot reject the null hypothesis that pre-trend estimators (β^l for

[18]Since CFPS has been conducted biennially, one period in our study includes two academic years.

[19]β^l is a weighted average, across time periods t, of DID regressions comparing the $t - l - 1$ to t outcome evolution, in groups whose treatment changed from untreated to treated for the first time in $t - l$, the first-time switchers, and the groups that had remained untreated by period t the not-yet switchers (control group).

$-3 \leq l < -1$) insignificantly deviate from 0.[20]

The specification controls for county fixed effects, λ_c , which net out county-specific yet time-invariant characteristics, and period fixed effects, λ_t, accounting for aggregate shocks that affect all counties in a given period. $Z_c \times \lambda_t$ stands for county characteristics interacted with period fixed effects. These county characteristics include an indicator for whether the county was classified as the Chinese State Poverty County before the implementation of SNIP, and other policies related to nutrition and education announced by county c.[21][22] Finally, variable X_{ict} denotes individual-level characteristics, including age, square of age, gender, and indicator variables for whether the mother and the father completed middle school. We cluster the standard errors at the county c level to account for serial correlation in outcomes within counties, and compute standard errors using 200 bootstrap replications.

For each child development outcome in our main analysis, we provide the event-study graph generated by equation (9). As robustness checks, we also present the event study figures generated by the canonical TWFE model, and by a set of recently proposed estimators that are robust to treatment effect heterogeneity in the presence of staggered design (Borusyak et al., 2021; Cunningham, 2021; Sun and Abraham, 2021). Additionally, we summarize our findings in tables that report weighted averages of the dynamic estimates for the post-treatment effects, with weights proportional to the number of switchers for event-time l.

4 Results

4.1 Baseline

This section quantifies the SNIP effects on child development outcomes. In Table 3, we present the weighted average estimates of the dynamic effects from equation (9), and each

[20] At least the series of placebo estimators cannot be jointly significant.

[21] List of Chinese State Poverty County: https://www.gov.cn/gzdt/2012-06/14/content_2161045.htm

[22] These policies include Breakfast with Love, Nutritious Meal Project, Free Breakfast to Boarding Students, Egg and Dairy Project and Student Milk Project. Breakfast with Love provided free breakfast to left-behind children in rural regions, especially remote mountainous areas. Nutritious Meal Project offered 2 to 3 nutritious meals per week, with meat and vegetables, to children from low-income families in primary or junior high school in Chongqing. Free Breakfast to Boarding Students provided free breakfasts to students who boarded on campus in Fujian. Egg and Dairy Project and Student Milk Project offered free protein-rich foods to students for Shaanxi. However, none of these programs are large-scale ones in China. In other words, these above-mentioned programs only carried out in some counties and covered a small number of students under compulsory education.

row corresponds to a specific outcome. Panel A focuses on health measures, Panel B delves into cognitive development and Panel C exclusively addresses noncognitive and behavioral outcomes. Column 1 presents the weighted average estimates, with the standard errors enclosed in parentheses, Column 2 presents the number of observations used in the analysis, and Column 3 presents the mean value of each outcome for the never-treated group as a reference point for comparison and as a benchmark against which the treatment effects can be evaluated. Figure 3a-Figure 3c plot the event-study coefficients β^l.

4.1.1 Physical & Mental Health Outcomes

Figure 3a presents the evolution of DID_l estimates along with their 95% confidence intervals for physical and mental health outcomes. All estimated coefficients before the intervention exhibit a relatively flat profile and insignificantly deviate from 0, providing suggestive evidence in support of the parallel trend assumption. Meanwhile, the point estimates for the instantaneous effect generally suggest insignificance across all physical health measures. However, after the first academic year of implementing the SNIP, we observe a pronounced decline in the rate of *stunting*, which indicates the lasting effect of the program on this critical growth-related measure. Despite no significant changes for *underweight*, we observe a substantial reduction in the probabilities of *obesity* and *overweight* one academic year after the policy implementation, thereby underscoring the program's effectiveness in addressing childhood obesity concerns.[23] In terms of mental health outcomes, we find minimal dynamic effects given that the dynamic estimates in the post-policy periods close to zero. Therefore, the SNIP has a limited influence on mental health indicators over time.

Consistent to the findings in Figure 3a, panel A of Table 3 reveals compelling evidence of the positive impacts of participation in the SNIP on various physical health- and growth-related indicators of children. First, we observe a significant 6.5% reduction in the probability of *hospitalization*, accounting for 84.4% relative to the control mean. The program also demonstrates its efficacy in preventing *stunting* with a notable 6.5% decrease in the incidence of this growth-

[23]This finding should be interpreted cautiously given that the lack of growth standards for underweight children aged 10—18 years may lead to an inaccurate interpretation of the overall effect and rapid growth tendencies as underweight. De Brauw and Mu (2011) suggests that *stunting* is a more convincing growth indicator than *underweight* for children.

related issue. The average increase in *height* by approximately 4.533 *cm* indicates that the SNIP contributes to the physical development of the participating children. Although not statistically significant, the estimate for *underweight* remains negative at approximately 2.5%.[24] In addition, we observe significant reductions of 6.5% and 8.9% in the probabilities of *obesity* and *overweight*, respectively. However, our results provide limited evidence concerning the impact of the SNIP on mental health outcomes. The magnitude of change in mental health indicator *depression index* is relatively small with an estimated effect size of 0.005 standard deviations.

4.1.2 Cognitive Outcomes

The SNIP significantly increased the cognitive development outcomes as shown in Figure 3b. Again, we find evidence in favor of the common-trend assumption.[25] While there is no significant change in *dropout* rate before high school, frequency of *absence* began to decrease after 1 academic year of the introduction of SNIP. Furthermore, *cognitive test index* and self-rated *academic performance* exhibit increases after the adoption of the policy.

Panel B of Table 3 capture the average treatment impacts of the SNIP on cognitive outcomes among school-aged children. Regarding school performance, the reductions in *dropout* rate and frequency of *absence* account for 23.9% and 32.6% of the control mean, respectively.[26] These findings suggest that the SNIP may have played a positive role in keeping students in school. We then investigate the effects of the program on cognitive skills by assessing objective and subjective measures concurrently. Results show that the respondents' *cognitive test index*, which encompasses arithmetic and reading abilities, increases by approximately 0.115 standard deviations following the implementation of the SNIP. Similarly, the self-rated *academic performance* demonstrates a substantial increase of 0.391 standard deviations, signaling noteworthy improvements in objective and subjective academic achievements. These findings underscore the positive impacts of the SNIP on cognitive development, including quantitative skills and self-perceived academic performance.

[24] Weight-for-age standards from the WHO are unavailable for children aged 10—18 years, thereby resulting in fewer observations for this regression (World Health Organization, 2007).

[25] The wide confidence interval for the estimate in the -6 $\sim$ -5 academic years may be attributed to a potentially smaller number of switchers, which lead to increased standard errors.

[26] To address the potential sample selection issue, we further conduct bounds estimation as a robustness check and present the results in Table A4c.

4.1.3 Noncognitive and Behavioral Outcomes

Panel C of Table 3 presents the results on noncognitive and behavioral outcomes.[27] With regard to attitudes toward factors contributing to success, the treated group places significantly greater emphasis on *importance of effort* after the introduction of SNIP, with an increase of 0.210 standard deviations. The estimate on the perception toward *importance of luck* is negative but imprecisely estimated. Taking together, we interpret these results as evidence of the program's influence on shift in attitudes of children's beliefs about the determinants of success. The sustained increase in *importance of effort* shown in Figure 3c further supports this finding. In addition, we find no significant impact on *Rosenberg self-esteem index*, which increases by 0.055 standard deviations on average.[28]

For the behavioral outcomes, we examine *learning behavior index* and the three-dimensional *positive behavior scales. Learning behavior index* shows a noteworthy increase of 0.359 standard deviations at the 5% significance level, thereby indicating enhanced learning behaviors. For the *positive behavior scales*, the ability engaged in *social competence* and *autonomy* of the treated children increase by 0.315 and 0.528 standard deviations, respectively, which highlight the positive impacts of the SNIP on their social and behavioral development. For a more granular understanding, we further investigate the effects of the SNIP on each component of *learning behavior index* and *positive behavior scales* as shown in Supplementary Table A3a and Table A3b, respectively. In general, the items of *learning behavior index*, including *study hard*, *self-check homework*, *disciplined*, *tidiness*, and *play after homework* show significant improvements. The increase in *social competence index* is significantly driven by *be curious*, which significantly increases by 0.734 standard deviations. For the *compliance index*, the targeted children are more likely to wait for their own turn and complete their tasks as they are told. Considering *autonomy index*, the ratings of *play after homework* and *self-reliant* significantly increase by 0.526 and 0.249 standard deviations, respectively.[29] Figure 3c plots the event-study coefficients on

[27] Due to the specific age-related questions related to noncognitive and behavioral outcomes and limited waves of data availability, as shown in Supplementary Table A1a and Table A1b, the number of observations for these outcomes is relatively smaller and the number of placebo and dynamic estimators can be calculated is more constrained than those for the other dependent variables.

[28] The effects of the SNIP on each item of *Rosenberg self-esteem index* are listed in Table A3a.

[29] The items *play after homework* in *learning behavior index* and *autonomy index* are rated by the children and parents, respectively.

noncognitive and behavioral outcomes. We again find evidence in support of the parallel trends assumption, with pre-trends being centered around zero. Specifically, these indices experience an immediate and significant increase at the introduction of SNIP.

4.2 Magnitude Comparison

4.2.1 Physical Health Outcomes and Cognitive Skill

Given that prior research has primarily focused on nutrition programs' impacts on outcomes particularly related to physical health status and cognitive skills, we aim to offer a comparative perspective in terms of magnitude. Figure 4a and Figure 4b illustrate the point estimates and 95% confidence intervals for *height*, *overweight*, and *obesity* prevalence and the standardized *cognitive test index* over varying time frames from previous studies (in blue) and our work (in red).

When examining impacts on *height*, we find that the SNIP has a more substantial growth in a *height* by approximately 4.53 *cm*. By contrast, the study by Lundborg et al. (2022) on the Swedish School Lunch Reform reports a 0.77 *cm* and 0.65 *cm* increase in height for boys and girls with average age 54, respectively.[30] Notably, the average height in their sample is 178.96 *cm* and 166.67 *cm* for boys and girls, respectively, whereas the average height in our sample before and after treatment is 128.70 *cm* and 151.11 *cm*. The children studied in our work tend to be younger and shorter, thereby resulting in a potentially higher marginal benefit from the nutrition program, which may potentially explain the relative larger magnitudes found in our study. The reduction in the prevalence of *overweight* and *obesity* is not clearly evident in the short run (Millimet et al., 2010; Abouk and Adams, 2022) and even shows a significant opposite direction by 2% and 3% in some cases.[31] These two studies analyze two school feeding policies in United States, using the same dataset Early Childhood Longitudinal Study Kindergarten Class, which follows a nationally representative cohort of children throughout the United States from kindergarten to through the fifth grade. However, our estimator, which measures the

[30]The original estimates from Lundborg et al. (2022) are taken from Columns (4) and (5) of Table 5 in their work.

[31]The raw estimates for overweight and obesity as reported by Millimet et al. (2010) are derived from Column (1) in Panels IV and V of Table 1, respectively. Correspondingly, the original estimates for overweight and obesity in the study conducted by Abouk and Adams (2022) are extracted from Column (1) in Panels A and B of Table 3, respectively.

average treatment effect of switchers over 0-7 academic years, shows a substantial decrease in the prevalence of unhealthy weight, with reductions of 6.5% for *overweight* and 8.9% for *obesity.* The differential findings may be explained by focusing on different groups. We analyze the impacts of SNIP on the school-aged children, while they investigate the effects of a school feeding program on kindergarten children.

To facilitate the comparisons in cognitive outcomes, we have rescaled the estimates from earlier studies and our work, by calculating the school feeding programs' impacts in units of the standard deviation changes of *cognitive test index* and incorporating scores of math and reading tests into the index.[32] We find that the impact of the SNIP on *cognitive test index* increases along with the duration of exposure to the program.

4.2.2 Noncognitive and Behavioral Outcomes

The comparison in Figure 4c - Figure 4e present the comparative analysis on noncognitive and behavioral outcomes. As the first study to investigate the causal impacts of a school feeding program on noncognitive outcomes, there is no studies in the literature that are directly comparable to ours. We then benchmark our estimates against impacts of other interventions or shocks in childhood and adolescence on noncognitive results. Specifically, Giuliano and Spilimbergo (2014) find that one standard deviation increase in exposure to economic recession measures at age 18-25 is associated with a 0.017 standard deviations increase in the rated importance of luck versus effort, which aligns with our finding that exposure to a school feeding program is associated with a reduction in the rated importance of luck versus effort by approximately

[32] Changes in standard deviations are not directly provided in the study by Abouk and Adams (2022), therefore, we use the within-school standard deviations to make adjustments. Specifically, the original estimate indicates that the nutrition program increases reading scores by 0.0307, and the within-school standard deviations is 0.42 as shown in Column (1) of Table 5 in their paper. Hence, we estimate that the program will increase reading scores by $\frac{0.0307}{0.42} = 0.073$ standard deviations. Similarly, we find that the program will increase math scores by $\frac{0.0123}{0.6} = 0.0205$ standard deviations, with original estimate taken from Column (4) of Table 5. Ultimately, we take the average of the two estimates for math and reading scores, which is 0.106 standard deviations. Meanwhile, for Frisvold (2015), changes are directly presented in standard deviations for math and word tests. Therefore, we take the average of original estimates 0.091 for math test and 0.122 for reading test, which are the estimates in the brackets listed in Columns (3) and (6) in Table 3, respectively.

0.305 standard deviations.[33][34] Since Giuliano and Spilimbergo (2014) examines the impacts of negative macroeconomic shock on individual beliefs, our study centers on a child welfare program which may alter children's beliefs consistently. Additionally, Akee et al. (2018) used the revenues of a new casino to identify the effects of an unconditional government cash transfer program on children's three dimensions of the Big Five personality traits during adolescence, and found positive effect sizes of 0.200 standard deviations for conscientiousness, 0.292 standard deviations for agreeableness, and 0.311 standard deviations for neuroticism.[35]

Figure 4d presents a comprehensive comparative analysis of learning behaviors with a focus on school interventions that aim to bolster the cognitive skills of students. Our study, which centers on school feeding programs as a form of income transfer, provides a unique vantage point for this examination. Pugatch and Wilson (2018) underscore the significance of peer tutoring classes in stimulating students' incentive to attend more tutoring sessions, thereby fostering cognitive skill development. Their original estimate, which reflects a 0.079 increase in the probability of attending tutor classes, translates to an effect size of 0.174 standard deviations.[36] Paloyo et al. (2016) investigate the impact of incentives on students' participation in peer learning sessions and observe a noteworthy increase of 0.117 standard deviations in the number of peer learning sessions.[37] This intervention demonstrates the potency of targeted incentives in promoting collaborative learning environments. Cornelissen and Dustmann (2019) investigate the effect of an additional schooling year before the age of 7 on disruptive behavior and report a substantial reduction of 0.42 standard deviations in disruptive behavior. This intervention emphasizes the formative role of early educational experiences in shaping behavior.[38] Apart from direct student

[33]The original estimate of Giuliano and Spilimbergo (2014) indicate that one more standard deviation exposed to recession during the 18-25 years old increases the self-reported importance of luck versus effort by 0.017 standard deviations in Column (3) of Table 1.

[34]To facilitate the comparison, we use the difference between estimates for *importance of luck* and *effort* to indicate the importance of luck versus effort.

[35]We take the original estimates from Columns (3)—(5) in panel B of Table 3 in their work.

[36]Their original estimate reflects that providing peer tutoring classes increases the probability of attending tutor classes by 0.079 in Column (1) of Table 2. We utilize the control mean of 0.29 from Figure 2 to compute the standard deviations, which amounts to 0.454 ($\sqrt{0.29 \times (1-0.29)^2 + 0.71 \times 0.29^2}$). This calculation is particularly relevant as the dependent variable in this context is a binary variable. The original estimate suggests that the implementation of tutoring services increases the likelihood for students to attend tutor classes by 0.079. When standardized by the calculated standard deviations, this effect size equates to 0.174 standard deviations ($\frac{0.079}{0.454}$).

[37]To gauge the change in standard deviations, we take and divide the original estimate 0.464, from Column (1) in panel A of Table 2, by the standard deviations of 3.98, as indicated in the summary statistics Table 1. This calculation provides a measure of the effect size in terms of standard deviations.

[38]Disruptive behaviors are assessed through continuous observations of the child in the reception class, facilitated

interventions, Alan and Ertac (2018) investigate a teacher training program designed to enhance noncognitive skills and find that teacher training leads to a 10.4% decrease in the probability for students to receive low behavior grades.[39] In light of these comparisons, we observe that school feeding programs, which are categorized under income welfare initiatives, are notably effective in influencing learning behaviors. However, teacher training programs exhibit an even higher efficacy, thus underscoring the essential role of educators in molding students' cognitive and noncognitive development.

Figure 4e presents a comprehensive comparative analysis of interventions aimed at fostering behavioral outcomes, with a particular focus on income-based and educational initiatives. Akee et al. (2018) find that exposure to the unconditional government cash transfer program decreased behavior and emotional disorder symptoms by 0.183 and 0.306 standard deviations, respectively.[40] Heckman et al. (2020) find that a home visiting program aimed at encouraging caregivers to engage with their children in developmentally appropriate ways can significantly reduce social-emotional skills by 0.222 standard deviations within half a year.[41] However, these effects become statistically insignificant one year after the program adoption. Cornelissen and Dustmann (2019) highlight the positive impact of an additional year of schooling and observe substantial increases of 0.780 standard deviations in creative development and 0.756 standard deviations in personal, social, and emotional development skills.[42] In comparison, our findings of the impacts of a school nutrition program on *social competence*, *compliance*, and *autonomy* indices suggest that income transfers and school feeding programs yield similar levels of effectiveness. This comparative analysis offers valuable insights into the diverse approaches targeting

by a booklet in which teachers meticulously document the child's accomplishments. The original estimate indicates that one-month additional schooling at age 7 will decrease the disruptive behavior by 0.035 standard deviations, derived from Column (6) of Panel B in Table 5. In Figure 4d, we employ an inverse interpretation of the estimation results, and find that the good behavior index increases by 0.42 standard deviations when the child is subjected to an additional year of schooling (0.035×12).

[39]The overarching objective of the educational program is to instill in children the practice of considering the future ramifications of their choices when making decisions across time. The original estimate is derived from Column (1) in Table 9. After examining the standard deviations of the dummy variable for low behavior grades, which amounts to 0.15 in Column (1) of Table 2, we quantify the change to be 0.693 standard deviations ($\frac{0.104}{0.15}$).

[40]Original estimates of Akee et al. (2018) are taken from Columns (1) and (2) in Panel B of Table 3.

[41]Original estimates of Heckman et al. (2020) are taken from Column (3) of Table 2.

[42]The original estimate indicates that one-month additional schooling at age 5 will increase the creative development and emotional development behavior by 0.065 and 0.035 standard deviations, derived from Columns (1) and (5) of Panel A in Table 5, respectively. We recalculate the original estimates to account for the transition from monthly to annual figures for additional schooling ($0.065 \times 12 = 0.780$ and $0.063 \times 12 = 0.756$).

positive behavior outcomes and sheds light on the multifaceted strategies that can positively impact child development.

4.3 Robustness Checks

In this section, we conduct several robustness checks to ensure the reliability of our baseline results across multiple dimensions. First, we introduced county-specific linear time trends to capture potential unobserved county-specific differences evolving linearly with time, thus allowing us to account for any time-variant differences among different counties that may influence the outcomes. As shown in Table A4a, the incorporation of these trends does not alter the economic significance of the estimates, thereby indicating the robustness of our findings to potential county-specific effects. Second, to address potential issues related to negative weights in staggered adoption designs, we explore alternative estimators, including the methods proposed by Borusyak et al. (2021), Cunningham (2021), Sun and Abraham (2021), and TWFE. The consistency of our results across these alternative methods, as demonstrated in Figure A1, indicate the robustness of our baseline estimates.

Third, to mitigate the potential issue of false negatives and positives due to the multiple testing of program impacts on a rich set of child outcomes in the baseline analysis, we follow the approach outlined in Anderson (2008b) to compute for sharpened False Discovery Rate q-values, which offer a way to control for the expected proportion of Type I error rejections. In Table A4b, Column 2 displays the p-values, while Column 3 shows the corresponding sharpened q-values. The stability of these sharpened q-values compared with the baseline p-values, reaffirms the robustness of our findings to potential false rejections.

Fourth, we perform bound estimation to account for potential sample selection bias arising from the program effect of dropout rates. Table 3 shows that the likelihood of *dropout* before high school is reduced by approximately 1.88%. Given this estimate, we perform bound estimation wherein we replace the top 1.88% and bottom 1.88% of outcomes with missing values. Table A4c reveals that the estimates resulting from the baseline regression fall within the range delineated by the two bound estimations, thus confirming that the sample selection is less of a concern.

Lastly, we alternatively define the weight indicators using domestic and international standards other than the WHO Growth Standards to assess the sensitivity of our findings to the definitions of growth indicators. Table A4d presents the specifics of these standards, which encompass the institution, year, and criteria for defining weight indicators. The comprehensive analysis in Table A4e underscores the robustness of our results across various weight standards.[43]

4.4 Heterogeneous Effects

4.4.1 Initial Time of Exposure

Table 4a investigates the heterogeneous effects across different initial times of exposure to the SNIP. We divide children sample based on the criterion of whether the program was firstly implemented in the individual's county of residence during her/his primary or middle school years. Those children who were initially affected by this policy as primary school students demonstrate a significant 7% decrease in their *hospitalization*, which corresponds to a 0.192 times decrease in their monthly school absenteeism. This finding underscores the positive impacts of the SNIP on the physical health outcomes of children who were exposed to this program at an earlier age. Meanwhile, those children who were initially affected by this program as middle school students experience fewer occurrences of *stunting*, which aligns with the WHO's recommendation that age 10-18 years is a critical period for children's height development (World Health Organization, 2007). Our findings affirm that middle-school-aged children grow 4.776 *cm* taller on average as a result of the SNIP. Interestingly, the program has more significant impacts on the behavioral outcomes of these children, particularly in terms of the *compliance* and *autonomy* indices. Therefore, initial exposure to the program during middle school years may have a more pronounced effect on certain aspects of children's behavior and attitudes.

4.4.2 Gender

Table 4b explores the heterogeneous effects across gender to provide a nuanced understanding of how the SNIP influences girls and boys differently. Girls and boys demonstrate significant improvements in their physical health outcomes as a result of the program, with boys benefit slightly more than girls. For instance, the incidences of *underweight* and *hospitalization* among

[43] While the estimates corresponding to the International Obesity Task Force (IOTF) standards lack statistical significance, they still maintain a negative direction. It is also worth mentioning that the IOTF standards were established in 2000, predating other standards. Consequently, for the baseline results, we reasonably opt to adhere to the WHO standards set in 2007 given their contemporaneity with the policy's initiation in 2009.

boys substantially decrease by 9.6% and 8.2%, respectively. These results are consistent with the pronounced decrease in the frequency of *absence* among boys by 0.155 times per month, thereby confirming the positive impact of the program on boys' physical health. Meanwhile, girls experience significantly greater benefits in their *cognitive test index* compared with boys, thereby suggesting that the SNIP has a particularly meaningful role in enhancing the cognitive skills of girls by 0.214 standard deviations. This result is further supported by the observation that girls exhibit higher levels of confidence in their academic performance and place a greater emphasis on their effort for future achievement, which aligns with their increased *cognitive test index*. We also find that the SNIP plays a significant role in narrowing the gender gap in cognitive skills, which may contribute to improving the overall status of females in the labor market. With regard to behavioral outcomes, we find that girls initially outperform boys prior to the implementation of the program. However, the program leads to a more significant increase in the *learning behavior index* and *autonomy index* of boys than those of girls. In other words, the program narrows the behavioral gap between boys and girls by positively affecting the behavior of the former.

4.4.3 Parents' Education Level

Table 4c examines the heterogeneous effects of the SNIP across different levels of mothers' education. We divide children sample according to whether the child's mother has completed middle school given that middle school education represents the median educational level within our sample. Those children born to mothers with lower educational levels experience significantly greater improvements in physical health outcomes compared with those who were born to mothers with higher educational levels. This distinction is particularly notable in reducing *hospitalization* by 9.3%, thus signifying the substantially positive impact of the SNIP on the health outcomes of children from less educated households. Furthermore, children born to mothers who have completed middle school tend to exhibit shorter stature before the implementation of the program. However, following the implementation of the program, this subgroup experiences a more pronounced acceleration in growth by 4.656 *cm*. Specifically, the rates of *underweight*, *overweight*, and *obesity* have significantly decrease by 6.4%, 11.9%, and 9.4%, respectively, for children born to less-educated mothers. This result suggests a notable improvement in the nutritional status of children coming from households with lower maternal education levels. In terms of cognitive outcomes, the rate of *dropout* before high school substantially decreases by 8% among children who were born to mothers who have not completed middle school. This positive trend is indicative of the program's effectiveness in promoting continued school attendance among children from less-educated households.

With regard to cognitive development, children born to mothers with lower education levels experience a significant increase of approximately 0.181 standard deviations in the *cognitive test index* and 0.575 standard deviations in self-rated *academic performance*, thus underscoring the positive impact of the SNIP on their cognitive development. While these two groups show no significant differences in their noncognitive outcomes, they show some notable distinctions in their behavioral outcomes. Specifically, the *learning behavior index* and *autonomy index* significantly increase by 0.402 and 0.615 standard deviations, respectively, for children born to lower-educated mothers, thereby suggesting that the SNIP not only enhances cognitive development but also fosters positive learning habits and autonomy among this subgroup. Table 4d shows the heterogeneous effect of the program according to by fathers' education level. Generally, we do not observe significant differences in the physical health of the two subgroups. However, the *cognitive test index*, *importance of effort*, and *autonomy index* of children born to lower-educated fathers increase significantly as a result of the SNIP. These results provide compelling evidence showing that children coming from households with lower parental education levels tend to benefit more significantly from the SNIP, thus highlighting the program's effectiveness in narrowing socio-economic gaps across generations and ultimately improving the outcomes of children from less-privileged backgrounds.

5 Mechanism

The above findings indicate the substantial impacts of the SNIP on child development outcomes. To explicate these estimated effects, we undertake an analysis of potential mechanisms guided by our conceptual framework proposed in Section 2. Specifically, we partition our mechanism analysis into three subsections: (i) parental labor supply and income, (ii) nutrition intake, monetary and time investment, and (iii) parenting styles and family dynamics. The definition of channel variables are listed in Table A5a and Table A5b.[44]

5.1 Parental Labor Supply and Income

Parental labor supply and income belong to a potential pathway through which exposure to the SNIP could impact child development outcomes. Parents in the SNIP-exposed counties, tend to allocate less time to breakfast or lunch preparation for their children after adoption of the policy, potentially expanding their available work hours and income. [45] Such positive income effects could generate large developmental effects on children. Using parents sample from CFPS, we test whether the SNIP affect parental labor market outcomes in both extensive and intensive margins.[46] Panel A of Table 5 reports the estimated results. We find a significant increase of nearly 6.8% in parents' labor force participation due to the program's adoption. Although the effect on parents' employment status lacks statistical significance, the estimate remains positive and economically substantial at around 5.5%. With respect to the intensive margin, *monthly hours worked* shows an insignificant increase of approximately 15 hours, while *annual income* increases by 14.5%, which is significant at the 10% level. [47]

A related potential mechanism could be that exposure to SNIP may have differently affected the employment statuses and working sectors of fathers and mothers, resulting in different time allocations between work outside and inside the home. In Table A6, we present the estimated results on the status and sectors of employment separately for mothers and fathers. The results show that both mothers and fathers experience heightened involvement in the *labor force* participation as a result of the program. More importantly, the results in Panel B of Table A6 show that fathers in counties exposed to SNIP experienced relatively significant increases in *monthly hours worked* and *annual income*. These changes are driven by a significant shift of employment from agricultural to service sectors for fathers.

[44]Since the answer to questions related to family financial decisions indicate the annual income/expenses in last year, then we adjust the time variables when using monetary variables (*annual income*, *annual food expenses*, *annual education expenses*, *annual medical expenses*) as outcomes, by replacing original time values with one year before.

[45]Previous research has highlighted the time constraints imposed by such parental responsibilities (Holford and Rabe, 2022; Lundborg et al., 2022).

[46]The definitions of labor market outcomes are listed in Table A5a.

[47]*Annual income* were available for employed individuals, including self-employed parents engaged in activities such as agriculture or family business operations.

5.2 Nutrition Intake, Monetary and Time Investment

Positive "income shocks" and alterations in parental time allocation, triggered by the SNIP, have the potential to reconfigure the parent's intertemporal budget and time constraints. This, in turn, could lead to increased nutrition, monetary, and time investment in the child. The enhancements in these direct investment may exert a positive influence on the overall development of children. Panel B of Table 5 shows the results for changes in nutrition intakes, monetary and time investment in the child. The estimate in the first row indicate a notable increase in the likelihood of having *eggs & dairy* in children's diets by 9.7%. This shift, which is closely linked to the observed improvements in height and reductions in abnormal weight indicators, indicates that the provision of nutritious options, i.e., eggs and dairy, through the program positively contributes to the overall health and growth of children. With regard to the monetary and time investment from parents, we comprehensively examine a wide array of aspects, including food, educational, and medical expenses and tutoring time spent on children. The 32.3% decrease in *annual food expenses* reveals a substantial crowding-out effect, which aligns with the conceptual framework where the nutrition subsidy triggers income and substitution effects on household food expenses. In this case, the substitution effect dominates, leading to a shift from household meals to school meals. This transition is underpinned by the program's provision of more nutritious meals.

Meanwhile, the considerable 21.8% increase in *annual education expenses* since the program's initiation corresponds with the observed enhancements in children's *cognitive test index* and self-rated *academic performance*, thus highlighting the positive impacts of the program on their educational outcomes. Although statistically insignificant, the effect on children's *annual medical expenses* maintains a negative trend. We also examine the impacts of the SNIP on overall family expenses and the structure of family expenses in Table A7 and find significant structural changes in family expense components. Specifically, the proportion allocated to food expenses significantly decreases by approximately 9%, with the expenditures redirected toward clothing, transportation, and education. These changes indicate a potential shift in household budget allocation priorities in response to the program. With regard to time investment, we find that parents are increasingly engaged in their children's studies, with *tutoring hours* increasing by

0.346 hours per week. This heightened involvement underscores the program's potential to foster a more supportive learning environment within households.

5.3 Parenting Styles and Family Dynamics

Recent studies underscore the significance of parenting styles and family dynamics in influencing various facets of child development, including school achievement (Masud et al., 2015) and noncognitive and behavioral outcomes (Oshino et al., 2007; Suchman et al., 2007, etc.). Positive income shocks and shifts in parental time allocation induced by the SNIP may, in turn, foster improvements in parenting styles and family dynamics. Such changes can potentially enhance the effectiveness of direct investment in children, leading to more favorable development outcomes. Leveraging information on parent-child interactions from the CFPS, we empirically examine whether there was an amelioration in parenting styles and family dynamics within families residing in counties exposed to SNIP after the implementation.

In alignment with the framework proposed by Darling and Steinberg (1993), we classify parenting approaches into four primary archetypes, *authoritative*, *authoritarian*, *permissive*, and *uninvolved*. This classification is based on the levels of responsiveness (warmth and sensitivity) and demandingness (control) exhibited by parents toward their children. Detailed illustration of these archetypes can be found in Figure A2 and specific survey questions in Table A5b.[48] The analysis in Panel C of Table 5 unveils noteworthy shifts in the choice of parenting styles for families living in counties exposed to SNIP after the implementation. Notably, the percentage of *authoritative* parents substantially increases by 32.1%, which is accompanied by a significant decline of 25.6% in the proportion of *uninvolved* parents. Despite showing a slight reduction, the proportions of the other two parenting styles, *authoritarian* and *permissive*, remain relatively stable. This observed transition toward more *authoritative* parenting styles, characterized by higher levels of responsiveness and demandingness, may, in part, contribute to the observed improvements in child development outcomes.

As a crucial aspect of familial relationships, family dynamics encompass the intricate web

[48] To identify each parenting style type, we employ median values from the corresponding wave as cutoff points to categorize two subscales into high and low categories. Specifically, high responsiveness and low demandingness are conceptualized as *permissive* parenting, high responsiveness and high demandingness as *authoritative* constraint, low responsiveness and high demandingness as *authoritarian* control, and low responsiveness and low demandingness as *uninvolved* parenting.

of economic and emotional interactions among family members (Hoffman and Weiss, 1987). Table A5b shows the definition of family dynamics and the corresponding questions used from CFPS. The coefficient estimates in Panel C of Table 5 unveils significant enhancements in various dimensions of family dynamics in response to the SNIP. There is a significant reduction in the frequency of quarrels among family members per month, with 0.536 times decrease in conflicts between children and parents and 0.455 times decrease in disputes between fathers and mothers. The declining trend suggests a more harmonious and interactive family environment with fewer instances of tension and disagreements. We also observe a 0.585 times increase in the monthly frequency of deep conversations between children and their parents, signifying a positive shift toward more meaningful and open communications within the family unit.

Parents also demonstrate increased involvement in their children's education as reflected by a significant 0.133 standard deviations increase in their agreement on *parents check homework*. This increased oversight does not crowd out self-checking homework habits as reflected by the notable 0.287 standard deviations increase in children's *self-check homework* in Panel B of Table A3a. In other words, parents' increased support in homework-related activities complements, rather than hinders, their children's autonomous learning behaviors. The observed changes in family dynamics underscore a notable increase in parental involvement and support for their children, which can be attributed, in part, to parents' altruistic motives driven by their desire for their children's future development and well-being. The SNIP not only impacts child outcomes directly but also fosters positive transformations within family dynamics, contributing to a more nurturing and supportive family environment.

6 Discussion

6.1 Crowding Out Effect on Household Food Expenditure

In evaluation of the SNIP, we observe a substantial crowding-out effect of school feeding program on food expenditures per household per person. Previous research has also uncovered crowding-out effects in the school feeding programs of other countries, such as the National School Lunch Program (NSLP) and Community Eligible Provision (CEP) in the United States and Universal Infant Free School Meals (UIFSM) in the United Kingdom (Long, 1991; Holford and Rabe, 2022; Marcus and Yewell, 2022). Those programs implemented in developed countries generally demonstrated partial "crowding-out effects" on household food expenditures. For instance, Long (1991) finds that an additional dollar receiving from NSLP diminishes normal household food expenditures by roughly 61 cents. Holford and Rabe (2022) confirm that exposing an additional child to the UIFSM reduces the supermarket shopping and dining out expenditures of households, and Marcus and Yewell (2022) reveal the significant impact of the CEP on the grocery expenditures of households with children, translating to a USD 11 decrease in their monthly food purchases.

To compare the magnitude of the estimated crowding out effect in our study to those from previous studies, we quantifies the extent to which an additional unit of subsidy displaces annual household spending on food per person (i.e., "crowding-out magnitude"), and rescale the programs' impact estimates, in the same unit of currency, relative to annual amount of nutrition subsidies. The comparison results are illustrated in Figure 5. The first estimate originate directly the seminal work by Long (1991), however, it is pertinent to acknowledge that these estimates do not belong to causal inference.[49] The estimate by Holford and Rabe (2022) suggests that in an ineligible household, an additional eligible child to the free meals policy leads to a reduction in supermarket shopping and eating out expenditures by GBP 6.207 and GBP 3.023 per individual per four weeks.[50] We rescale the crowding out effect magnitude in their work as 0.275.[51]

Additionally, the raw estimate from the paper by Marcus and Yewell (2022) indicates that exposure to school feeding program correlates with a reduction in monthly household food expenditure by USD 10.65, and we rescale the crowding-out magnitude as 0.296.[52][53] In our

[49] See Column (1) in Table 3 of the paper by Long (1991).

[50] As listed in Column (2) of Table 5 in the work by Holford and Rabe (2022).

[51] Holford and Rabe (2022) posit that annual funding for the program approximates GBP 437 per pupil per year. We subsequently ascertain the crowding out effect magnitude as $\frac{(6.207 + 3.023) \times 13}{437} \approx 0.275$.

[52] As indicated in Column (1) in Panel A of Table 3 in the study by Marcus and Yewell (2022).

[53] We estimate the school feeding program will lead to a reduction in annual household food expenditure by USD 127.8 (10.65×12). Given the average household size of 2.4 refer to Column (1) in Table 1, the reduction in household food expenditure per capita approximates USD $\frac{127.8}{2.4} \approx 53.25$. In terms of the cost of a free meal, the average expenditure in 2019 is approximately USD 2.9 (U.S. Department of Agriculture, 2019). Since the implementation of the Community Eligibility Provision in 2014, we discount the meal cost to 2014 assuming a long-term risk-free rate of 3% per annum, and proceed under the assumption of 170 schooling days each year World Population Review (2023). The average number of covered children within each household is approximated at $0.237 \times 1.788 \approx 0.424$. Consequently, the computed nutrition subsidy stands at $\frac{2.9}{1.03^5} \times 170 \times 0.424 \approx 180.312$.

study, this crowding-out effect is estimated to be approximately 0.763, which is notably larger than those generated by programs in developed countries.[54]

This disparity in magnitude can be attributed to three potential reasons. First, consumption patterns can significantly differ between developing and developed countries. We speculate that food, particularly children's nutritional intake, may function as a "Giffen Good" in China, particularly in rural areas, while it behaves as a "Normal Good" in developed countries, such as the United States and United Kingdom. Marcus and Yewell (2022) suggest that households benefiting from school feeding programs similar to the CEP may allocate a portion of their subsidies toward purchasing higher-quality, healthier food. However, such behavior may be less prevalent in developing countries. Although our data limitations prevent us from directly investigating purchasing behavior, the divergent responses may be indicative of this phenomenon. Second, we uncover heterogeneous crowding-out effects based on mothers' education levels. Table A8 in the Appendix shows that such effect is significantly more substantial for children born to lower-educated mothers. This large effect on household food expenditure supports the notion that parents in China may not utilize the "nutrition subsidy" to supplement their children's nutrient intake. They tend to spend this subsidy in purchasing other items instead of higher-quality food, as reported in Table A7. Third, given that the program has a 100% take-up rate (Ministry of Education, China, 2014a), our estimates reflect the treatment-on-treated scenario in contrast to previous studies where partial compliance is present. Consequently, the magnitudes in their estimates may appear smaller due to this partial compliance factor.

6.2 Cost-benefit Analysis

Using the methods proposed by Hendren and Sprung-Keyser (2020), we conduct a cost-benefit analysis of the SNIP. Figure 6 presents the costs and benefits of the government dis-

Therefore, the crowding out effect magnitude hovers around $\frac{53.25}{180.312} \approx 0.296$.

[54] We obtain our estimate by dividing the household food expenditure per person by the computed nutrition subsidy allocated to all eligible children within the household, and then use the new variable as the outcome in our analysis. The initial nutrition subsidy amounted to CNY 3 upon the commencement of the SNIP in 2011, and this standard was subsequently adjusted to CNY 4 from 2014 onward. This subsidy is allocated based on an assumption of 200 school days per annum. Therefore, the approximated annual nutrition subsidy would be calculated as CNY 733.33 ($\frac{3 \times 3 + 4 \times 6}{9} \times 200$). Meanwhile, parental data show that the average number of eligible children within each household is 1.529. Hence, we normalize the nutrition subsidy allocated to all eligible children within the household by the product of the approximated annual nutrition subsidy and the number of covered children in the household (733.33×1.529).

counted to 2011 as the base year, which marks the first implementation year of the SNIP. In the context of this study, Figure 6 shows the costs and benefits associated with sponsoring a typical child who entered first grade in primary school in academic year 2011. We assume an annual long-term risk-free rate of 3%. The government bears the cost of the nutrition subsidy, amounting to approximately CNY 5,833 (USD 926) over the 9-year exposure period.[55]

We categorize the benefits of the subsidy into five aspects.[56] First, this subsidy can lead to a CNY 233 (USD 36) increase considering the consumption tax from food purchases by schools with a consumption tax rate of 4%.[57] Second, according to Deschenes et al. (2020), the average annual expenses to treat one Chinese person suffering from obesity was CNY 200 (USD 32) in 2016. We then estimate the lifelong costs to address obesity as CNY 373 (USD 59).[58] Third, the program can increase one's future income by enhancing her/his physical and cognitive outcomes, which, in turn, can lead to higher income tax revenues for the government. Drawing on estimates from Vogl (2014), Harris (2019), we estimate how the school feeding programs can augment an individual's income by improving her/his physical status.[59] We also calculate the effect of the program on income tax through the *cognitive test index*, as referenced in Lindqvist and Vestman (2011).[60] We find that this program increases an individual's future income by 11.7% via her/his physical and cognitive outcomes. We project a substantial increase of approximately CNY 27,771 (USD 4,408) in income tax through these two child development outcomes.[61]

[55]This calculation is based on the policy details, where we compute the subsidy cost as $\left(\sum_{t=0}^{2} \frac{3}{(1+3\%)^t} + \sum_{t=3}^{8} \frac{4}{(1+3\%)^t}\right) \times 200 \approx 5833$.

[56]It is crucial to acknowledge that our calculations rely on estimates derived from previous studies conducted in different settings. Consequently, we interpret the results of our cost-benefit analysis as offering a general and suggestive understanding of the net benefits associated with SNIP, rather than facilitating precise calculations.

[57]We consider the increased consumption tax as a benefit given that the impact of the nutrition subsidy on overall household expenses is economically insignificant as shown in Table A7. Given that consumption tax rates typically range from 3% to 5%, we use the average as the referred tax rate.

[58]We deduce that the annual costs to address obesity in 2011 can reach CNY 172.522 with a risk-free rate of 3% ($\frac{200}{(1+3\%)^5} = 172.522$). The reduction in the probability of experiencing obesity is approximately 6.5%, and we assume this reduction can be sustained perpetually. Therefore, the perpetual benefit of preventing children from being obese amounts to about CNY 373.270 ($\frac{172.522}{0.03} \times 0.065$).

[59]We find that the nutrition program increases height by 4.533 *cm* and reduces the probability of experiencing obesity by 6.5%. Vogl (2014) demonstrates that a 1 *cm* increase in height is associated with hourly earnings gains of 2.3%, while Harris (2019) shows that adolescent obesity leads to a 3.5% decrease in mid-career wages. Therefore, the gain in future income via physical channels is estimated to be around 10.7% ($4.533 \times 0.023 + 0.065 \times 0.035$).

[60]In our study, the causal impact of the school feeding program increases the *cognitive test index* by 0.115 standard deviations. Lindqvist and Vestman (2011) state that one standard deviation increase in cognitive ability predicts an 8.9% increase in wages. Therefore, the anticipated increase in future earnings via cognitive skills is approximately 1% (0.115×0.089).

[61]The targeted child who was exposed to the program as a first-year primary school student in 2011 will enter

Fourth, we place significant emphasis on how the program increases income through noncognitive and behavioral outcomes. As noted by Lindqvist and Vestman (2011), one standard deviation increase in noncognitive ability is associated with a 6.9% increase in wages.[62] Accordingly, we estimate that noncognitive and behavioral outcomes will augment future income by approximately 11.4%, a figure of equal importance to the return via physical and cognitive outcomes at 11.7%.[63] Specifically, the increase in income tax stemming from noncognitive outcomes may reach CNY 27,176 (USD 4,314), which is close to the returns derived from physical and cognitive outcomes. Previous studies have primarily focused on the positive effects of the program on physical and cognitive outcomes, which are vital components of human capital (Afridi, 2010; Frisvold, 2015; Anderson et al., 2018; Chakraborty and Jayaraman, 2019; Bütikofer et al., 2018; Lundborg et al., 2022). However, they underestimate the benefit of school feeding programs on noncognitive outcomes, which are of equal importance in building human capital. Overall, the gross and net benefits of the nutrition program to the government amount to CNY 55,553 (USD 8,818) and CNY 49,720 (USD 7,892), respectively. The increasing revenue derived from enhanced noncognitive and behavioral outcomes accounts the gross benefits for approximately 48.9%.

7 Conclusion

This study estimates the causal effects of a nationwide school feeding program on child development outcomes in China. Employing a binary treatment and a staggered design, we adopt the methodology proposed by De Chaisemartin and d'Haultfoeuille (2022) to compute the DID_l estimator, thereby allowing heterogeneous and dynamic effects.

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the job market in the year 2027. Therefore, we employ the average wage income (CNY 3,724) of new graduates from high vocational schools in some poverty areas, including Shanxi, Gansu, and Ningxia, in 2020 to predict the wage in 2027 (National Bureau of Statistics, China, 2021). Moreover, the annual growth rate of salaries for high vocational graduates was 6% prior to the COVID-19 pandemic. Given that the retirement ages for males and females in China are 60 and 50 years, respectively, we adopt the average of 55 years as the retirement age for the child. The individual enters the job market at 22 years and exits the labor force at 55 years. Moreover, given that the projected yearly income exceeds CNY 60,000, we apply a tax rate of 10% over the portion above the threshold (National Bureau of Taxation, China, 2022). For instance, the anticipated increase in income tax in year t, discounted to the base year, is expressed as $\frac{3724 \times 12 \times (1+6\%)^{(t-2020)}}{(1+3\%)^{(t-2011)}} \times 10\%$.

[62] In their study, they broadly categorize all skills other than cognitive ones as noncognitive outcomes.

[63] The SNIP is estimated to enhance noncognitive outcomes by 1.561 standard deviations, encompassing the *importance of effort*, *learning behavior*, *social competence*, *compliance*, and *autonomy* indices.

Drawing from a nationally representative sample of Chinese households, our empirical analysis unveils salient positive impacts of the SNIP on children across diverse dimensions. First, the exposed children exhibit improved physical health indicators after the implementation of the program. Specifically, participation in SNIP yields a substantive increase in *height* by 4.533 *cm*, concomitant with reductions in the incidence of *hospitalization*, *stunting*, *overweight*, and *obesity* by 0.065, 0.065, 0.089, and 0.065 percentage, respectively. Second, beneficiaries of the program manifest enhanced *cognitive test index* by 0.115 standard deviations, elevated self-rated *academic performance* by 0.391 standard deviations, and diminished monthly *absenteeism* by 0.089 occurrences. Third, the program's influence extends to noncognitive and behavioral outcomes, notably evidenced by a rise of 0.210 standard deviations in the rated *importance of effort* to future achievement, which is an important measure of noncognitive outcomes. Regarding behavioral outcomes, discernible improvements are observed in the *learning behavior*, *social competence*, and *autonomy* indices, each registering increases of 0.359, 0.315, and 0.528 standard deviations, respectively. These effects are generally more pronounced among marginalized groups, particularly among girls and children with mothers possessing lower levels of education.

Our results exhibit robustness across multiple checks. We introduce county-specific linear time trends to absorb county differences evolving linearly with time, utilize alternative advanced difference-in-differences estimates (Borusyak et al., 2021; Cunningham, 2021; Sun and Abraham, 2021), perform multiple hypotheses tests to address false rejection issues (Anderson, 2008a), apply bound estimation to mitigate sample selection concerns, and consider other definitions of growth standards.

In examining potential channels for these observed changes, we find significant enhancements in parental labor supply, nutrition intake, direct parental investment on children, parenting styles, and family dynamics. The nutrition subsidy, characterized as an "income shock", induces both quantity of investment (monetary and time investment from parents) and quality margin (effectiveness) of parental investment.

Our study faces limitations in the sense that we primarily focus on the impacts of school feeding programs on child development outcomes and ignore the long-term effects on the labor market outcomes of the exposed children. The implementation timeline of the SNIP in China, occurring later than in comparably studied countries such as the United States, the United

Kingdom, and Sweden, poses obstacles to our research. Given that a substantial proportion of the targeted children had not entered the job market by the last survey year in 2020, we are precluded from empirically examining the effects of the SNIP on their labor market outcomes. Despite this limitation, our study makes a significant contribution to the enlarging body of research on noncognitive and behavioral outcomes in children. Notably, previous estimates of the welfare importance of these school feeding programs, though already substantial, may have been underestimated due to the omission of noncognitive and behavioral outcomes. This contribution is particularly salient as it elucidates a crucial channel for explaining the long-term effects of school nutrition programs on labor market performance. Moreover, our findings sheds light on the importance of school feeding programs in terms of parenting styles and family dynamics, illustrating their roles in enhancing child development outcomes. They furnish novel empirical evidence on how public programs can influence the adoption of parenting styles and family dynamics, subsequently impacting the production process of child development outcomes. This quality margin of family investment, regrettably overlooked in previous economic studies evaluating school programs on child development outcomes, emerges as a new point for future research.

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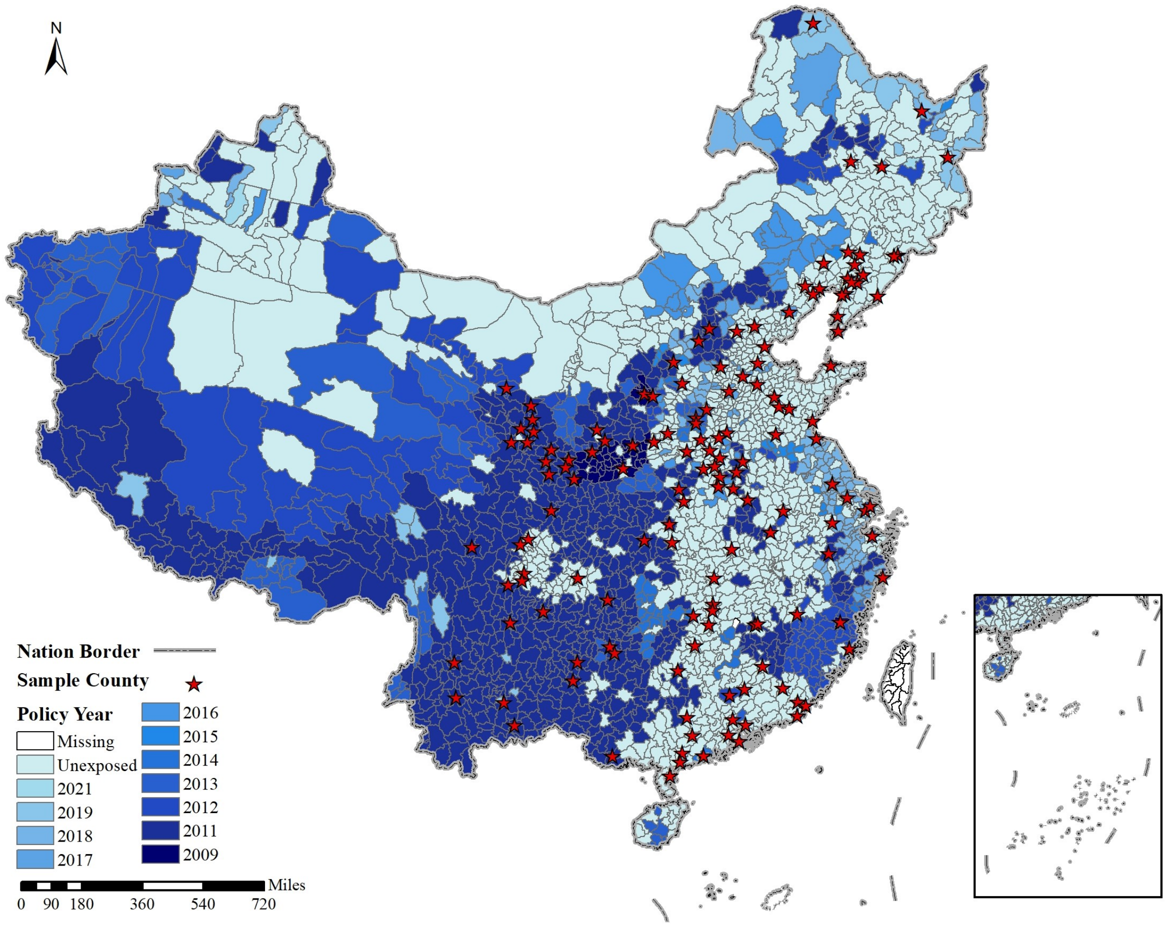
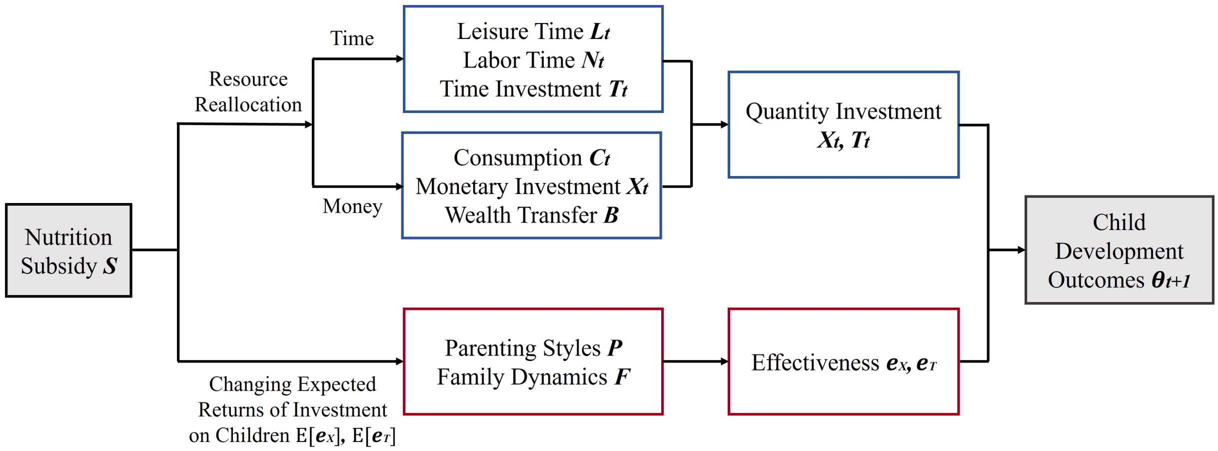
A Figure

Figure 1. The Rollout of Student Nutrition Improvement Program throughout China



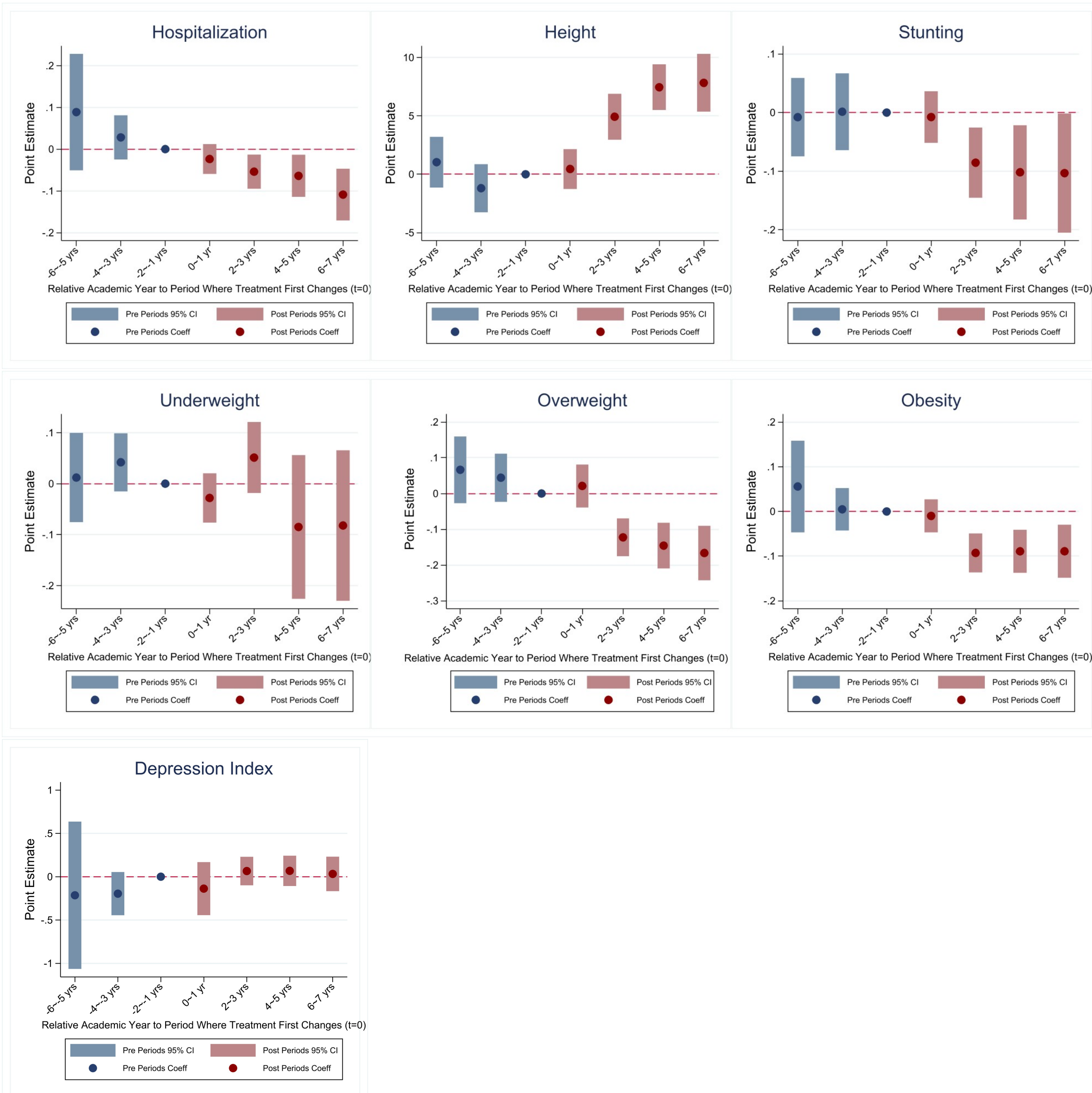
Notes: This figure illustrates the progression of the SNIP across Chinese counties up to the year 2021. Deeper shades of blue in the map signify an earlier initial time of exposure to SNIP, while white areas indicate a lack of available data on the policy in those regions. Surveyed counties included in our analysis are marked with red stars.

Figure 2. Conceptual Framework of Potential Channels from Nutrition Subsidy to Child Development Outcomes



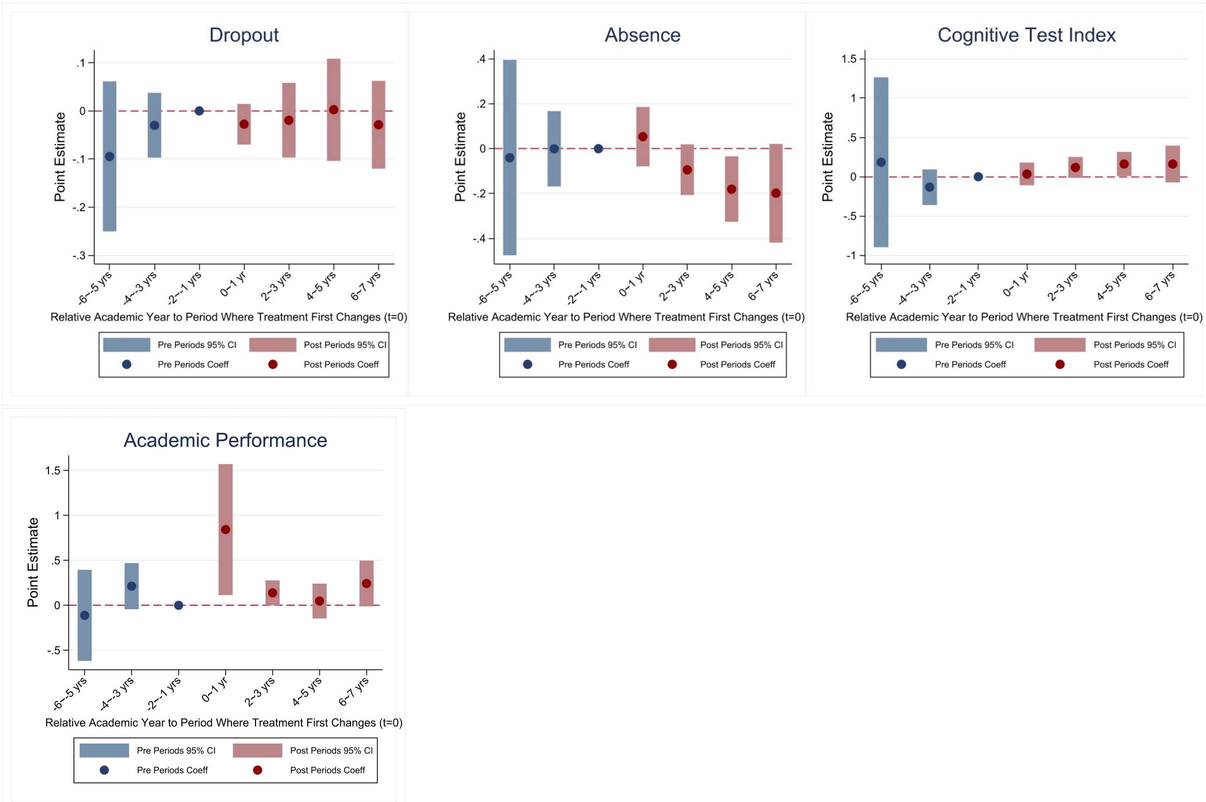
Notes: This figure outlines two primary pathways by which the nutrition subsidy (S) contributes to child development outcomes (θ_{t+1}). First, the "income shock" triggers the household decision-makers' reallocation of resources by , influencing factors such as labor supply (N_t), monetary investment (X_t), and time investment (T_t) in children. This, in turn, affects the quantity of investment in children's development. Second, the unearned "income shock" changes expected returns from monetary and time investment ($\mathbb{E}[e_X]$, $\mathbb{E}[e_T]$), subsequently shaping parenting styles (P) and family dynamics (F). Both the quantity of investment (monetary investment X_t, time investment T_t) and the quality margin or effectiveness of the investment (e_X, e_T) collectively determine child development outcomes (θ_{t+1}).

Figure 3a. Effects of SNIP on Physical and Mental Health Outcomes



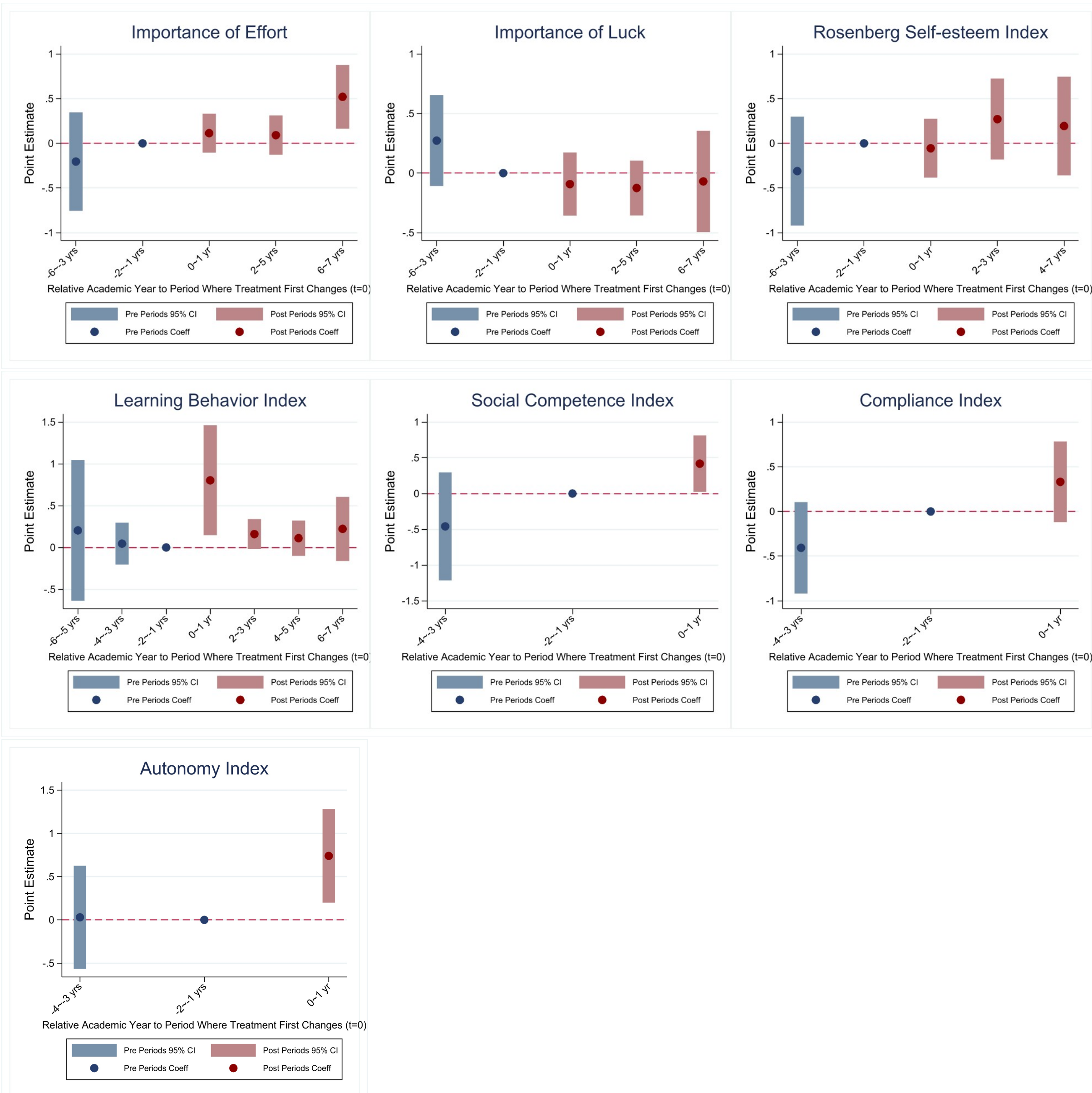
Notes: This figure illustrates the impacts of SNIP on physical and mental health outcomes. Each graph presents the event-study coefficients β^l based on equation (9) using the DID_l estimation method proposed by De Chaisemartin and d'Haultfoeuille (2022). The blue dots represent estimates for placebo effects, while the red dots represent dynamic effects. For the $|l|^{th}$ placebo estimator β^l $(l = -3, -2, -1)$, a comparison is made between the outcomes evolution of first-time switchers and not-yet switchers, from the last period before the treatment change for first-time switchers to the $|l|^{th}$ period before that change. The omitted reference category corresponds to the outcomes evolution of first-time switchers and not-yet switchers from the last period before the treatment change for first-time switchers to one period (1 or 2 academic years) before that change. Thus, the $|l|^{th}$ placebo assesses whether parallel trends hold over $|l-1|$ periods, determining the number of periods over which parallel trends must hold for the l^{th} dynamic effect to be unbiased. Dynamic effect estimators β^l $(l = 0, 1, 2, 3)$ compare the outcomes evolution of first-time switchers and not-yet switchers from the last period before the treatment change for first-time switchers to the l^{th} period after that change. The bars represent 95 percent confidence intervals. All standard errors are clustered at the county c level and computed using 200 bootstrap replications.

Figure 3b. Effects of SNIP on Cognitive Outcomes



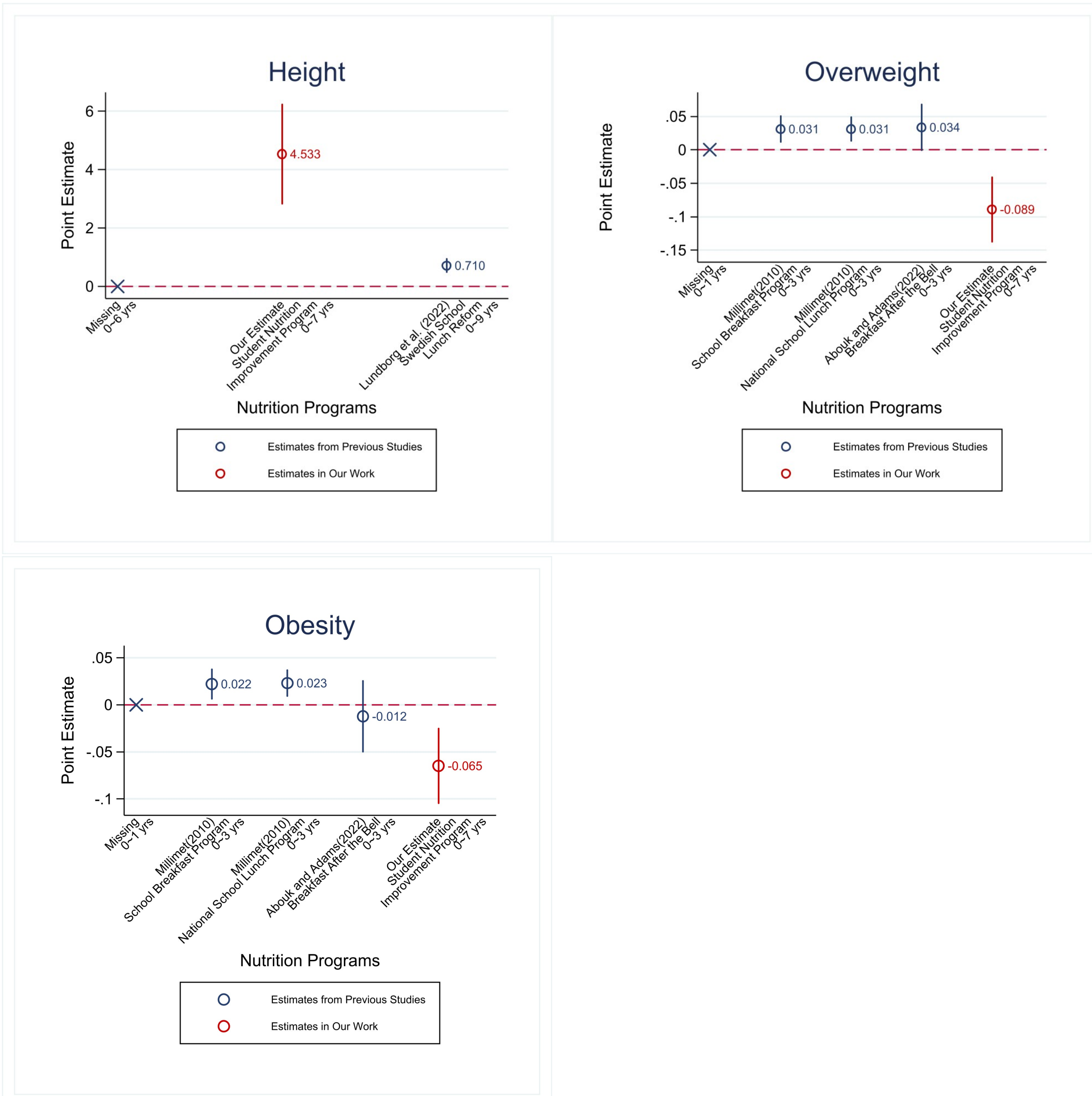
Notes: This figure illustrates the impacts of SNIP on cognitive outcomes. Each graph presents the event-study coefficients β^l based on equation (9) using the DID_l estimation method proposed by De Chaisemartin and d'Haultfoeuille (2022). The blue dots represent estimates for placebo effects, while the red dots represent dynamic effects. For the $|l|^{th}$ placebo estimator β^l $(l = -3, -2, -1)$, a comparison is made between the outcomes evolution of first-time switchers and not-yet switchers, from the last period before the treatment change for first-time switchers to the $|l|^{th}$ period before that change. The omitted reference category corresponds to the outcomes evolution of first-time switchers and not-yet switchers from the last period before the treatment change for first-time switchers to one period (1 or 2 academic years) before that change. Thus, the $|l|^{th}$ placebo assesses whether parallel trends hold over $|l-1|$ periods, determining the number of periods over which parallel trends must hold for the l^{th} dynamic effect to be unbiased. Dynamic effect estimators β^l $(l = 0, 1, 2, 3)$ compare the outcomes evolution of first-time switchers and not-yet switchers from the last period before the treatment change for first-time switchers to the l^{th} period after that change. The bars represent 95 percent confidence intervals. All standard errors are clustered at the county c level and computed using 200 bootstrap replications.

Figure 3c. Effects of SNIP on Noncognitive and Behavioral Outcomes



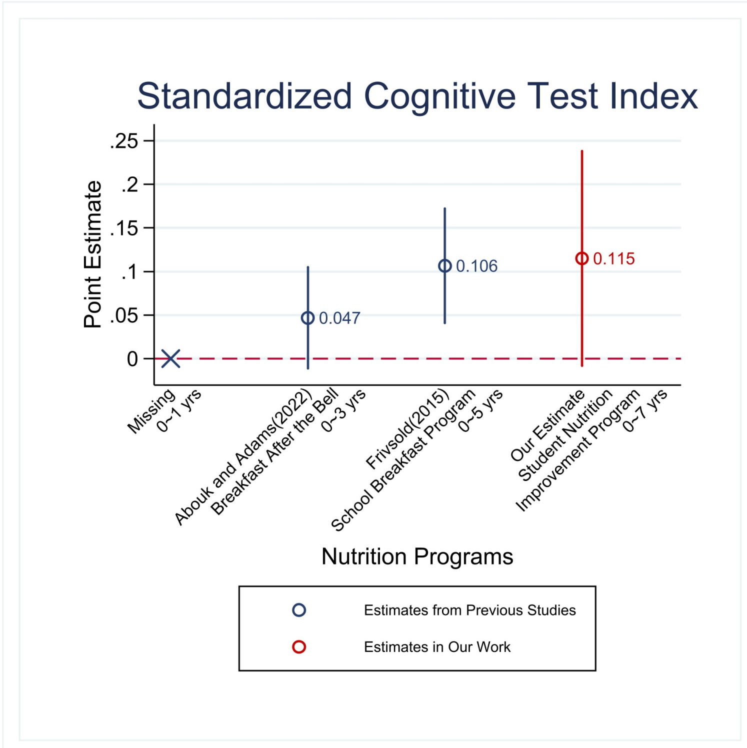
Notes: This figure illustrates the impacts of SNIP on noncognitive and behavioral outcomes. Each graph presents the event-study coefficients β^l based on equation (9) using the DID_l estimation method proposed by De Chaisemartin and d'Haultfoeuille (2022). The blue dots represent estimates for placebo effects, while the red dots represent dynamic effects. For the $|l|^{th}$ placebo estimator β^l ($l = -3, -2, -1$), a comparison is made between the outcomes evolution of first-time switchers and not-yet switchers, from the last period before the treatment change for first-time switchers to the $|l|^{th}$ period before that change. The omitted reference category corresponds to the outcomes evolution of first-time switchers and not-yet switchers from the last period before the treatment change for first-time switchers to one period (1 or 2 academic years) before that change. Thus, the $|l|^{th}$ placebo assesses whether parallel trends hold over $|l-1|$ periods, determining the number of periods over which parallel trends must hold for the l^{th} dynamic effect to be unbiased. Dynamic effect estimators β^l ($l = 0, 1, 2, 3$) compare the outcomes evolution of first-time switchers and not-yet switchers from the last period before the treatment change for first-time switchers to the l^{th} period after that change. Except for the learning behavior index, the remaining variables are not surveyed in each wave, as indicated in Table A1a. Therefore, the maximum placebo and dynamic periods that we can estimate for other variables are displayed in Figure 3a and Figure 3b. The bars represent 95 percent confidence intervals. All standard errors are clustered at the county c level and computed using 200 bootstrap replications.

Figure 4a. Magnitudes Comparison about the Effect of School Nutrition Programs on Physical Health Outcomes



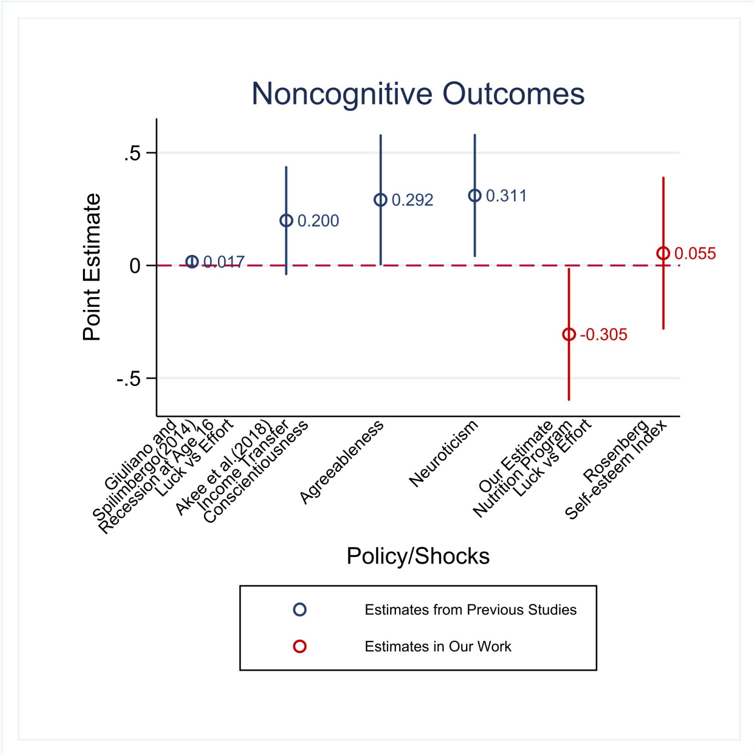
Notes: The figure presents the impacts of school nutrition programs on children's physical health outcomes. Estimates from previous studies are depicted in blue, while our estimates are indicated in red. The x-axis also denotes the corresponding school nutrition programs and years post-treatment. (i) The top-left panel compares our estimate for height with the estimate derived from the study by Lundborg et al. (2022). The estimate from Lundborg et al. (2022) is computed by averaging the original estimates of 0.77 *cm* and 0.65 *cm* taken from Table 5, Columns (4) and (5). (ii) The top-right and bottom-left panels compare our estimates for overweight and obesity with the estimates derived from the papers by Millimet et al. (2010) and Abouk and Adams (2022), respectively. The estimates for overweight and obesity from Millimet et al. (2010) are extracted from Column (1) in Panel IV and V of Table 1, respectively. The estimates for overweight and obesity from Abouk and Adams (2022) are sourced from Column (1) in Panel A and B of Table 3, respectively. See the text for further details.

Figure 4b. Magnitudes Comparison about the Effect of School Nutrition Programs on Children's Cognitive Outcomes



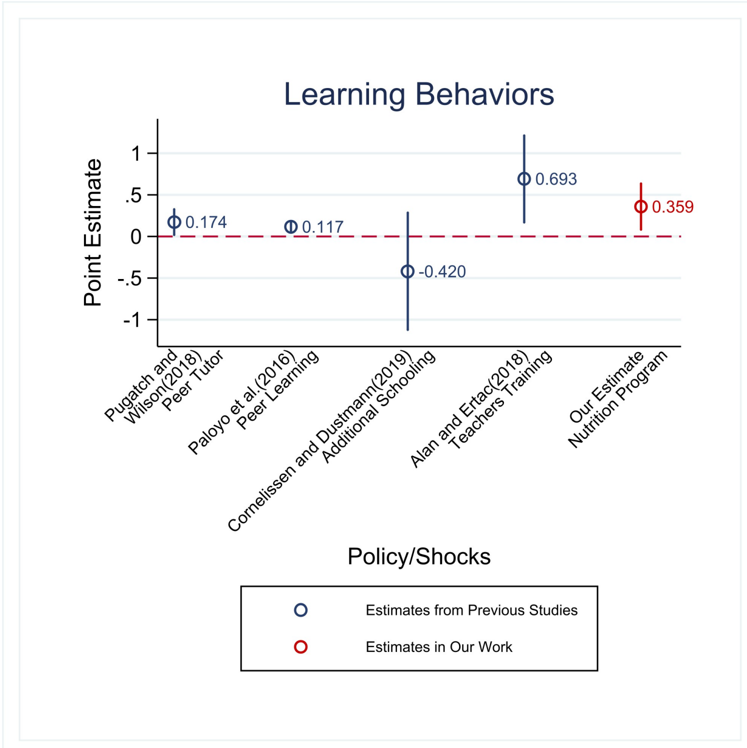
Notes: The figure presents the effects of school nutrition programs on children's cognitive outcomes. Estimates from previous studies are shown in blue, while our estimates are indicated in red. The x-axis also denotes the corresponding school nutrition programs and years post-treatment. The figure compares our estimate for the cognitive test index with the estimates derived from the papers by Frisvold (2015) and Abouk and Adams (2022). We have rescaled their estimates to be comparable with ours. Changes in the cognitive test index are measured in standard deviations after incorporating only math and word tests into the index. (i) The original estimate in the work by Abouk and Adams (2022) indicates that the nutrition program increases reading scores by 0.0307, and the within-school standard deviation is 0.42, as shown in Column (1) of Table 5. Thus, we estimate that the program will increase reading scores by $\frac{0.0307}{0.42} = 0.073$ standard deviations. Similarly, we find that the program will increase math scores by $\frac{0.0123}{0.6} = 0.0205$ standard deviations, with the original estimate from Column (4) of Table 5. Ultimately, we take the average of the two estimates for math and reading scores, which is 0.106 standard deviations. (ii) For Frisvold (2015), changes are directly presented in standard deviations for math and word tests. Therefore, we take the average of the original estimates: 0.091 for the math test and 0.122 for the reading test, which are the estimates in the brackets listed in Columns (3) and (6) in Table 3. See the text for further details.

Figure 4c. Magnitudes Comparison about the Effect of Economics Shocks/ Welfare Programs on Noncognitive Outcomes



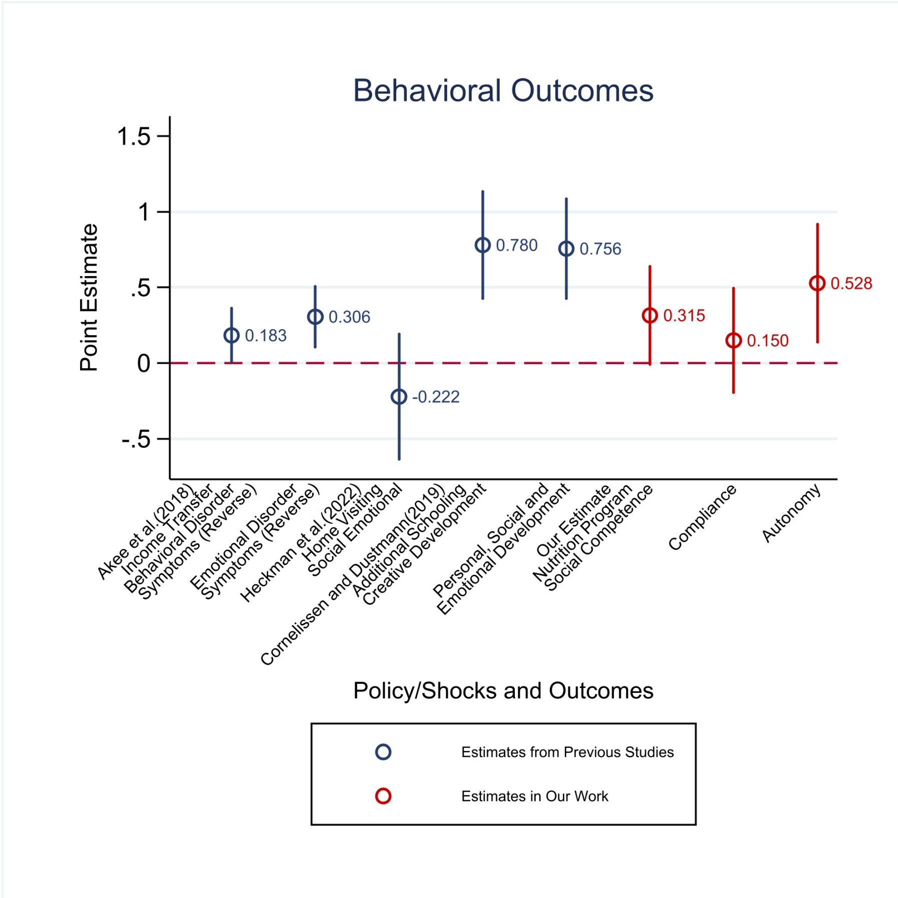
Notes: The figure illustrates the effects of shocks/programs on children's noncognitive outcomes. Estimates from previous studies are represented in blue, while our estimates are highlighted in red. The x-axis also denotes the corresponding shocks/programs and outcomes of interest. The figure compares our estimate for noncognitive outcomes with the estimates derived from the papers by Giuliano and Spilimbergo (2014) and Akee et al. (2018). For Giuliano and Spilimbergo (2014), the original estimate indicates that one standard deviation in exposure to recession during the ages of 18-25 increases the self-reported importance of luck versus effort by 0.017 standard deviations in Column (3) of Table 1. Estimates in the paper by Akee et al. (2018) suggest that receiving Casino Transfers can increase conscientiousness, agreeableness, and neuroticism by 0.200, 0.292, and 0.311 standard deviations, respectively. We take the original estimates from Column (3)–(5) in Panel B of Table 3. See the text for further details.

Figure 4d. Magnitudes Comparison about the Effect of Educational Programs on Learning Behaviors



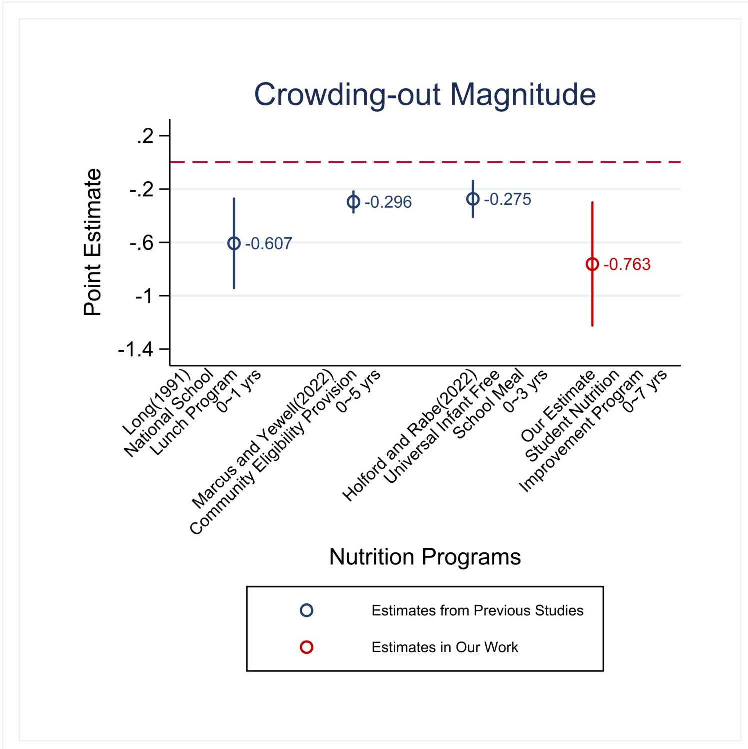
Notes: The figure presents the effects of educational programs on children's learning behaviors. Estimates from previous studies are represented in blue, while our estimates are highlighted in red. The x-axis denotes the corresponding programs. The figure compares our estimate for learning behavior outcomes with estimates derived from the papers by Paloyo et al. (2016), Alan and Ertac (2018), Pugatch and Wilson (2018), and Cornelissen and Dustmann (2019). (i) In the paper by Pugatch and Wilson (2018), the raw estimate indicates that providing peer tutoring classes increases the probability of attending tutor classes by 0.079 in Column (1) of Table 2, and we translate it to an effect size of 0.174 standard deviations. (ii) Paloyo et al. (2016) investigate the impact of incentives on students' participation in peer learning sessions and observe a noteworthy increase of 0.117 standard deviations in the number of peer learning sessions. (iii) Cornelissen and Dustmann (2019) show that incentives increase students' participation in peer learning sessions by 0.464 sessions, taken from Column (1) in panel A of Table 2. We rescale the impact as a 0.117 standard deviations increase in the number of peer learning sessions. The original estimate of Cornelissen and Dustmann (2019) indicates that one-month additional schooling at age 7 will decrease disruptive behavior by 0.035 standard deviations, derived from Column (6) of Panel B in Table 5. Therefore, an additional schooling year before the age of 7 is regarded to reduce disruptive behavior by 0.420 standard deviations. (iv) Alan and Ertac (2018) find that a teacher training program leads to a 10.4% decrease in the probability for students to receive low behavior grades, as listed in Column (1) of Table 9. After considering the standard deviations of the dummy variable for low behavior grades, which amounts to 0.15 in Column (1) of Table 2, we quantify the change to be 0.693 standard deviations. See the text for further details.

Figure 4e. Magnitudes Comparison about the Effect of Children Welfare Programs on Behavioral Outcomes



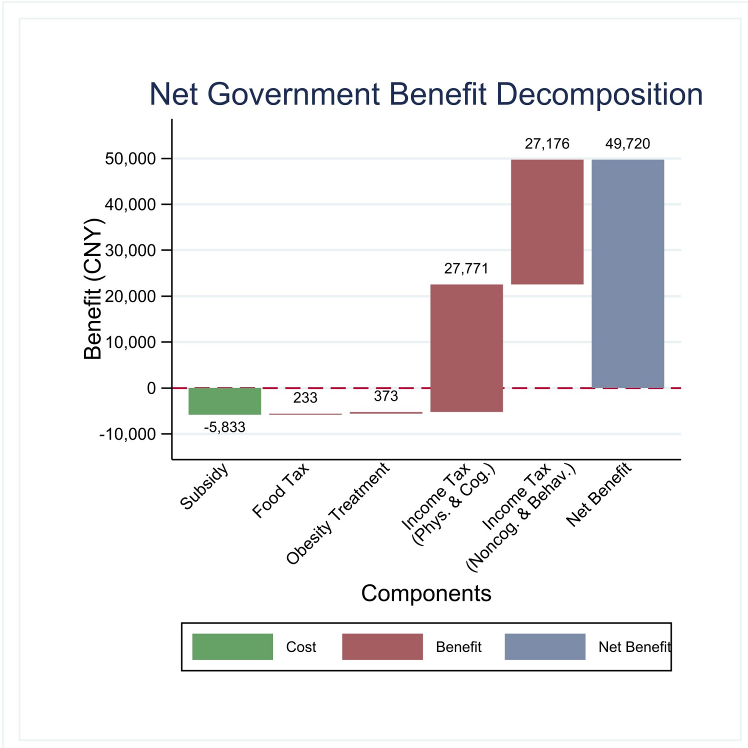
Notes: The figure presents the effects of children welfare programs on children's behavioral outcomes. Estimates from previous studies are represented in blue, while our estimates are highlighted in red. The x-axis denotes the corresponding programs and outcomes of interest. The figure compares our estimate for behavioral outcomes with estimates derived from the papers by Akee et al. (2018), Cornelissen and Dustmann (2019), and Heckman et al. (2020). (i) The original estimates in the paper by Akee et al. (2018) are taken from Columns (1) and (2) in Panel B of Table 3, reflect that Casino Transfer decreases behavioral and emotional disorder symptoms by 0.183 and 0.306 standard deviations, respectively. (ii) Heckman et al. (2020) find that a home visiting program can significantly reduce social-emotional skills by 0.222 standard deviations within half a year, referring to Column (3) of Table 2. The original estimate from (iii) Cornelissen and Dustmann (2019) indicates that one-month additional schooling at age 5 will increase creative development and emotional development behavior by 0.065 and 0.035 standard deviations, derived from columns (1) and (5) of Panel A in Table 5, respectively. We recalculate the original estimates to account for the transition from monthly to annual figures for additional schooling ($0.065 \times 12 = 0.780$ and $0.063 \times 12 = 0.756$). See the text for further details.

Figure 5. Magnitude Comparison about School Feeding Programs' Crowding Out Effect on Household Expenditure



Notes: The figure presents estimates of household food expenditure extracted from referenced papers along the x-axis (Long, 1991; Holford and Rabe, 2022; Marcus and Yewell, 2022), normalized for comparison with our own estimate. Estimates from previous studies are depicted in blue, while our estimates are represented in red. The x-axis also denotes the school nutrition programs and corresponding years post-treatment. (i) Original estimates in the work by Long (1991), derived from Column (1) of Table 3, suggest that an additional USD 1 from NSLP diminishes normal household food expenditures in the United States by roughly 61 cents. (ii) Holford and Rabe (2022) suggest that in an ineligible household, an additional eligible child under the free meals policy leads to a reduction in supermarket shopping and eating out expenditures by GBP 6.207 and GBP 3.023 per individual per four weeks, as shown in Column (2) of Table 5 respectively. The study also posits that annual funding for the program approximates GBP 437 per pupil per year; therefore, we calculate the crowding-out effect magnitude as 0.275. (iii) The original estimate by Marcus and Yewell (2022) indicates that exposure to a school feeding program correlates with a reduction in monthly household food expenditure by USD 10.65, as indicated in Column (1) in Panel A of Table 3. Since their study does not provide the cost of the nutrition program, we estimate the cost of the program referring to the report released by U.S. Department of Agriculture (2019). With this calculation, the crowding-out effect magnitude is around 0.296 in their study. We normalize the raw household food expenditure per individual by the product of the approximated annual nutrition subsidy and the number of covered children in the household, finding that the magnitude of crowding-out effects of the SNIP is approximately 0.763. See the text for further details.

Figure 6. The Cost-benefit Analysis of the SNIP



Notes: The figure illustrates the governmental cost decomposition measured by CNY, if a first-grade child in targeted primary schools was subsidized in the year 2011. The bars are color-coded, with green representing the cost, red representing the benefit, and blue indicating the net benefit of the SNIP. The cost of the SNIP is estimated to be around CNY 5,833 (USD 926), stemming from the nutrition subsidy provided to schools. The benefits of the SNIP are derived from three main aspects: (i) food tax, (ii) reduced fees for obesity treatment, and (iii) increased income tax due to enhanced child development outcomes. Each benefit amount measured in CNY is positioned above the red bar. The benefits from food tax and reduced obesity treatment fees are CNY 233 (USD 37) and 373 (USD 59), respectively. The benefit from increased income tax due to physical and cognitive enhancements is CNY 27,771 (USD 4,408). Additionally, the benefit from increased income tax resulting from noncognitive and behavioral enhancements is CNY 27,176 (USD 4,314), a component often overlooked in prior studies. Overall, the net benefit of the SNIP is approximately CNY 49,720 (USD 7,892). Refer to the text for further details.

B Table

Table 1a. Definition of Physical Health Outcomes

Physical Health Measures	
Hospitalization	Were you hospitalized in last year? *(1. Yes; 0. No)*
Height	The respondent's height *(in Centimeter)*?
WHO Growth Standards	
Stunting	Children aged under 19 years old are defined as stunting if height-for-age is less than 2 standard deviations below the median.
Underweight	For children aged under 10, underweight is defined as weight-for-age smaller than 2 standard deviations below median; For adults aged above 19, underweight is defined with BMI smaller than 18.5.
Overweight	For children aged under 5, overweight is defined as weight-for-height greater than 2 standard deviations above median; For children aged 5—19, overweight is defined as BMI-for-age greater than 1 standard deviation above the median; For adults aged above 19, overweight is defined with BMI greater than or equal to 25.
Obesity	For children aged under 5, obesity is defined as weight-for-height greater than 3 standard deviations above the median; For children aged 5—19, obesity is defined as BMI-for-age greater than 2 standard deviations above the median; For adults aged above 19, obesity is defined with BMI greater than or equal to 30.

Notes: We use the one year before the interview date as the time variable when using *hospitalization* as an outcome. For example, if a respondent answers the corresponding question in the year 2012, the answer should reflect the physical health status of this respondent in the year 2011. We replace the value of original time variable for that respondent with 2011.

Table 1b. Definition of Mental Health Outcomes

Mental Health Measures	
Depression Index	We standardize K6 score/CES-D score for each wave to create Depression Index: the higher the score, the higher the individual's degree of depression.
	The following are some descriptions of people's mental statuses. Please select according to your statuses in the past month. (1. Never; 2. Once a month; 3. 2—3 times a month; 4. 2—3 times a week; 5. Almost every day)
	6—item Kessler Psychological Distress Scale —2010 and 2014
[1]	Feel depressed and cannot cheer up no matter what you are doing.
[2]	Feel nervous.
[3]	Feel upset and cannot remain calm.
[4]	Feel hopeless about the future.
[5]	Feel that everything is difficult.
[6]	Think life is meaningless.
	Here are some descriptions of people's mental statuses. Please select according to your statuses in the past week. (1. Never; 2. Sometimes (1—2 days); 3. Often (3—4 days); 4. Most of the time (5—7 days))
	Center for Epidemiologic Studies Depression (20 items) —2012 and 2016
[1]	I am worried about some trivial things.
[2]	I have a poor appetite and do not want to eat.
[3]	I feel depressed despite the help from relatives and friends.
[4]	I find myself not worse than others. (reverse)
[5]	I cannot concentrate on things.
[6]	I am in a low spirit.
[7]	I find it difficult to do anything.
[8]	I find the future promising. (reverse)
[9]	I feel that I have been a loser for a long time.
[10]	I feel scared.
[11]	I cannot sleep well.
[12]	I feel happy. (reverse)
[13]	I talk less than usual.
[14]	I feel lonely.
[15]	I find that people are not friendly to me.
[16]	I have a happy life. (reverse)
[17]	I cried or I want to cry.
[18]	I feel sad.
[19]	I find that others do not like me.
[20]	I feel that I cannot continue with my life.
	Center for Epidemiologic Studies Depression (8 items) —2018 and 2020
[1]	I am in a low spirit.
[2]	I find it difficult to do anything.
[3]	I cannot sleep well.
[4]	I feel happy. (reverse)
[5]	I feel lonely.
[6]	I have a happy life. (reverse)
[7]	I feel sad.
[8]	I feel that I cannot continue with my life.

Notes: Full marks for K6 is 6*4=24 and full marks for CES-D is $3\times20=60$ (20 items) $3\times8=24$ (8 items).

Table 1c. Definition of Cognitive Outcomes

Cognitive Outcomes	
School Performance	
Dropout	Whether you drops out before high school? *(1. Yes; 0. No)*
Absence	In the most recent month when you were not on vacation, how many times have you taken a leave of absence or cut a class?
Cognitive Skill	
Cognitive Test Index	The average of standardized mathtest/number series and wordtest/memory test scores is to create the cognitive index: the higher the score, the higher cognitive skill individual has.
[1]	Word test score *(Wave 2010, 2014 and 2018)*
[2]	Math test score *(Wave 2010, 2014 and 2018)*
[3]	Memory Test Score *(Wave 2012, 2016 and 2020)*
[4]	Number Series Test Score *(Wave 2012, 2016 and 2020)*
	We standardize the item listed as follows.
Academic Performance	How would you rate your academic performance? *(Range from 1—5; 1. Extremely Unsatisfied; 5. Extremely Satisfied.)*

Table 1d. Definition of Noncognitive Outcomes

Noncognitive Outcomes	
	The following are some factors affecting one's success. Please answer according to your own opinion. (1. Totally disagree; 2. Disagree; 3. Neither agree nor disagree; 4. Agree; 5. Totally agree)
	We standardize each item listed as follows.
Importance of Effort	How important is effort to one's future achievement?
Importance of Luck	How important is luck to one's future achievement?
	How much do you agree with the following statement? (0. Totally disagree; 1.Disagree; 2. Agree; 3. Totally agree)
Rosenberg Self-esteem	Sum of the following items is z-standardized to create the Self-esteem index: the higher the score, the higher the individual's degree of approval toward her/himself.
[1]	I feel that I'm a person of worth, at least on an equal basis with others.
[2]	I feel that I have a number of good qualities.
[3]	All in all, I am inclined to feel that I am a failure (reverse).
[4]	I am able to do things as well as most other people.
[5]	I feel I do not have much to be proud of (reverse).
[6]	I take a positive attitude toward myself.
[7]	On the whole, I am satisfied with myself.
[8]	I wish I could have more respect for myself (reverse).
[9]	I certainly feel useless at times (reverse).
[10]	At times I think I am no good at all (reverse).

Table 1e. Definition of Behavioral Outcomes

Behavioral Outcomes	
	The following questions are related to your daily activities. Please answer according to the actual situation. (1. Totally disagree; 2. Disagree; 3. Neither agree nor disagree; 4. Agree; 5. Totally agree)
Learning Behavior Index	We standardize the sum of following items to create learning behavior index: the higher the score, the higher the individual's degree of learning habits.
[1]	This child studies very hard.
[2]	This child checks her/his homework several times after it is finished to make sure it is correct.
[3]	This child does not play until she/he finishes her/his homework.
[4]	This child can concentrate her/his attention when she/he is doing something.
[5]	This child obeys the rules.
[6]	This child likes to arrange her/his own things in order.
	*The following questions are about your views on *** (Interviewed Child's name). Please answer according to your own experience and opinion without overthinking.(1. Totally disagree; 2. Disagree; 3. Neither agree nor disagree; 4. Agree; 5. Totally agree)*
	Three-dimensional Positive Behavior Scales
Social Competence Index	The sum of responses to the 8 questions is standardized to create the social competence index: the higher the score, the higher the individual's degree of social competence.
[1]	This child is optimistic in nature.
[2]	This child does things very carefully and in order.
[3]	This child is curious and likes to explore. She/he loves new experiences.
[4]	This child gets on well with others her/his age.
[5]	This child can tolerate the mistakes made by others her/his age during games and other activities.
[6]	This child likes to help others while playing or doing other activities.
[7]	This child is able to overcome fidgeting easily.
[8]	This child is well liked by others her/his age.
Compliance Index	The sum of responses to the 6 questions is standardized to create the compliance index: the higher the score, the higher the individual's degree of compliance.
[1]	This child waits for her/his turn while playing or doing other activities.
[2]	This child thinks first before acting and is not impulsive.
[3]	This child usually does what you tell him/her to do.
[4]	This child can concentrate attention when she/he is doing something.
[5]	This child obeys the rules.
[6]	Once the child starts to do something, she/he will complete it no matter what happens.
Autonomy Index	The sum of responses to the 2 questions is standardized to create the autonomy index: the higher the score, the higher the individual's degree of autonomy.
[1]	This child tries her/his best to do things independently.
[2]	This child does not play until she/he finishes her/his homework.

Table 2a. Summary Statistics of Children Sample

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
		Untreated			Treated		Difference
Number of Observations		19,864			7,104		[5]-[2]
Variables	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Diff.**
Physical and Mental Health Measures							
Hospitalization	13,836	0.083	0.276	5,235	0.063	0.243	-0.020**
Height	18,842	128.7	30.51	6,743	151.1	19.93	22.400***
Stunting	18,102	0.238	0.426	6,092	0.197	0.398	-0.040*
Underweight	11,175	0.124	0.330	1,484	0.197	0.398	0.072***
Overweight	18,255	0.270	0.444	6,606	0.159	0.365	-0.111***
Obesity	18,255	0.146	0.354	6,606	0.066	0.249	-0.080***
Depression Index	9,024	-0.114	0.929	5,870	0.028	0.969	0.143***
Cognitive Outcomes							
Dropout	14,946	0.077	0.267	6,898	0.108	0.310	0.031**
Absence	7,741	0.277	0.954	4,794	0.304	1.067	0.027
Cognitive Test Index	7,286	0.069	0.909	4,637	0.112	0.942	0.043
Academic Performance	5,904	3.326	0.925	3,132	3.361	0.940	0.035
Noncognitive and Behavioral Outcomes							
Importance of Effort	3,678	4.161	0.910	2,421	4.151	0.905	-0.010
Importance of Luck	3,677	2.714	1.238	2,413	2.686	1.244	-0.028
Rosenberg Self-esteem	2,370	3.656	2.431	1,518	3.648	2.225	-0.008
Learning Behavior Score	6,406	22.24	3.113	3,755	22.76	2.932	0.512***
Social Competence Score	2,757	29.80	3.496	702	30.20	3.580	0.401*
Compliance Score	2,301	21.77	3.130	720	22.30	3.214	0.532***
Autonomy Score	2,141	7.228	1.416	677	7.526	1.360	0.298***
Nutrition Intake, Monetary, and Time Investment							
Egg & Dairy	4,467	0.792	0.406	2,241	0.743	0.437	-0.049**
Annual Food Expenses	19,015	3,283	3,564	6,905	3,003	2,995	-280.836*
Annual Education Expenses	17,306	2,647	4,774	5,541	3,398	5,538	751.120***
Annual Medical Expenses	13,166	1,000	4,840	3,568	687.6	2,970	-312.628***
Tutoring Hours	16,575	1.589	3.535	4,274	1.599	3.817	0.010
Parenting Styles and Family Dynamics							
Authoritative	2,640	0.167	0.373	1,733	0.182	0.386	-0.018
Authoritarian	2,640	0.310	0.463	1,733	0.292	0.455	0.015
Permissive	2,640	0.139	0.346	1,733	0.158	0.365	0.019
Uninvolved	2,640	0.384	0.486	1,733	0.368	0.482	-0.016
Quarrels with Parents	5,944	0.932	2.673	3,195	1.061	2.676	0.129*
Quarrels between Parents	5,667	0.601	1.816	3,061	0.676	1.910	0.075
Talks with Parents	4,073	1.957	3.991	3,191	1.738	3.257	-0.219*
Parents Check Homework	11,049	3.144	1.364	3,969	2.991	1.350	-0.153**
Individual and Family Characteristics							
Age	19,862	9.520	5.029	7,104	14.170	3.513	4.651***
Gender (male=1)	19,864	0.525	0.499	7,104	0.522	0.500	-0.003
Father's Years of Schooling	19,484	7.966	3.389	6,923	6.223	4.065	-1.743***
Mother's Years of Schooling	19,412	6.978	3.812	6,899	4.294	4.234	-2.685***
Number of Households	19,791	5.357	2.009	7,083	5.252	1.791	-0.105

Notes: This table provides summary statistics for the children sample. Columns 1—3 focus on the subsample from untreated counties as of the time of survey. Columns 4—6 focus on beneficiaries who reside in counties that had the SNIP ("treated") at survey. Column 7 reports the mean difference between Column 2 and Column 5. We report the summary statistics of total scores instead of standardized values, for *academic performance*, *importance of effort* & *luck*, *Rosenberg self-esteem*, *learning behavior score*, *social competence score*, *compliance score*, and *autonomy score*. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 2b. Summary Statistics of Parents Sample

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
		Untreated			Treated		Difference
Number of Observations		24,040			17,058		[5]-[2]
Variables	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**Diff.**
Parental Labor Supply and Income							
Labor Force Participation Rate	23,893	0.772	0.351	16,839	0.829	0.320	0.057***
Employment Rate	20,970	0.947	0.208	15,286	0.980	0.120	0.034***
Monthly Hours Worked	16,772	163.7	114.9	9,149	193.6	104.8	29.899***
Annual Income	18,271	16,539	15,108	13,281	15,537	15,264	-1,002.512
Mothers' Labor Supply and Income							
In Labor Force or Not	12,512	0.682	0.466	8,414	0.765	0.424	0.083***
Employed or Not	8,531	0.947	0.225	6,434	0.973	0.162	0.027***
Monthly Hours Worked	6,971	127.0	129.6	3,061	158.8	127.9	31.727***
Annual Income	7,434	12,473	12,308	5,413	11,608	12,549	-864.852
Agriculture Industry or Not	7,593	0.386	0.487	5,136	0.429	0.495	0.042
Manufacture Industry or Not	7,593	0.236	0.425	5,136	0.181	0.385	-0.055**
Service Industry or Not	7,593	0.358	0.479	5,136	0.372	0.484	0.015
Fathers' Labor Supply and Income							
In Labor Force or Not	11,284	0.872	0.334	8,240	0.894	0.308	0.021
Employed or Not	9,842	0.957	0.203	7,363	0.988	0.109	0.031***
Monthly Hours Worked	6,764	195.4	115.0	3,790	222.0	95.11	26.596***
Annual Income	8,239	19,204	18,175	6,202	17,790	17,939	-1,414.032
Agriculture Industry or Not	8,628	0.290	0.454	6,077	0.298	0.457	0.008
Manufacture Industry or Not	8,628	0.193	0.395	6,077	0.152	0.359	-0.041**
Service Industry or Not	8,628	0.491	0.500	6,077	0.535	0.499	0.044
Family Expenditures							
Total Annual Expenses	18,020	53,922	65,490	6,713	85,942	1,456,323	32,019.859
Proportion of Each Item							
Food	17,825	0.357	0.189	6,651	0.312	0.196	-0.045***
Dress	17,807	0.051	0.052	6,682	0.054	0.058	0.003
Housing	17,723	0.108	0.138	6,484	0.142	0.161	0.034***
Daily	17,735	0.091	0.115	6,636	0.086	0.114	-0.006
Medical	17,975	0.095	0.136	6,692	0.091	0.128	-0.005
Transport & Communication	17,756	0.090	0.079	6,667	0.095	0.082	0.005
Education	17,940	0.116	0.151	6,682	0.146	0.192	0.031***
Leisure	16,234	0.001	0.029	5,712	0.001	0.020	-0.000

Notes: This table provides summary statistics for the parents sample. Columns 1—3 focus on the subsample from untreated counties as of the time of survey. Columns 4—6 focus on beneficiaries who reside in counties that had the SNIP ("treated") at survey. Column 7 reports the mean difference between Column 2 and Column 5. Significance level: *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Effects of SNIP on Child Development Outcomes

VARIABLES	[1] Estimate	[2] N	[3] Control Mean
Panel A: Physical and Mental Health Measures			
Hospitalization	-0.065***	37,248	0.077
	(0.022)		
Height	4.533***	41,603	131.173
	(0.865)		
WHO Growth Standards			
Stunting	-0.065**	38,900	0.207
	(0.029)		
Underweight	-0.025	19,149	0.116
	(0.025)		
Overweight	-0.089***	40,703	0.254
	(0.025)		
Obesity	-0.065***	40,703	0.131
	(0.020)		
Depression Index	0.005	24,755	-0.140
	(0.081)		
Panel B: Cognitive Outcomes			
School Performance			
Dropout	-0.019	37,315	0.078
	(0.035)		
Absence	-0.089	20,544	0.274
	(0.054)		
Cognitive Skill			
Cognitive Test Index	0.115*	17,811	0.160
	(0.063)		
Academic Performance	0.391**	13,218	-0.032
	(0.156)		
Panel C: Noncognitive and Behavioral Outcomes			
Noncognitive Outcomes			
Importance of Effort	0.210**	8,423	0.031
	(0.093)		
Importance of Luck	-0.095	8,416	0.043
	(0.115)		
Rosenberg Self-esteem Index	0.055	3,693	-0.045
	(0.171)		
Behavioral Outcomes			
Learning Behavior Index	0.359**	14,278	-0.061
	(0.141)		
Social Competence Index	0.315*	3,256	0.031
	(0.165)		
Compliance Index	0.150	2,827	0.020
	(0.177)		
Autonomy Index	0.528***	2,647	-0.024
	(0.200)		

Notes: This table explores the effects of SNIP on child development outcomes, with physical and mental health outcomes in Panel A, cognitive outcomes in Panel B, noncognitive and behavioral outcomes in Panel C. All regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. Control Mean in Column 3 measures the mean of outcome for never-treated group. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table 4a. Heterogeneous Effects by Initial Time of Exposure

	Primary School			*Middle School*		
	[1]	[2]	[3]	[4]	[5]	[6]
VARIABLES	Estimate	N	Control Mean	Estimate	N	Control Mean
Panel A: Physical and Mental Health Measures						
Hospitalization	-0.070**	32,524	0.082	-0.057	18,073	0.052
	(0.034)			(0.036)		
Height	3.754***	36,353	126.744	4.776***	20,904	144.871
	(0.988)			(1.105)		
WHO Growth Standards						
Stunting	-0.062	35,454	0.222	-0.157**	17,528	0.160
	(0.039)			(0.063)		
Underweight	-0.006	12,614	0.112			
	(0.021)					
Overweight	-0.106***	35,549	0.279	-0.057*	20,505	0.203
	(0.033)			(0.034)		
Obesity	-0.077***	35,549	0.148	-0.044	20,505	0.085
	(0.029)			(0.034)		
Depression Index	0.114	19,896	-0.152	-0.154	17,643	-0.139
	(0.104)			(0.110)		
Panel B: Cognitive Outcomes						
School Performance						
Dropout	-0.039	31,444	0.061	0.073***	21,085	0.082
	(0.040)			(0.025)		
Absence	-0.192**	17,957	0.280	-0.136	13,634	0.288
	(0.097)			(0.107)		
Cognitive Skill						
Cognitive Test Index	0.069	13,998	0.040	0.043	13,086	0.192
	(0.097)			(0.082)		
Academic Performance	0.242*	11,997	-0.008	0.618**	6,144	-0.039
	(0.128)			(0.281)		
Panel C: Noncognitive and Behavioral Outcomes						
Noncognitive Outcomes						
Importance of Effort	-0.096	4,861	0.033	0.229	5,024	0.024
	(0.308)			(0.143)		
Importance of Luck	-0.023	4,861	0.073	-0.031	5,024	0.052
	(0.294)			(0.152)		
Rosenberg Self-esteem Index	-0.035	2,986	-0.044	0.106	1,255	-0.054
	(0.142)			(0.241)		
Behavioral Outcomes						
Learning Behavior Index	0.372***	11,546	-0.060	0.429***	9,235	-0.059
	(0.112)			(0.182)		
Social Competence Index	0.241	2,796	0.020	-0.045	1,450	0.091
	(0.272)			(0.307)		
Compliance Index	0.186	2,323	0.001	0.865**	1,453	0.039
	(0.200)			(0.390)		
Autonomy Index	0.487	2,197	-0.031	0.710**	1,410	0.002
	(0.273)			(0.361)		

Notes: This table elucidates the heterogeneous effects of the SNIP on child development outcomes across subgroups, with Panel A focusing on physical and mental health outcomes, Panel B on cognitive outcomes, and Panel C on noncognitive and behavioral outcomes. The children's sample is stratified based on the criterion of whether the program was firstly implemented in the individual's county of residence during her/his primary or middle school years. Columns 1—3 and Columns 4—6 present the results using the baseline equation (9), utilizing the subsample of initial time of exposure at primary and middle school years, respectively. Columns 1 and 4 report the weighted average of dynamic estimates β_l for the post-treatment periods in the corresponding subsamples (De Chaisemartin and d'Haultfoeuille, 2022). All regressions control for age, age square, gender, father's education level, mother's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Standard errors in parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Columns 2 and 5 reflects the number of first differences of the outcome and of the treatment used in the estimation in the subsample of initial time of exposure at primary and middle school years, respectively. The Control Mean in Columns 3 and 6 represents the mean of outcomes for the never-treated group in the corresponding subsamples. Since the WHO does not provide standards for underweight in children aged 10–18 (World Health Organization, 2007), we are unable to estimate the effect on *underweight* among those who were initially affected by the policy as middle school students. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table 4b. Heterogeneous Effects by Gender

	Male			*Female*		
	[1]	[2]	[3]	[4]	[5]	[6]
VARIABLES	Estimate	N	Control Mean	Estimate	N	Control Mean
Panel A: Physical and Mental Health Measures						
Hospitalization	-0.082**	19,841	0.089	-0.025	17,249	0.063
	(0.038)			(0.031)		
Height	5.215***	21,961	131.332	3.558***	19,586	130.995
	(1.097)			(0.835)		
WHO Growth Standards						
Stunting	-0.095***	20,679	0.215	-0.064*	18,168	0.198
	(0.034)			(0.033)		
Underweight	-0.096***	10,095	0.113	0.014	8,595	0.119
	(0.031)			(0.029)		
Overweight	-0.105***	21,503	0.300	-0.062**	19,144	0.202
	(0.034)			(0.030)		
Obesity	-0.042	21,503	0.162	-0.076***	19,144	0.098
	(0.033)			(0.022)		
Depression Index	0.034	12,832	-0.162	-0.066	11,740	-0.118
	(0.106)			(-0.097)		
Panel B: Cognitive Outcomes						
School Performance						
Dropout	-0.026	19,616	0.080	-0.021	17,486	0.077
	(0.031)			(0.029)		
Absence	-0.155**	10,718	0.329	0.033	9,612	0.217
	(0.079)			(0.069)		
Cognitive Skill						
Cognitive Test Index	0.034	9,024	0.099	0.214***	8,537	0.222
	(0.067)			(0.079)		
Academic Performance	0.334*	6,948	-0.098	0.510**	6,031	0.039
	(0.174)			(0.202)		
Panel C: Noncognitive and Behavioral Outcomes						
Noncognitive Outcomes						
Importance of Effort	0.038	4,283	0.010	0.356*	3,755	0.054
	(0.132)			(0.186)		
Importance of Luck	-0.097	4,282	0.033	-0.111	3,749	0.053
	(0.153)			(0.151)		
Rosenberg Self-esteem Index	-0.068	1,542	0.000	-0.024	1,531	-0.091
	(0.217)			(0.203)		
Behavioral Outcomes						
Learning Behavior Index	0.425**	7,207	-0.225	0.300***	6,652	0.106
	(0.211)			(0.101)		
Social Competence Index	0.323	1,623	-0.001	0.326	1,494	0.068
	(0.197)			(0.209)		
Compliance Index	0.086	1,360	-0.073	0.264	1,284	0.120
	(0.211)			(0.191)		
Autonomy Index	0.754**	1,263	-0.125	0.180	1,177	0.084
	(0.334)			(0.210)		

Notes: This table elucidates the heterogeneous effects of the SNIP on child development outcomes across subgroups, with Panel A focusing on physical and mental health outcomes, Panel B on cognitive outcomes, and Panel C on noncognitive and behavioral outcomes. The children's sample is stratified based on gender. Columns 1—3 and Columns 4—6 present the results using the baseline equation (9), utilizing the subsample of male and female, respectively. Columns 1 and 4 report the weighted average of dynamic estimates β_l for the post-treatment periods in the corresponding subsamples (De Chaisemartin and d'Haultfoeuille, 2022). All regressions control for age, age square, father's education level, mother's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Standard errors in parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Columns 2 and 5 reflects the number of first differences of the outcome and of the treatment used in the estimation in the subsample of male and female, respectively. The Control Mean in Columns 3 and 6 represents the mean of outcomes for the never-treated group in the corresponding subsamples. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table 4c. Heterogeneous Effects by Mothers' Education Level

	Above Middle School			***Below Middle School***		
	[1]	[2]	[3]	[4]	[5]	[6]
VARIABLES	Estimate	N	Control Mean	Estimate	N	Control Mean
Panel A: Physical and Mental Health Measures						
Hospitalization	0.005	19,916	0.085	-0.093***	16,568	0.063
	(0.040)			(0.027)		
Height	4.656***	22,523	127.856	3.621***	18,931	135.745
	(0.865)			(1.090)		
WHO Standards						
Stunting	-0.082***	21,355	0.192	-0.061	17,434	0.221
	(0.029)			(0.037)		
Underweight	0.019	9,596	0.095	-0.064**	6,811	0.146
	(0.026)			(0.033)		
Overweight	-0.047	22,126	0.256	-0.119***	18,426	0.250
	(0.037)			(0.030)		
Obesity	-0.039	22,126	0.134	-0.094***	18,426	0.127
	(0.028)			(0.025)		
Depression Index	-0.070	11,082	-0.181	-0.006	13,326	-0.108
	(0.094)			(0.117)		
Panel B: Cognitive Outcomes						
School Performance						
Dropout	0.011	19,026	0.062	-0.080*	18,056	0.093
	(0.023)			(0.043)		
Absence	-0.099	9,457	0.252	-0.105	10,750	0.293
	(0.074)			(0.086)		
Cognitive Skill						
Cognitive Test Index	-0.024	7,134	0.216	0.181**	10,232	0.121
	(0.072)			(0.081)		
Academic Performance	0.062	6,049	-0.013	0.575***	6,899	-0.057
	(0.111)			(0.219)		
Panel C: Noncognitive and Behavioral Outcomes						
Noncognitive Outcomes						
Importance of Effort	0.186	3,736	0.086	0.155	4,269	-0.037
	(0.183)			(0.157)		
Importance of Luck	-0.044	3,744	0.005	0.105	4,256	0.070
	(0.165)			(0.168)		
Rosenberg Self-esteem Index	0.027	1,285	-0.006	-0.070	1,887	-0.072
	(0.281)			(0.178)		
Behavioral Outcomes						
Learning Behavior Index	0.132	5,634	-0.015	0.402***	7,830	-0.104
	(0.138)			(0.148)		
Social Competence Index	0.296	1,563	0.043	0.171	1,538	0.009
	(0.265)			(0.140)		
Compliance Index	0.145	1,185	-0.009	-0.050	1,430	0.053
	(0.213)			(0.187)		
Autonomy Index	0.276	1,108	-0.014	0.615***	1,328	-0.040
	(0.311)			(0.225)		

Notes: This table elucidates the heterogeneous effects of the SNIP on child development outcomes across subgroups, with Panel A focusing on physical and mental health outcomes, Panel B on cognitive outcomes, and Panel C on noncognitive and behavioral outcomes. The children's sample is stratified based on whether the respondent's mother has completed middle school. Columns 1—3 and Columns 4—6 present the results using the baseline equation (9), utilizing the subsample of children born to mothers with higher and lower education levels, respectively. Columns 1 and 4 report the weighted average of dynamic estimates β_l for the post-treatment periods in the corresponding subsamples (De Chaisemartin and d'Haultfoeuille, 2022). All regressions control for age, age square, gender, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Standard errors in parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Columns 2 and 5 reflects the number of first differences of the outcome and of the treatment used in the estimation in the subsample of children born to mothers with higher and lower education levels, respectively. The Control Mean in Columns 3 and 6 represents the mean of outcomes for the never-treated group in the corresponding subsamples. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table 4d. Heterogeneous Effects by Fathers' Education Level

	Above Middle School			***Below Middle School***		
	[1]	[2]	[3]	[4]	[5]	[6]
VARIABLES	Estimate	N	Control Mean	Estimate	N	Control Mean
Panel A: Physical and Mental Health Measures						
Hospitalization	-0.043	23,331	0.082	-0.049	13,121	0.068
	(0.048)			(0.040)		
Height	5.090***	26,071	129.509	2.237*	15,396	134.523
	(0.844)			(1.311)		
WHO Standards						
Stunting	-0.114***	24,550	0.198	-0.023	14,243	0.225
	(0.031)			(0.047)		
Underweight	0.004	11,191	0.106	-0.059*	5,522	0.139
	(0.027)			(0.034)		
Overweight	-0.060**	25,590	0.255	-0.088*	14,965	0.253
	(0.024)			(0.046)		
Obesity	-0.058***	25,590	0.132	-0.068*	14,965	0.132
	(0.028)			(0.025)		
Depression Index	0.002	13,953	-0.159	0.022	10,340	-0.114
	(0.099)			(0.127)		
Panel B: Cognitive Outcomes						
School Performance						
Dropout	-0.015	22,588	0.062	-0.039	14,410	0.104
	(0.023)			(0.043)		
Absence	-0.001	11,768	0.248	-0.153*	8,363	0.313
	(0.074)			(0.087)		
Cognitive Skill						
Cognitive Test Index	0.039	9,232	0.197	0.139**	8,173	0.111
	(0.070)			(0.068)		
Academic Performance	0.515***	7,498	-0.020	0.289*	5,399	-0.086
	(0.196)			(0.152)		
Panel C: Noncognitive and Behavioral Outcomes						
Noncognitive Outcomes						
Importance of Effort	-0.014	4,736	0.047	0.258*	3,133	0.002
	(0.132)			(0.155)		
Importance of Luck	-0.046	4,735	0.017	-0.222	3,124	0.091
	(0.170)			(0.162)		
Rosenberg Self-esteem Index	0.080	1,659	0.018	-0.022	1,485	-0.117
	(0.210)			(0.204)		
Behavioral Outcomes						
Learning Behavior Index	0.132***	7,919	-0.048	0.198	5,941	-0.086
	(0.213)			(0.163)		
Social Competence Index	0.318	1,933	0.017	-0.083	1,116	0.055
	(0.265)			(0.218)		
Compliance Index	0.298	1,546	0.005	0.282	1,065	0.045
	(0.200)			(0.313)		
Autonomy Index	0.327	1,466	-0.033	0.482**	980	-0.004
	(0.240)			(0.210)		

Notes: This table elucidates the heterogeneous effects of the SNIP on child development outcomes across subgroups, with Panel A focusing on physical and mental health outcomes, Panel B on cognitive outcomes, and Panel C on noncognitive and behavioral outcomes. The children's sample is stratified based on whether the respondent's father has completed middle school. Columns 1—3 and Columns 4—6 present the results using the baseline equation (9), utilizing the subsample of children born to fathers with higher and lower education levels, respectively. Columns 1 and 4 report the weighted average of dynamic estimates β_l for the post-treatment periods in the corresponding subsamples (De Chaisemartin and d'Haultfoeuille, 2022). All regressions control for age, age square, gender, mother's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Standard errors in parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Columns 2 and 5 reflects the number of first differences of the outcome and of the treatment used in the estimation in the subsample of children born to fathers with higher and lower education levels, respectively. The Control Mean in Columns 3 and 6 represents the mean of outcomes for the never-treated group in the corresponding subsamples. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Potential Mechanism: Parental Labor Outcomes, Monetary and Time Investment in Children, Parenting Styles and Family Dynamics

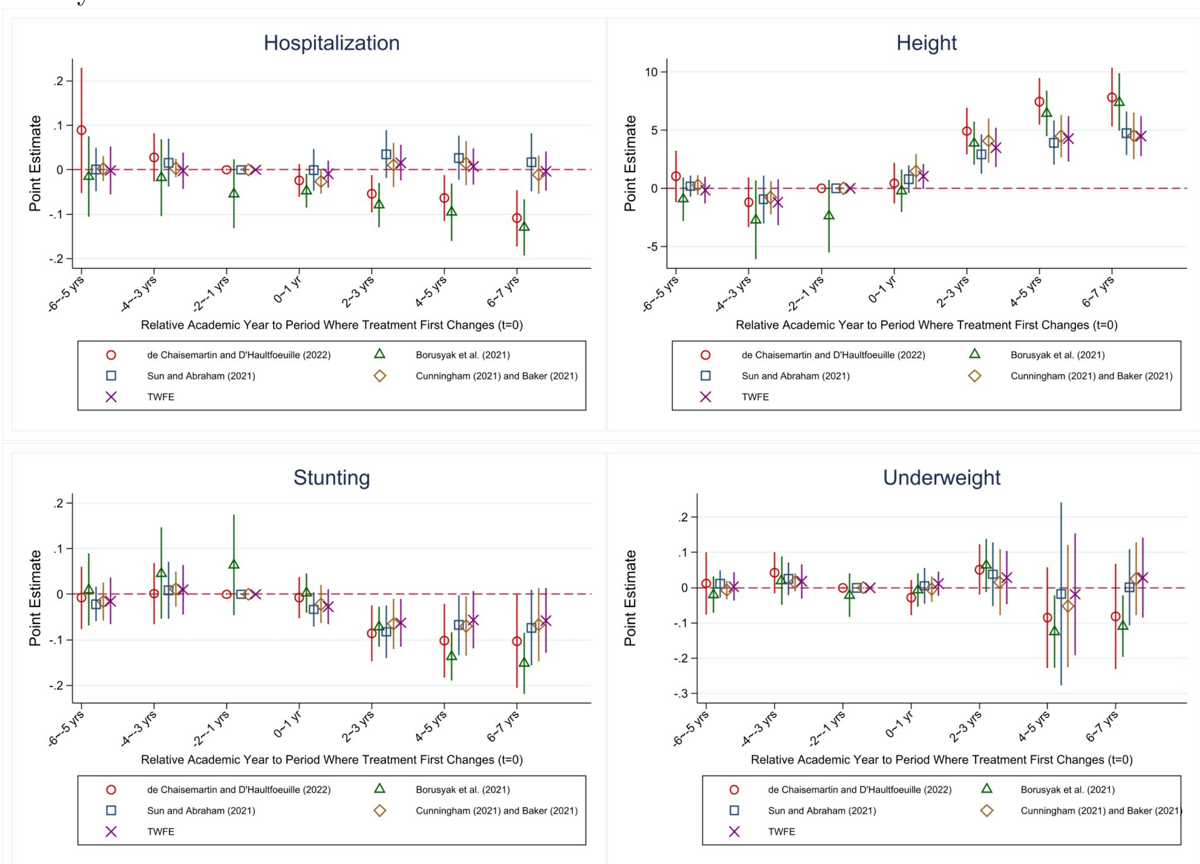
	[1]	[2]	[3]
VARIABLES	Estimate	N	Control Mean
Panel A: Parental Labor Supply and Income			
Labor Force Participation Rate	0.068*	50,699	0.801
	(0.036)		
Employment Rate	0.055	46,927	0.959
	(0.042)		
Monthly Hours Worked	15.023	32,229	176.913
	(11.690)		
Annual Income	0.145*	43,122	9.180
	(0.086)		
Panel B: Nutrition Intake, Monetary and Time Investment			
Egg & Dairy	0.097**	5,837	0.823
	(0.049)		
Annual Food Expenses *(in log)*	-0.323***	42,718	7.805
	(0.095)		
Annual Education Expenses *(in log)*	0.218**	32,124	7.363
	(0.105)		
Annual Medical Expenses *(in log)*	-0.056	22,163	5.872
	(0.156)		
Tutoring Hours	0.346	30,802	1.636
	(0.331)		
Panel C: Parenting Styles and Family Dynamics			
Parenting Styles			
Authoritative	0.321***	6,389	0.318
	(0.106)		
Authoritarian	-0.017	6,389	0.168
	(0.046)		
Permissive	-0.048	6,389	0.136
	(0.058)		
Uninvolved	-0.256**	6,389	0.378
	(0.105)		
Family Dynamics			
Quarrels with Parents	-0.536**	13,272	0.995
	(0.215)		
Quarrels between Parents	-0.455***	12,742	0.627
	(0.159)		
Talks with Parents	0.585	7,661	1.979
	(0.381)		
Parents Check Homework	0.133*	25,104	-0.101
	(0.079)		

Notes: This table examines the effects of the SNIP on potential channels, with parental labor supply and income in Panel A, and nutrition intake, monetary and time investment in Panel B, along with parenting styles and family dynamics in Panel C. Regressions in Panel A use the parents sample, controlling for age, age square, gender, education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Regressions in Panel B and C use the children sample, controlling for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. The Control Mean in Column 3 measures the mean of outcomes for the never-treated group. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

C Appendix Figures & Tables

Figure A1. Effects of SNIP on Child Development Outcomes with Alternative Advanced DD Estimators

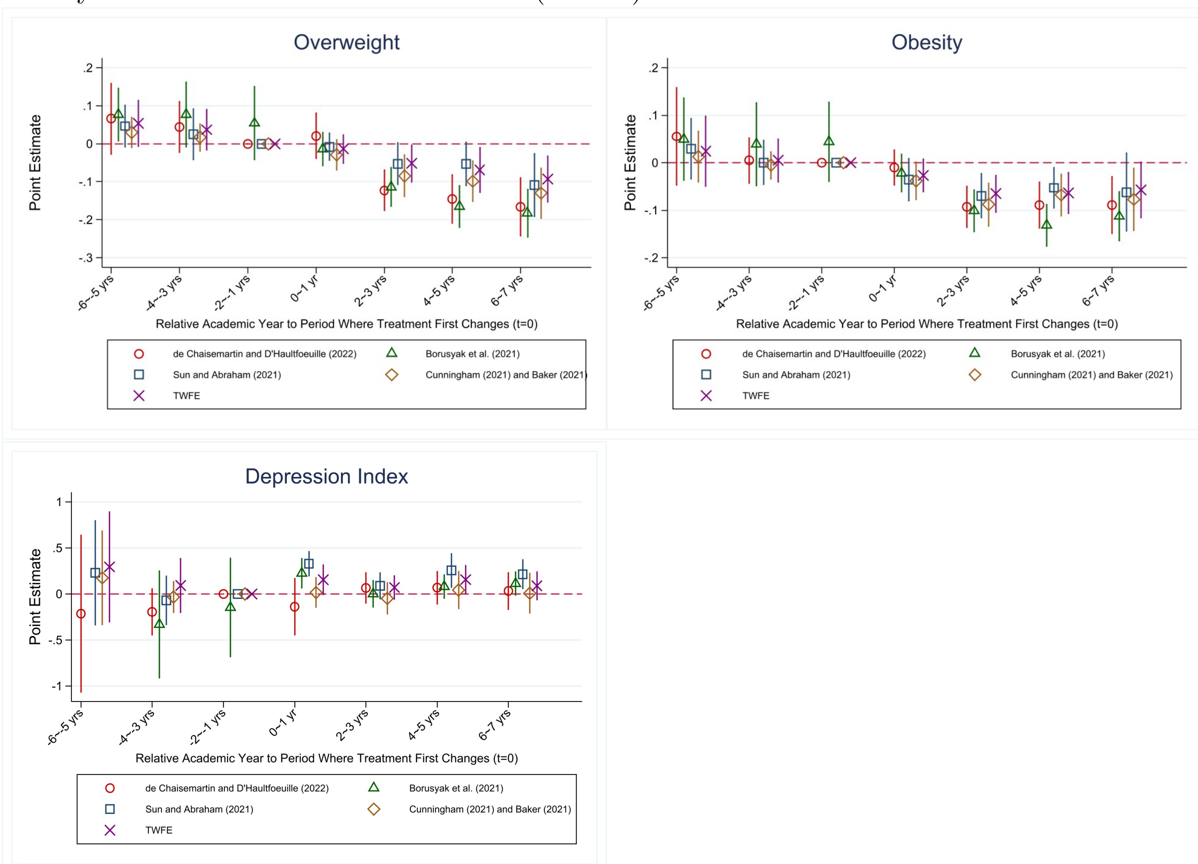
A. Physical and Mental Health Measures



Notes: This figure overlays the event-study plots of child development outcomes, as per equation (9), constructed using five distinct estimators: De Chaisemartin and d'Haultfoeuille (2022) (depicted in red with circle markers), Borusyak et al. (2021) (in green with triangle markers), Sun and Abraham (2021) (in blue with square markers), Cunningham (2021) (in linen with rhombus), and TWFE (in purple with cross markers). The time and group variables align with the definitions in equation (9). The bars denote 95 percent confidence intervals and all regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Notably, the initial four estimators remain unbiased in the presence of heterogeneous dynamic treatment effects, while the TWFE introduces potential bias due to negative weights (Goodman-Bacon, 2021). The standard errors of estimators from De Chaisemartin and d'Haultfoeuille (2022) are clustered at the county c level, computed using 200 bootstrap replications. The standard errors of estimators from TWFE, Borusyak et al. (2021), Cunningham (2021), and Sun and Abraham (2021) are also clustered at the county c level. The method proposed by Callaway and Sant'Anna (2021), *csdid*, calculates standard 2×2 DD estimators for each group and time. Given the limited number of treated counties in some waves (as listed in Table A2), some 2×2 estimators might be omitted. Consequently, the effects obtained using this methodology cannot be estimated.

Figure A1. Effects of SNIP on Child Development Outcomes with Alternative Advanced DD Estimators (Cont'd)

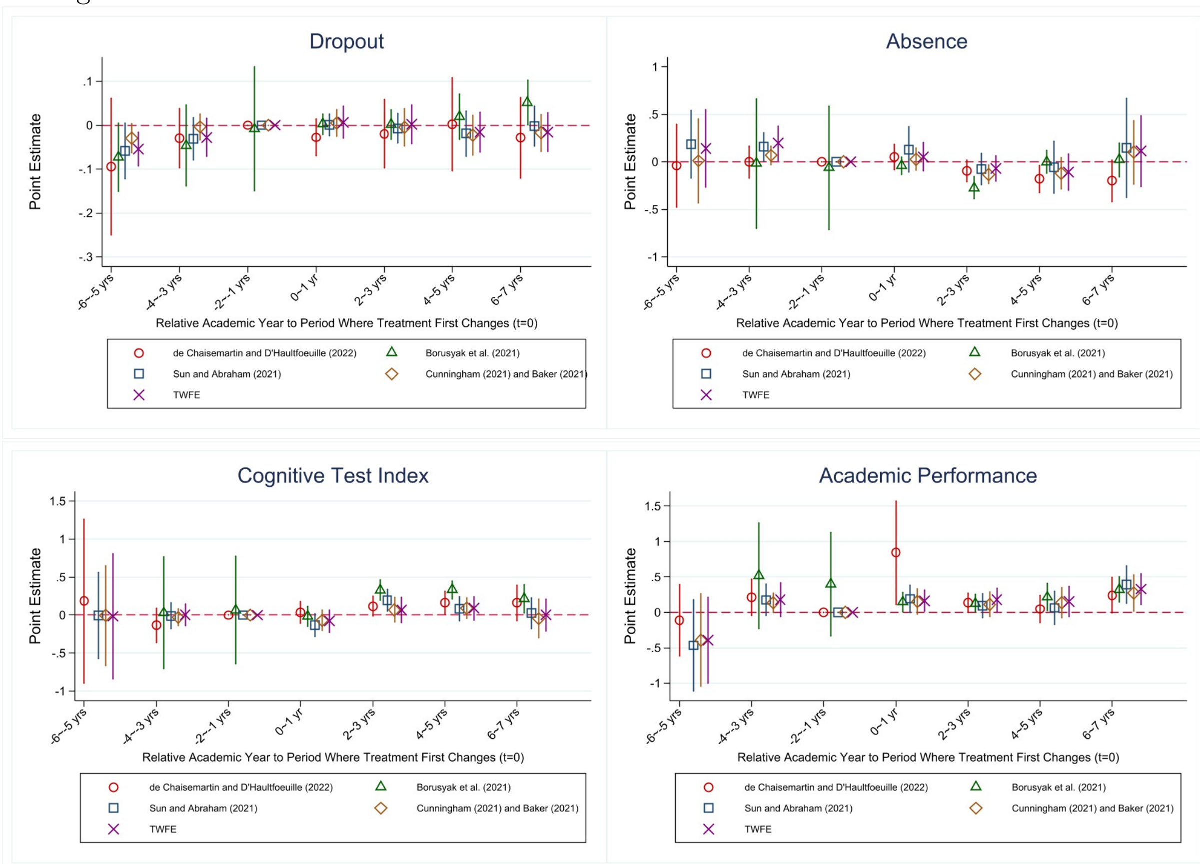
A. Physical and Mental Health Measures (Cont'd)



Notes: This figure overlays the event-study plots of child development outcomes, as per equation (9), constructed using five distinct estimators: De Chaisemartin and d'Haultfoeuille (2022) (depicted in red with circle markers), Borusyak et al. (2021) (in green with triangle markers), Sun and Abraham (2021) (in blue with square markers), Cunningham (2021) (in linen with rhombus), and TWFE (in purple with cross markers). The time and group variables align with the definitions in equation (9). The bars denote 95 percent confidence intervals and all regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Notably, the initial four estimators remain unbiased in the presence of heterogeneous dynamic treatment effects, while the TWFE introduces potential bias due to negative weights (Goodman-Bacon, 2021). The standard errors of estimators from De Chaisemartin and d'Haultfoeuille (2022) are clustered at the county c level, computed using 200 bootstrap replications. The standard errors of estimators from TWFE, Borusyak et al. (2021), Cunningham (2021), and Sun and Abraham (2021) are also clustered at the county c level. The method proposed by Callaway and Sant'Anna (2021), *csdid*, calculates standard 2×2 DD estimators for each group and time. Given the limited number of treated counties in some waves (as listed in Table A2), some 2×2 estimators might be omitted. Consequently, the effects obtained using this methodology cannot be estimated.

Figure A1. Effects of SNIP on Child Development Outcomes with Alternative Advanced DD Estimators (Cont'd)

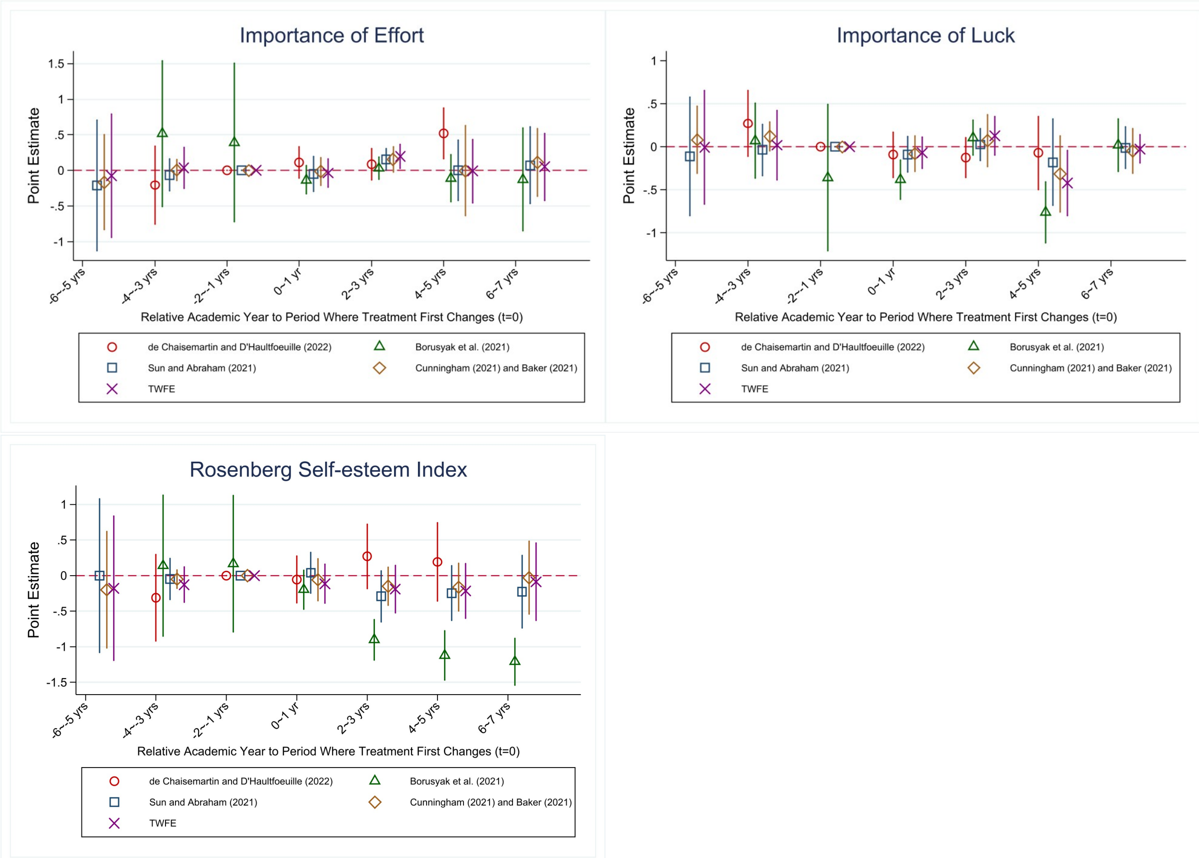
B. Cognitive Outcomes



Notes: This figure overlays the event-study plots of child development outcomes, as per equation (9), constructed using five distinct estimators: De Chaisemartin and d'Haultfoeuille (2022) (depicted in red with circle markers), Borusyak et al. (2021) (in green with triangle markers), Sun and Abraham (2021) (in blue with square markers), Cunningham (2021) (in linen with rhombus), and TWFE (in purple with cross markers). The time and group variables align with the definitions in equation (9). The bars denote 95 percent confidence intervals and all regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Notably, the initial four estimators remain unbiased in the presence of heterogeneous dynamic treatment effects, while the TWFE introduces potential bias due to negative weights (Goodman-Bacon, 2021). The standard errors of estimators from De Chaisemartin and d'Haultfoeuille (2022) are clustered at the county c level, computed using 200 bootstrap replications. The standard errors of estimators from TWFE, Borusyak et al. (2021), Cunningham (2021), and Sun and Abraham (2021) are also clustered at the county c level. The method proposed by Callaway and Sant'Anna (2021), *csdid*, calculates standard 2×2 DD estimators for each group and time. Given the limited number of treated counties in some waves (as listed in Table A2), some 2×2 estimators might be omitted. Consequently, the effects obtained using this methodology cannot be estimated.

Figure A1. Effects of SNIP on Child Development Outcomes with Alternative Advanced DD Estimators (Cont'd)

C. Noncognitive Outcomes



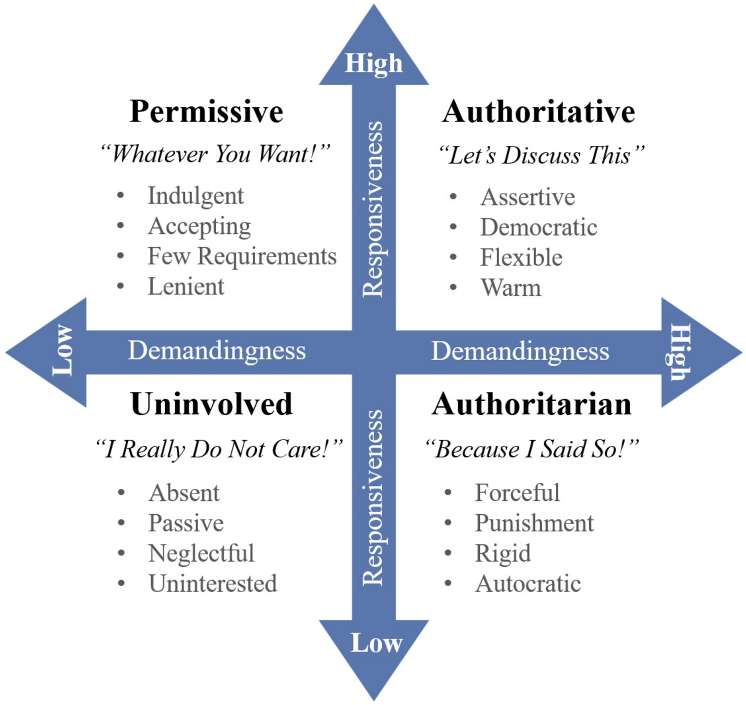
Notes: This figure overlays the event-study plots of child development outcomes, as per equation (9), constructed using five distinct estimators: De Chaisemartin and d'Haultfoeuille (2022) (depicted in red with circle markers), Borusyak et al. (2021) (in green with triangle markers), Sun and Abraham (2021) (in blue with square markers), Cunningham (2021) (in linen with rhombus), and TWFE (in purple with cross markers). The time and group variables align with the definitions in equation (9). The bars denote 95 percent confidence intervals and all regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Notably, the initial four estimators remain unbiased in the presence of heterogeneous dynamic treatment effects, while the TWFE introduces potential bias due to negative weights (Goodman-Bacon, 2021). The standard errors of estimators from De Chaisemartin and d'Haultfoeuille (2022) are clustered at the county c level, computed using 200 bootstrap replications. The standard errors of estimators from TWFE, Borusyak et al. (2021), Cunningham (2021), and Sun and Abraham (2021) are also clustered at the county c level. The method proposed by Callaway and Sant'Anna (2021), *csdid*, calculates standard 2×2 DD estimators for each group and time. Given the limited number of treated counties in some waves (as listed in Table A2), some 2×2 estimators might be omitted. Consequently, the effects obtained using this methodology cannot be estimated.

Figure A1. Effects of SNIP on Child Development Outcomes with Alternative Advanced DD Estimators (Cont'd)

D. Behavioral Outcomes

Notes: This figure overlays the event-study plots of child development outcomes, as per equation (9), constructed using five distinct estimators: De Chaisemartin and d'Haultfoeuille (2022) (depicted in red with circle markers), Borusyak et al. (2021) (in green with triangle markers), Sun and Abraham (2021) (in blue with square markers), Cunningham (2021) (in linen with rhombus), and TWFE (in purple with cross markers). The time and group variables align with the definitions in equation (9). The bars denote 95 percent confidence intervals and all regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Notably, the initial four estimators remain unbiased in the presence of heterogeneous dynamic treatment effects, while the TWFE introduces potential bias due to negative weights (Goodman-Bacon, 2021). The standard errors of estimators from De Chaisemartin and d'Haultfoeuille (2022) are clustered at the county c level, computed using 200 bootstrap replications. The standard errors of estimators from TWFE, Borusyak et al. (2021), Cunningham (2021), and Sun and Abraham (2021) are also clustered at the county c level. The method proposed by Callaway and Sant'Anna (2021), *csdid*, calculates standard 2×2 DD estimators for each group and time. Given the limited number of treated counties in some waves (as listed in Table A2), some 2×2 estimators might be omitted. Consequently, the effects obtained using this methodology cannot be estimated.

Figure A2. Four-type Parenting Styles



Notes: Each parenting style is discernible through specific characteristics, as well as varying degrees of responsiveness (indicating how warm and sensitive parents are to their children's needs) and demandingness (reflecting the level of control parents exert to influence their children's behaviors).

Table A1a. Respondents of Outcomes

Variables	Respondents					
	Wave 2010	**Wave 2012**	**Wave 2014**	**Wave 2016**	**Wave 2018**	**Wave 2020**
Physical and Mental Health Measures						
Hospitalization	All	All	All	All	All	All
Height	All	All	All	All	All	All
WHO Growth Standards						
Stunting	0—19	0—19	0—19	0—19	0—19	0—19
Underweight	0—10; 18+	0—10; 18+	0—10; 18+	0—10; 18+	0—10; 18+	0—10; 18+
Overweight/Obesity	All	All	All	All	All	All
Depression Index	10+	10+	10+	10+	10+	10+
Cognitive Outcomes						
School Performance						
Dropout	6+	6+	6+	6+	6+	6+
Absence	10+ in school	10+ in school	10+ in school	10+ in school	10+ in school	10+ in school
Cognitive Skill						
Cognitive Test Index						
Word & Math Test	10+	X	10+	X	10+	X
Memory & Number Series Test	X	10+	X	10+	X	10+
Academic Performance	10—15	10—15	10—15	10—15	10—15	10—15
Noncognitive and Behavioral Outcomes						
Noncognitive Outcomes						
Importance of Effort/ Luck	12; 14; 16+	10—15	10—21 with no historical records in last wave	X	X	10—21
Rosenberg Self-esteem Index	10	10; 12; 14	10—21 with no historical records	10—23 with no historical records	10—23 with no historical records	X
Behavioral Outcomes						
Learning Behavior Index	6+ in school	6+ in school	6+ in school	6+ in school	6+ in school (25% random selection)	10+ in school
Social Competence/ Compliance / Autonomy Index	7; 11; 15	3; 7; 11; 15	3—15 with no historical records in wave 2012	X	X	X

Notes: Weight-for-age reference data are unavailable beyond age 10 due to the inherent limitation of this indicator, which fails to distinguish between height and body mass during the pubertal growth spurt. This period can lead to misinterpretation, where children may appear to have excess weight (by weight-for-age) when, in reality, they are experiencing increased height (World Health Organization, 2007). (Source: https://www.who.int/tools/growth-reference-data-for-5to19-years/indicators/weight-for-age-5to10-years). The Rosenberg Self-esteem Index comprises 9 questions in wave 2012 and 10 questions in waves 2010, 2014, 2016, and 2018. Therefore, we are unable to construct the self-esteem index for the year 2012 to maintain uniformity in the questions used across different waves. The variables labeled with X indicate that the questions related to the corresponding variable are not survey in some waves.

Table A1b. Respondents of Channels

Variables	Respondents					
	Wave 2010	**Wave 2012**	**Wave 2014**	**Wave 2016**	**Wave 2018**	**Wave 2020**
Parental Labor Supply and Income						
Labor Force/ Employed/ Monthly Hours Worked/ Annual Income *(in log)* / Occupation	All	All	All	All	All	All
Family Expenses						
Total Annual Expenses *(in log)*	All	All	All	All	All	All
Proportion of Items	All	All	All	All	All	All
Nutrition Intakes, Monetary and Time Investment						
Egg & Dairy	10+	10+	10+	X	X	X
Annual Food Expenses *(in log)*	All	All	All	All	All	All
Annual Education Expenses *(in log)*	3+ in school	3+ in school	3+ in school	3+ in school	3+ in school	3+ in school
Annual Medical Expenses *(in log)*	All	All	All	All	All	All
Tutoring Hours	0—15 in school	0—15 in school	0—15 in school	0—15 in school	0—15 in school	0—15 in school
Parenting Styles and Family Dynamics						
Parenting Styles						
Authoritative/ Authoritarian/ Permissive /Uninvolved	11	11; 13; 15	10—15	X	X	10—15
Family Dynamics						
Quarrels with Parents/ Quarrels between Parents/ Talks with Parents	10—15	10—15	10—15	10—15	10—15	10—15
Parents Check Homework	6—15	6—15	6—15	3—15	3—15	3—19

Notes: The variables labeled with X indicate that the questions related to the corresponding variable are not survey in some waves.

Table A2. Implementation Academic Year of Survey Counties in CFPS

County Name	**Adoption Year**	**County Name**	**Adoption Year**
Xiuyu	2009	Huangpu	2012
Gutian	2009	Luwan	2012
Baqiao	2009	Xuhui	2012
Baishui	2009	Changning	2012
Suide	2009	Putuo	2012
Jiulongpo	2010	Zhabei	2012
Shangsi	2011	Hongkou	2012
Jingdong	2011	Yangpu	2012
Binchuan	2011	Minxing	2012
Yuexi	2011	Baoshan	2012
Guanyang	2011	Jiading	2012
Baokang	2011	Pudong	2012
Jiangyin	2011	Jinshan	2012
Haizhou	2011	Songjiang	2012
Jiangdu	2011	Qingpu	2012
Huaning	2011	Nanhui	2012
Mengzi	2011	Fengxian	2012
Wushan	2011	Chongming	2012
Wuchuan	2011	Yingde	2012
Wangmo	2011	Qilihe	2012
Leishan	2011	Baiyin	2012
Changshun	2011	Qinzhou	2012
Chunan	2011	Liangzhou	2012
Yuyao	2011	Xifeng	2012
Yuhuan	2011	Kaili	2013
Qingchuan	2011	Neixiang	2013
Qingshen	2011	Changzhi	2013
Gong	2011	Yangxi	2014
Jinyang	2011	Ningwu	2015
Daofu	2011	Liulin	2016
Yangyuan	2011	Qinglong	2017
Huiyuan	2011	Julu	2017
Jinkouhe	2011	Wuyi	2017
Tuocheng	2011	Pingyu	2017
Huaibin	2011	Xinle	2019
Huaiyang	2011	She	2019
Yuzhong	2011	Sanhe	2019
Jingtai	2011	Feixi	Not Yet
Qingshui	2011	Guangde	Not Yet
Wushan	2011	Dieshan	Not Yet
Lingtai	2011	Dongxihu	Not Yet
Ningxian	2011	Xiling	Not Yet
Tongwei	2011	Xinfeng	Not Yet
Lintao	2011	Qingyuan	Not Yet
Lixian	2011	Lichuan	Not Yet
Liangdang	2011	Furong	Not Yet
Linxia	2011	Yuetang	Not Yet

Notes: The adoption year refers to academic year, i.e., the fall semester in 2009 and spring semester in 2010 belong to the same academic year 2009. The counties labelled with *Not Yet* had not implemented the nutrition policy until the end of 2020. Since the first survey wave of CFPS is year 2010, then always-treated individuals in counties implemented the policy before 2011 will be recognized as always-treated groups in the design. Hence, they will be automatically excluded from the regression sample.

Table A2. Implementation Academic Year of Survey Counties in CFPS (Cont'd)

County Name	**Adoption Year**	**County Name**	**Adoption Year**
Hengshan	Not Yet	Weidu	Not Yet
Yueyang	Not Yet	Huiyuan	Not Yet
Qiyang	Not Yet	Dengzhou	Not Yet
Louxing	Not Yet	Suiping	Not Yet
Dujiangyan	Not Yet	Tianhe	Not Yet
Shifang	Not Yet	Nansha	Not Yet
Chongwen	Not Yet	Wengyuan	Not Yet
Yunhe	Not Yet	Jinwan	Not Yet
Tahe	Not Yet	Jinjiang	Not Yet
Acheng	Not Yet	Pengjiang	Not Yet
Didao	Not Yet	Leizhou	Not Yet
Xingan	Not Yet	Maonan	Not Yet
Saertu	Not Yet	Gaozhou	Not Yet
Tiedong	Not Yet	Dongguan	Not Yet
Tonghua	Not Yet	Rongcheng	Not Yet
Ningjiang	Not Yet	Huilai	Not Yet
Zhangqiu	Not Yet	Luoding	Not Yet
Yiyuan	Not Yet	Dadong	Not Yet
Pengzhou	Not Yet	Su Jiatun	Not Yet
Penglai	Not Yet	Zhongshan	Not Yet
Donggang	Not Yet	Wafangdian	Not Yet
Laicheng	Not Yet	Tiexi	Not Yet
Ling	Not Yet	Lishan	Not Yet
Wanrong	Not Yet	Mingshan	Not Yet
Quwo	Not Yet	Zhenxing	Not Yet
Yingze	Not Yet	Taihe	Not Yet
Hangu	Not Yet	Dashiqiao	Not Yet
Zhongyuan	Not Yet	Fuxin	Not Yet
Weishi	Not Yet	Liaoyang	Not Yet
Mengjin	Not Yet	Tieling	Not Yet
Jia	Not Yet	Chaoyang	Not Yet
Hua	Not Yet	Longgang	Not Yet
Yanjin	Not Yet	Faku	Not Yet
Jiefang	Not Yet	Xingning	Not Yet

Notes: The adoption year refers to academic year, i.e., the fall semester in 2009 and spring semester in 2010 belong to the same academic year 2009. The counties labelled with *Not Yet* had not implemented the nutrition policy until the end of 2020. Since the first survey wave of CFPS is year 2010, then always-treated individuals in counties implemented the policy before 2011 will be recognized as always-treated groups in the design. Hence, they will be automatically excluded from the regression sample.

Table A3a. Effects of SNIP on Items of Rosenberg Self-esteem and Learning Behavior Indices

VARIABLES	[1] Estimate	[2] N	[3] Control Mean
Panel A: Items of Rosenberg Self-esteem Index			
Person Worth	0.075	3,693	-0.001
	(0.174)		
Good Quality	-0.161	3,693	-0.036
	(0.164)		
Be Failure	-0.029	3,693	0.015
	(0.209)		
As Well As	-0.028	3,693	-0.053
	(0.194)		
Not Proud	-0.178	3,693	0.037
	(0.149)		
Positive Attitude	0.169	3,693	-0.019
	(0.193)		
Self Satisfy	-0.168	3,693	0.006
	(0.186)		
More Respect	0.079	3,693	0.004
	(0.150)		
Feel Useless	0.120	3,693	-0.004
	(0.154)		
Not Good	-0.099	3,693	0.002
	(0.180)		
Panel B: Items of Learning Behavior Index			
Study Hard	0.316**	14,278	-0.067
	(0.124)		
Concentrate	0.079	14,278	-0.065
	(0.072)		
Self-check Homework	0.287*	14,278	-0.027
	(0.152)		
Disciplined	0.187**	14,278	-0.042
	(0.077)		
Tidiness	0.205**	14,278	-0.014
	(0.085)		
Play After Homework	0.280**	14,278	-0.029
	(0.125)		

Notes: This table explores the effects of SNIP on items of *Rosenberg self-esteem index* in Panel A, and those of *learning behavior index* in Panel B. All regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. Control Mean in Column 3 measures the mean of outcome for never-treated group. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table A3b. Effects of SNIP on Items of Positive Behavior Scale

VARIABLES	[1] Estimate	[2] N	[3] Control Mean
Panel A: Items of Social Competence Index			
Cheerful	0.112	3,256	0.036
	(0.149)		
Neat Work	0.194	3,256	0.011
	(0.163)		
Be Curious	0.734***	3,256	0.025
	(0.222)		
Get Along	0.050	3,256	0.015
	(0.128)		
Tolerate Others	-0.152	3,256	-0.019
	(0.143)		
Help Others	0.296*	3,256	0.020
	(0.169)		
Get Over	-0.034	3,256	0.021
	(0.131)		
Be Admired	0.251	3,256	0.037
	(0.158)		
Panel B: Items of Compliance Index			
Concentrate	-0.052	2,827	0.005
	(0.167)		
Disciplined	-0.188	2,827	0.031
	(0.116)		
Accomplish	0.002	2,827	0.015
	(0.139)		
Wait for Turn	0.497**	2,827	-0.018
	(0.230)		
Not Impulsive	-0.170	2,827	-0.003
	(0.151)		
Do Tell	0.388**	2,827	0.006
	(0.170)		
Panel C: Items of Autonomy Index			
Play After Homework	0.526**	2,647	-0.015
	(0.215)		
Self-reliant	0.249	2,647	-0.005
	(0.156)		

Notes: This table explores the effects of SNIP on items of *positive behavior scales*, with items of social competence index in Panel A, those of compliance index in Panel B, and those of autonomy index in Panel C. All regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. Control Mean in Column 3 measures the mean of outcome for never-treated group. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table A4a. Robustness Check I: Controlling County-specific Linear Time Trend

VARIABLES	[1] Estimate	[2] Estimate	[3] N	[4] Control Mean
Panel A: Physical and Mental Health Measures				
Hospitalization	-0.065***	-0.015	37,248	0.077
	(0.022)	(0.020)		
Height	4.533***	6.588***	41,603	131.173
	(0.865)	(1.117)		
WHO Growth Standards				
Stunting	-0.065**	-0.114***	38,900	0.207
	(0.029)	(0.020)		
Underweight	-0.025	-0.016	19,149	0.116
	(0.025)	(0.024)		
Overweight	-0.089***	-0.126***	40,703	0.254
	(0.025)	(0.022)		
Obesity	-0.065***	-0.089***	40,703	0.131
	(0.020)	(0.019)		
Depression Index	0.005	-0.024	24,755	-0.140
	(0.081)	(0.076)		
Panel B: Cognitive Outcomes				
School Performance				
Dropout	-0.019	-0.013	37,315	0.078
	(0.035)	(0.017)		
Absence	-0.089	-0.032	20,544	0.274
	(0.054)	(0.047)		
Cognitive Skill				
Cognitive Test Index	0.115*	0.290***	17,811	0.160
	(0.063)	(0.054)		
Academic Performance	0.391**	0.327**	13,218	-0.032
	(0.156)	(0.154)		
Panel C: Noncognitive and Behavioral Outcomes				
Noncognitive Outcomes				
Importance of Effort	0.210**	0.167**	8,423	0.031
	(0.093)	(0.080)		
Importance of Luck	-0.095	-0.187*	8,416	0.043
	(0.115)	(0.104)		
Rosenberg Self-esteem Index	0.055	-0.022	3,693	-0.045
	(0.171)	(0.144)		
Behavioral Outcomes				
Learning Behavior Index	0.359**	0.278**	14,278	-0.061
	(0.141)	(0.126)		
Social Competence Index	0.315*	0.216	3,256	0.031
	(0.165)	(0.136)		
Compliance Index	0.150	0.267*	2,827	0.020
	(0.177)	(0.141)		
Autonomy Index	0.528***	0.589***	2,647	-0.024
	(0.200)	(0.173)		

Notes: This table rigorously examines the impacts of SNIP on child development outcomes, comparing baseline specifications with models that control for county-specific linear time trends. Physical and mental health outcomes are presented in Panel A, cognitive outcomes in Panel B, and noncognitive and behavioral outcomes in Panel C. The regressions in Column 1 incorporate controls for age, age square, gender, mother's education level, father's education level, the poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies, following the framework of equation (9). The regressions in Column 2 further introduce the county-specific linear time trend and include all variables from the baseline regression. Columns 1 and 2 report the weighted average of dynamic estimates β_l for the post-treatment periods, utilizing the DID_l estimation method proposed by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 3 reflects the number of first differences of the outcome and of the treatment used in the estimation. Column 4 provides the Control Mean, representing the mean of the outcome for the never-treated group. Significance level: * p<0.10, ** p<0.05, *** p<0.01.

Table A4b. Robustness Check II: Multiple Hypotheses Testing

VARIABLES	[1] Estimate	[2] p-value	[3] Sharpened q-value	[4] N	[5] Control Mean
Panel A: Physical and Mental Health Measures					
Hospitalization	-0.065***	0.003	0.013	37,248	0.077
	(0.022)				
Height	4.533***	0.000	0.000	41,603	131.173
	(0.865)				
WHO Growth Standards					
Stunting	-0.065**	0.026	0.033	38,900	0.207
	(0.029)				
Underweight	-0.025	0.325	0.176	19,149	0.116
	(0.025)				
Overweight	-0.089***	0.000	0.002	40,703	0.254
	(0.025)				
Obesity	-0.065***	0.001	0.007	40,703	0.131
	(0.020)				
Depression Index	0.005	0.951	0.464	24,755	-0.140
	(0.081)				
Panel B: Cognitive Outcomes					
School Performance					
Dropout	-0.019	0.589	0.284	37,315	0.078
	(0.035)				
Absence	-0.089	0.100	0.081	20,544	0.274
	(0.054)				
Cognitive Skill					
Cognitive Test Index	0.115*	0.067	0.058	17,811	0.160
	(0.063)				
Academic Performance	0.391**	0.012	0.026	13,218	-0.032
	(0.156)				
Panel C: Noncognitive and Behavioral Outcomes					
Noncognitive Outcomes					
Importance of Effort	0.210**	0.025	0.033	8,423	0.031
	(0.093)				
Importance of Luck	-0.095	0.408	0.195	8,416	0.043
	(0.115)				
Rosenberg Self-esteem Index	0.055	0.746	0.357	3,693	-0.045
	(0.171)				
Behavioral Outcomes					
Learning Behavior Index	0.359**	0.011	0.026	14,278	-0.061
	(0.141)				
Social Competence Index	0.315*	0.056	0.054	3,256	0.031
	(0.165)				
Compliance Index	0.150	0.397	0.195	2,827	0.020
	(0.177)				
Autonomy Index	0.528***	0.008	0.024	2,647	-0.024
	(0.200)				

Notes: This table illustrates the results of multiple hypotheses testing, focusing on physical and mental health outcomes in Panel A, cognitive outcomes in Panel B, and noncognitive and behavioral outcomes in Panel C. All regressions controls for age, age square, gender, mother's education level, father's education level, the poor county indicator interacted with wave dummies, and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods, utilizing the DID_l estimation method suggested by De Chaisemartin and d'Haultfoeuille (2022). Columns 2 presents the p-value in baseline regression, and Column 3 shows the sharpened q-value using the approach proposed by Anderson (2008b). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 4 reflects the number of first differences of the outcome and of the treatment used in the estimation. Column 5 provides the Control Mean, representing the mean of the outcome for the never-treated group. Significance level: * p<0.10, ** p<0.05, *** p<0.01.

Table A4c. Robustness Check III: Bound Estimation

VARIABLES	[1] Estimate	[2] Estimate	[3] Estimate
Panel A: Physical and Mental Health Measures			
Hospitalization	-0.065***		
	(0.022)		
Height	4.533***	4.324***	5.090***
	(0.865)	(0.867)	(0.822)
WHO Growth Standards			
Stunting	-0.065**	-0.062**	-0.076***
	(0.029)	(0.030)	(0.029)
Underweight	-0.025	-0.023	-0.038
	(0.025)	(0.025)	(0.025)
Overweight	-0.089***	-0.104***	-0.085***
	(0.025)	(0.025)	(0.024)
Obesity	-0.065***	-0.082***	-0.063***
	(0.020)	(0.020)	(0.020)
Depression Index	0.005	-0.068	0.026
	(0.081)	(0.079)	(0.080)
Panel B: Cognitive Outcomes			
School Performance			
Dropout	-0.019		
	(0.035)		
Absence	-0.089	-0.183***	-0.089
	(0.054)	(0.052)	(0.054)
Cognitive Skill			
Cognitive Test Index	0.115*	0.089	0.155**
	(0.063)	(0.063)	(0.065)
Academic Performance	0.391**	0.391**	0.423***
	(0.156)	(0.156)	(0.158)
Panel C: Noncognitive and Behavioral Outcomes			
Noncognitive Outcomes			
Importance of Effort	0.210**	0.210**	0.267***
	(0.093)	(0.093)	(0.096)
Importance of Luck	-0.095	-0.106	-0.066
	(0.115)	(0.115)	(0.102)
Rosenberg Self-esteem Index	0.055	0.007	0.099
	(0.171)	(0.170)	(0.173)
Behavioral Outcomes			
Learning Behavior Index	0.359**	0.321**	0.412***
	(0.141)	(0.142)	(0.132)
Social Competence Index	0.315*	0.275*	0.358**
	(0.165)	(0.165)	(0.164)
Compliance Index	0.150	0.128	0.192
	(0.177)	(0.177)	(0.176)
Autonomy Index	0.528***	0.528***	0.540***
	(0.200)	(0.200)	(0.201)

Notes: This table explores the results of bound estimations, focusing on physical and mental health outcomes in Panel A, cognitive outcomes in Panel B, noncognitive and behavioral outcomes in Panel C. All regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). Estimates in Columns 2 and 3 are derived using the same method yet different samples, by replacing the top and bottom 1.88% of corresponding outcomes with missing values, respectively. Since *hospitalization* and *dropout* are 0/1 dummy from original questionnaire, we cannot conduct bound estimation on these two variables. For other binary variables, such as *stunting*, *underweight*, *overweight*, *obesity*, we drop top and bottom using variables (i.e. BMI/BMI-for-age) which are used to define this dummies, respectively. All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table A4d. Alternative Definition of Growth Indicators Scale

Standards	***Organization***	***Year***	***Age***	***Indicators***	***Definition***
IOTF Standards	International Obesity Task Force	2000	2-18 yrs	*Overweight*	For children aged 2—18, overweight is BMI value > the cutoff points for males and females separately; For adults, overweight is defined with BMI ≥ 25.
				Obesity	For children aged 2—18, obesity is BMI value > the cutoff points for males and females separately; For adults, obesity is defined with BMI ≥ 30.
WGOC Standards	National Health Commission, China	2018	6-18 yrs	*Overweight*	For children aged 6—18, overweight is BMI value > the cutoff points for males and females separately; For adults, overweight is defined with BMI ≥ 25.
				Obesity	For children aged 6—18, obesity is BMI value > the cutoff points for males and females separately; For adults, obesity is defined with BMI ≥ 30.
Students' Physical Test Standards	Ministry of Education, China	2014	6-22 yrs	*Underweight*	For students aged 6—22, underweight is BMI value ≤ the cutoff points for males, females and different grades separately; For adults, overweight is defined with BMI < 18.5.
				Overweight	For students aged 6—22, overweight is BMI value ≥ the cutoff points for males, females and different grades separately; For adults, overweight is defined with BMI ≥ 25.
				Obesity	For students aged 6—22, obesity is BMI value ≥ the cutoff points for males, females and different grades separately; For adults, obesity is defined with BMI ≥ to 30.

Source: IOTF Standards — Cole et al. (2000); WGOC Standards — National Health Commission, China (2018); Students' Physical Test Standards — Ministry of Education, China (2014b).

Table A4e. Robustness Check IV: Effects of SNIP on Alternative Growth Indicators

	[1]	[2]	[3]
VARIABLES	Estimate	N	Control Mean
Panel A: WHO Growth Standards (Baseline)			
Underweight	-0.025	19,149	0.116
	(0.025)		
Overweight	-0.089***	40,703	0.254
	(0.025)		
Obesity	-0.065***	40,703	0.131
	(0.020)		
Panel B: IOTF Standards			
Overweight	-0.020	40,221	0.223
	(0.027)		
Obesity	-0.029	40,221	0.111
	(0.020)		
Panel C: WGOC Standards			
Overweight	-0.056*	34,914	0.212
	(0.030)		
Obesity	-0.042*	34,914	0.111
	(0.023)		
Panel D: Students' Physical Test Standards			
Underweight	0.061**	34,914	0.153
	(0.028)		
Overweight	-0.046*	34,914	0.168
	(0.026)		
Obesity	-0.052**	34,914	0.080
	(0.025)		

Notes: This table explores the effects of SNIP on alternative growth indicators as defined in Supplementary Table A4d, with indicators defined by *WHO Growth Standards (Baseline)* in Panel A, those defined by *IOTF Standards* in Panel B, those defined by *WGOC Standards* in Panel C, and those defined by *Students' Physical Test Standards* in Panel D. All regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. Control Mean in Column 3 measures the mean of outcome for never-treated group. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table A5a. Definition of Parental Labor Supply and Income, Nutrition Intake, Monetary and Time Investment

Parental Labor Supply and Income, Nutrition Intake, Monetary and Time Investment	
Parental Labor Supply and Income	
In the Labor Force	Having work (including self-employed) or searching for a job in the last month? *(1. Yes; 0. No)*
Employed	Are you employed by others or self-employed? *(1. Yes; 0. No)*
Monthly Hours Worked	Hours spent on working in last month
Annual Income *(in log)*	The amount of money received from work in last year
Agriculture Industry	Current occupation belongs to agriculture industry *(1. Yes; 0. No)*
Manufacture Industry	Current occupation belongs to manufacture industry *(1. Yes; 0. No)*
Service Industry	Current occupation belongs to service industry *(1. Yes; 0. No)*
Nutrition Intake, Monetary and Time Investment	
Egg & Dairy	Whether took eggs or dairy in last month *(1. Yes; 0. No)*
Annual Food Expenses *(in log)*	The amount of household food expenditures per family member in last year
Annual Education Expenses *(in log)*	The amount of the child's educational expenditures in last year
Annual Medical Expenses *(in log)*	The amount of the child's medical expenditures in last year
Tutoring Hours	The average hours that father and mother spent on tutoring the child's study in each week during last semester

Notes: Regarding parental labor supply, the average of both mother's and father's labor market outcomes (i.e., labor force participation, employment status, monthly hours worked, and annual income) within each household is considered. For example, if a child's mother is employed while the father has stopped job searching, the household labor force participation rate for that child is calculated as 50%. In the case of a child from a single-parent family with an employed parent, the household labor force participation rate is 100%. For self-employed individuals, *annual income* is the net profit from their own business (i.e., agriculture). Agriculture industry includes agriculture, forestry, stock-breeding, fishing, and mining. Manufacturing industry encompasses all jobs related to manufacturing. Service industry covers various sectors such as construction, transportation, information technology, wholesale and retail, accommodation, catering, finance, real estate, leasing, research, environment, residence service, health, social welfare, culture, sports, amusement, and education. When using monetary outcomes (*annual income*, *annual food expenses*, *annual education expenses*, and *annual medical expenses*) as dependent variables, we use the one year before the interview time point as the time variable. For example, if a respondent answers the corresponding question in the year 2012, the response reflects the annual income/expenditures of this respondent in the year 2011. We replace the original value of time variable for that respondent with 2011.

Table A5b. Definition of Parenting Styles and Family Dynamics

Parenting Styles & Family Dynamics	
Parenting Styles	*We use principal-component analysis method to create two dimensions, parents' responsiveness and demandingness. And we take the median as the cutoff point of these two dimensions separately.*
Authoritative	Responsive as well as demanding
Authoritarian	Not responsive enough but demanding
Permissive	Not demanding but only responsive
Uninvolved	Both unresponsive and undemanding
	Here are some descriptions of how parents/guardians treat their children. According to the actual situation in the past year, please select how your parents/guardians treated you. (1. Never 2. Rarely 3. Sometimes 4. Often 5. Always)
	Responsiveness
[1]	Enjoyed talking things over with me.
[2]	The parents/guardians encouraged you to do things with great effort.
[3]	Spoke to me in a warm and friendly voice.
[4]	The parents/guardians encouraged you to think independently.
[5]	When you did something wrong, the parents/guardians would ask about the reasons and talk to you about what you should do.
[6]	The parents/guardians would tell you the reasons when they asked you to do something.
[7]	The parents/guardians praised you.
	Demandingness
[1]	The parents/guardians asked about what happened to you at school.
[2]	The parents/guardians told stories to you.
[3]	The parents/guardians played with you, for example, playing chess or playing outside.
[4]	The parents attended parent-teacher meetings at school.
[5]	The parents/guardians checked your homework.
[6]	The parents/guardians helped you with your schoolwork.
Family Dynamics	
Quarrels with Parents	In the past month, how many times did you quarrel with your parents? *(0-50)*
Quarrels between Parents	In the past month, how many times did your parents quarrel with each other? *(0-50)*
Talks with Parents	In the past month, how many times did you and your parents have heart-to-heart talk? *(0-50)*
	We standardize the item listed below.
Parents Check Homework	How often did you check the child's homework in last year? *(1. Never 2. Rarely (once a month) 3. Sometimes (once a week) 4. Often (2-4 times a week) 5. Very often (5-7 times a week))*

Table A6. Potential Mechanism: Mothers' and Fathers' Labor Outcomes

VARIABLES	[1] Estimate	[2] N	[3] Control Mean
Panel A: Mothers' Labor Supply and Income			
Labor Force	0.070*	26,263	0.715
	(0.040)		
Employed	0.045	20,190	0.955
	(0.042)		
Monthly Hours Worked	-1.152	12,101	144.834
	(10.503)		
Annual Income	0.058	17,974	8.873
	(0.106)		
Agriculture Industry	-0.037	17,569	0.332
	(0.027)		
Manufacture Industry	-0.009	17,569	0.261
	(0.020)		
Service Industry	0.037	17,569	0.387
	(0.025)		
Panel B: Fathers' Labor Supply and Income			
Labor Force	0.073**	24,150	0.897
	(0.039)		
Employed	0.045	22,133	0.968
	(0.041)		
Monthly Hours Worked	36.630***	12,625	206.796
	(13.654)		
Annual Income	0.164**	19,557	9.170
	(0.083)		
Agriculture Industry	-0.051	19,298	0.245
	(0.037)		
Manufacture Industry	-0.022	19,298	0.204
	(0.020)		
Service Industry	0.059**	19,298	0.525
	(0.029)		

Notes: This table explores the effects of SNIP on parental labor supply and income, with mothers' labor outcomes in Panel A, and fathers' labor outcomes in Panel B. We keep only female and male observations in regressions in Panel A and B, respectively. All regressions control for age, age square, education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. Control Mean in Column 3 measures the mean of outcome for never-treated group. Significance Level: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A7. Potential Mechanism: Items of Household Expenditures

VARIABLES	[1] Estimate	[2] N	[3] Control Mean
Total Annual Expenses *(in log)*	-0.004	31,557	10.612
	(0.060)		
Proportion of Each Item			
Food	-0.090***	31,332	0.355
	(0.022)		
Clothing	0.013**	31,214	0.051
	(0.006)		
Housing	0.002	30,824	0.111
	(0.011)		
Daily	-0.006	31,270	0.090
	(0.009)		
Medical	0.006	31,546	0.092
	(0.011)		
Transport & Communication	0.018***	31,124	0.089
	(0.006)		
Education	0.023	31,373	0.124
	(0.016)		
Leisure	-0.002	31,255	0.006
	(0.002)		

Notes: This table explores the effects of SNIP on household total annual expenditures and proportion of each item. All regressions control for age, age square, gender, mother's education level, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. Column 1 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9), using the DID_l estimation suggested by De Chaisemartin and d'Haultfoeuille (2022). All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Column 2 reflects the number of first differences of the outcome and of the treatment used in the estimation. Control Mean in Column 3 measures the mean of outcome for never-treated group. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.

Table A8. Crowding-out Effect on Household Food Expenditure by Mothers' Education Level

	Whole Sample			***Above Middle School***			***Below Middle School***		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
VARIABLES	Estimate	N	Control Mean	Estimate	N	Control Mean	Estimate	N	Control Mean
Crowding-out Magnitude									
Re-scaled Annual Household Food	-0.763***	42,863	3.177	-0.148	22,773	3.378	-0.989***	20,030	2.948
Expenditure per Person	(0.236)			(0.275)			(0.245)		

Notes: This table illustrates the heterogeneity of crowding-out effect on household food expenditure across mothers' education level. Children sample is divided based on the criterion of whether the respondent's mother has completed middle school. Columns 1—3 indicate the baseline regression results, while Columns 4—6 and Columns 7—9 show the results derived from separate regressions, using the children born with higher and lower educated mothers, respectively. Columns 1, 4, and 7 reports the weighted average of dynamic estimates β_l for the post-treatment periods according to equation (9) (De Chaisemartin and d'Haultfoeuille, 2022), using corresponding subsamples. All regressions control for age, age square, gender, father's education level, poor county indicator interacted with wave dummies and competing policies interacted with wave dummies. All standard errors in the parentheses are clustered at the county c level and computed using 200 bootstrap replications. Number of observations in Columns 2, 5, and 8 reflects the number of first differences of the outcome and of the treatment used in the estimation in the whole sample, subsamples of children born to high-/low-educated mothers, respectively. Control Mean in Columns 3, 6, and 9 measure the mean of outcome for never-treated group in corresponding sample/subsamples. Significance Level: * p<0.10, ** p<0.05, *** p<0.01.