Nutritious School Meals and Educational Outcomes*

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Abstract

This paper estimates the impact of school meals quality on student outcomes. We take advantage of a staggered implementation of a national program that improved the nutritional content of meals in public schools in Chile starting in 2015. Using a Difference-in-Difference approach and national student-level data over six years, we estimate a credible Intention-to-Treat impact of healthier meals on Math and Reading test scores. We find an average increase of 0.036 standard deviations in combined scores. The students from the poorest and rural households present the largest effects. We explore possible mechanisms including attendance. We show indirect evidence that supports the main hypothesized mechanism, the improvement of food nutrients. In particular, we find evidence that the students from low-income households that are more often exposed to these nutritious meals are the ones who get the largest increase in their test scores. Finally, we calculate that it would cost 87 USD per year to raise a student's test score in 0.1 standard deviations by providing healthier meals.

Keywords: Nutrition, School Meals, Education, Early life

JEL Codes: H52, I18, I25, I28, I38

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1 Introduction

Disparities in human capital accumulation have been documented as a key predictor of development differences among countries (Barro 1991). To close this gap the development agencies and governments in developing countries have implemented costly programs to increase schooling participation and to improve determinants of human capital accumulation. For example reduction in class size, flexible pay for teachers, full school day or access to free health insurance, among others. One of the world's most common interventions are school meals programs (Alderman et al. 2018). Today, 161 countries feed at least some of their school children, meaning that one in every two children receive meals as part of government policies (WFP 2020). The school meals programs' (SMP) goals are to reduce cost of education, to alleviate the consequences of poverty and to improve health in order to develop human capital (Alderman et al. 2018). The literature has shown that SMPs increase attendance in low school participation areas (Adelman et al. 2008), and improved health independently of school participation rates (Aurino et al. 2020, Wang et al. 2021 and Bommer et al. 2020).

Given their wide adoption (WFP 2020) and the program's positive effects on the extensive margin, the attention of the policymakers has shifted from quantity to quality of the calories provided. Improving a student's micronutrient intake can reduce susceptibility to infections and increase cognitive function even in situations where the total calorie consumption does not change (Adelman et al. 2008). Several countries have targeted the nutritional requirements of school meals as their main goal (USDA 2012, WFP 2017, GCNF 2019). Most recently the President of the United States, Joe Biden, define as one of the nation priorities to increase healthy eating and physical activity by 2030 for all Americans making at least 9 million more children eligible for free school meals, a major first step for free meals for every single student. The recent inflationary shocks and the disruption of the global food supply chain has hit school meal budgets, making it difficult for meal providers to maintain meal quality conditional on their budget (SNA 2021). Yet still may be a cost effective way of countries to raise human capital. Therefore, this highlight the importance of documenting the causal effects of the quality of food on cognitive development.

This paper aims to identify whether the quality of calories affects later student performance and to what extent. We exploit the differences in the timing of Chilean schools to being compelled to improve the nutritional composition of the meals served by vendors. Starting in 2015, the JUNAEB[1] implemented nationally mandated improvements in the nutritional content of meals. The timing of the adoption of the healthier meals was based on the pre-existing schedule which assigns meal vendors to schools that have been taking place since the late 1990s. This schedule divided the country into three school groups. Each year the schools within a group are assigned to a different meal vendors. These contracts last three years. Therefore, after the introduction of the nutritional improvements in 2015, the first school group of schools was immediately impacted in 2015, the second school group was impacted in 2016, and the third school group in 2017. Critically

[1]This is the agency in charge of managing the federal resources allocated to school meals.

to the research design, the timing of these staggered adoptions are exogenous to the conditions of the schools in the municipalities.

To recover an average treatment on the treated (ATE), we estimate difference-in-differences (DID) model using the Callaway and Sant'Anna 2021 method. We focus on public schools, which enroll 40% of the national students, the majority of which are from more disadvantaged backgrounds. Virtually all public schools receive meals through the SMP. To estimate the causal effect of the healthier meals on academic achievement, we use individual administrative records with information on national standardized test scores. Our six-year repeated cross-sectional database includes all Chilean 4th graders attending public schools (approximately 64,000 students and 5,100 schools per year).

The results of this study indicate that the healthier menu increases test scores in average by about 0.036 standard deviations (0.032 Reading and 0.033 Math) relative to the previous less healthy menu. This is equivalent to an additional hour to the school week (Lavy 2016), or to increasing the school year by five days (B. Hansen 2011).We find that the effects are larger and significant for rural students and for those belonging to the lowest-income households. These results shed some light that the students more likely nutritionally deprived are the ones who are getting the largest results from these healthier meals and it supports that the quality of the meals is improving cognition. The effect of the healthier school meals appear to be larger in Math and Reading test scores in the second year than in the first one implying dynamic effects on the the treatment.

The magnitude of these effects are in line with previous educational research. When incorporating a cost-benefit analysis, providing healthier school meals seems more appealing since it increases test scores at a cheaper cost than other educational policies. Considering the dollar cost per 0.1 standard deviations of test score gains to compare cost-effectiveness, we find that it would cost about $87 per year to raise a student's test score by 0.1 standard deviations. In contrast, the same increase costs $232 in the weekend feeding program in North Carolina[2], $1591 in the Tennessee STAR experiment[3], and $1674 in the Florida's extended school day program (Figlio et al. 2018).

It is important to identify if these estimated effects can plausibly be attributed to adopting healthier meals for the validity of the results. To that end, we begin by showing the raw test scores plots to visually conclude that the pre-treatment dynamics of the treatment groups do not differ from the ones of the control group units. Then, we run an event-study specification showing that the DID coefficients in the pre-treatment periods are not statistically different from zero. In addition, we run several robustness and placebo checks. First, these results are robust to estimates using the De Chaisemartin and d'Haultfoeuille 2020 approach that also corrects for dynamic and heterogeneous treatment effects, and the traditional TWFE method. Second, we use a shorter sample of years for sixth grade, finding results in the same line as with fourth graders. Third, we estimate pre-treatment placebos or pseudo-ATT's. They are what we would have estimated effect of participating in the treatment to be (on impact) if the treatment had occurred in that

[2]Inflation adjusted to 2021$.

[3]Original costs estimates from Krueger 1999 inflation-adjusted by Anderson et al. 2018, and then by us.

period pre-treatment (instead of when it actually occurred). We find no statistically significant pre-treatment placebos.

Finally, we explore indirect ways to support the possible mechanism since our data do not permit us to test directly. The policy only changed the nutritional composition of meals; therefore, the main candidate is the biological link between food quality and cognition. First, we investigate changes in obesity and attendance rates that can mean that health status is improving, and we do not find significant results. Second, we explore exposure to these nutritious meals. We find evidence that students who attend more often to school are the ones who get the largest increase in their test scores. This pattern is pronounced for students from low-income households and a lesser extent, for medium-income students. These children are more likely to benefit from healthier meals since they come from the most nutritionally deprived households and are more likely to receive free meals. This pattern is not present in high-income students. Therefore, these results provide indirect evidence that the improved dietary content of the meals increases cognitive development.

The contributions of this paper are threefold. First, this paper relates to the literature on the education production function (Hanushek 2002, Hanushek and J. A. Luque 2003, Das et al. 2013). School meals are a school input. In general, the literature has shown that providing meals to children at school have positive effect on students' outcomes (Dotter 2013, Imberman and Kugler 2014, Frisvold 2015, Corcoran et al. 2016, Kurtz et al. 2020, Schwartz and Rothbart 2020, Ruffini 2021), and in some cases positive long terms effects in economic, educational and health outcomes (Lundborg et al. 2022). These effects can come from the provision of calories, an increase in attendance, or the meals' quality. Previous research is heavily focused on the extensive margin of the SMP. This research look at the intensive margin, it sheds light on understanding the effect of the quality of meals on student performance, a key component that has been understudied.

This paper also relates to the nascent literature that explores the effect of the quality of meals on educational outcomes. In general, the medical literature has found positive effects of specifics nutrients on cognitive development (Bell et al. 2015, Goodwill and Szoeke 2017, Francis and Stevenson 2013). However, these papers study small scale interventions who lack from external validity and causal interpretation. In the context of the economic literature, just two papers study the effect of quality in a SMP, they both have found positive effects on test scores (Belot and James 2011 and Anderson et al. 2018). Our research design provides some advantages to the previous studies. The staggered adoption of the healthier meals based on an existence process of assignment of meals vendors to schools provides an exogenous variation in the treatment conditional on time and school characteristics. The universal undertaking and the homogeneous minimal healthy requirements allow us to address concerns regarding selection into the treatment and provides external validity to the results.

Second, we contribute by quantifying the effect on rural and urban schools, the first type of school less explored in this literature. This distinction is relevant since rural students belong to poorer households, have a likely worse nutritional baseline (Ver Ploeg et al. 2009), and their school inputs may be very different from the ones in urban areas (Nanney et al. 2016, Cuadros-Meñaca et al. 2022). In terms of estimation, since this research exploits the timing of the adoption of healthier meals in a DID approach, we address the challenge of heterogeneous dynamic treatment effects using the method proposed by Callaway and Sant'Anna 2021, which allows estimating a proper average treatment on the treated (ATT).

Finally, this work contributes to understanding the effects of targeted policies that improve conditions in late childhood. This middle period between birth and adulthood allows reaching a large share of children through the education system at a low cost (Lundborg et al. 2022). In addition, other authors argue that the returns to investment as soon as possible in children from disadvantaged environments are higher than the returns of investment and remediation for young adolescents from similar environments (Cunha et al. 2006, Bailey et al. 2017). For example, in-school education policies such as class size reduction and flexible pay for teachers find positive effects on educational outcomes (Gilraine et al. 2018, Biasi 2021). Out-of-school policies targeting school-age children such as hookworm eradication, mandatory vaccination laws, and access to health insurance find educational, labour market, and health positive outcomes (Bleakley 2007, Luca 2016 Arenberg et al. 2020 Bütikofer and Salvanes 2020).

This paper proceeds in Section 2 by reviewing the literature of SMP and the one that links healthy food and cognition, a description of the Chilean School Feeding Program, and presents the identification strategy. Section 3 describes the data, the empirical strategy and the internal validity of the estimates. Section 4 presents the main results and the heterogeneous analysis. Section 5 tests which of the mechanisms could explain the previous results. Section 6 presents a discussion and a cost-benefit analysis and Section 7 summarizes the findings and concludes.

2 Background

2.1 Linking Nutritious School Meals and Cognitive Development

The SMP aims to improve child's outcomes by reducing schooling costs for parents, making it more attractive or less expensive to send their children to school and invest in their education. Additionally, the SMP is an input into the education production function that positively impacts student attainment. The literature that studies the effect of SMPs on student achievement has found either positive (Hinrichs 2010, Dotter 2013, Imberman and Kugler 2014, Frisvold 2015, Chakraborty and Jayaraman 2019, Schwartz and Rothbart 2020, Kurtz et al. 2020, Kim 2021, Ruffini 2021) or null results (McEwan 2013, Leos-Urbel et al. 2013, Corcoran et al. 2016, Cuadros-Meñaca et al. 2022). To the best of our knowledge, the literature has identified three channels through which SMP affects student achievement: enrolment and attendance, provision of calories, and improvement in nutritional food quality. This paper focuses on the third channel. This subsection will describe how the dietary components of meals affect student achievement.

Much of the evidence of the effects of healthy food comes from the medical literature, and these studies are usually observational or clinical trials. These papers have found that specific nutrients affect behavior and cognitive development. On the one hand, some nutrients positively affect them. Concerning behavior, low levels of vitamin B, vitamin D, or omega-3 fatty acids are documented to worsen impulsive behavior and ADHD (Patrick and Ames 2015, Kaplan et al. 2004). Concerning cognitive development, the high levels of antioxidants present in fruits and vegetables prevent neuronal oxidative damage (Kang et al. 2005), and long-chain omega-3 polyunsaturated fatty acids help with learning and memory (Stonehouse 2014). In the same line, vitamins B and D, fiber, protein, and water also have positive effects on cognition (Goodwill and Szoeke 2017, Naiman A Khan et al. 2015, Mahoney et al. 2005, N. Khan et al. 2015).

On the other hand, refined carbohydrates, junk food, saturated fats, and high-fat diets have the opposite negative effect. Refined carbohydrates impair frontal, limbic, and hippocampal systems, disrupting learning, memory, and cognition. Additionally increases oxidative stress and brain inflammation (Francis and Stevenson 2013). In the same way, because the area that modulates cognitive control in children and adolescents is still not completely developed, over-consumption of junk food generates deficits in learning and memory through an increased reward-seeking behavior (Reichelt and Rank 2017, Andersen and Teicher 2009). Moreover, a high-fat diet is associated with a cognitive decline through the "microbiota-gut-brain axis" because it alters the healthy microbiota present in the gut tract (Beilharz et al. 2015, Proctor et al. 2017).

Moreover, nutritious food may affect student performance through other channels more likely to take place in longer-time horizons. First, healthy meals can improve overall health and make students less prone to illness. These students miss fewer school days and increase learning[4]. Second, better nutrients in food can reduce obesity and improve cognition. The medical literature has shown a negative relationship between obesity and cognitive development (Liang et al. 2014. In terms of mechanism explaining this negative association, Stanek et al. 2011 finds that, in otherwise healthy individuals, obesity is associated with reduced white matter integrity. Disruption of white matter pathways can reduce neural transmission speed and slow information processing. In addition to decreasing executive and working memory. All of which are essential components in the cognition and learning process.

2.2 The Chilean School Meals Program

The SMP is a nationally-mandated, government-led program dependent on the National Board of School Aid and Scholarships (JUNAEB). While its first objective was to address high levels of undernutrition among children, it has been evolving to handle the changes in students' intake of energy and nutrients. Currently, the SMP provides mostly breakfast and lunch, with a small percentage of students also receiving an evening snack[5].

The SMP targets all students attending public or charter schools (private subsidized schools), which more than 90 percent of students in the country attend. The program covers virtually all public schools and 57 percent of voucher schools. The students to be eligible need to belong to the

[4] See Jomaa et al. 2011 for a review of SMP effects in health in developing countries, and Hinrichs 2010, Gundersen and Kreider 2009 for the effects in developed countries.

[5] JUNAEB. "Programa De Alimentación Escolar (PAE)." Accessed November 28, 2021. https://www.junaeb.cl/programa-de-alimentacion-escolar.

60% poorest household in Chile. A high rate of the students attending public schools are eligible, however, not all of them take the free meals up. The take up is 60 percent of students in public schools and 32 percent of students in charter schools[6].

The students receive daily meals for about 200 days a year, covering between 40 percent and 60 percent of their daily energy requirements. The meals resemble home-cooked meals, and except for rare exceptions, fast food (or foods high in salt, sugar and fats) is not served. In terms of the student acceptance of the meals, a qualitative study has been conducted every year since 2011 by the JUNAEB. The students show similar satisfaction levels over the years, rating the SMP with a grade of 5 out of 7.[7].

In 2015 the JUNAEB decided to introduce modifications to the nutritional composition of meals to make them healthier and in that way address these negative obesity trends. Although the nutritional status of Chilean students changed from high undernutrition in the 1960s to almost complete eradication in the late 1980s (Vio et al. 2008), in the last years, children's obesity rates have become a national concern. Currently, the obesity and overweight rates are 24% and 51% respectively. These differences become larger by SES: students from the lowest income quintile are 40% more likely to be obese than the ones from the highest. Additionally, the obesity rates are 5 percentage points higher in rural areas relative to urban areas (Junaeb 2016).

The new minimal nutritional requirements changes introduced modifications to the three types of meals served by the program: breakfast, lunch, and a dinner snack. The new meals did not modify the number of calories. They increased the food that is rich in compounds or nutrients that positively affects cognition and reduced the processed food that negatively impacts cognition. According to table 1 there is an increase in fruits, vegetables, fish, meat, dried fruits and water and a reduction in refined carbohydrates and sugars. Moreover, the size of the side dish was diminished, and the portion of the protein was increased[8].

2.3 Identification Strategy

The identification strategy relies on the staggered adoption of these healthier meals by schools. The timing of the adoption of the healthier meals was based on the pre-existing schedule of auctions[9] that have been taking place since the late 1990s which assigns meal vendors to schools. For the matching, JUNAEB divides the country into three school groups (see Figure 1). Each of these

[6]Source: JUNAEB master file, 2014; Ministry of Education enrollment file, 2014; and author's calculations

[7]Students are asked to rate between 1 to 7 (The Chilean grading system goes from 1 to 7, where 1 is the worst and 7 is the best) the acceptability (smell, taste, presentation and temperature, among others), variety and quantity of meals. Students show similar satisfaction levels with the service: approximately 65 percent of the students rate with grade 5 and above the items previously mentioned across the years. Sources: Junaeb 2011, Consulting 2012, ClioDinamica 2013, ClioDinamica 2014, ClioDinamica 2015 and Junaeb 2016.

[8]More detailed information about these modifications can be found in table A.1 on the appendix and a sum up of the effect found by the medical literature in table A.2.

[9]The SMP auction process works in a two-step procedure. First, the agency defines the technical requirements regarding nutritional specifications, minimum quality operating conditions, and infrastructure. Second, firms that satisfy these technical requirements are allowed to compete on prices in the bidding process. The second step imposes market share restrictions for bidders and awards the contracts in multiple sequential auctions to promote diversification and competition among bidders.

Table 1: 2015 Changes in Nutritional Requirements in the SMP.

Food or Compound	Cognition	Food (change in # servings)
Antioxidants	Positive	Salads (↑ 70%), Vegetables Side Dish (↑ 20%), Fruit (↑ 25%).
Vitamins, Omega-3 Fatty Acid	Positive	Avocado (↑ 33%), Salads (↑ 70%), Vegetables Side Dish (↑ 20%), Fruit (↑ 25%) and Fish (↑ 15%)
Water	Positive	Mandatory on trait
Protein	Positive	Beef, chicken, pork (↑ 25%)
Fiber	Positive	Granola (added), Oats (↑ 50%) and Whole wheat bread (↑ 50%).
Refined Carbohydrates	Negative	White Bread (↓ 30%), Cereal (eliminated), Rice, Pasta (↓ 12%).
Refined Sugars	Negative	Jam, Honey, Caramel (↓ 50%), Cereal and Oat Cookies (eliminated) Jelly with canned fruits (↓ 50%)

school groups includes municipalities that are both geographically close and far away[10]. Each school group goes through an assignment process for consecutive years, and each meal contract within the school group lasts three years. As a result, the nutritional changes to the meals could be implemented only in the first school group of municipalities in 2015 since the other two school groups were under the old contract. Therefore, the second school group adopted healthier meals in 2016 and the third one in 2017 (see Figure 2). Therefore, this creates treated and control groups up to the second year of the implementation of the healthier meals.

Critical to the purpose of the identification strategy, we claim that the rollout of the healthier meals adoption by schools was not correlated to student characteristics, in particular, with test scores since it was based on the existing process of assignment of meals vendors to school. Consequently, we take advantage of the staggered introduction of these modifications to capture the causal effect of nutritional improvements in meals on educational outcomes as measured by national tests.

3 Data and Empirical Strategy

3.1 Data

To analyze the effects of the changes in the nutritional composition of school meals on all students in 4th grade attending public schools, we will use data from three sources the Ministry of Education, the Quality of Education Agency, and the Chilean public procurement market. These databases contain individual standardized test results, student and school characteristics, and the nutritional requirements for meals vendors assigned to schools in each year. The data ranges from 2011 to

[10]For example, in the group of school treated in 2015 the municipalities of *Loncoche* and *Torres del Paine* are 1,200 km (730 miles) away with no other municipality belonging to the group of school treated in 2015 between those two. But in the samethe group of school treated in 2015, the municipality of *Villarrica* is adjacent to *Loncoche* municipality, and the municipality of *Natales* is adjacent to *Torres del Paine*.

Figure 1: Rollout of the Healthier Meals.

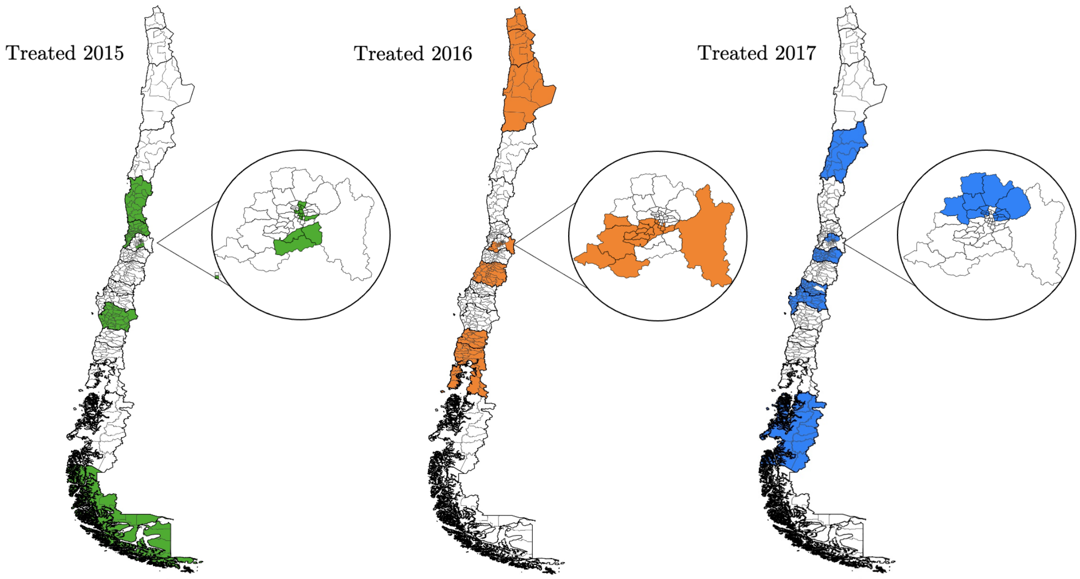
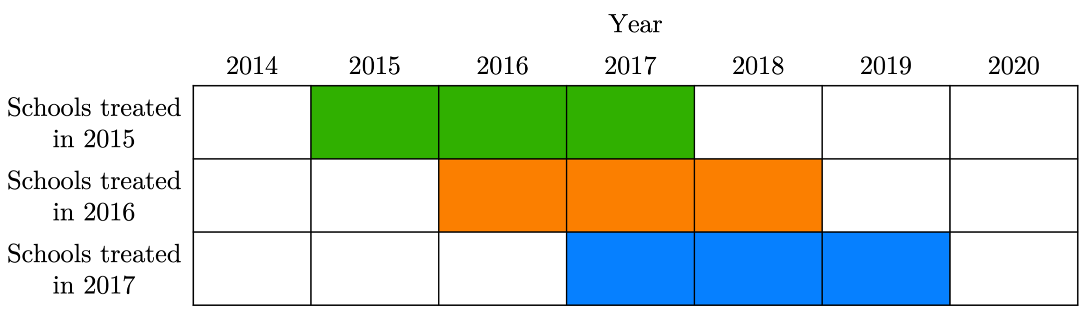


Figure 2: Treated and Control groups.



2016, and the sample consists of approximately 64,000 students and 5,100 schools per year. We describe each type of information in detail below.

Individual standardized test results. The Education Quality Measurement System (SIMCE, for the acronym in Spanish) is a centralized battery test dependent on the Quality of Education Agency, used to measure learning outcomes related to the national curriculum. Depending on some conditions, cohorts of students take the test in the 2nd, 4th, 6th, 8th grades (primary and middle school), 10th or 11th grades (2nd and 3rd years of high school). The SIMCE can test students in Maths, Reading and Writing (henceforth, Reading), Social Sciences, and Natural Sciences topics.

Starting in 2005, at the end of the school year, the students in the 4th grade take the test yearly. The students in 10th (8th) grade take the test each even (odd) year. The Ministry of Education has not yet determined the frequency of the 2nd, 6th and 11th-grade tests. In addition, SIMCE tests only Math and Reading each year, and social and natural sciences are not tested each year[11].

[11] For example, if 4th graders in year t took the natural sciences test, 4th graders in year t+1 will take the social

Because the JUNAEB implemented the nutritional changes in a staggered fashion, and we only have yearly data of 4th graders in Math and Reading subjects, the main estimations of this paper will consider 4th graders exclusively.

Control variables. Student's information come from two sources. The first is the SIMCE's survey (household income, mother education) and the base of Enrollment from the Ministry of Education (gender, age, attendance). Finally, the schools characteristics come from Enrollment data (urbal/rural area, full-day school) and the Educators database (students to teacher ratio).

Table 2 shows the descriptive statistics for the schools treated in 2015-16-17 before they adopt the healthier SMP. The students in Schools 2015 are the least advantaged in terms of test scores and household income, while Schools in 2016 and 2017 are more similar. In terms of the type of school, students belonging to the school 2015 are less likely to study in a rural school. Other characteristics such as gender, age, mother schooling, full school day and student/teacher ratio are similar across school groups. Therefore, the students in Schools 2015 seem worse off than the other two school groups, along with some dimensions. This comparison would lead to estimating a biased effect, and thereby, the estimation strategy that takes into account dynamic effects to control for those observable differences between school groups of schools, avoiding any potential bias from the pre-existence differences between them.

Table 2: Descriptive Statistics by Schools Timing of the Healthier Meals.

	(1) Schools 2015	(2) Schools 2016	(3) Schools 2017
Math Score	243.3	247.7	251.2
	(49.01)	(49.72)	(49.80)
Reading Score	253.4	256.6	258.9
	(50.14)	(50.20)	(49.77)
Gender	0.503	0.506	0.506
	(0.500)	(0.500)	(0.500)
Age	9.968	9.946	9.956
	(0.389)	(0.380)	(0.383)
Mother schooling	11.26	11.03	11.11
	(3.270)	(3.366)	(3.364)
Income	262,184.3	284,325.7	278,190.4
	(238,073.1)	(272,187.4)	(262,084.6)
Rural(=1)	0.159	0.240	0.212
	(0.366)	(0.427)	(0.409)
Full school day(=1)	0.402	0.376	0.364
	(0.490)	(0.484)	(0.481)
Students per teacher	18.24	20.69	18.67
	(11.11)	(6.576)	(6.358)
Observations	75,630	93,245	91,485

Note: values reported correspond to average values. Standard deviations are presented in parentheses.

Changes in nutritional requirements of meals. Information regarding the timing of when

science test.

a school contract starts and ends and the minimal nutritional requirements comes from the Chilean public procurement market. Each year, the JUNAEB uploads the terms to the public procurement market to its website. This document defines technical specifications regarding nutritional requirements, minimum quality operating conditions, and infrastructure.

3.2 Difference-in-Differences Specification

The identification strategy used in this paper comes from the staggered adoption of the SMP with the change in nutritional requirements moving to healthier meals. This variation allows us to compare test scores from students in schools who already started receiving more nutritious meals with those who have not yet started it. Because in the third year all school are treated, we can compare healthier meals over two years between early and later school adopters of the changed meals[12]. The usual way to estimate a DID model in this context would be using TWFE.

However, the recent econometric literature has raised concerns about interpreting the estimates from the TWFE model as the average treatment effect in cases when there are multiple groups that adopt the treatment in different points in time (Goodman-Bacon 2021, Callaway and Sant'Anna 2021, Sun and Abraham 2021). The problem arises when TWFE uses the already treated groups as controls groups. Under dynamic effect over time in treated groups, they are not good controls groups since their trends are not parallel to the untreated groups.

Additionally, in the absence of dynamic treatment effects but heterogeneous effects across groups, TWFE will also be biased. The TWFE estimator weights more observations that are in the middle of the panel and less the ones who are at the end. Therefore, TWFE will calculate a parameter unique to the length of the cross sections we are using, not the actual average treatment effect (see Goodman-Bacon 2021 for a discussion). The only situation where the TWFE is equal to the ATT is when all ATT's from different groups are the same. Nevertheless, this is unlikely to happen in designs with many groups and periods that adopt the treatment in a staggered fashion (De Chaisemartin and d'Haultfoeuille 2020).

As a consequence as our main estimates, we follow the method proposed by Callaway and Sant'Anna 2021 to address these concerns. This model explicitly allows for multiple periods, variation in the timing of the treatment and the parallel trends assumption holding potentially only after conditioning on observed covariates. In this case we estimate "group-time average treatment effects":

$$ATT(g,t) = E[Y_t - Y_{g-1}|G_g = 1] - E[Y_t - Y_{g-1}|D_t = 0] \tag{1}$$

Where g is year the group was first treated (2015 corresponds to school group treated in 2015, 2016 to school group treated in 2016, and 2017 to school group treated in 2017), t is a point in time, G_g is a binary variable that is equal to one if a unit is first treated in period g, and D_t is a binary variable equal to one if the unit is treated in period t and zero otherwise.

[12]Notice that the last treated school group will be treated as a never treated since in 2017 we do not have an untreated group.

We then calculate the overall effect suggested by Callaway and Sant'Anna 2021 of having healthier meals by aggregating these group-time average treatment effects together:

$$\delta = \frac{1}{\kappa} \sum_{g=2015}^{2017} \sum_{t=2012}^{2016} w(g,t) ATT(g,t) \tag{2}$$

Where ATT(g,t) is defined in 1, G corresponds to the time period that a unit is first treated, and

$$\begin{aligned} w(g,t) &= \mathbb{1}\{t \geq g\} P(G = g | G \leq 2016) \\ \kappa &= \sum_{g=2015}^{2017} \sum_{t=2012}^{2016} P(G = g | G \leq 2016) \end{aligned}$$

We also present the TWFE estimation that takes the following form:

$$y_{ist} = \beta_0 + \delta \sum_{st} H_{st} + \beta X_{it} + \alpha Z_{st} + \lambda_s + \gamma_t + \varepsilon_{ist} \tag{3}$$

Where the dependent variable y_{ist} denotes the outcome variable (Math or Reading test in s.d. units[13]) for the student i in school s and year t. H_{sgt} is an indicator function that takes the value 1 from a student attending school s, and in year t receives a healthier meal and zero otherwise. X_{it} is a vector of student characteristics, and Z_{st} are school characteristics. Student characteristics include mother education, gender, age, and household income. School characteristics include an indicator function for rurality, students to teacher ratio, and indicator function for school full day. Finally, the school and year fixed effects are λ_s and γ_t, respectively.

The coefficient of interest, δ, estimates an intention to treat (ITT) parameter. Even though virtually all public schools receive school meals, not all students from a targeted school receive meals[14]. We interpret this parameter as the average effect of the healthier SMP on student test scores for treated students relative to students not yet treated. We cluster at the municipality level since the meal vendor's contract are assigned at the municipality level[15].

The key assumption is that students from schools treated and not yet treated would have similar test scores trends in the absence of the change in the nutritional composition of the meals. Although this assumption is not directly testable, we provide evidence by looking at the test scores trends and at an event time study after conditioning on covariates.

[13] The test scores are standardized by year.

[14] In the case of public schools in Chile, 60 percent of these students receives free meals.

[15] According to Abadie et al. 2017, there are two motivations to cluster your standard errors. The first one is the sampling design of the data. In our case this data is all fourth grades that took the test in Chile, so our data does not aim to represent the population since it is the population. The second reason is the experimental design. Since the contracts of meals vendors are assigned at the municipality level, we cluster at the municipality level.

3.3 Event Time Study

We estimate a more flexible model that visually provides evidence of the parallel trends assumption and the dynamic of the effect. The specification is:

$$\delta_{es}(e) = \sum_{g=2015}^{2017} \sum_{t=2012}^{2016} \mathbb{1}\{t - g = e\} P(G = g | t - g = e) ATT(g, t) \tag{4}$$

Where $\delta_{es}(e)$ is the average effect of participating in the treatment e periods after the treatment was adopted across all groups that are ever observed to have participated in the treatment for exactly e time periods.

The event study is also computed using TWFE:

$$y_{ist} = \beta_0 + \sum_{k=-5, k \neq -1}^{2} \delta_t D_{sk} + \beta X_{it} + \alpha Z_{st} + \lambda_s + \gamma_t + \varepsilon_{ist} \tag{5}$$

The variable D_{sk} represents an indicator that takes the value of one for each school's pre and post-treatment periods k and zero otherwise. In this case, we normalized the coefficient on the year prior to the start of the improve in nutritional quality of the meals, $\delta_{-1} = 0$. Therefore each coefficient δ_k should be interpreted as the average change in test scores in period k of the students in the schools treated with the improvement in the quality of the meals relative to the students in schools not yet treated, and all these coefficients are relative to δ_{-1}.

This specification is useful in this context since it allow us to capture the dynamic of the effect on treated schools. Also, it allows us to visually test the key identification assumption of the parallel trends that states that in the absence of the treatment test scores from treated and untreated schools would have evolved in parallel. In other words, if there is any spurious correlation between treated and untreated schools, the estimates from δ_{-5} to δ_{-2} should be significantly different from zero. If this assumption holds, they would be zero.

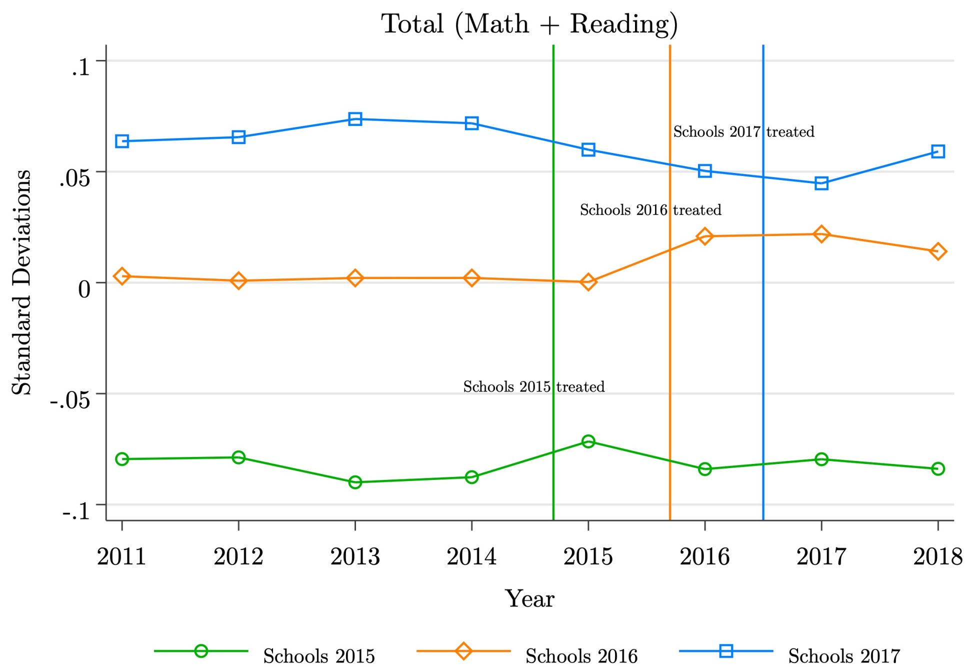
3.4 Internal Validity

Raw Test Scores

We conduct several tests on the validity of the parallel trend assumption. First, we look at the raw test scores in pre-treatment plots balance between treatment and control groups. Figure 3 shows the average Math and Reading test scores for the group of schools treated in different years. Schools 2015 is the early adopter, schools 2016 is the middle adopter, and schools 2017 is the late adopter. A key requirement for the DID strategy is that the test scores across the different schools behave similarly before adopting the healthier meals.

The figure shows that in terms of combined Math and Reading standardized scores, the school groups behaved similarly before the first group of schools is treated in 2015. After these schools are treated, an increase in both test scores is seen for these schools, while schools 2016 and 2017 continue to behave similarly in both test scores. After the group of schools 2016 is treated, an increase was seen in 2016 in Math and Reading test scores. Therefore, Figure 3 provides visual evidence that the parallel trends assumption before each school group is treated holds. In other words, the pre-treatment dynamics of the early treated schools do not appear to differ from those not yet treated[16].

Figure 3: Raw Math+Reading Test Scores 4th grade: 2011-2018



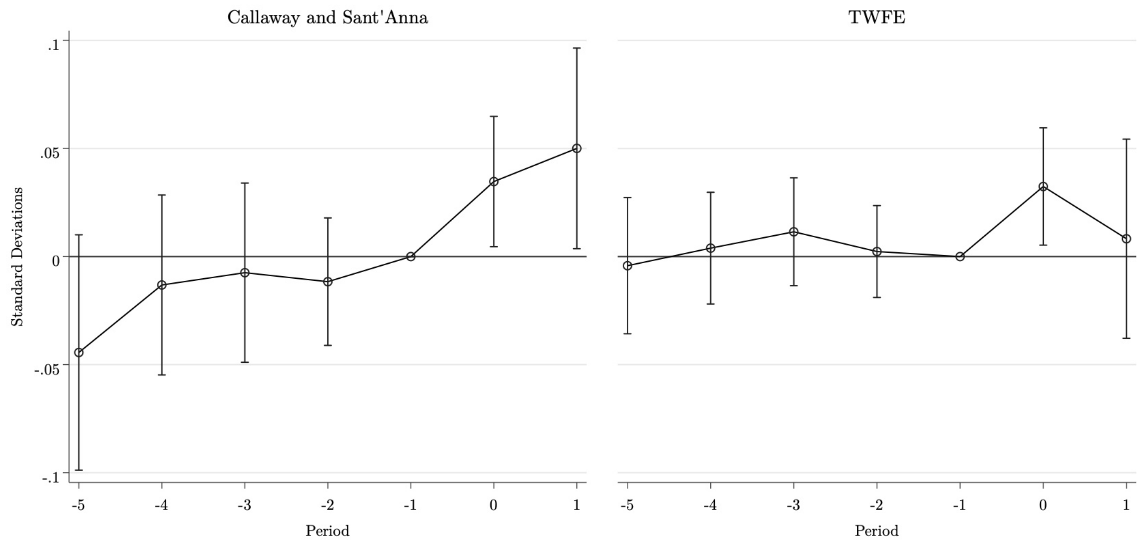
Parallel Trends Assumption

Figure 4 shows the event-time study for the total test scores for the Callaway and Sant'Anna 2021 and the TWFE estimates. In both cases, the parallel trends assumption holds since all of the parameters from periods -5 to -2 are indistinguishable from zero. Next, we move to the analysis by subject. Figures 5 and 6 shows the event-time study for the Math and Reading test scores using Callaway Sant'Anna and TWFE respectively. Both panels support the parallel trends assumption for the Math and Reading tests since each pre-adoption coefficient from period -5 to -2 is statistically indistinguishable from zero.

Finally, Callaway and Sant'Anna 2021 allows us to test the parallel trends assumption by a hypothesis test under the null that all coefficients pre-adoption are zero. In the three cases, combined scores, Math and Reading, the test does not reject the null hypothesis (p-values of 0.60, 0.43 and 0.70, respectively, in column 4 on the bottom of the tables 4 and 5), reassuring the absence of pre-trends before the adoption of the treatment and, therefore, the validity of the causal estimates.

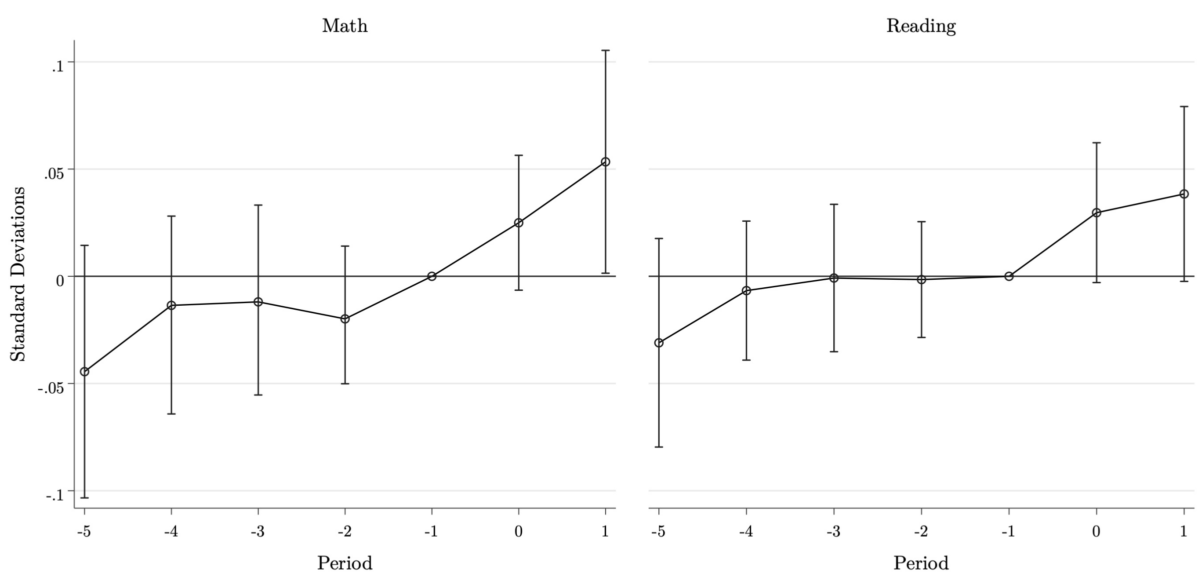
[16] On the appendix, figure A.1 shows the raw test scores for Math and Reading separately.

Figure 4: Event Study Total (Math + Reading) Test Scores: CS and TWFE.



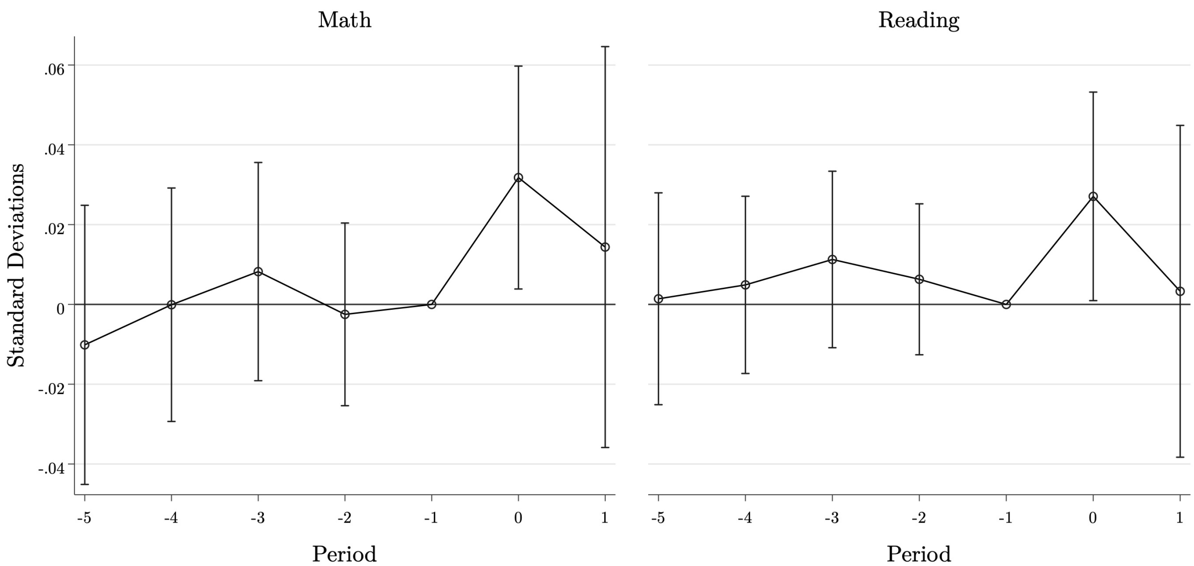
Note: The figure presents results from the individual-level event study framework from the approach from Callaway and Sant'Anna 2021. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure 5: Event Study by subject using Callaway and Sant'Anna's estimator



Notes: The figure presents results from the individual-level event study framework in Equation(5). All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure 6: Event Study by subject using TWFE



Notes: The figure presents results from the individual-level event study framework in Equation(5). All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Selection on Observables

One potential threat to the identification assumption is that the estimated effect can be confounded with changes in the composition of the school groups that happen at the same time that the healthier meals were adopted by schools. If that is the case, the effect captured in this paper may be more related to changes in socio-economics demographics in families from children or students characteristics in the treated schools instead of the effect of the healthier meals itself. To check this potential concern, we explore the correlation of the observed characteristics with the timing of the introduction of the new menu.

Table 3 shows the estimated correlation between healthier SMP and students and school characteristics. The results show no economically significant correlation in all cases. Just column 2 present a significant coefficient; however, this effects relative to the average features is small. For example, being a girl is significant and positively correlated to the treatment: on average, being a girl is 0.7 percent more likely in treated schools. The effect is way small compared to the mean of being a girl in the sample (50 percent).

Table 3: The correlation between student and school characteristics and the timing of the healthier SMP.

	(1) Mother Educ.	(2) Girl†	(3) Age	(4) Income	(5) Rural†	(6) Students/Teacher	(7) Full School Day†
Healthier	-0.0339	0.0088*	0.0016	-2.0410	-0.0082	0.2282	-0.0082
	(0.0356)	(0.0047)	(0.0039)	(3361.4)	(0.0050)	(0.1458)	(0.0050)
Mean Y	11.06	0.50	9.96	298501.90	0.21	18.34	0.77
Observations	385,796	385,796	385,796	385,796	385,796	385,796	385,796

Note: Each column represents a separate regression using Callaway and Sant'Anna 2021 method. The dependent variable is a student characteristic. Observations are at the individual school/year level. All columns include school and year fixed effects. † means that the variable is a dummy. Standard errors are clustered at the municipal level and are in parentheses. *$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4 Results

4.1 Main Estimates

Table 4 reports the main results from the Equation 2 on combined Math and Reading scores. Columns 1 to 4 vary the students and school characteristics. Column 5 presents the TWFE estimates with all covariates and controlling by school and year fixed effects. Our preferred specification is column 4 which uses Callaway and Sant'Anna 2021 method and controls for all student and school characteristics.

Based on Column 4, the average effect of the healthier SMP on combined test scores is an increase of 0.036 s.d. in schools that adopted the improved menu. This is equivalent to an additional hour to the school week (Lavy 2016), or to increasing the school year by five days (B. Hansen 2011). The exclusion of additional controls does not drastically affect the estimates in columns 1 to 4, meaning that the identification of the effect of the treatment comes from the treatment itself and not from the observable characteristics. The effects from Columns 1 to 4 range between 0.027 and 0.036 s.d., and all coefficients are statistically different from zero and statistically similar between them. Column 5 presents the analogous TWFE estimates, which translates into a rise of 0.028 s.d. Comparing columns 4 and 5, TWFE tends to underestimate the estimated parameter.

In Table 5, we report the estimates divided by subject. Panels A and B report the estimates for the Math and Reading test scores, respectively. The average effect of the healthier SMP increased the Math and Reading test scores by 0.034 and 0.032 s.d., respectively (Column 4). TWFE is also smaller in magnitude but not statistically different from the CS estimates. Both Math and Reading effects are significant at conventional levels and stable across different specifications.

4.2 Event Time Study Results

Figure 4 displays the dynamic of the effect. We found a positive dynamic effect in compound tests after the implementation of the policy. In particular, the effect in the second period is larger than in

Table 4: The effect of healthier SMP on Test Scores (Math + Reading)

	CS				TWFE
	(1)	(2)	(3)	(4)	(5)
Healthier	0.0272*	0.0322**	0.0284*	0.0359**	0.0277**
	(0.0165)	(0.0162)	(0.0169)	(0.0161)	(0.0140)
Individual Controls	No	Yes	No	Yes	Yes
School Controls	No	No	Yes	Yes	Yes
Observations	382,305	382,305	382,305	382,305	382,305
Pretrends = 0 (p-value)	0.9378	0.7777	0.9031	0.6041	0.8115
$Adj - R^2$					0.148

Notes: Each column represents a separate regression. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors clustered at the municipal level appear in parentheses—number of clusters: 340. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. Column 1 considers the staggered implementation of the policy, using the Callaway and Sant'anna's (2021) estimator. Columns 2 to 5 include year and school fixed effects. The null hypothesis of the pretrends test is the presence of parallel trends. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 5: The effect of a healthier SMP by subject.

	CS				TWFE
	(1)	(2)	(3)	(4)	(5)
Panel A: Math (SD)					
Healthier	0.0278*	0.0293*	0.0284*	0.0336**	0.0287**
	(0.0170)	(0.0169)	(0.0169)	(0.0163)	(0.0146)
Observations	385,796	385,796	385,796	385,796	385,796
Pretrends = 0 (p-value)	0.8711	0.6807	0.7231	0.4342	0.746
$Adj - R^2$					0.154
Panel B: Reading (SD)					
Healthier	0.0260*	0.0301**	0.0273*	0.0323**	0.0219*
	(0.0157)	(0.0154)	(0.0162)	(0.0155)	(0.0131)
Observations	384,029	384,029	384,029	384,029	384,029
Pretrends = 0 (p-value)	0.9598	0.8101	0.9444	0.7019	0.8887
$Adj - R^2$					0.116
Individual Controls	No	Yes	No	Yes	Yes
School Controls	No	No	Yes	Yes	Yes

Notes: Each column represents a separate regression. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors clustered at the municipal level appear in parentheses—number of clusters: 340. Individual covariates include the mother's years of education, household income, gender and age of the student. School covariates include a dummy for the rurality of school, full-school day, and students to teacher ratio. Column 1 considers the staggered implementation of the policy, using the Callaway and Sant'anna (2021) estimator. Columns 2 to 5 include year and school fixed effects. The null hypothesis of the pretrends test is the existence of parallel trends. * p < 0.1, ** p < 0.05, *** p < 0.01.

the first one. In contrast, Figure 4 shows the TWFE event study estimates in the second period are smaller than in the first one. This difference may be attributed to the fact that the Callaway and Sant'Anna 2021 estimates takes into account the presence of heterogeneous effects across groups and time.

In terms of the dynamic of the effect in both subjects, the results follow the same pattern from the total scores estimates in Figure 4. Figures 5 and 6 show a larger effect the second period providing evidence of dynamic treatment effects. In contrast, both figures show that the TWFE estimates have a smaller effect in the second period than in the first one.

4.3 Heterogeneity Analysis

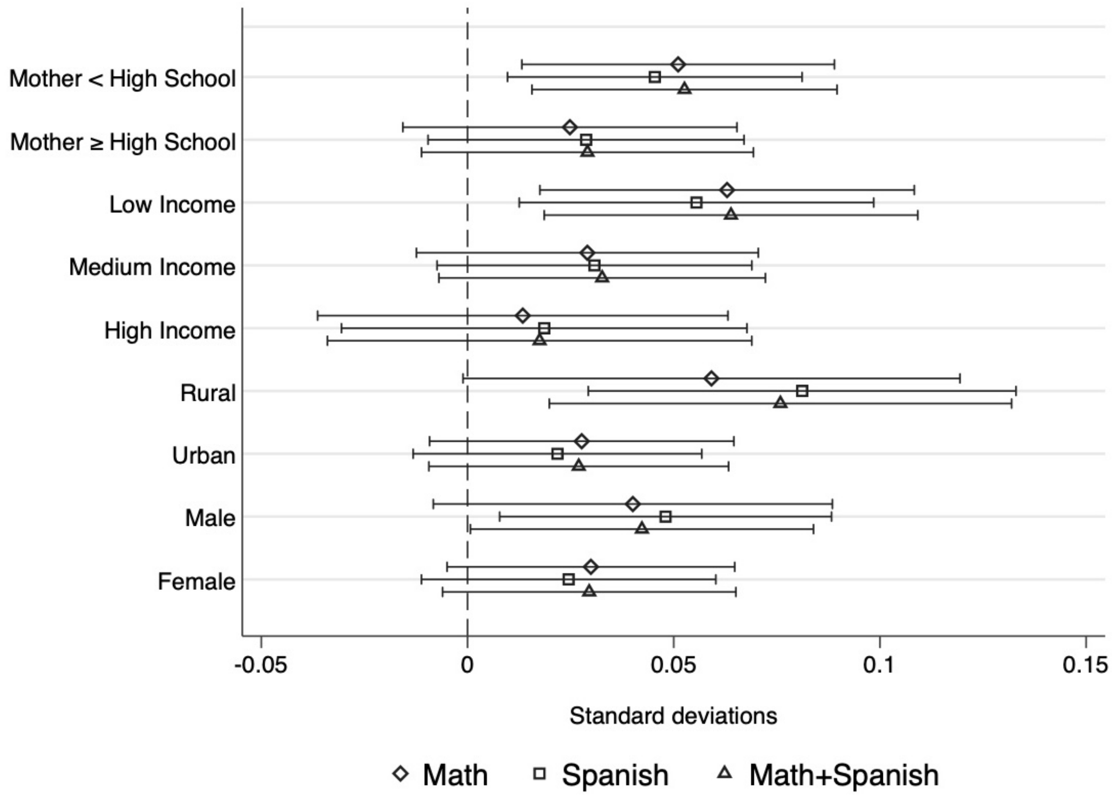
In this subsection, we use characteristics of the students and the schools to investigate the possible heterogeneous effects by groups using Callaway and Sant'Anna 2021 methodology. Since we do not have information about the take-up, or students' food quality insecurity (lack of relevant macro and micronutrients), a heterogeneity analysis will help us understand the pathways from which the healthier meals operate. By looking at which groups are more affected, we might provide evidence of the mechanisms driving the improvement of test scores.

Figure 7 shows the effects of the combined and separated test scores. First, we analyze the variables related directly or indirectly to wealth: household income and education of the mother. An analysis of wealth levels could reveal two relevant aspects to consider. We would expect to see a higher effect on children from the lower-income households than the ones from higher-incomes. Lower-income students are more likely to be nutritionally deprived (Mosdøl et al. 2008, Mark et al. 2012), so this intervention could benefit more the most nutritionally challenged group and also this group is more likely to take up the free meals.

For this analysis, we divided the sample into terciles of household income. We find that students from more disadvantaged backgrounds increase their test scores by a significant 0.064 s.d. compared to 0.033 and 0.017 s.d. for the second and third tercile, respectively. The latter finding goes in the same line as Anderson et al. 2018 and opposite to Belot and James 2011. Moreover, the differences between the first and third income tercile are significant. In this context, the results make sense since the students that the SMP targets come from more disadvantaged backgrounds as we previously stated. Moreover, the students with mothers who had less than high school completed significantly increased their combined test scores by 0.052 s.d. In contrast, children from mothers with more or equal completed high education by 0.029 s.d. This results supports the one based on income since mother education is highly correlated with household income.

Second, we analyze an aspect that has not been explored yet in this literature: the heterogeneous effect of healthier meals among rural and urban students. Children from rural schools increase their scores by most (0.076 s.d.) compared to urban children (0.027 s.d.). This result can be considered a difference in household wealth since it is more likely to find students from relatively poorer households in rural than in urban areas. But even if we could observe the same income in both groups, another factor might be involved: access to healthier food. According to the JUNAEB's

Figure 7: The effect of the healthier SMP by different groups (CS).



Notes: The figure presents results from the individual-level framework from Callaway and Sant'Anna 2021 methodology for different groups of interest. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Nutritional Report, students from rural areas have higher obesity rates than students from urban areas in all measured grades (Pre K, Kinder, 1st, 5th and 11th grades). One of the factors that the institution theorizes as an explanation for this difference is the availability, variety and accessibility to healthier foods (Junaeb 2014). Consequently, rural students might benefit more from healthier meals if their nutritional baseline is lower.

Third, we start by analyzing heterogeneous effects by gender because the literature has found a different impact of healthier (Belot and James 2011) and unhealthier foods (Schiltz and De Witte 2022) on student achievement between girls and boys. We find that the program's effect seems stronger for boys. Girls increase their test scores by 0.030 s.d. while boys by 0.042 s.d. This result is different than the results found by Belot and James 2011 for healthier meals in the context of UK schools, which found larger effects for girls than boys. Nonetheless, in the context of the provision of meals in schools, some authors have found larger effect on test scores for boys than girls (Kurtz et al. 2020, Chakraborty and Jayaraman 2019) and while others equal effects (Imberman and Kugler 2014, Schwartz and Rothbart 2020). Still, although we found these differences by gender, these estimates are not statistically different.

Figure 7 also shows the heterogeneous effect by subject. We find similar patterns to the combined test scores estimates. Notably, the effect for rural schools is larger and significant, especially for Reading and to a lesser extent for Math. In the case of household income, the effect is larger for more disadvantaged households in both subjects. The effect for children with mothers with schooling equal or less than secondary is larger in both subjects but more pronounced in Reading. Finally, the impact is larger for boys than for girls in both subjects.

4.4 Robustness Checks

In this section, we run robustness checks to the main results. First, we use the De Chaisemartin and d'Haultfoeuille 2020 approach that corrects for heterogeneous dynamic and groups effects as Callaway and Sant'Anna 2021 does. Since the parallel trend assumption in Chaisemartin and D'Haultfoeuille (CH) does not hold after conditioning on observed covariates, it allows us to include linear geographical trends to relax the identification assumption by focusing on deviations in the test scores from long-run trends caused by the implementation of the healthier meals. The combined Math and Reading results are presented on table A.3. Column 1 is our preferred CS estimate and from columns 2 to 6, we present the CH estimates including and excluding different covariates and adding municipality linear trends. The results go from an average increase of 0.036 to 0.043 s.d. similar in magnitude to our preferred estimates in column 1. The estimates by subject are presented in table A.4 and the conclusions are similar to the previous one. Finally, we present the event studies[17] from this methodology from figures A.4 to A.7 adding and excluding municipality linear trends and the conclusions remain the same.

Second, Table A.5 on the appendix shows that the estimated effects are robust to clustering at school and province levels. Third, we estimate pre-treatment placebos or pseudo-ATT's. They are what we would have estimated effect of participating in the treatment to be (on impact) if the treatment had occurred in that period pre-treatment (instead of when it actually occurred). Figure A.11 shows that none of the pre-treatment pseudo-ATT's or placebos are statistically significant, meaning that there are no anticipation effects. This test also serves as a parallel pre-trends test, and as we previously stated, no significant effect is found. Moreover, figure A.12 shows the effect for Math and Reading separately, the interpretation from the previous total tests scores remains the same in both cases. Finally, Table A.8 shows that the TWFE estimates are robust to incorporate different geographical linear trends.

Finally, we use a sample of 6th graders instead of 4th graders that are used in the main estimates. If the improved meals positively affect the test scores, we should observe a similar pattern for other grades. The caveat for this analysis is that we have fewer years to estimate the effect (two years pre- and post-treatment) and analyze the pre-trends. Table A.9 shows an increase of 0.018 s.d. on Math and Reading tests combined; however, this effect is not significant at conventional levels. In the case of Math, we found a significant effect an increase of 0.027 s.d. and no effect for Reading.

[17]These event studies present placebos estimates instead of estimates pre-treatment using period -1 as baseline and they will be explained in the following paragraph.

In terms of the 6th grade results, the literature investigating the effect of food provision has found similar results when comparing lower with higher grades. For instance, Howard 2011 studies the link between food insecurity for school-aged children and non-cognitive skills and concludes that these effects are stronger for children in the early years of development. Kurtz et al. 2020 found that a weekend feeding program in Northwest North Carolina increased Reading test scores significantly only for 3rd graders and to a lesser extent for 4th and 5th graders. Also, Ruffini 2021 studied the school free meal program in the US (specifically, the Community Eligibility Provision program) and found that the largest effects are more concentrated in elementary grades (3-5) than middle ones (6-8). Using the same program, for South Carolina, Gordanier et al. 2020 found an increase in Math test scores for elementary but not for middle school students.

5 Suggestive Mechanisms

The adoption of healthier SMP increases the test scores by 0.036 s.d. We follow the current literature to understand the hypothetical mechanism behind these results. The first underlying mechanism is the exposure to nutritious food: Better nutrition leads to improved behaviour and cognitive development that later affect educational achievement, as reviewed in Section 2.1. In this case, the data does not allow to directly test biological channels like previously described. However, it is possible to test indirectly that health is improving.

5.1 Calories

It is possible that the change in nutritional requirements leads to changes in calorie intake. As presented in Section 2.1, some evidence asserts that augmenting the number of calories increases short-term memory and attention. Figlio and Winicki 2005 found that the increase of calories in the school meals on testing days allowed the students to obtain better scores. However, McEwan 2013 found no effect in the context of an increase in calories in Chilean schools in 2006. As mentioned in the Section 2.3 and shown in Table A.1, there was no change in the number of calories in breakfast and lunch, and there was a reduction from 250 to 200 calories in the evening snack. However, it is unlikely that this change in calories could have had any meaningful impact since, mainly, the students have breakfast and lunch, and only a small number of students eat the evening snack at school (see Section 2.2). Therefore, we can rule out that this channel may explain the results.

5.2 Obesity

An improvement in the composition of the nutrients of the schools' meals may lead to a reduction in obesity rates, therefore finding evidence of health status improvements can explain partially increases in test scores[18]. In general, the medical literature has found a negative relationship

[18] Some authors argue that school meals increase body mass (see Schanzenbach 2009, Millimet et al. 2010 for evidence in the US). Nevertheless, this should not be a problem in this case. First, there is also evidence that participating in school meals does not increase body weight (see Mirtcheva and Powell 2013, Dunifon and Kowaleski-

between obesity and cognition (Liang et al. 2014).

A direct way to test whether the program reduced body mass would be by looking at obesity rate changes in fourth graders. Nevertheless, the obesity rate data is only available at the school level for Pre-Kinder, Kinder and First graders. Analyzing the impact of the change in nutrition in school meals on obesity rates in Kinder and 1st grades[19] will indirectly show whether the nutritional improvement of meals partially improved students' health, at least in this specific indicator. This analysis is still useful since, first, the reformulation of the SMP nutritionally improved meals for all grades (Junaeb 2017). Second, younger children are more receptive to nutritional changes (Just and Price 2013, Belot et al. 2016), and nutritional interventions at early ages translate more effectively in reduction in body weight (Belot et al. 2018). The last point may provide indirect evidence of the changes in obesity rates for fourth graders. If no effect is found for earlier ages, it probably would mean that finding reductions in obesity rates at upper levels will be even more challenging. However, the reader should take this analysis cautiously.

The effect of the SMP nutritional improvements on obesity rates in children is shown in Table 6. First, the Table depicts that the average obesity rate is 23%, with a higher value for males (25%) than for females (20%). Second, it displays in column 1 that neither economic nor statistically significant effect is found in either overweight or obesity rates, and this conclusion remains for boys. In the case of girls, there exist an increase of 1%, however, this effect is small and goes in the opposite direction of an improvement in health based in the obesity index. A reason why we do not find significant larger results can be that the improvement in nutritional quality did not change the number of calories in the meals. This can imply that although the students are not changing their body weight, they are consuming better nutrients that improve their cognitive development, which can still explain the increase in their test scores. It is important to highlight that the goal of the policy was not to reduce obesity rates by changing the amount of calories, it was by encouraging healthy habits that can have long-lasting effects and are difficult to identify in the short-term.

5.3 Attendance

Better nutrition leads to better overall health status and therefore, students are less likely to missing fewer lessons because of illness[20] (Anderson et al. 2018). Consequently, the students are more often exposed to learning, which implies better educational achievement. To carry out this analysis, we leverage in two empirical strategies. The first one is comparing attendance between cross-repeated

Jones 2004 for the US and Lundborg et al. 2022 for Sweden). Second, we are analyzing a change in the composition of meals (intensive margin) and not a change in participation in SMP (extensive margin). Third, the Chilean School Meals resemble homemade preparations and junk food is provided only on limited occasions. Fourth, Caro 2020 exploits the discontinuity on meals eligibility in Chilean 1st Graders finding no increase in obesity rates.

[19] We focus on Kinder and First grade since enrollment is mandatory for 1st grade and in the case of Kinder, although that enrollment is not mandatory, 96% of these children in this age attend, that is not the case for Pre-Kinder.

[20] Another popular hypothesized channel would be that students attend more often to get these healthier meals. This might be true in situations where the treatment is the provision of school meals vs no meals. It is unlikely that students are going to attend more often to eat more vegetables and salads. So, we believe that if any channel is operating thought the attendance channel, it would be overall health status.

Table 6: The effect of a healthier SMP on obesity rates.

	(1)	(2)	(3)
	All	Boy	Girl
Panel A: Overweight rate			
Healthier	0.0080	0.0057	0.0103*
	(0.0059)	(0.0070)	(0.0061)
Mean Y	0.51	0.51	0.48
Observations	38,681	38,681	38,681
Panel B: Obesity rate			
Healthier	0.0073	0.005	0.0105**
	(0.0046)	(0.0059)	(0.0043)
Mean Y	0.23	0.25	0.20
Observations	38,681	38,681	38,681

Notes: Each column represents a separate regression using the methodology from Callaway and Sant'Anna 2021. The dependent variable is the overweight or obesity rate for Pre-Kinder, Kinder and First grade. Observations are at the school year level. Standard errors are clustered at the municipal level and appear in parentheses—number of clusters: 340. School covariates include a dummy for the rurality of school and full-school day. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

sections as our main equation 3. The second one, since we have attendance at the individual level for all students each year, we can estimate an individual fixed model using TWFE[21].

Table 7 shows these results. Column 1 and 2 show the estimates from Callaway and Sant'Anna 2021 and the TWFE model for equation 3 and columns 3 for individual fixed effects. Column 1 points out that adopting the healthier SMP decreased attendance by 0.03 percent, while in column 2, the effect becomes a decrease of 0.18 percent. Even though in column 2 the effect is significant, the estimate is not economically meaningful since it is almost zero. Being conservative and taking the largest estimate into account, a decrease in attendance of 0.18 percent translates into 0.2 days or 2.6 hours fewer attended on average. The individual FE model in columns 3 leads to similar results. It is worth-noting that the estimated effect is a precise zero estimate since the standard errors are quite small.

This finding allows us to rule out that healthier meals affected attendance, as the results found in the literature of school meals. In general, the literature studying the provision and quality of school meals at large scales has found a null effect on attendance. In the case of quality of meals Anderson et al. 2018 found a not significant effect on attendance, and Belot and James 2011 found a significant decrease in authorized absenteeism of 0.7 days which quite small to explain their results.

[21] The model to estimate in this case is:

$$y_{ist} = \beta_0 + \delta \sum_{st} H_{st} + \beta X_{it} + \alpha Z_{st} + \lambda_s + \gamma_t + \omega_i + \varepsilon_{ist} \tag{6}$$

In the case of provision of meals, as we discussed in section 5, no effect has been found for most studies in large scale programs and in medium to high-income countries (McEwan 2013, Leos-Urbel et al. 2013, Dotter 2013, Imberman and Kugler 2014, Frisvold 2015, Corcoran et al. 2016, Kurtz et al. 2020, Cuadros-Meñaca et al. 2022, Schwartz and Rothbart 2020).

Table 7: The effect of the healthier SMP on attendance

	DID		Individual FE
	(1) CS	(2) TWFE	(3) TWFE
	(1)	(2)	(3)
Healthier	-0.0006	-0.0018*	-0.0016
	(0.0012)	(0.0011)	(0.001)
Mean Y	0.9277	0.9277	0.9248
% change	-0.06%	-0.19%	-0.17%
Observations	387,496	387,496	1,846,512
$Adj - R^2$	-	0.154	0.517

Notes: Each column represents a separate regression. The dependent variable is the percentage of attendance from 0 to 1 unit. Observations are at the individual year level. Standard errors are clustered at the municipal level, and they appear in parentheses—number of clusters: 340. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. All regressions include school and year fixed effects. Columns 1 and 2 estimate using equation 3 and columns 3 uses an individual FE model from equation 6. Column 2 includes year and school fixed effects. Column 3 includes year, school and individual fixed effects. * p < 0.1, ** p < 0.05, *** p < 0.01.

5.4 Exposure to nutritious food

From the results of section 5.3, we estimated a precise zero estimate in attendance caused by the improvement in the quality of the meals[22]. Therefore, we carry out an analysis based on attendance as a measure of the intensity of the treatment. In this analysis, we use the Callaway and Sant'Anna 2021 approach; however, results using TWFE are in the same line and are shown in the appendix.

If healthier meals meaningfully impact cognition, the students more exposed to them would perceive the larger gains since they eat these meals more frequently. In this case, the students more exposed are likely to be the ones who attend more often to school. Table 8 shows the program's effect on test scores based on the tercile of attendance. In Panel A, we analyze the impact on combined test scores. From Columns 1 to 3, we show that the effect increases on the level of attendance. Students in the low distribution of attendance do not increase their test scores, while the students in the medium and high distribution increase their test scores by a significant 0.04 and

[22] We acknowledge that it may exist endogeneity concerns and these results should be taken with caution. In addition, to provide more evidence on the zero effect, we test several specifications to rule out a change in the attendance distribution due to the program. First, we compare observable characteristics of different cohorts of students affected and not affected by the treatment in terms of the current attendance (low, medium and high), and we conclude that they are statistically similar. Second, we create groups based on past attendance (low, medium and high) and estimate the effect of the treatment on current attendance for each group finding no significant effects.

Table 8: The effect of a healthier SMP by rate of attendance.

	(1)	(2)	(3)
		Attendance	
	Low	Medium	High
Panel A: Total (SD)			
Healthier	-0.0003	0.0402*	0.0802***
	(0.0217)	(0.0222)	(0.0231)
Observations	124,373	130,463	127,486
Panel B: Math (SD)			
Healthier	0.0102	0.0302	0.0736***
	(0.0215)	(0.0223)	(0.0239)
Observations	126,038	131,561	128,202
Panel C: Reading (SD)			
Healthier	-0.0090	0.0408*	0.0743***
	(0.0211)	(0.0219)	(0.0218)
Obs	125,164	130,972	127,905
Mean Attendance	0.865	0.946	0.983

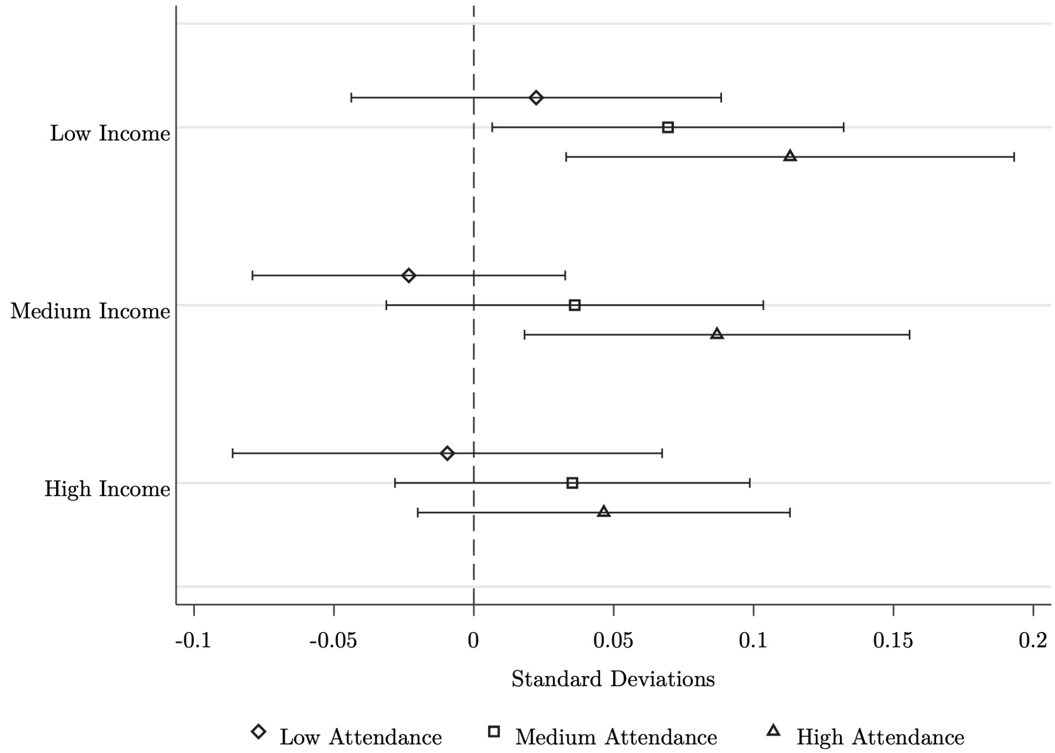
Notes: Each column represents a separate regression using the methodology from Callaway and Sant'Anna 2021. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors clustered at the municipal level appear in parentheses—number of clusters: 340. Individual covariates include years of mother education, household income, gender and age of the student. School covariates include a dummy for the rurality of school, full-school day, and students to teacher ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

0.08 s.d. The same pattern repeats in Panels B and C for Math and Reading test scores. These tables point out that the students who attended more often are the ones who are gaining the most from these healthier meals since they are more likely to receive them.

Next, we explore whether this pattern found in Table 8 is present and stronger in groups that are more nutritional deprived, i.e., the children from the poorest households. In Figure 8, we find an increasing effect by the level of attendance in students from low-income households and a lesser extent the ones from medium-income. The explanation for the previous result may be that children from low-income families are more likely to come from more nutritional deprived groups and at the same time, they are more likely to receive the benefit of free meals. In the case of the students from high-income households, we do not observe this pattern and the results lack from statistical significance. In the same line from the argument above, they are less likely to come from nutritionally deprived households and to receive these free meals.

Overall, these results show that the students more often exposed to the healthier meals are the ones who are getting the larger effects. Additionally, the students who are more likely to be nutritionally deprived and more likely to receive the free meals are the ones experiencing the larger

Figure 8: The effect of a healthier SMP on Total score by level of attendance and income.



Notes: The figure presents results from Callaway and Sant'Anna for different income/attendance groups. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

gains. Although this is not direct evidence that the nutritional content of the meals is the channel explaining these results, this results provide indirect evidence that goes in the same direction as this mechanism.

6 Discussion

The estimates from this paper yield an 0.036 s.d. increase in test scores which is consistent with Anderson et al. 2018 results from healthier meals in schools in California. Our results deviate from Belot and James 2011, which estimates an increase between 0.11 and 0.2 s.d.. Still, they point out that their results are relatively high and should be interpreted only as the positive direction of the effect of the healthier meals. In terms of magnitude, using the benchmark from Cohen 1969, the effect looks small. However, recent discussion (Duncan and Magnuson 2013) and research (Kraft 2020) have updated the benchmark metric of educational interventions taking into account sample size and scope of the intervention, among others, as factors to consider whether the magnitude can be considered small or large. With respect to these last metrics, the results of this paper are in line with studies involving more than 2,000 individuals (Kraft 2020).

It might also be useful to contrast the results of this paper (intensive margin) with results from papers that evaluate the effect of the provision of meals (extensive margin) to know where this result stands in relation to the broad SMP literature. SMPs can be thought of as the composition of different mechanisms that affect school achievement. Among them are an increase in attendance, the number of calories, the number of consumed meals, an increase in parent investment caused by the saved money, and finally, the nutritional improvement of the food. Thereby, we would expect to find our result systematically smaller than the ones found in the literature evaluating the provision of meals. This literature has found increases as small as 0.027 - 0.032 s.d. (Ruffini 2021, Schwartz and Rothbart 2020), medium as 0.050 - 0.010 s.d. (Gordanier et al. 2020, Kim 2021, Imberman and Kugler 2014, Schwartz and Rothbart 2020) and large as 0.110 - 0.300 s.d. (Dotter 2013, Chakraborty and Jayaraman 2019, Aurino et al. 2020). All these papers mention improved nutrition as a potential factor boosting the increase in test scores; however, none of them can separate the contribution of each mechanism. The findings of this study suggest being aligned with the economic evidence of school interventions since they are located inside the lower range of magnitudes of SMP effects on educational outcomes.

Providing a full cost-benefit analysis of this program is challenging because SMPs affect a wide set of outcomes such as education, social protection and health (Gelli et al. 2014). Still, we can do a rough exercise. The average healthy vendor meal contract is $202 (2021 $) per test-taker per school year[23]. Over the 180-day academic year, a healthy school meal contract costs about $1.12 per test-taker day. The new contract that includes more nutritious meals is 18.2% more expensive than the previous one, implying a difference of $31.2 per test-taker per school year. We consider the dollar cost per 0.1 standard deviations of test score gains to compare cost-effectiveness. Using the cost difference of $31.2 per test-taker per school year and an estimated effect of 0.036 standard deviations, we find that it would cost about $87 per year to raise a student's test score by 0.1 standard deviations by switching the previous menu to a healthier one. This numbers is similar to the one calculated in Anderson et al. 2018 for healthier school meals in California.

In contrast to other educational intervention, the same 0.1 s.d. increase costs $1591 per year in the Tennessee STAR experiment[24]. Additionally, Kurtz et al. 2020 states that an increase of a student's test score by 0.05 s.d. in reading test scores costs $837 per year in Florida's extended school day program (Figlio et al. 2018) versus $209 cost per year in increasing 0.09 s.d. in reading for a weekend feeding program in North Carolina[25]. Therefore, in terms of these programs, improving the quality of meals seems to be an appealing intervention from a cost-benefit point of view. Additionally, the improvement of school meals has positive effects in the long term. Lundborg et al. 2022 found a rise in schooling and an increase in 3% of lifetime income in Sweden [26].

[23]Calculations made by the authors based on Resolución Exenta N 44 (2015), Resolución Exenta N 125 (2016) and Resolución Exenta N 4 (2017) of JUNAEB

[24]Original costs estimates from Krueger 1999 inflation-adjusted by Anderson et al. 2018, and then by us.

[25]Inflation adjusted to 2021 $

[26]They argue that their benefit-to-cost ratio is twice the ratios reported by the Head Start program, showing the

On top of that, from a policy perspective, the coefficient and costs are not the only variables to consider. Scalability is particularly important when evaluating the policy relevance of the effect sizes. Concerning this point, Aurino et al. 2020 emphasizes that small-scale programs implementing food assistance (the most common in low and medium-income countries) might also "employ complex or unsustainable supply chain logistics" that might fail to translate into real-world programs. If the SMP wants to have universal coverage, scalability would not be an important issue. First, because it is a nationally-mandated government-run school meals program, there would not be costs associated, for example, with coordinating different states with different school meals policies. Second, because the assignment process of meals vendors to schools was created to to minimize cost and limit the market power concentration, the assignment auction process itself might alleviate the negative externalities if the number of beneficiaries increases.

7 Conclusion

This paper exploits variation in the nutritional quality of meals resulting from the staggered adoption of a healthier school menu in 2015 to quantify their effect on the academic performance of 4th graders in Chilean public schools. The adoption was based on a policy from the late '90s that was implemented to promote competition and minimize costs among meal vendors and was not related to student outcomes. We use the CS method to estimate a DID strategy under staggered adoption and dynamic heterogeneous treatment effects. We find that adopting a healthier menu increases test scores by 0.036 s.d. in combined Math and Reading test scores. The effect is 0.032 s.d. for Reading and 0.034 s.d. for Math. Scaling by the share of eligible students (60 percent), this effect implies increases in test scores by approximately 0.06 s.d. The effects are also larger and remain significant for students from the poorest households and those attending rural schools.

We conduct several robustness checks that allow us to support the identifying assumption that the exact timing of the rollout of healthier school meals is uncorrelated with other time-varying factors that may affect test scores. Additionally, we analyze possible mechanisms. The main candidate is the biological link between food nutrients and cognition. However, our data do not permit us to directly test it. Instead, we are able to reject alternative channels such as the number of calories, obesity and attendance. We find evidence that students who attend more often to school are the ones who get the largest increase in their test scores. This increasing pattern on attendance is particularly stronger and significant for students from the poorest households. These children are more likely to come from more nutritional deprived households and at the same time, they are more likely to receive the benefit of free meals. These findings can be thought of as indirect evidence of the effect of the nutritional content of the meals on student performance.

Even though these results might appear modest, they are in line with the new empirical benchmarks in educational interventions when accounting for effect size heterogeneity, as seen in Kraft 2020. In terms of cost-benefit analysis, it would cost \$ 87 to raise 0.1 s.d., which is appealing

reach that high-quality nutrition can have on relevant outcomes in the short and long-run.

compared to other school interventions. For instance, the Tennessee STAR experiment cost around $1591 per year, the extended school day program in Florida cost $837 to increase 0.05 s.d. in reading, and the weekend feed program in North Carolina cost $209 to raise 0.09 s.d. in reading too. Finally, these healthier school meals appear to be a very appealing policy to keep supporting and expanding from a policy perspective. Given that the meals are provided through a very rigorous and centralized process, the scalability can be easily added to the current meal bidding process reaching even more students in other settings.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge (2017). *When should you adjust standard errors for clustering?* Tech. rep. National Bureau of Economic Research.

Adelman, Sarah, Daniel Gilligan, and Kim Lehrer (2008). *How effective are food for education programs?: A critical assessment of the evidence from developing countries.* Vol. 9. Intl Food Policy Res Inst.

Alderman, Harold, Ugo Gentilini, and Ruslan Yemtsov (2018). *The 1.5 Billion People Question.*

Andersen, Susan L and Martin H Teicher (2009). "Desperately driven and no brakes: developmental stress exposure and subsequent risk for substance abuse". In: *Neuroscience & Biobehavioral Reviews* 33.4, pp. 516–524.

Anderson, Michael L, Justin Gallagher, and Elizabeth Ramirez Ritchie (2018). "School meal quality and academic performance". In: *Journal of Public Economics* 168, pp. 81–93.

Anjos, Tania et al. (2013). "Nutrition and neurodevelopment in children: focus on NUTRIMENTHE project". In: *European journal of nutrition* 52.8, pp. 1825–1842.

Arenberg, Samuel, Seth Neller, and Sam Stripling (2020). *The impact of youth Medicaid eligibility on adult incarceration.* Tech. rep. Working Paper.

Aurino, Elisabetta, Aulo Gelli, Clement Adamba, Isaac Osei-Akoto, and Harold Alderman (2020). "Food for thought? Experimental evidence on the learning impacts of a large-scale school feeding program". In: *Journal of Human Resources*, 1019–10515R1.

Bailey, Drew, Greg J Duncan, Candice L Odgers, and Winnie Yu (2017). "Persistence and fadeout in the impacts of child and adolescent interventions". In: *Journal of research on educational effectiveness* 10.1, pp. 7–39.

Barro, Robert J (1991). "Economic growth in a cross section of countries". In: *The quarterly journal of economics* 106.2, pp. 407–443.

Beilharz, Jessica E, Jayanthi Maniam, and Margaret J Morris (2015). "Diet-induced cognitive deficits: the role of fat and sugar, potential mechanisms and nutritional interventions". In: *Nutrients* 7.8, pp. 6719–6738.

Bell, Karen FS et al. (2015). "Neuronal development is promoted by weakened intrinsic antioxidant defences due to epigenetic repression of Nrf2". In: *Nature communications* 6.1, pp. 1–15.

Belot, Michèle, Noémi Berlin, Jonathan James, and Valeria Skafida (2018). "The formation and malleability of dietary habits: A field experiment with low income families". In.

Belot, Michèle and Jonathan James (2011). "Healthy school meals and educational outcomes". In: *Journal of health economics* 30.3, pp. 489–504.

Belot, Michèle, Jonathan James, and Patrick Nolen (2016). "Incentives and children's dietary choices: A field experiment in primary schools". In: *Journal of health economics* 50, pp. 213–229.

Biasi, Barbara (2021). "The labor market for teachers under different pay schemes". In: *American Economic Journal: Economic Policy* 13.3, pp. 63–102.

Bleakley, Hoyt (2007). "Disease and development: evidence from hookworm eradication in the American South". In: *The quarterly journal of economics* 122.1, pp. 73–117.

Bommer, Christian, Nitya Mittal, and Sebastian Vollmer (2020). "The Impact of Nutritional Interventions on Child Health and Cognitive Development". In: *Annual Review of Resource Economics* 12, pp. 345–366.

Bütikofer, Aline and Kjell G Salvanes (2020). "Disease control and inequality reduction: Evidence from a tuberculosis testing and vaccination campaign". In: *The Review of Economic Studies* 87.5, pp. 2087–2125.

Callaway, Brantly and Pedro HC Sant'Anna (2021). "Difference-in-differences with multiple time periods". In: *Journal of Econometrics* 225.2, pp. 200–230.

Caro, Juan Carlos (2020). "Child development and obesity prevention: evidence from the Chilean School Meals Program". In.

Chakraborty, Tanika and Rajshri Jayaraman (2019). "School feeding and learning achievement: evidence from India's midday meal program". In: *Journal of Development Economics* 139, pp. 249–265.

ClioDinamica (2013). *Estudio evaluación de la satisfacción de los usuarios del Programa de Alimentación Escolar*. URL: `https://www.junaeb.cl/estudios/alimentacion-estudiantil`.

— (2014). *Estudio evaluación de la satisfacción de los usuarios del Programa de Alimentación Escolar*. URL: `https://www.junaeb.cl/estudios/alimentacion-estudiantil`.

— (2015). *Estudio evaluación de la satisfacción de los usuarios del Programa de Alimentación Escolar*. URL: `https://www.junaeb.cl/estudios/alimentacion-estudiantil`.

Cohen, Jacob (1969). *Statistical power analysis for the behavioral sciences*. Academic press.

Consulting, DM (2012). *Encuesta de Satisfacción de Usuarios del Programa de Alimentación Escolar*. URL: `https://www.junaeb.cl/estudios/alimentacion-estudiantil`.

Corcoran, Sean P, Brian Elbel, and Amy Ellen Schwartz (2016). "The effect of breakfast in the classroom on obesity and academic performance: Evidence from New York City". In: *Journal of Policy Analysis and Management* 35.3, pp. 509–532.

Cuadros-Meñaca, Andres, Michael R Thomsen, and Rodolfo M Nayga Jr (2022). "The effect of breakfast after the bell on student academic achievement". In: *Economics of Education Review* 86, p. 102223.

Cunha, Flavio, J James Heckman, Lance Lochner, and Dimitriy V Masterov (2006). "Interpreting the evidence on life cycle skill formation". In: *Handbook of the Economics of Education* 1, pp. 697–812.

Das, Jishnu, Stefan Dercon, James Habyarimana, Pramila Krishnan, Karthik Muralidharan, and Venkatesh Sundararaman (2013). "School inputs, household substitution, and test scores". In: *American Economic Journal: Applied Economics* 5.2, pp. 29–57.

De Chaisemartin, Clément and Xavier d'Haultfoeuille (2020). "Two-way fixed effects estimators with heterogeneous treatment effects". In: *American Economic Review* 110.9, pp. 2964–96.

Dotter, Dallas (2013). "Breakfast at the desk: The impact of universal breakfast programs on academic performance". In: *Unpublished manuscript.*

Duncan, Greg J and Katherine Magnuson (2013). "Investing in preschool programs". In: *Journal of economic perspectives* 27.2, pp. 109–32.

Dunifon, Rachel and Lori Kowaleski-Jones (2004). *Exploring the Influence of the National School Lunch Program on Children.* Citeseer.

Figlio, David, Kristian L Holden, and Umut Ozek (2018). "Do students benefit from longer school days? Regression discontinuity evidence from Florida's additional hour of literacy instruction". In: *Economics of Education Review* 67, pp. 171–183.

Figlio, David and Joshua Winicki (2005). “Food for thought: the effects of school accountability plans on school nutrition”. In: *Journal of public Economics* 89.2-3, pp. 381–394.

Francis, Heather and Richard Stevenson (2013). “The longer-term impacts of Western diet on human cognition and the brain”. In: *Appetite* 63, pp. 119–128.

Frisvold, David E (2015). “Nutrition and cognitive achievement: An evaluation of the School Breakfast Program”. In: *Journal of public economics* 124, pp. 91–104.

GCNF (2019). *School Meal Programs Around the World: Report Based on the Global Survey of School Meal Programs.* URL: https://survey.gcnf.org/wp-content/uploads/2021/03/GCNF_School-Meal-Programs-Around-the-World_Report_2021_Final.pdf.

Gelli, Aulo, Francisco Espejo, Jing Shen, and Elizabeth Kristjansson (2014). *Putting it all together: Aggregating impacts of school-feeding programmes on education, health and nutrition: two proposed methodologies.* Tech. rep. WIDER Working Paper.

Gilraine, Michael, Hugh Macartney, Robert McMillan, et al. (2018). *Education Reform in General Equilibrium: Evidence from California's Class Size Reduction.* National Bureau of Economic Research.

Goodman-Bacon, Andrew (2021). “Difference-in-differences with variation in treatment timing”. In: *Journal of Econometrics.*

Goodwill, Alicia M and Cassandra Szoeke (2017). “A systematic review and meta-analysis of the effect of low vitamin D on cognition”. In: *Journal of the American Geriatrics Society* 65.10, pp. 2161–2168.

Gordanier, John, Orgul Ozturk, Breyon Williams, and Crystal Zhan (2020). “Free lunch for all! the effect of the community eligibility provision on academic outcomes”. In: *Economics of Education Review* 77, p. 101999.

Gundersen, Craig and Brent Kreider (2009). “Bounding the effects of food insecurity on children's health outcomes”. In: *Journal of health economics* 28.5, pp. 971–983.

Hansen, Benjamin (2011). “School year length and student performance: Quasi-experimental evidence”. In: *Available at SSRN 2269846.*

Hansen, Stine Normann, Pernille Tveden-Nyborg, and Jens Lykkesfeldt (2014). “Does vitamin C deficiency affect cognitive development and function?” In: *Nutrients* 6.9, pp. 3818–3846.

Hanushek, Eric A (2002). “Publicly provided education”. In: *Handbook of public economics* 4, pp. 2045–2141.

Hanushek, Eric A and Javier A Luque (2003). “Efficiency and equity in schools around the world”. In: *Economics of education Review* 22.5, pp. 481–502.

Hinrichs, Peter (2010). “The effects of the National School Lunch Program on education and health”. In: *Journal of Policy Analysis and Management* 29.3, pp. 479–505.

Howard, Larry L (2011). “Does food insecurity at home affect non-cognitive performance at school? A longitudinal analysis of elementary student classroom behavior”. In: *Economics of Education Review* 30.1, pp. 157–176.

Imberman, Scott A and Adriana D Kugler (2014). “The effect of providing breakfast in class on student performance”. In: *Journal of Policy Analysis and Management* 33.3, pp. 669–699.

Jomaa, Lamis H, Elaine McDonnell, and Claudia Probart (2011). “School feeding programs in developing countries: impacts on children's health and educational outcomes”. In: *Nutrition reviews* 69.2, pp. 83–98.

Junaeb (2011). *Reporte de Análisis Medición Opinión Usuaria 2011.* URL: https://www.junaeb.cl/estudios/alimentacion-estudiantil.

— (2014). *Mapa Nutricional.* URL: https://www.junaeb.cl/mapa-nutricional.

— (2016). *Reporte de Análisis Medición Opinión Usuaria 2011.* URL: https://www.junaeb.cl/estudios/alimentacion-estudiantil.

Junaeb (2017). *Programa de Alimentación Escolar (PAE).* URL: `https://www.junaeb.cl/programa-de-alimentacion-escolar`.

Just, David R and Joseph Price (2013). "Using incentives to encourage healthy eating in children". In: *Journal of Human resources* 48.4, pp. 855–872.

Kang, Jae H, Alberto Ascherio, and Francine Grodstein (2005). "Fruit and vegetable consumption and cognitive decline in aging women". In: *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society* 57.5, pp. 713–720.

Kaplan, Bonnie J, Jennifer E Fisher, Susan G Crawford, Catherine J Field, and Bryan Kolb (2004). "Improved mood and behavior during treatment with a mineral-vitamin supplement: an open-label case series of children". In: *Journal of child and adolescent psychopharmacology* 14.1, pp. 115–122.

Kaur, Randeep (2021). "Estimating the impact of school feeding programs: Evidence from mid day meal scheme of India". In: *Economics of Education Review* 84, p. 102171.

Khan, NA, LB Raine, ES Drollette, MR Scudder, NJ Cohen, AF Kramer, and CH Hillman (2015). "The relationship between total water intake and cognitive control among prepubertal children". In: *Annals of Nutrition and Metabolism* 66.Suppl. 3, pp. 38–41.

Khan, Naiman A, Lauren B Raine, Eric S Drollette, Mark R Scudder, Arthur F Kramer, and Charles H Hillman (2015). "Dietary fiber is positively associated with cognitive control among prepubertal children". In: *The Journal of nutrition* 145.1, pp. 143–149.

Kim, Yoonjung (2021). "The Effects of Universal Free Lunch Provision on Student Achievement: Evidence from South Korea". In.

Kraft, Matthew A (2020). "Interpreting effect sizes of education interventions". In: *Educational Researcher* 49.4, pp. 241–253.

Krueger, Alan B (1999). "Experimental estimates of education production functions". In: *The quarterly journal of economics* 114.2, pp. 497–532.

Kurpad, Anura V, Bernice S Edward, and Isabelle Aeberli (2013). "Micronutrient supply and health outcomes in children". In: *Current Opinion in Clinical Nutrition & Metabolic Care* 16.3, pp. 328–338.

Kurtz, Michael D, Karen Smith Conway, and Robert D Mohr (2020). "Weekend feeding ("BackPack") programs and student outcomes". In: *Economics of Education Review* 79, p. 102040.

Lamport, Daniel J, Caroline Saunders, Laurie T Butler, and Jeremy PE Spencer (2014). "Fruits, vegetables, 100% juices, and cognitive function". In: *Nutrition reviews* 72.12, pp. 774–789.

Lavy, Victor (2016). "Expanding school resources and increasing time on task: Effects on students' academic and non-cognitive outcomes". In: *Journal of the European Economic Association.*

Leos-Urbel, Jacob, Amy Ellen Schwartz, Meryle Weinstein, and Sean Corcoran (2013). "Not just for poor kids: The impact of universal free school breakfast on meal participation and student outcomes". In: *Economics of education review* 36, pp. 88–107.

Liang, J, BE Matheson, WH Kaye, and KN Boutelle (2014). "Neurocognitive correlates of obesity and obesity-related behaviors in children and adolescents". In: *International journal of obesity* 38.4, pp. 494–506.

Lowette, Katrien, Lina Roosen, Jan Tack, and Pieter Vanden Berghe (2015). "Effects of high-fructose diets on central appetite signaling and cognitive function". In: *Frontiers in nutrition* 2, p. 5.

Luca, Dara Lee (2016). "The effects of mandatory vaccination laws on childhood health and adult educational attainment". In: *Available at SSRN 1987898.*

Lundborg, Petter, Dan-Olof Rooth, and Jesper Alex-Petersen (2022). "Long-term effects of childhood nutrition: Evidence from a school lunch reform". In: *The Review of Economic Studies* 89.2, pp. 876–908.

Mahoney, Caroline R, Holly A Taylor, Robin B Kanarek, and Priscilla Samuel (2005). "Effect of breakfast composition on cognitive processes in elementary school children". In: *Physiology & behavior* 85.5, pp. 635–645.

Mark, Sean, Marie Lambert, Jennifer O'Loughlin, and Katherine Gray-Donald (2012). "Household income, food insecurity and nutrition in Canadian youth". In: *Canadian journal of public health* 103.2, pp. 94–99.

McEwan, Patrick J (2013). "The impact of Chile's school feeding program on education outcomes". In: *Economics of Education Review* 32, pp. 122–139.

Millimet, Daniel L, Rusty Tchernis, and Muna Husain (2010). "School nutrition programs and the incidence of childhood obesity". In: *Journal of Human Resources* 45.3, pp. 640–654.

Mirtcheva, Donka M and Lisa M Powell (2013). "National school lunch program participation and child body weight". In: *Eastern Economic Journal* 39.3, pp. 328–345.

Mosdøl, Annhild, Bob Erens, and Eric J Brunner (2008). "Estimated prevalence and predictors of vitamin C deficiency within UK's low-income population". In: *Journal of public health* 30.4, pp. 456–460.

Nanney, Marilyn S, Amy Shanafelt, Qi Wang, Robert Leduc, Ellen Dodds, Mary Hearst, Martha Y Kubik, Katherine Grannon, and Lisa Harnack (2016). "Project BreakFAST: Rationale, design, and recruitment and enrollment methods of a randomized controlled trial to evaluate an intervention to improve school breakfast program participation in rural high schools". In: *Contemporary clinical trials communications* 3, p. 12.

Patrick, Rhonda P and Bruce N Ames (2015). "Vitamin D and the omega-3 fatty acids control serotonin synthesis and action, part 2: Relevance for ADHD, bipolar disorder, schizophrenia, and impulsive behavior". In: *The FASEB Journal* 29.6, pp. 2207–2222.

Proctor, Cicely, Parameth Thiennimitr, Nipon Chattipakorn, and Siriporn C Chattipakorn (2017). "Diet, gut microbiota and cognition". In: *Metabolic brain disease* 32.1, pp. 1–17.

Reichelt, Amy C and Michelle M Rank (2017). "The impact of junk foods on the adolescent brain". In: *Birth defects research* 109.20, pp. 1649–1658.

Ruffini, Krista (2021). "Universal access to free school meals and student achievement: Evidence from the Community Eligibility Provision". In: *Journal of Human Resources*, 0518–9509R3.

Schanzenbach, Diane Whitmore (2009). "Do school lunches contribute to childhood obesity?" In: *Journal of Human Resources* 44.3, pp. 684–709.

Schiltz, Fritz and Kristof De Witte (2022). "Sugar rush or sugar crash? Experimental evidence on the impact of sugary drinks in the classroom". In: *Health Economics* 31.1, pp. 215–232.

Schwartz, Amy Ellen and Michah W Rothbart (2020). "Let them eat lunch: The impact of universal free meals on student performance". In: *Journal of Policy Analysis and Management* 39.2, pp. 376–410.

SNA (2021). *2021 Supply Chain Survey Report.*

Stanek, Kelly M, Stuart M Grieve, Adam M Brickman, Mayuresh S Korgaonkar, Robert H Paul, Ronald A Cohen, and John J Gunstad (2011). "Obesity is associated with reduced white matter integrity in otherwise healthy adults". In: *Obesity* 19.3, pp. 500–504.

Stonehouse, Welma (2014). "Does consumption of LC omega-3 PUFA enhance cognitive performance in healthy school-aged children and throughout adulthood? Evidence from clinical trials". In: *Nutrients* 6.7, pp. 2730–2758.

Sun, Liyang and Sarah Abraham (2021). "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects". In: *Journal of Econometrics* 225.2, pp. 175–199.

USDA (Jan. 2012). *Nutrition standards in the National School Lunch and USDA School Breakfast Programs.* URL: https://www.federalregister.gov/documents/2012/01/26/2012-

1010/nutrition-standards-in-the-national-school-lunch-and-school-breakfast-programs.

Ver Ploeg, Michele et al. (2009). *Access to affordable and nutritious food: measuring and understanding food deserts and their consequences: report to congress.* Tech. rep.

Vio, Fernando, Cecilia Albala, and Juliana Kain (2008). "Nutrition transition in Chile revisited: mid-term evaluation of obesity goals for the period 2000–2010". In: *Public health nutrition* 11.4, pp. 405–412.

Wang, Dongqing, Sachin Shinde, Tara Young, and Wafaie W Fawzi (2021). "Impacts of school feeding on educational and health outcomes of school-age children and adolescents in low-and middle-income countries: A systematic review and meta-analysis". In: *Journal of global health* 11.

WFP (2017). *Smart school meals: nutrition-sensitive national programmes in latin america and the caribbean: a review of 16 countries.*

— (2020). *State of School Feeding Worldwide 2020.* URL: https://www.wfp.org/publications/state-school-feeding-worldwide-2020.

Wood, Julie M and Sanjay Gupta (2015). "Vitamin D and neurocognitive disorder due to Alzheimer's disease: A review of the literature". In: *, 27, 2* 27.2, 1E–7E.

Zielińska, Monika A, Agata Białecka, Barbara Pietruszka, and Jadwiga Hamułka (2017). "Vegetables and fruit, as a source of bioactive substances, and impact on memory and cognitive function of elderly." In: *Postepy higieny i medycyny doswiadczalnej (Online)* 71, pp. 267–280.

A Appendix

Table A.1: Change of nutritional requirements for 4th grade students meals

	Before 2015 auction	After 2015 auction	Change
Calories			
Breakfast	250	no change	–
Lunch	450	no change	–
Evening snack	250	200	↓
Total sucrose intake	23 grams	15 grams	↓
Breakfast ***(in times per month)***			
White bread	12	8	↓
Jam, honey or dulce de leche	4	2	↓
Margarine	3	2	↓
Egg	4	3	↓
Partly skimmed milk	20 to 22	16	↓
Breaskfast cereal	2	eliminated	↓
Large oat cookie	2	eliminated	↓
Yogurt	2	4 to 8	↑
Whole wheat bread	4	6	↑
Avocado	2	3	↑
Cheese	2	3	↑
Granola	–	incorporated	↑
Oats	2	4	↑
Dried fruit	–	incorporated	↑
Lunch ***(in times per month)***			
Jelly with fruit	4	2	↓
Potato, rice and pasta	250, 70 and 70 grs.	220, 60 and 60 grs.	↓
Legumes side dish	1	eliminated	↓
Salads	4	6 (w/ larger portions)	↑
Salad + protein (tuna, egg, chicken)	4	5	↑
Meats (beef, chicken, pork)	7	8 (w/ larger portions)	↑
Fish	4	4 (w/ larger portions)	↑
Vegetables side dish	5	6	↑
Fresh fruit	8	10	↑
Legumes main dish (w/ egg, beef, cheese)	5	5	–
Egg	4	4	–
Dairy-based desserts	6	6	–
Yogurt	2	2	–
Canned fruit	2	2	–
Water	Available upon request	Mandatory in tray	
Evening Snack			
Dried fruit	-	incorporated	↑
Large oat cookie or similar	60 grams max	40 grams max	↓

Note: This Table illustrates changes in nutritional requirements after the 2015 auction. Modifications decreased the grams of daily sucrose intake, the number of processed foods on the menu and increased fresh fruits and vegetables. Schools 2015 started receiving this menu in 2015, Schools 2016 in 2016 and Schools 2017 in 2017. Source: Prepared by the author based on information of auctions 85-16-LP12 and 85-10-LP14.

Table A.2: Nutritious Food Effects on Cognition

Food or Compound	Cognition	Channel	Literature Review
Antioxidants	Positive	Inhibit reactions accompanying neurodegeneration and prevents cognitive impairment.	Bell et al. 2015, Lamport et al. 2014, Zielińska et al. 2017 .
Vitamins, Omega-3 Fatty Acids	Positive	Neuroprotective properties (vitamin D) Axioxident properties (vitamin C) Maintain neuronal function (omega-3)	Anjos et al. 2013, Goodwill and Szoeke 2017, S. N. Hansen et al. 2014, Kurpad et al. 2013, Stonehouse 2014, Wood and Gupta 2015.
Water	Positive	Increases visual attention and memory (Brain activation was related to thirst affecting areas that are related to vision and memory).	Kaur 2021
Protein	Positive	Increases alertness and motivation (due to the Tryptophan and tyrosine effect on dopamine and norepinephrine synthesis).	Mahoney et al. 2005
Fiber	Positive	Release of short-chain fatty acid that affects memory.	Naiman A Khan et al. 2015
Refined Carbohydrates	Negative	Impairments in frontal, limbic, and hippocampal systems.	Francis and Stevenson 2013
Refined Sugars	Negative	Phosphorylation levels of insulin receptor, synapsin 1 and synaptophysin.	Lowette et al. 2015, Reichelt and Rank 2017

Table A.3: The effect of healthier SMP on Math+Spanish: Chaisemartin and D'Haultfoeuille.

	CS	Chaisemartin and D'Haultfoeuille				
	(1)	(2)	(3)	(4)	(5)	(6)
Healthier	0.0359**	0.0383***	0.0361***	0.0382***	0.0361***	0.0435**
	(0.0161)	(0.0135)	(0.0135)	(0.0136)	(0.0135)	(0.0177)
Individual Controls	Yes	Yes	No	Yes	No	Yes
School Controls	Yes	Yes	Yes	No	No	Yes
Municipality Trends	No	No	No	No	No	Yes
Observations	382,305	382,305	382,305	382,305	382,305	382,305
Pretrend test = 0 (p-value)	0.6041					

Notes: Each column represents a separate regression using different clusters. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors are clustered and appear in parentheses. Individual covariates include the mother's education, household income, gender and age of the student. School covariates include a dummy for the rurality of school, full-school day, and students to teacher ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: The effect of healthier SMP by subject: Chaisemartin and D'Haultfoeuille.

	CS	Chaisemartin and D'Haultfoeuille				
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Math (SD)						
Healthier	0.0336**	0.0375***	0.0342**	0.0375***	0.0343**	0.0349*
	(0.0163)	(0.0142)	(0.0141)	(0.0142)	(0.0141)	(0.0181)
Observations	385,796	385,796	385,796	385,796	385,796	385,796
Pretrend test = 0 (p-value)	0.4342					
Panel B: Reading (SD)						
Healthier	0.0323**	0.0329**	0.0324**	0.0328**	0.0323**	0.0424**
	(0.0155)	(0.0141)	(0.0142)	(0.0142)	(0.0142)	(0.0182)
Observations	384,029	384,029	384,029	384,029	384,029	384,029
Pretrend test = 0 (p-value)	0.7019					
Individual Controls	Yes	Yes	No	Yes	No	Yes
School Controls	Yes	Yes	Yes	No	No	Yes
Municipality Trends	No	No	No	No	No	Yes

Notes: Each column represents a separate regression using different clusters. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors are clustered and appear in parentheses. Individual covariates include education of the mother, household income, gender and age of the student. School covariates include a dummy for the rurality of school, full-school day, and students to teacher ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: The effect of healthier SMP by different clusters.

	(1)	(2) School	(3)	(4)	(5) Province	(6)	(7)	(8) Region	(9)
	Total (SD)	Math (SD)	Spanish (SD)	Total (SD)	Math (SD)	Spanish (SD)	Total (SD)	Math (SD)	Spanish (SD)
Healthier	0.0359**	0.0336**	0.0323**	0.0359**	0.0336**	0.0323**	0.0359**	0.0336*	0.0323**
	(0.0152)	(0.0161)	(0.0139)	(0.0159)	(0.0160)	(0.0142)	(0.0178)	(0.0185)	(0.0143)
# Clusters	5040	5040	5040	67	67	67	18	18	18
Observations	382,305	385,796	384,029	382,305	385,796	384,029	382,305	385,796	384,029

Notes: Each column represents a separate regression using different clusters. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors are clustered and appear in parentheses. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for the rurality of school, full-school day, and students to teacher ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: The effect of healthier SMP by different Timing of Adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Timing 1			Timing 2			Timing 3		
	Total (SD)	Math (SD)	Spanish (SD)	Total (SD)	Math (SD)	Spanish (SD)	Total (SD)	Math (SD)	Spanish (SD)
Healthier	-0.0241	-0.0274	-0.0179	0.0002	-0.0012	-0.0002	0.0094	0.0006	0.0168
	(0.0174)	(0.0188)	(0.0154)	(0.0183)	(0.0201)	(0.0158)	(0.0171)	(0.0180)	(0.0155)
Observations	382,305	385,796	384,029	382,305	385,796	384,029	382,305	385,796	384,029
Pretrend test = 0	0.9043	0.9206	0.7714	0.5868	0.7788	0.2616	0.9021	0.7951	0.8159

Notes: Each column represents a separate regression using different clusters. The dependent variable is the test scores measured in standard deviations. Timing 1 means that Group 1 was first treated in 2017, Group 2 in 2016 and Group 3 in 2015. Timing 2 means that Group 1 was first treated in 2017, Group 2 in 2015 and Group 3 in 2016. Timing 3 means that Group 1 was first treated in 2015, Group 2 in 2017 and Group 3 in 2016. Observations are at the individual year level. Standard errors are clustered and appear in parentheses. Individual covariates include the mother's education, household income, gender and age of the student. School covariates include a dummy for the rurality of school, full-school day, and students to teacher ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: The placebo effect of healthier SMP by lagged adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	One lag			Two lags			Three lags		
	Total (SD)	Math (SD)	Spanish (SD)	Total (SD)	Math (SD)	Spanish (SD)	Total (SD)	Math (SD)	Spanish (SD)
Healthier	-0.0241	-0.0274	-0.0179	0.0002	-0.0012	-0.0002	0.0094	0.0006	0.0168
	(0.0174)	(0.0188)	(0.0154)	(0.0183)	(0.0201)	(0.0158)	(0.0171)	(0.0180)	(0.0155)
Observations	382,305	385,796	384,029	382,305	385,796	384,029	382,305	385,796	384,029
Pretrend test = 0	0.9043	0.9206	0.7714	0.5868	0.7788	0.2616	0.9021	0.7951	0.8159

Notes: Treatment Three lags means that each group adopted the healthier SMP two years earlier, Treatment Two Lags means that each group adopted the healthier SMP two years earlier, and Treatment One Lag only one year earlier. Observations are at the individual year level. Standard errors are clustered and appear in parentheses. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Estimates using Different Geographic Linear Trends.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	School trends			Municipality trends			Province trends			Region trends		
	Total (SD)	Math (SD)	Reading (SD)	Total (SD)	Math (SD)	Reading (SD)	Total (SD)	Math (SD)	Reading (SD)	Total (SD)	Math (SD)	Reading (SD)
Healthier	0.0389**	0.0350**	0.0337**	0.0394**	0.0344**	0.0350**	0.0277*	0.0227	0.0263*	0.0260*	0.0192	0.0252*
	(0.0156)	(0.0160)	(0.0150)	(0.0159)	(0.0164)	(0.0151)	(0.0162)	(0.0168)	(0.0154)	(0.0159)	(0.0167)	(0.0151)
Observations	382,305	385,796	384,029	382,305	385,796	384,029	382,305	385,796	384,029	382,305	385,796	384,029
$Adj - R^2$	0.152	0.161	0.115	0.150	0.157	0.117	0.148	0.155	0.116	0.148	0.154	0.116

Notes: Each column represents a separate regression using different clusters. Each regression control for different geographic linear trends using TWFE. Observations are at the individual year level. Standard errors are clustered and appear in parentheses. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. Also, all regressions include school and fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: The effect of healthier SMP on 6th grade

	(1)	(2)	(3)	(4)	(5)	(6)
	Total		Math		Reading	
	CS	TWFE	CS	TWFE	CS	TWFE
Healthier	0.0183	0.00182	0.0277*	0.0126	0.0056	-0.00871
	(0.0150)	(0.0124)	(0.0152)	(0.0128)	(0.0147)	(0.0121)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
School Controls	Yes	Yes	Yes	Yes	Yes	Yes
School FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Observations	241,769	241,769	244,698	244,698	243,342	243,342
Adjusted R2	-	0.170	-	0.178	-	0.132
Pretrend test = 0 (p-value)	0.9589		0.705		0.9844	

Notes: Each column represents a separate regression. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors clustered at the municipal level appear in parentheses—number of clusters: 340. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. CS columns take into account the staggered implementation of the policy, using the Callaway and Sant'anna (2021) estimator. TWFE estimates include year and school fixed effects. The null hypothesis of the pretrends test is the presence of parallel trends. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A.10: The effect of healthier SMP by different groups (CS).

	Gender		Mother's education		Rurality		Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Male	Female	Less eq than HS	More than HS	Rural	Urban	Low	Medium	High
Panel A: Math+Reading (SD)									
Healthier	0.0422**	0.0295*	0.0526***	0.028	0.0758***	0.0269	0.0638***	0.0326	0.0174
	(0.0212)	(0.0181)	(0.0188)	(0.0205)	(0.0285)	(0.0185)	(0.0231)	(0.0201)	(0.0262)
Observations	189,345	192,163	234,025	147,259	79,408	301,635	156,822	100,899	122,767
Panel B: Math (SD)									
Healthier	0.0400*	0.0299*	0.0511***	0.0248	0.0591*	0.0276*	0.0629***	0.029	0.0074
	(0.0246)	(0.0177)	(0.0193)	(0.0206)	(0.0307)	(0.0188)	(0.0231)	(0.0211)	(0.0260)
Observations	191,241	193,751	236,244	148,528	80,012	304,509	158,264	101,856	123,850
Panel C: Spanish (SD)									
Healthier	0.0480**	0.0245	0.0454**	0.0287	0.0811***	0.0218	0.0555**	0.0307*	0.0185
	(0.0205)	(0.0182)	(0.0182)	(0.0195)	(0.0264)	(0.0178)	(0.0219)	(0.0194)	(0.0250)
Observations	190,320	192,902	235,137	147,870	79,691	303,070	157,550	101,325	123,334

Notes: Each column represents a separate regression. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors are clustered at the municipality level and appear in parentheses. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table A.11: The effect of healthier SMP by different groups (TWFE).

	Gender		Mother's education		Rurality		Income		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Male	Female	< HS	≥ HS	Rural	Urban	Low	Medium	High
Panel A: Math+Reading (SD)									
Healthier	0.0247	0.0295*	0.0340**	0.0236	0.0574**	0.0197	0.0425**	0.0180	0.0290
	(0.0159)	(0.0165)	(0.0164)	(0.0163)	(0.0245)	(0.0159)	(0.0191)	(0.0180)	(0.0176)
Observations	189,345	192,163	178,166	203,176	79,408	301,635	156,822	100,899	122,767
$Adj-R^2$	0.146	0.150	0.126	0.132	0.144	0.150	0.134	0.130	0.154
Panel B: Math (SD)									
Healthier	0.0261	0.0325**	0.0324*	0.0268	0.0380	0.0257	0.0442**	0.0165	0.0325*
	(0.0169)	(0.0171)	(0.0166)	(0.0175)	(0.0256)	(0.0172)	(0.0197)	(0.0195)	(0.0180)
Observations	191,241	193,751	179,879	204,943	80,012	304,509	158,264	101,856	123,850
$Adj-R^2$	0.154	0.158	0.135	0.140	0.155	0.154	0.140	0.136	0.162
Panel C: Reading (SD)									
Healthier	0.0189	0.0222	0.0297*	0.0169	0.0658***	0.0105	0.0345*	0.0147	0.0215
	(0.0149)	(0.0157)	(0.0159)	(0.0151)	(0.0228)	(0.0145)	(0.0182)	(0.0162)	(0.0175)
Observations	190,320	192,902	179,039	204,025	79,691	303,070	157,550	101,325	123,334
$Adj-R^2$	0.105	0.108	0.098	0.102	0.112	0.117	0.107	0.102	0.119

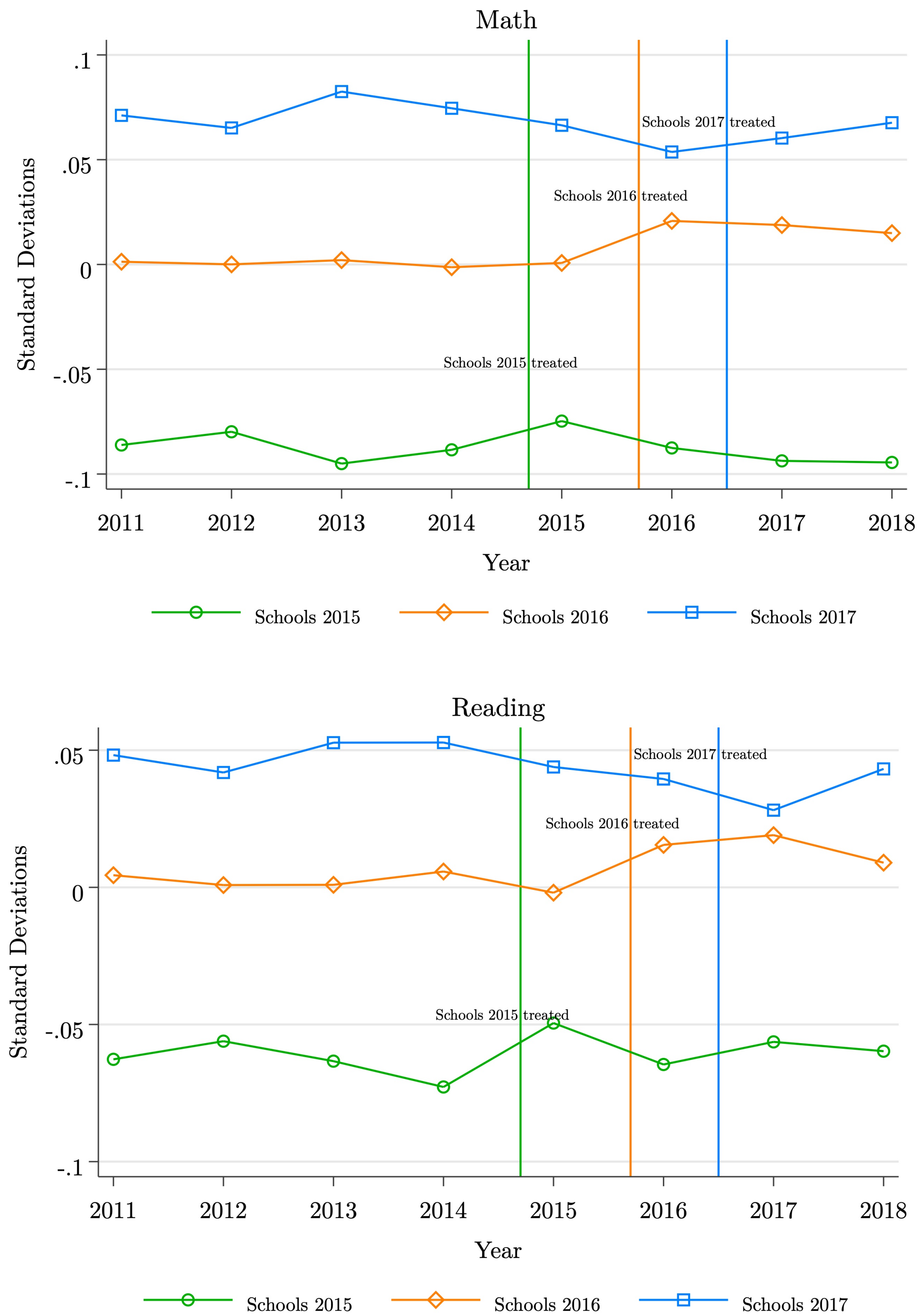
Notes: Each column represents a separate regression. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors are clustered at the municipality level and appear in parentheses. Individual covariates include years of education of the father, years of education of the mother, presence of parents at home, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. Also, all regressions include school and fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.12: The effect of healthier SMP by rate of attendance (TWFE)

	(1)	(2)	(3)
		Attendance	
	Low	Medium	High
Panel A: Total (SD)			
Healthier	0.0150	0.0356**	0.0483**
	(0.017)	(0.0174)	(0.0201)
Observations	133,905	125,496	122,041
$Adj - R^2$	0.151	0.142	0.145
Panel B: Math (SD)			
Healthier	0.0263	0.0318*	0.0494**
	(0.0171)	(0.0172)	(0.0223)
Observations	135,675	126,546	122,707
$Adj - R^2$	0.153	0.148	0.155
Panel C: Reading (SD)			
Healthier	0.0017	0.0338*	0.0394**
	(0.0166)	(0.0181)	(0.017)
Observations	134,754	125,986	122,424
$Adj - R^2$	0.119	0.111	0.112
Mean Attendance	0.865	0.946	0.983

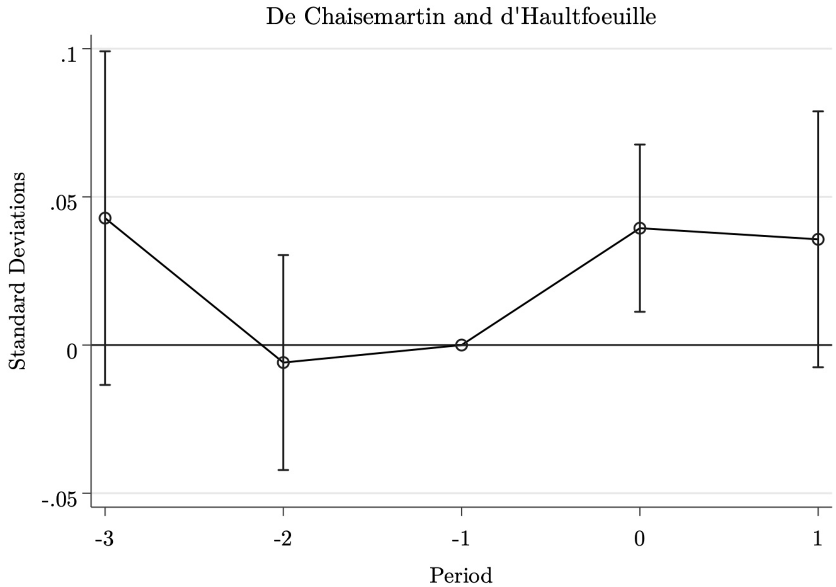
Notes: Each column represents a separate regression using TWFE approach. The dependent variable is the test scores measured in standard deviations. Observations are at the individual year level. Standard errors clustered at the municipal level appear in parentheses—number of clusters: 340. Individual covariates include years of education of the mother, household income, gender and age of the student. School covariates include a dummy for rurality of school, full-school day, and students to teacher ratio. Also, all regressions include school and fixed effects. * p < 0.1, ** p < 0.05, *** p < 0.01.

Figure A.1: Raw Test Scores 4th: 2011-2018



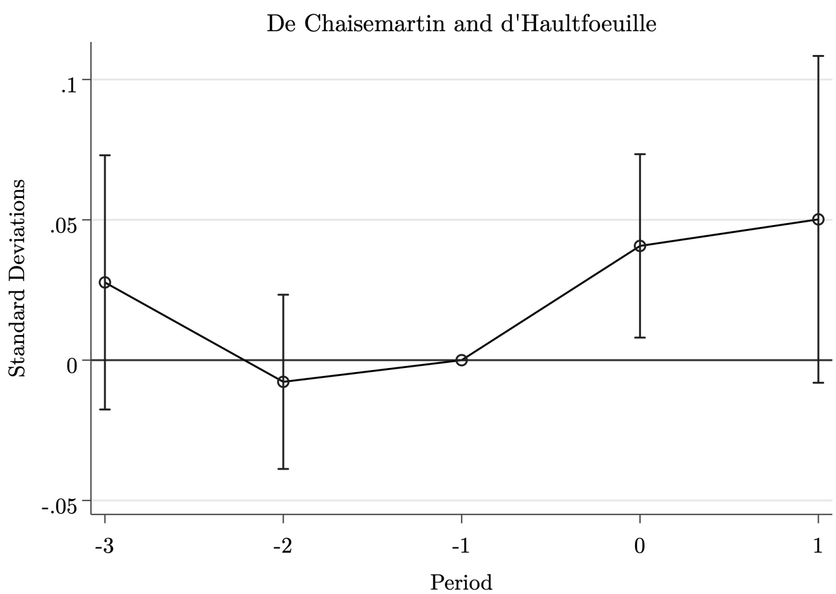
Note: These figures present the raw test scores for 4th graders in public schools in Math and Reading, respectively, between 2011 and 2018. The line with the circle marker corresponds to schools that started to receive nutritious meals in 2015. The line with a diamond marker and the line with a square marker corresponds to Schools 2016 and 2017 began to receive the healthy meals in 2016 and 2017, respectively.

Figure A.2: Event Study: Total (Math+Reading) 4th



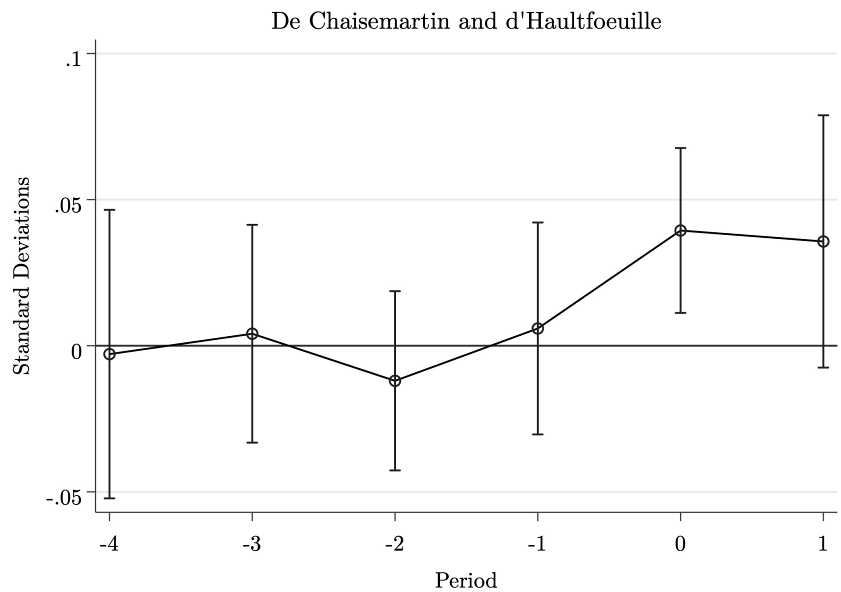
Note: The figure presents results from the individual-level event study framework from the approach from De Chaisemartin and d'Haultfoeuille 2020. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.3: Event Study Linear Trends: Total (Math+Reading) 4th



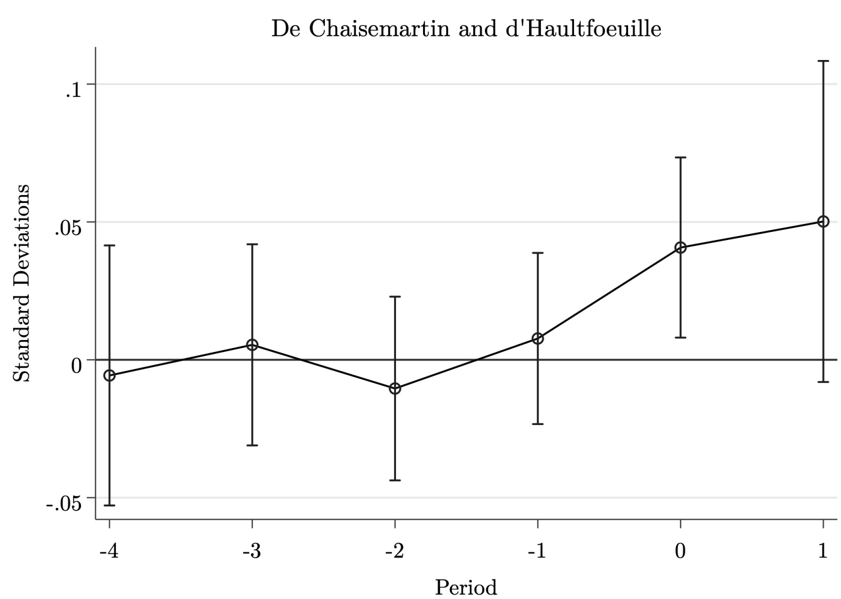
Note: The figure presents results from the individual-level event study framework from the approach from De Chaisemartin and d'Haultfoeuille 2020. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.4: Event Study with Placebos: Total (Math+Reading) 4th



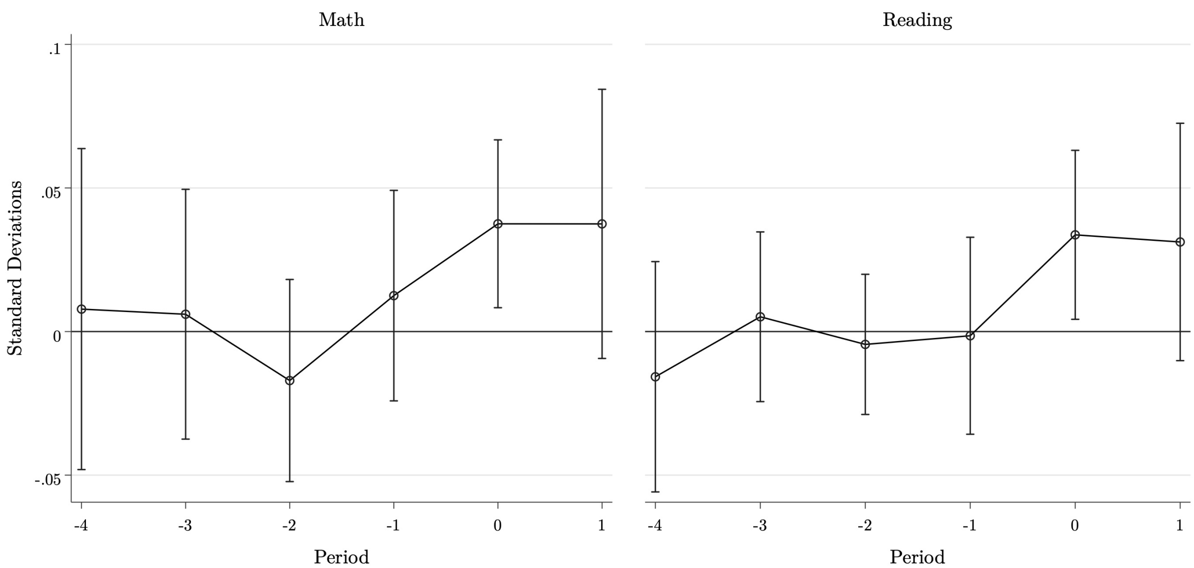
Note: The figure presents results from the individual-level event study framework from the approach from De Chaisemartin and d'Haultfoeuille 2020. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.5: Event Study Placebos + Linear Trends: Total (Math+Reading) 4th



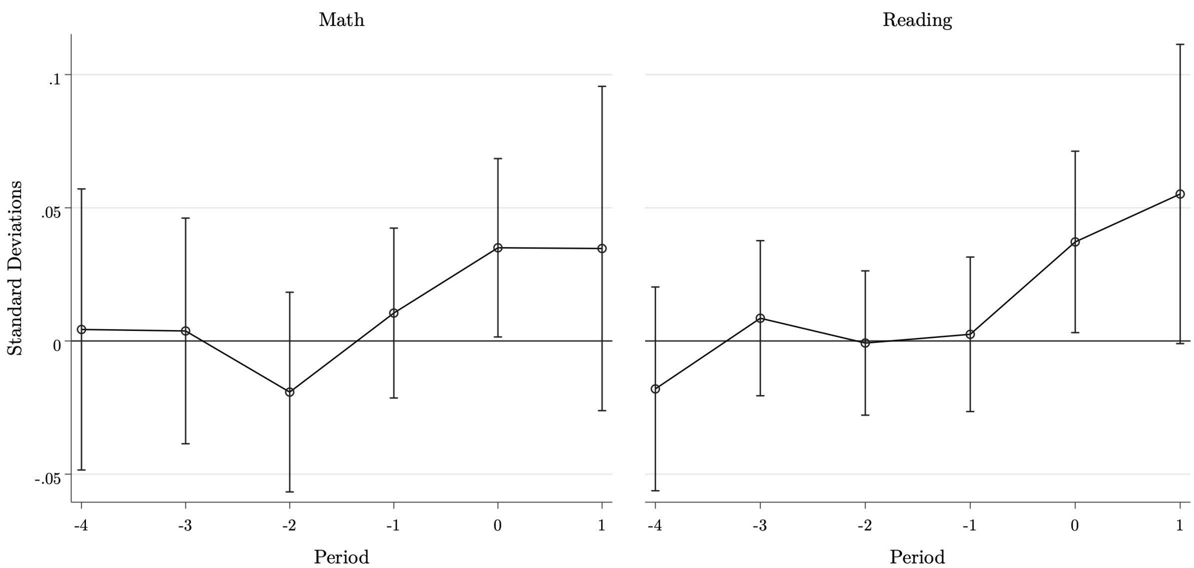
Note: The figure presents results from the individual-level event study framework from the approach from De Chaisemartin and d'Haultfoeuille 2020. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.6: Event Study with Placebos by subject using Chaisemartin and D'Haultfoeuill's method



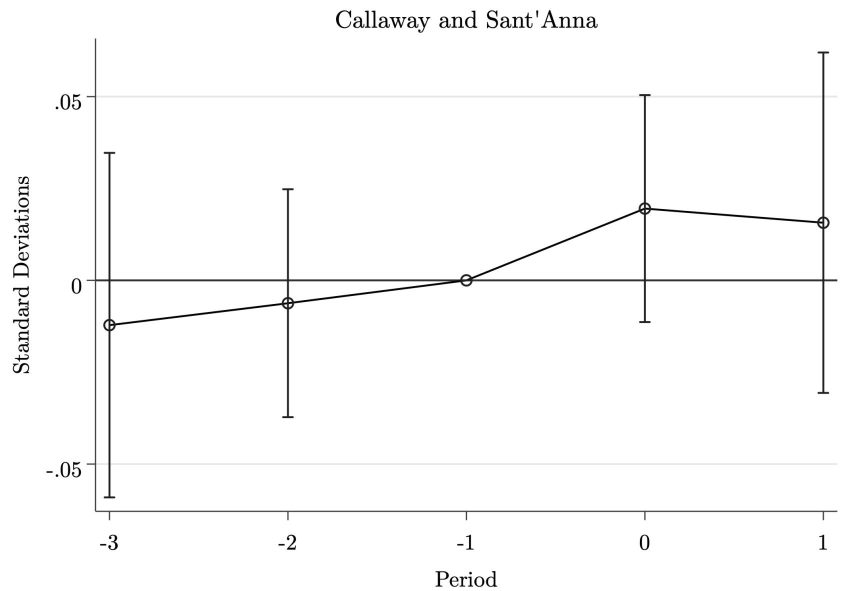
Notes: The figure presents results from the individual-level event study framework in Equation(5). All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

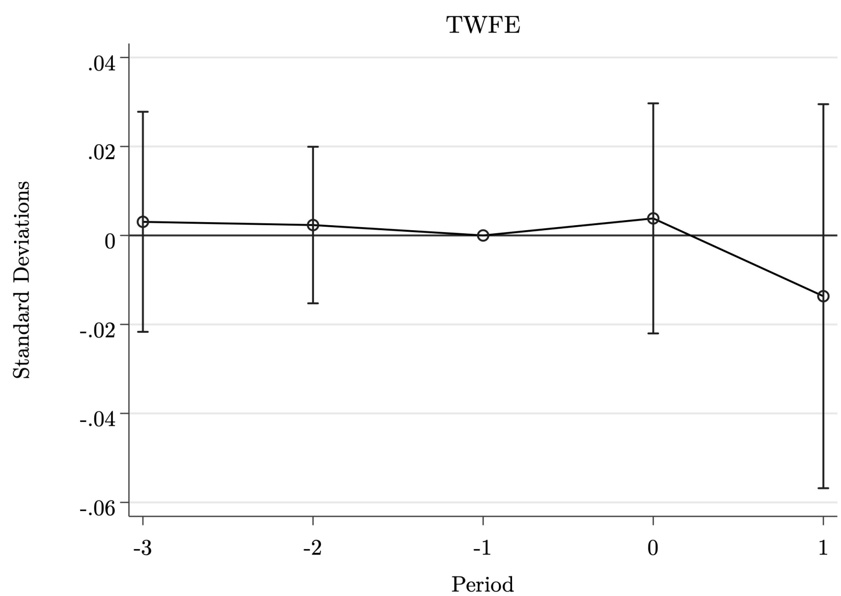
Figure A.7: Event Study Placebo + Linear Trends by subject using Chaisemartin and D'Haultfoeuill's method



Notes: The figure presents results from the individual-level event study framework in Equation(5). All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

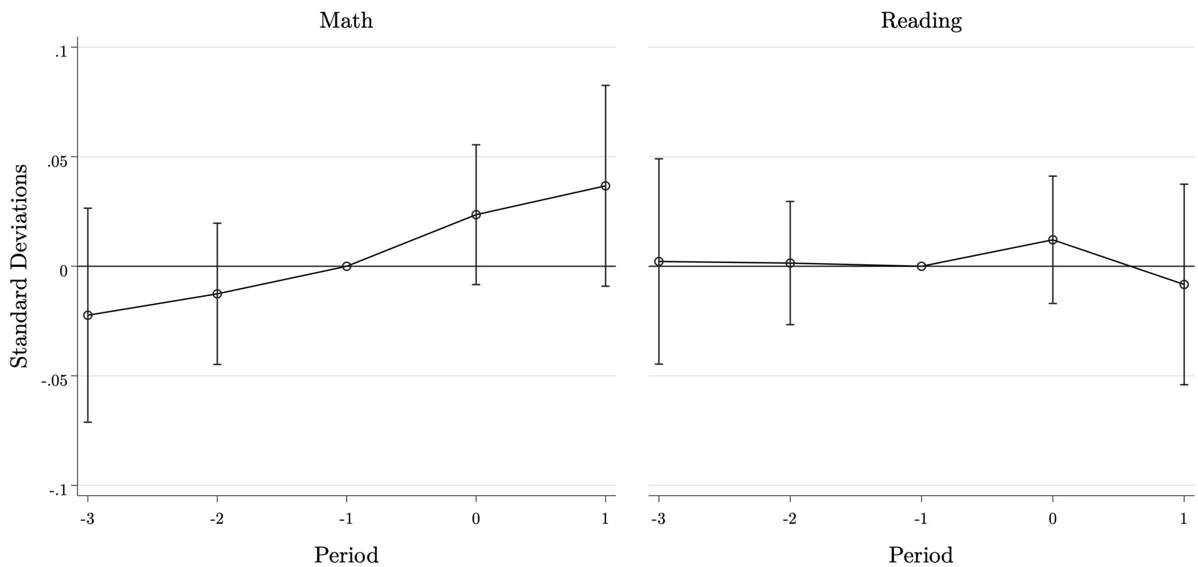
Figure A.8: Event Study: Total (Math+Reading) 6th





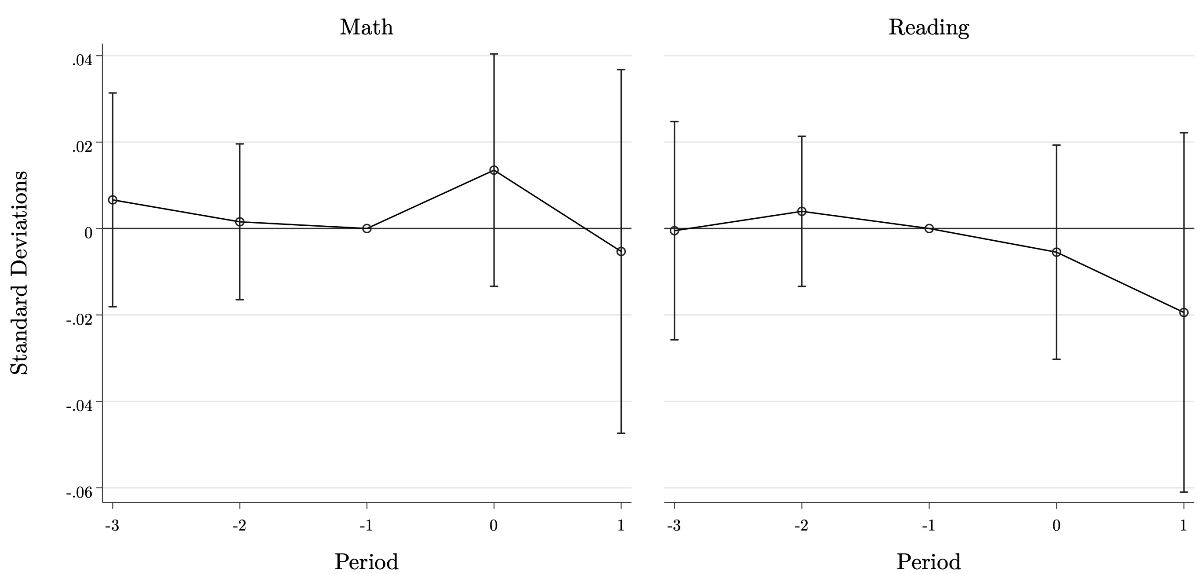
Note: The figure presents results from the individual-level event study framework from the approach from Callaway and Sant'Anna 2021. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.9: Event Study: CS



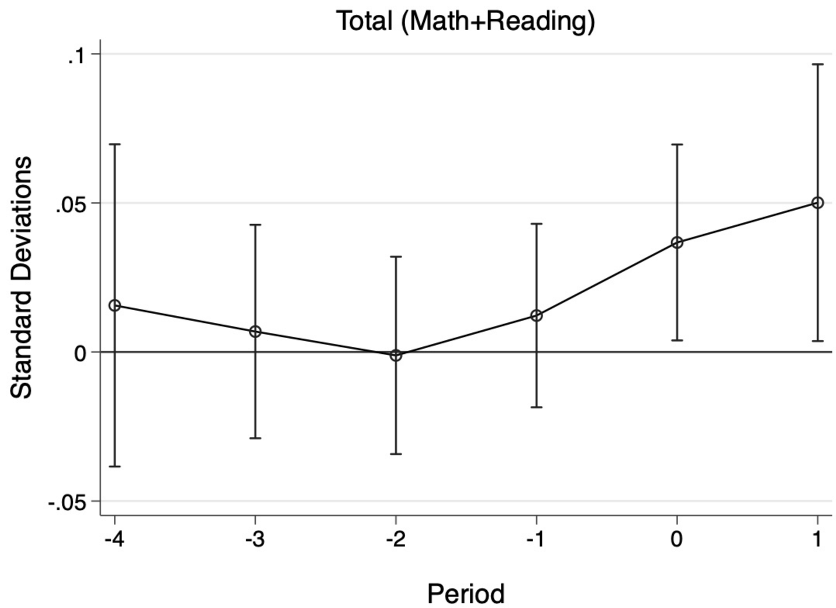
Note: The figure presents results from the individual-level event study framework from the approach from Callaway and Sant'Anna 2021. All specifications include controls for student and school characteristics. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.10: Event Study: TWFE



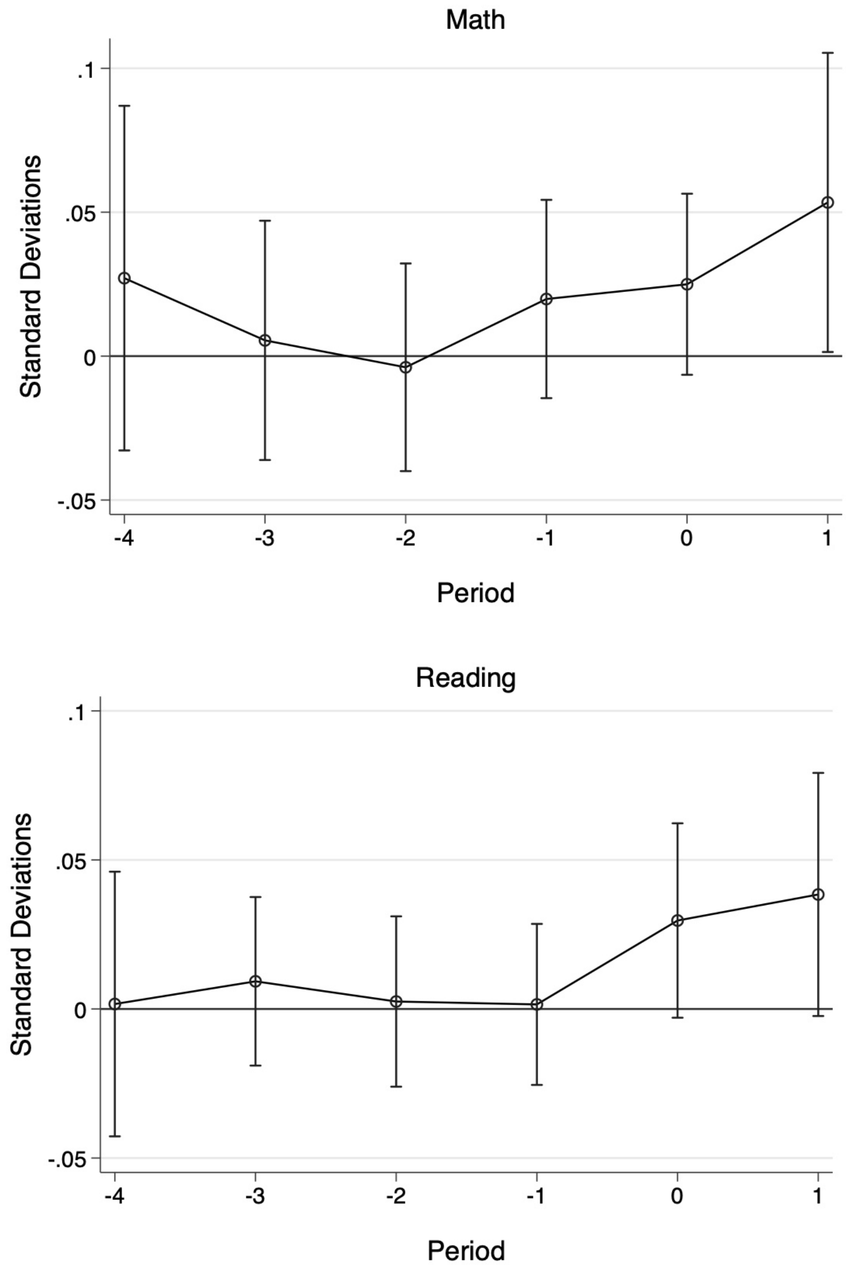
Notes: The figure presents results from the individual-level event study framework in Equation(5). All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.11: Event Study with Placebos (CS)



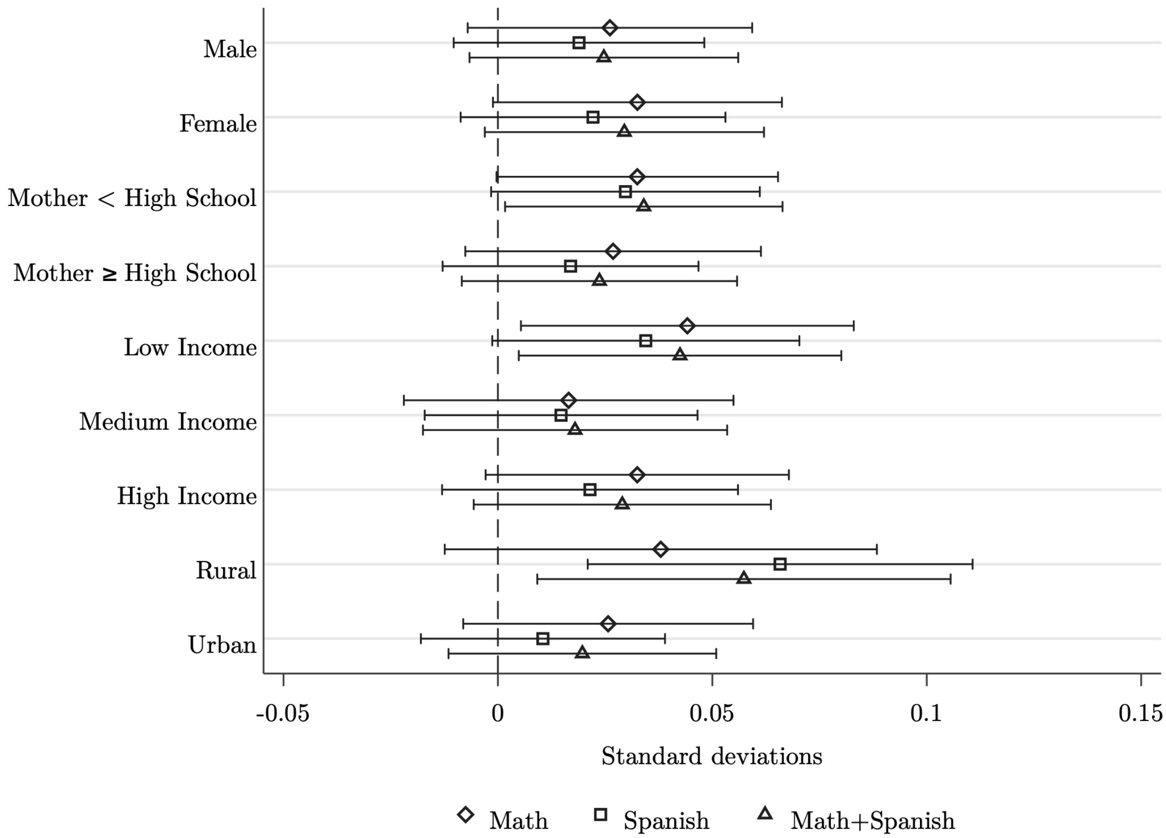
Note: These figures present the placebo estimates before the healthier meals started for 4th graders in public schools in Math and Reading, respectively, between 2011 and 2018. The line with the circle marker corresponds to schools that started to receive nutritious meals in 2015. The line with a diamond marker and the line with a square marker corresponds to Schools 2016 and 2017 began to receive the healthy meals in 2016 and 2017, respectively.

Figure A.12: Event Study with Placebos by Subject (CS)



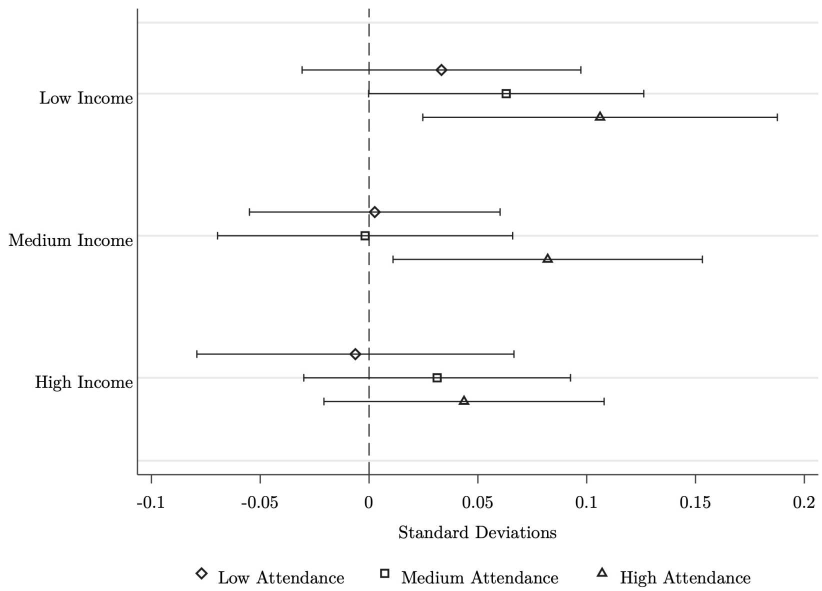
Note: These figures present the placebo estimates before the healthier meals started for 4th graders in public schools in Math and Reading, respectively, between 2011 and 2018. The line with the circle marker corresponds to schools that started to receive nutritious meals in 2015. The line with a diamond marker and the line with a square marker corresponds to Schools 2016 and 2017 began to receive the healthy meals in 2016 and 2017, respectively.

Figure A.13: The effect of a healthier SMP by different groups (TWFE).



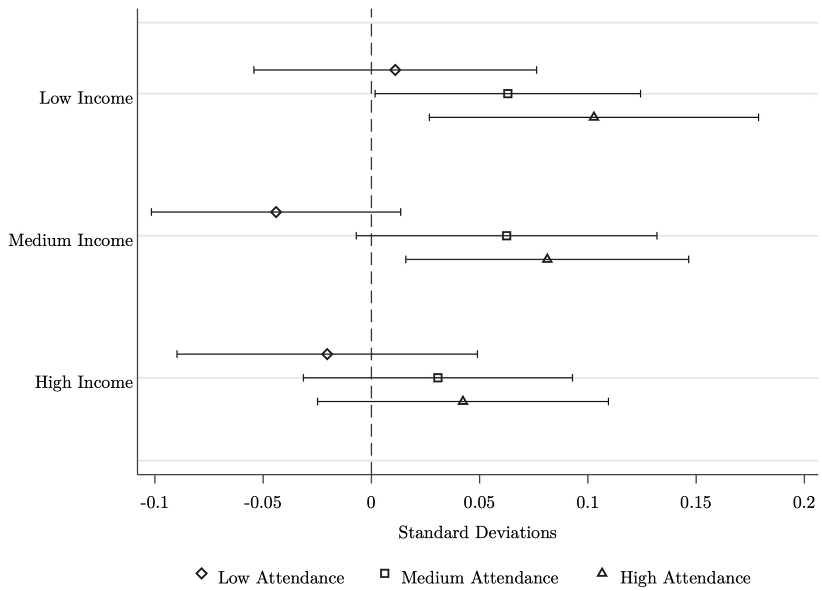
Note: The figure presents results from the individual-level framework in Equation (3) for different groups of interest. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.14: The effect of a healthier SMP on Math by level of attendance and income (CS).



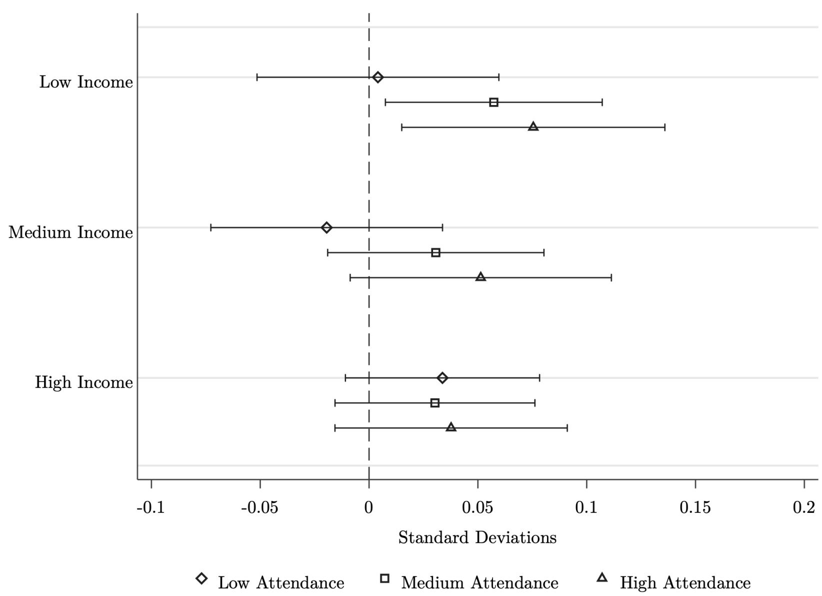
Note: The figure presents results from TWFE for different income/attendance groups. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.15: The effect of a healthier SMP on Reading by level of attendance and income (CS).



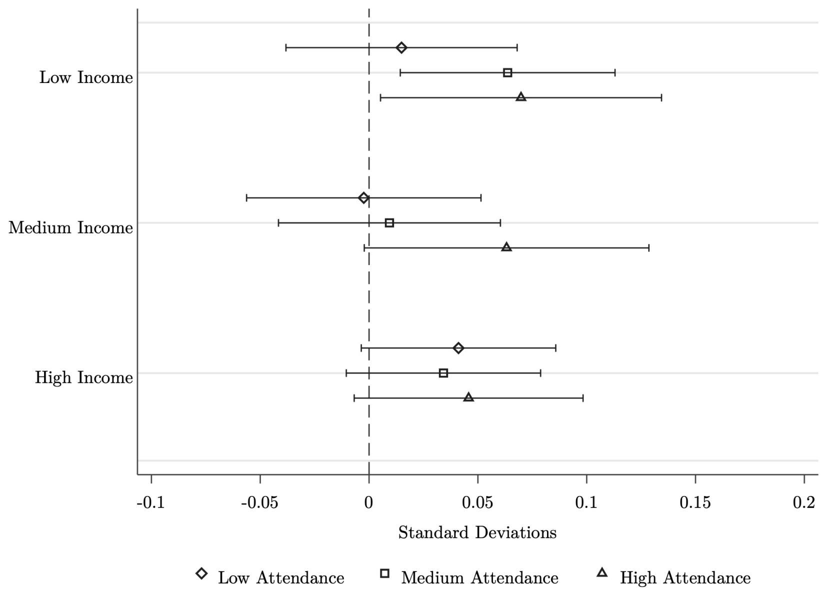
Note: The figure presents results from TWFE for different income/attendance groups. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.16: The effect of a healthier SMP on (Math+Reading) by level of attendance and income (TWFE).



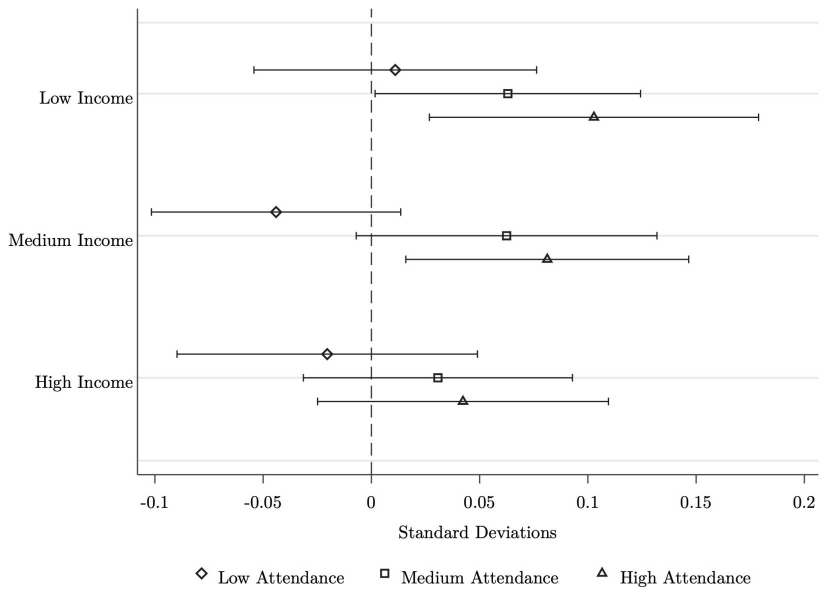
Note: The figure presents results from TWFE for different income/attendance groups. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.17: The effect of a healthier SMP on Math by level of attendance and income (TWFE).



Note: The figure presents results from TWFE for different income/attendance groups. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.

Figure A.18: The effect of a healthier SMP on Reading by level of attendance and income (TWFE).



Note: The figure presents results from TWFE for different income/attendance groups. All specifications include controls for student and school characteristics and year and school fixed effects. Bars denote 95 percent confidence intervals from robust standard errors and are clustered at the municipality level.