The Effects of Universal Free Lunch Provision on Student Achievement: Evidence from South Korea

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Abstract

This paper examines the impact of the Universal Free Lunch Program (UFLP) on student achievement in South Korea. I leverage the staggered rollout of the UFLP across South Korean provinces and employ difference-in-differences strategies to estimate the causal effects of the program. Taking advantage of rich school-level data, I find that providing a free lunch to all students leads to improvements in academic achievement on average. I also test for heterogeneous effects and find that the benefits of the UFLP appear universally across different baseline participation rates in the means-tested lunch subsidy. After exploring numerous potential mechanisms including changes in school lunch participation, I find suggestive evidence of the increased participation in and expenditures on the after-school programs that are not free. These results suggest that parents used the saved lunch fees for educational investment and highlight the importance of mental accounting.

Keywords: school lunch, test scores, educational policy
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1 Introduction

Despite the differences in culture, wealth, and academic policy across nations, school meals are a crucial source of nutrition intake for many students: 300 million children in 85 countries participate in large-scale school meal programs worldwide (Global Child Nutrition Foundation 2021). Many of these countries also provide school meal subsidies. South Korea's Ministry of Education reports that in 2016, the Universal Free Lunch Program (UFLP) cost 2.8 billion USD, or 0.2 percent of GDP (Ministry of Education 2021). Still, proper evaluation requires weighing the program's cost against its social welfare maximizing benefits. School meals are a type of schooling input, as students receive school meals in classrooms or on school grounds. Increasing schooling inputs positively relates to better academic achievement, higher earnings (Murnane et al. 2000; Currie and Thomas 2001; Heckman and Vytacil 2001; Dougherty 2003; Heckman et al. 2006; Deming 2009; Chetty et al., 2011) and other important later life outcomes including health (Lleras-Muney 2005; Eide, Showalter, and Goldhaber 2010; Weinstein and Skinner 2010; Clark and Royer 2013).

This paper examines the impacts of South Korea's Universal Free Lunch Program (UFLP) on students' academic achievement. By leveraging the staggered implementation and rich administrative data, I estimate the intent-to-treat effect of the UFLP, and find that the program reduced underachievement by 13 percent and improved test scores by 0.06 standard deviations. I explore potential channels and find evidence that parents react to the additional disposable income (saved lunch fees, approximately $700 per year) by allocating it towards educational investment. I find increased participation in and spending on academic after-school programs, which are generally not free. The UFLP's impacts are robust to sparser or more saturated specifications and the inclusion of province characteristics.[1] Moreover, these effects are found universally across different baseline participation rates in the means-tested lunch subsidy for both average standardized scores and the percentage of underachieving

[1] These checks are discussed in detail in section 6, including the DID_M estimates of de Chaisemartin and D'Haultfoeuille (2020) and the related results.

students. These results are consistent with the implication of the UFLP as an in-kind transfer to relatively higher income families, since lower income families had access to means-tested lunch subsidies prior to the UFLP.

There are several reasons why the UFLP and the South Korean context are worth investigating. First, the UFLP reached all students from elementary to high school without any kinds of means-testing, unlike other meal programs. For example, the Midday meal program in India is only for public primary school students, and the Community Eligibility Provision (CEP) in the US targets schools with a relatively high percentage of students eligible for free or reduced-price lunches. Second, the UFLP is large, making up approximately 5 percent of total local government educational expenditures. Given the size of the program, understanding the impacts of the UFLP helps justify its existence, especially when an increase in enrollment and school lunch participation is relatively less likely in the South Korean setting (OECD 2017, 2021a, 2021b).[2] Third, South Korea provides a testing ground for the effects of universal meal provision when means-tested lunch subsidy is already in place. As most countries provide school meal subsidies for students with relatively low family incomes (OECD 2017), this study can provide pertinent policy implications for many other countries that might consider universal school meal provision.

This paper contributes to two distinct strands of literature. The first is studies that focus on the impact of school meal subsidies and their effect on various outcomes, including health (Bhattacharya et al. 2006; Schanzenbach 2009; Gundersen, Kreider, and Pepper 2012; Berry et al. 2020) and academic achievement (Hinrichs 2010; Leos-Urbel et al. 2013; Frisvold 2015; Schwartz and Rothbart 2020; Chakraborty and Jayaraman 2019; Gordanier et al. 2020; Ruffini 2020). While this literature is heavily based on evidence from the US, this paper can add to the generalizability of findings in the literature. This paper finds improvements in standardized scores of 0.05 to 0.11 standard deviations due to the implementation of the UFLP. The magnitude of improved standardized scores is comparable to the estimated

[2] School lunch participation had been close to 100 percent before the UFLP. See section 5.1.1 for more details.

effects found in Chakraborty and Jayaraman (2019) in India, and Schwartz and Rothbart (2019), Ruffini (2021) and Gordanier et al. (2020) in the US. Moreover, my results suggest that the program is relatively cost-effective compared to many other educational programs in the US setting, including a 10 percent increase in spending and class size reduction (Yeh, 2010).

The second strand studies household consumption decisions. The estimates imply that parents reallocate the additional disposable income towards the students. The estimates imply that students on average participate in 0.4 more after-school programs throughout the year, or 5 months' worth of participation in one program. Back-of-the-envelope estimates of the cost of this increased academic after-school program participation suggest 12 to 25 percent of the saved lunch fee is spent on students' education.[3] Empirical results examining the effects of providing benefits earmarked for children provide insights that parents are likely to spend the benefit on children (Lundberg, Pollak and Wales 1997; Hener 2017; Jones et al. 2019) by increasing spending on education and non-food items, although (partial) crowd-out in food spending is observed (Chakraborty and Jayaraman 2020; Handbury and Moshary 2020).[4] This increase in spending on children can be linked to the mental accounting framework (Thaler 1990, 1998, and 1999). I find suggestive evidence of an increase in the academic after-school program participation due to the implementation of the UFLP, which indicates increased spending on education.[5]

More broadly, this paper also relates to the literature that studies the impacts of public assistance programs on children's outcomes, including academic achievement. Because changes in school lunch participation in the South Korean context are unlikely, as I show in panel (a) of figure 1, the UFLP operates as an in-kind transfer. For example, Milligan and Stabile (2011) and Dahl and Lochner (2012) find that tax benefits improve children's

[3] Unlike in the US, these programs are generally not free.

[4] Lundberg, Pollak and Wales (1997) and Kenney (2008) also point out that this phenomenon is prone to be greater if the child benefits are controlled by the mother. Before the UFLP, school lunch fees were generally paid by mothers as shown by anecdotal evidence (Ryu et al. 2011) and research on household financial management (Lee and Yang 2008).

[5] I discuss the more related studies in appendix section A.

academic achievement and various health measures. Akee et al. (2010) also find that an exogenous increase in household income from transfer payments led to higher education attainment for the children in affected households.

This paper proceeds as follows. In section 2, I summarize the general information regarding the South Korean school system alongside the characteristics of the Universal Lunch Program. Section 3 describes the data. I discuss the estimation strategies in section 4, and present the results in section 5. I provide robustness checks and discuss the heterogeneous effects across baseline participation rate in the means-tested school subsidy in section 6. I address potential mechanisms in section 7, and conclude in section 8.

2 Background and Institutional Context

The UFLP replaced the already existing means-tested school lunch subsidy, but the timing of implementation or expansion of the ULFP was staggered due to the provincial governments' budgetary concerns.[6][7] The rollout information for all provinces is summarized in appendix tables A.1 to A. 4. Due to the staggered rollout procedures, in many cases the UFLP treated only some of the students within a school.

From the parents' perspective, lunch fees make up a large portion of education expenses. Depending on school levels, expenses include slightly different categories[8]. Starting with the UFLP, the government also added other policies to reduce the cost of education, including subsidies for school uniforms and textbooks. Still, these policies did not coincide with the timing of the UFLP implementation, and most of them did not occur until the end of the

[6] Students with family incomes less than 60 percent of the median income (considering family asset value) were eligible for the means-tested school lunch subsidy before the UFLP. The exact threshold for the eligibility can be slightly different in each province (Ministry of Education 2021).

[7] It is impossible to obtain the exact breakdown of the UFLP's budget, but on average, the provincial education budget in South Korea combines 60 percent of the Ministry of Education's budget (direct central government expenditures) and 40 percent of the provincial government's budget (Ministry of Education 2021). But approximately 80 percent of the provincial government's budget is supplemented by the central government (Hyeon and Shin 2016).

[8] These categories include entrance fees, tuition, operational support fees, school meal fees, and school uniform costs, but depending on the school level, some might not be included. For example, elementary schools almost never require a school uniform.

sample period of this study. This ensures that the estimated effects of the UFLP are not confounded with the effects of other educational subsidies.

Parents' payments to the schools can be sticky, especially since there is a widely adopted and convenient payment system which has applied to all fees that the parents pay to the schools since the late 1990s (Jeong 1997; Eum 1997). Through this system, parents provide the account number of one of their checking accounts to their children's schools, and give authorization to withdraw the deposit if needed (KFTC 2021). Since both school lunch and after-school program fees are processed through the same account, parents are likely to apply mental accounting to the fees, as these fees in total would be easily grouped together.

In panel (a) of figure 1, I plot the average value of students' participation in school lunch programs and the share of students who benefit from school lunch subsidies. This figure implies that the average participation rate in the school lunch programs was very close to one regardless of the UFLP implementation. In panel (b) of figure 1, I plot the average value of parents' and governments' contribution relative to the total yearly budget for school meals. A reduction in the parents' shares in contrast to the increase in the government's contribution is evident.

A reduction in parents' contributions leads to increased disposable income for families with school-aged children by saving school lunch expenses. Still, the extent of this increase differs by family income and participation in the means-tested school meal subsidy. If families were already participating in the means-tested lunch subsidy before the UFLP started, they would not experience an increase in disposable income.[9] The families ineligible for the means-tested lunch subsidy due to relatively higher income would experience an increase in disposable income due to the UFLP by saving lunch fees, which are approximately \$600-\$720 per year for each student. General details about the school system in South Korea can be found in Appendix section B.

[9] There are no official estimates regarding the take-up of the means-tested lunch subsidy. Yu, Lim and Kelly (2019) find suggestive evidence that the stigma can affect the take-up.

3 Data

3.1 EduData Service System Data

I use restricted data provided by EduData Service System (EDSS) from 2009 to 2016. This data sampled 70 percent of all schools in South Korea and contains various information about each school, such as the number of students, the number of teachers, school facilities, and school food expenditures. This data also contains information regarding the National Assessment of Educational Achievement (NAEA) exam for Korean, math, and English.[10] [11]

The sample consists of 20,310 school-by-year observations, and approximately 41 percent of school-by-year observations was either fully or partially treated during the sample period. Column (1) of table 1 reports the summary statistics of the academic achievement outcomes of interest, school characteristics, and variables related to school meal provision.

EDSS data has abundant information regarding school meal provision. In the South Korean context, most of the students get lunch from schools. Regardless of the treatment status, almost all students receive lunch from school. The share of students who receive school meal subsidies is roughly 23 percentage points higher in the treated schools. This share is roughly 0.5 among the treated schools, which falls short of the maximum value mostly due to the staggered adoption of the program even within a school. Per student meal expenditure is slightly greater for the treated schools, but this is likely due to inflation over the years and high schools generally having higher per student meal expenditures. By comparing the share of parents' contribution and the governments' contribution, the main source of funding for the school meals is parents among the pre-treatment observations and the government among the post-treatment observations. This change of source of funding is discussed in more detail in section 5.1.1.

[10] These test results are used to gauge the quality of school education, and to make sure that students at the lower tail of the score distribution follow the curriculum. Comparable exams are the National Assessment of Educational Progress (NAEP) in the US or the Standard Assessment Task in the UK.

[11] After 2016, the Ministry of Education stopped the comprehensive tests and sampled only three percent of the schools. The scores after 2016 are not available from the EDSS.

To investigate the changes in education expenditure due to the UFLP, I use the EDSS data to estimate the effects of the UFLP on after-school program participation and expenditures. EDSS data has information on how many students participated in both academic and non-academic after-school programs, and I use the average number of programs in which students participated in each school as an outcome to examine this potential underlying mechanism. In South Korea, most of the after-school programs are not free and parents have to make payments for the students to participate. Thus, increased after-school program participation implies increased expenditure.

Province Characteristics. The bottom panel of table 1 reports the province characteristics. I report the two financial independence indices that Statistics Korea publishes yearly.[12] The provincial government's financial independence is emphasized by many of the Ministry of Education's government officials as a crucial determinant of the UFLP implementation timing. Provinces with higher financial capacity, which is associated with a higher level of financial independence indices, were more likely to adopt the UFLP earlier. I also gauged superintendents' support for the UFLP using interviews and their election promises. I obtained the province-level unemployment rate series from the Korean Statistical Information Service (KOSIS).[13] Since the eligibility for the means-tested lunch subsidy largely depends on household income, the regional unemployment rate can affect the baseline participation in the means-tested subsidy, which can change the UFLP's impact.

3.2 Private Education Expenditures Survey

In this subsection, I describe the Private Education Expenditures Survey data (PES), which I utilize to investigate underlying mechanisms. The PES contains student-by-year repeated cross-section data and has information on approximately 55,000 middle (22,000) and high school (33,000) students each year. The parents and the teachers of the students answer

[12]For more information, visit https://www.index.go.kr/potal/main/EachDtlPageDetail.do?idx_cd=2857 and https://www.index.go.kr/potal/main/EachDtlPageDetail.do?idx_cd=2458.

[13]See https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=INH_1DA7104S&conn_path=I3 for more information.

the survey regarding the students' utilization of private tutoring and after-school programs. The PES data also provides the students' basic demographic information such as gender and school level (middle or high school), and family income in 8 categories. Table A.43 reports the summary statistics for the PES data.

In contrast to the EDSS data, the PES data has student-level participation and expenditure information on after-school program participation. However, the geographical information on the students' families is not as granular as the geographical information found in the EDSS data.

4 Estimation Strategy

4.1 Difference-in-differences

To estimate the effect of the Universal Free Lunch Program on the students' academic achievement, I implement a difference-in-differences framework. This estimation strategy exploits the timing difference across provinces and school levels.

The baseline difference-in-differences regression equation is as follows:

$$Y_{sdt} = \beta UFLPshare_{sdt} + \Phi X_{sdt} + \psi Z_{dt} + \lambda_s + \lambda_d \times t + \lambda_t + \epsilon_{sdt}, \tag{1}$$

where Y_{sdt} is the academic achievement outcomes (standardized score and the percent of underachieving students) of school s in province d in year t. $UFLPshare_{sdt}$ ranges from 0 to 1 and represents the share of the treated students in school s in province d in year t. The value of $UFLPshare_{sdt}$ can differ even in the same province. For example, if only the first graders to the second graders were treated in province p, then $UFLPshare_{sdt}$ is equal to the sum of the number of the first graders and the number of the second graders divided by the total number of students. The coefficient of interest is β. Fully treating the schools (i.e., increasing $UFLPshare_{sdt}$ from 0 to 1) increases the scores by β SD, on average.[14] X_{sdt} stands for the school-level controls such as teacher-student ratio, male-to-female student ratio, and the total number of students. λ_s represents the school fixed effects, λ_t represents the year fixed effects, and $\lambda_d \times t$ stands for the province-specific linear time trend.

There are two types of academic achievement information available in the EDSS data. The first type is the school-level average scores for Korean, math, and English.[15] The second type of information is the percentage of students at each achievement level in each school. The three achievement levels are "below-basic", "basic level", and "adequate" level.[16] The Ministry of Education sets the cutoff scores for all three achievement levels each year, and schools do not have control over the cutoffs. I define the percentage of the sum of the two lower levels ("below-basic" and "basic" level) as the percentage of underachieving students, and examine whether the UFLP improves students' academic achievement by reducing the percentage of underachieving students. This is the second outcome of interest, as it captures the distributional impacts of the UFLP.

Standard errors are clustered at each school level using the school identifiers, as the treatment intensity differs across schools even in the same province and year. To check for the robustness of the results, I also report estimates from sparser or more saturated models, such as those including province-level controls in section 6.[17]

The key identifying assumption in the difference-in-differences is the parallel trend in the achievement outcomes across the schools with earlier and later implementation of the UFLP.

[14] Similarly for the percentage of underachieving students, fully treating the schools reduces the underachieving students by β percentage points.

[15] The formula for standardizing the scores is as follows:

$$StandardizedScore_{slt} = \frac{RawScore_{slt} - Avg_{lt}}{SD_{lt}}, \tag{2}$$

where $RawScore_{slt}$ is the score of school s in school level l (which is either middle school or high school level) in year t. Avg_{lt} is the average score among the schools that are school level l in year t, and SD_{lt} is the standard deviation of scores of schools in school level l in year t.

[16] Since every student is classified as either one of these three levels, the sum of these three percentages for each school-year combination is automatically equal to one hundred.

[17] Province-level controls include two statistics for the financial independence for each province, the indicator having a value of one if the chief superintendent's stance supports the Universal Free Lunch Program, province-level GDP, and unemployment rates.

Descriptive statistics suggest that there the timing of the implementation of the UFLP is not correlated with either the school characteristics or the province characteristics. For the treated observations, the mean of the standardized scores for the post-treated observations is slightly lower, and the percentage of underachieving students is generally larger. As the top two panels report the summary statistics for the outcomes of interest, the differences between the post- and pre-treated observations do not mean selection on academic achievement since they contain the causal effects of the UFLP. Similarly, the evident decrease in parents' contribution and increase in the government's contribution to the school meal expenditure can be due to the expansion of the UFLP.

Column (2) of table 1 of presents the summary statistics for the treated observations, including the partially treated observations. Column (3) of table 1 includes the descriptive statistics of the pre-treated observations. Note that post-treated observations are generally in the later years, and the difference between the post-treated and pre-treated observations includes this component. In column (4) of table 1, I provide the regression estimates from a model with each of these characteristics as the dependent variable, and the regressor as the degree of the treatment intensity. This formally tests the correlation between the observable characteristics and the treatment intensity after accounting for the year fixed effects and the school fixed effects. Standard errors are clustered by using the school identifier.

None of the observable school or province characteristics imply a systematic relationship between the implementation of the UFLP. There are characteristics that show statistically significant differences across the pre- and post-treated observations. However, these differences are small, as they are usually around 2 to 3 percent of the mean, and do not exceed 7 percent of the mean. Some school characteristics are mechanically greater in the pre-treated observations, as the high schools are generally treated in the later years. For example, the number of teachers and students are generally smaller in the post-treated observations, likely due to the fact that the high schools have more students and teachers. And in some provinces, smaller schools are treated earlier. The male-to-female student ratio does not differ between the pre-treated and post-treated observations, which implies that the UFLP does not favor or target schools based on students' gender. The number of students who transfer in and transfer out also remained stable, which suggests a low chance of selection into treatment. Still, I include school characteristics in all specifications, and also include province characteristics for robustness checks.

4.2 Event Study

I utilize the event study regression to validate the parallel trend assumption in the difference-in-differences framework, to confirm that there are no statistically significant differences between the early adopters and late adopters of the ULFP in pre-treated periods. The years relative to the UFLP are calculated by subtracting the first year each school got treated using the program rollout information from the year of observation. I estimate the following event study regression model with school-level observables, school fixed effects, and year fixed effects:

$$Y_{sdt} = \sum_{\substack{j=-11 \\ j\neq-1}}^{+9} \beta_j I(YearsRelativeToUFLP = j)_{sdt} + \Phi X_{sdt} + \lambda_s + \lambda_t + \epsilon_{sdt}, \tag{3}$$

where Y_{sdt} is the academic achievement outcomes of interest in school s in province d in year t. $I(YearsRelativeToImplementation = j)_{sdt}$ is an indicator variable that has a value of one if school s in province d in year t has the years-relative-to-implementation equal to j. $j = -1$ is not included since it serves as a benchmark of all other β_j's, and these are the effects relative to the effect at $j = -1$. X_{sdt} includes the school-level information, the same as the information specified in equation (2). λ_s represents the school fixed effects, and λ_t represents the year fixed effects. I also consider models that include the same sets of province-level controls (Z_{dt}) as in equation (2).

If the β_j coefficients with $\tau < 0$ are not statistically different from zero, it supports the conclusion that there were no differential trends between the treated and the control groups, conditional on the control variables included in equation (3). I also report the statistical test results for the null hypothesis that the β_j's in the pre-periods are jointly equal to zero.

In appendix section C, I discuss the instrumental variable regression model, which uses the UFLP rollout information as an instrument for the share of subsidized students.

5 Results

5.1 Results from Difference-in-Differences

5.1.1 Direct Effects on School and Parent Food Spending

I present the difference-in-differences regression results using the model discussed in section 4 in table 2. These results show the changes in student participation and parents spending derived by the implementation of the UFLP. Standard errors are clustered at each school level using school identifiers. Column (1) of 2 focuses on the share of students on meal subsidies. Overall, the results are robust to the model specification choice, and the share of students on meal subsidies increased by 29 percentage points due to the UFLP, which is economically meaningful considering that the share cannot exceed one. Comparing the estimated effect to the mean of the outcome during the pre-treatment periods, the amount of increase is approximately 200 percent, which is also statistically significant.

Columns (2) and (3) of table 2 report the effect of the UFLP on the share of parents' and governments' contribution relative to the total expense for the school meals in each school, respectively. These two columns show how the main source of the school meal funding changed in response to the UFLP implementation. The share of parents' contribution decreased by 20 percentage points while the government's contribution increased by 19 percentage points. Compared to the mean of outcomes in pre-treatment periods reported in table 1, parents' contribution decreased by 25 percent, and government's contribution increased by 80 percent.

However, column (4) of table 2 suggests that the per-student yearly expenditure on school meals does not show a meaningful increase, as it suggests a $6 increase in yearly school meal expenditure per student. Available data does not have information on the nutritional content of the school meals. Considering the high correlation between food quality and price, this result suggests a lack of change in school lunch quality.

To summarize, the UFLP subsidized school meals for a greater share of students, but did not change the quality of school meals substantially based on a minimal change in the per-student meal expenses. Note that the schools already had an infrastructure to provide meals to the students before the initiation of the UFLP since almost all students received lunch from their schools before the UFLP. This suggests that the UFLP changed the funding structure of the school meals. I also report results using sparser or more saturated specifications in table A.5, and the results are qualitatively the same.[18]

5.1.2 Standardized Score Outcomes

I use the same difference-in-differences model, and table 3 reports the regression results for the standardized score outcomes. I present the results using the specification which includes school fixed effects, year fixed effects, school-level time-varying controls, and the province-specific linear time trends.

The results presented in panel A of table 3 imply a general improvement across all three subjects, with statistical significance. The standard errors are clustered at each school using the school identifiers. The magnitude of improvement spans from 0.05 to 0.11 SD depending on the subject, which is highly comparable to the effects that were found in other contexts. For example, Ruffini (2019) finds that the Community Eligibility Provision (CEP) increased students' math scores by 0.02 SD in the reduced-form estimation. Chakraborty and Jayaraman (2019) also find a similar size of improvement in math scores (0.09 SD) and reading (0.17 SD) due to the Midday Meal program.

A strand of literature that examined the impact of increased income due to public as-

[18] Column (3) of table A.5 reports the same coefficients as in table 2 for ease of comparison.

sistance on children's academic achievement also documented similar effects. Milligan and Stabile (2011) find that the Canadian Child Benefit expansion led to an increase in math scores by 0.07 SD for an increase in 1,000 USD of benefits. Dahl and Lochner (2012) also find a similar magnitude of increase (0.06 SD increase for 1,000 USD increased benefits) with the Earned Income Tax Credit (EITC) in the US. If I assume a linear relationship between the return in test scores and the saved lunch expenses, a 0.05 SD increase in math scores for 700 USD of saved lunch fees translates into a 0.07 SD from 1,000 USD worth of benefits.

Table A.6 shows that the improvement in standardized scores is robust to more saturated or sparser models for all three subjects. Column (3) of table A.6 reports the same results as panel A of Table 3 for ease of comparison. The increases in Korean and math scores are more robust to model choices than increases in the English scores. In addition, clustering the standard errors at province-by-year-by-school levels[19] suggests less strong statistical significance.

5.1.3 Percentage of Underachieving Students

Using the same difference-in-differences model as in the previous subsection, I study the effects of the UFLP on the percentage of underachieving students. The results are reported in panel B of table 3. For Korean, increasing the share of students subsidized by the UFLP from zero to one (i.e., moving from no universal lunch provision to full provision) reduces the percentage of underachieving students by 2.9 percentage points. In other words, the UFLP reduces the underachieving students in Korean by 14.5 percent of the mean, or by 16 percent of the sample standard deviation. For math, the UFLP implementation reduces the percentage of underachieving students in math by 4 percentage points, or by 11.5 percent of the mean, or by 17 percent of the sample standard deviation. For English, the UFLP reduces the percentage of underachieving students by 13.3 percent or by 17 percent of the standard deviation. The magnitude of the reduction in the percentage of underachieving students is

[19] This gives 256 clusters in all (=16 provinces in the sample $\times$ 2 school levels (middle, and high)$\times$ 8 years).

comparable to an accountability program in South Korea. Woo et al. (2015) find that the program decreased the underperforming students by 18 percent. [20]

Across all three subjects, the estimated reduction was robust to more saturated or sparser models such as those including the province-level controls and excluding the province-specific linear time trends. Table A.7 summarizes the estimation results using other models, and column (3) reports the same results as panel (b) of Table 3. The magnitude of the reduction in the percentage of underachieving students across different specifications is similar both in terms of magnitude and statistical significance, and even with the standard errors clustered at the province by year by school levels.

5.2 Event Study Results

5.2.1 Direct Effects on School and Parent Food Spending

In this section, I discuss the effect of the UFLP on directly related variables using the event study. As discussed in section 4, all event study regressions include school fixed effects, year fixed effects, school-level variables, and province-level variables. The results are reported in figure 2. The solid red line depicts point estimates, and the dashed black lines depict 95% confidence intervals, using the standard errors clustered at each school.

Panel (a) shows a gradual but substantial increase in the share of students receiving meal subsidies in each school due to the UFLP. After the share reaches almost one, which is the largest possible value, this share starts to decline. Panel (b) reports the event study results of the share of parents' contribution relative to the total expenditure, and Panel (c) shows the event study results of the share of the government contribution. These two results imply that the government's fund almost replaced what parents used to pay to the school for meals. Panel (d) presents the event study results of yearly per-student expenditures, and the unit of the outcome is USD. This variable can be considered a proxy for lunch quality, and the event

[20] Woo et al. (2015) studies the effect of an accountability program called "School For Improvement," which provided additional funding to underperforming schools, unlike in the US setting where under-performing schools face the risk of funding reduction.

study result suggests that there were no statistically significant changes in lunch quality.[21] [22]

For all four outcomes, pre-treatment period estimates are economically small and statistically indistinguishable from zero, which suggests that the parallel trend assumption holds. Specifically, a joint test using the estimates of pre-treatment indicators from 5 years before the treatment to 1 year before the treatment fails to reject the null hypothesis that these coefficients are jointly equal to zero at the 5 percent significance level.

5.2.2 Event study: Standardized Score and Percentage of Underachieving Students

Event study results provide visual evidence to verify the validity of the parallel trend assumption. In this subsection, I present two sets of event study graphs: figure 3 presents results for the standardized scores, and figure 4 shows results for the percentage of underachieving students. As discussed in section 4, all event study regressions include school fixed effects, year fixed effects, school-level variables, and province-level variables. The solid red line plots the estimated coefficients of each years-relative-to-implementation indicator, and the black dashed line plots the standard errors clustered at each school.[23]

Overall, the pre-treatment estimates (β_j with j<0) are not statistically different from zero.[24] This result supports the absence of differential trends before the UFLP was imple-

[21] Anecdotal evidence is very mixed: some schools report that it was easier to combine funds among other schools and bulk-buying of ingredients reduced costs by 3-5 percent, but many students and parents did not seem to experience much change in lunch quality (Lee, 2011; Kim, 2012; Hong, 2014).

[22] Per student lunch price was generally accepted as a proxy for lunch quality due to price-quality correlation, and Belot and James (2011) refers to the increased spending for school meals as evidence that the "Feed Me Better" program provided healthier meals than before. Andersen, Gallagher, and Ritchie (2017) uses a data from a Healthy Eating Index which is derived from a food component analysis by the United States Department of Agriculture (USDA). Unfortunately, a nutritional content-based school meal quality measure is not available in the South Korean context.

[23] During the sample period, years-relative-to-UFLP spans from -11 to +9, and I assign an indicator variable for each of these years-relative-to-implementation values. I present from 5 years before and after the implementation in figures 3 and 4. The graphs become less informative towards the minimum and maximum values of the years-relative-to-UFLP, since the number of observations for these endpoints is smaller compared to the observations for the years-relative-to-UFLP around zero.

[24] A joint test using the coefficients of the pre-treatment indicators from 10 years before the treatment (β_{-10}) to 2 years before the treatment (β_{-2}) fails to reject the null hypothesis at the 1 percent significance

mented, and the program expanded regardless of the schools' average achievement. In general, figures 3 and 4 suggest that the UFLP increases the standardized scores with statistical significance in the same year in which the school implemented the UFLP (i.e. when years-relative-to-implementation is equal to zero), and this increase fades away as time passes. Even though some pre-trend estimates of the percentage of underachieving students seem to exhibit an upward or downward trend, all of those estimates are not statistically significant.

I discuss the instrumental variable (IV) regression results in appendix section C. The IV results have the implication of the treatment on the treated (ToT), and the estimates imply that a 10 percentage point increase in the share of students receiving meal subsidies due to the UFLP improves standardized math scores by 0.22SD, and reduces the percentage of underachieving students in Korean by 14 percentage points.

6 Robustness and Heterogeneous Effects

6.1 Robustness checks

The main results discussed in section 5 are robust to the inclusion of province-level controls, as shown in previous tables, including appendix tables A.6 and A.13. I briefly discuss four additional robustness checks in this section. First, I replace the province-specific linear time trends with the sub-province-specific linear time trends. These results are summarized in appendix table A.16. Even with the sub-province-level linear time trends, I find an increase in the standardized scores and a decrease in the percentage of underachieving students with similar magnitude as the main results.

Second, I exclude the observations that are treated before 2013, the first year of the main sample. This robustness check is to address the concern of whether there was a selection into treatment based on some unobservable characteristics. Appendix tables A.17 and A.18 report the regression results, and the results do not change qualitatively with the main

level. The null hypothesis here is that the pre-treatment estimates are jointly equal to zero.

results.[25]

Third, I use the total number of students in each school and each year as weights. Appendix tables A.24 and A.25 present the weighted regression results. In general, the estimates are comparable to the main results reported in section 5.

Fourth, to examine the possiblity that the results are driven by one province only, I run 16 regressions by excluding the observations in one province from each. As appendix figure A.3 shows, the improvements in academic achievement outcomes are not driven by one province.

Finally, I incorporate recently developed difference-in-differences regression to consider the potential bias to the average treatment effects on the treated. This will be discussed in the following subsection.

6.1.1 Results by School Levels

I run the same difference-in-difference regression as in the previous subsections with the subsample of middle schools and high schools separately in order to investigate the source of the treatment effects. The middle school subsample spans from 2013 to 2016, and the high school subsample spans from 2009 to 2016. Among the 9,828 school-by-year observations of the middle school subsample, 7,568 observations are at least partially treated (77 percent of the subsample), and 7,147 observations are fully treated. Among the 10,482 school-by-year observations of the high school subsample, only 850 observations are at least partially treated (8 percent of the subsample), and 832 observations are fully treated.

For the standardized score outcomes, table A.8 reports the coefficient of interest for the middle school subsample, and table A.9 presents the coefficient of interest for the high school subsample. In general, the impacts of the UFLP on the percentage of underachieving

[25] The mean of standardized scores increased by 0.05, and the sample standard deviations decreased by 0.05 by excluding the early-treated observations. It is mechanical to see either a slight increase or decrease in the sample mean or sample standard deviation since approximately a third of the observations are dropped. Furthermore, standardizing the scores after the exclusion of the early treated schools provided qualitatively the same results. The results are reported in appendix table A.19.

students span from 0.06 SD to 0.12 SD for the high school subsample. The benefits of the UFLP among the middle school subsample prevails with statistical significance only for the Korean scores. For math and English scores, the effects were close to zero and statistically insignificant. In some specifications, small negative coefficients were found.

The reductions in the percentage of underachieving students are mostly found among the high school subsample. Appendix tables A.10 and A.11 report the regression results for middle school and high school subsamples, respectively. Even though the point estimates generally suggest that middle schools experienced a reduction in the percentage of underachieving students, only some of the estimates for Korean and English have statistical significance. But high schools show a greater reduction across all specifications and academic subjects.

These differences can be due to data availability: the middle school data is only available from 2013 to 2016. Considering that more than half of the middle schools were already treated, and the event study results in section 5.2.2 showing that the beneficial impacts of the UFLP are concentrated mainly in the early periods after the implementation, not finding extensive improvements in the standardized scores among middle school students is not surprising. On the contrary, high schools started to get treated across the provinces relatively later in the sample period, thus exhibiting the initial positive impact of the UFLP.

Effect on Dropout Rates. For the high school subsample, I utilize dropout information in the EDSS data and empirically test whether the UFLP caused a reduction in dropout per 100 students. Since middle school education has been compulsory in the whole country since 2002, I focus on the high school subsample. Panel A of Table A.12 summarizes the estimated impact of the UFLP on the number of dropouts per 100 students. No estimates are statistically significant at any of the conventional significance levels, but the point estimates imply a 7 percent decrease in dropout rates. Using the standard errors to create bounds, the estimate is consistent with an 18 percent reduction and a 6 percent increase in the number of dropouts per 100 students.[26] In sum, there is not enough evidence to conclude that the UFLP reduces dropout rates among high school students.

6.1.2 Results for an Alternative Measure of the Percentage of Underachieving Students

In this subsection, I use an alternative outcome that measures the percentage of underachieving students in each school. I examine the effects of the UFLP on the percentage of the students at the lowest achievement level ("below-basic" level) instead of the sum of the two lower achievement levels ("below-basic" and "basic" level), which I focused on in section 5. Focusing on the students at the lowest achievement level also helps understand who benefits from the UFLP the most across the score distribution.

Panel A of table 4 shows that the UFLP decreases the percentage of students at the lowest achievement level by approximately 1 to 2 percentage points, or by 21 to 34 percent of the mean. This benefit appears in both the middle school and high school subsamples. Panel B of table 4 shows that the middle schools benefit from the reduction in the number of students who are lowest achieving in Korean and math with statistical significance. Even though the effects are not statistically significant at conventional levels for English, the estimated coefficients suggest that the UFLP reduced the percentage of students at the "below-basic" level by 10 percent of the mean. Panel C of table 4 shows that the UFLP reduced the percentage of the lowest achieving students by 25 percent to 38 percent of the mean for the high school subsample. These estimates for the high school subsample were all statistically significant at the 1 percent level, showing a clear benefit on students' academic achievement due to the UFLP. Appendix tables A.13, A.14, and A.15 report the results for sparser or more saturated models, which lead to qualitatively the same conclusion.

[26] These bounds are derived by converting each of the bounds of the confidence interval to a percentage using the mean of the outcome.

6.1.3 Results with an Alternative Estimator

In this subsection, I incorporate two of the recently developed methods in the difference-in-differences literature. Recently, a strand of literature including Borusyak and Jaravel (2017), de Chaisemartin and D'Haultfoeuille (2020), Callaway and Sant'Anna (2020), Goodman-Bacon (2020), Sun and Abraham (2020), Athey and Imbens (2021), and Wooldridge (2021) has demonstrated how the coefficient estimated with the two-way fixed effects linear regression model is a biased estimate of the average treatment effect (ATE). This bias attached to the parameter of interest (ATE) can be large if the treatment is heterogeneous over time within units, and when the treatment has a staggered rollout.

I utilize the new estimator (DID_M) proposed by de Chaisemartin and D'Haultfoeuille (2020), which can be interpreted as a bias-corrected estimator of the classical difference-in-differences linear regression model (equation 1). Specifically, the coefficient estimated by the two-way fixed effects linear regression model can be decomposed into a weighted sum of average treatment effects of all possible comparisons of each treated group against other groups (never treated, already-treated, and later-treated), and these possible comparisons are referred to as 2-by-2 average treatment effects. In extreme cases where these weights are large negative numbers, even if the individual 2-by-2 average treatment effects are all positive, the weighted sum can be negative. The DID_M estimator of de Chaisemartin and D'Haultfoeuille (2020) is particularly suitable for the UFLP's setting since it allows for the continuous treatment.[27] They also provide another estimator (DID_M^{pl}) which plays a similar role as the pre-treatment coefficient in the classical event study (equation 3).

First, I report the DID_M estimate and show that the estimates reported in section 5 are robust to this bias correction. Second, I plot the weights of the 2-by-2 estimators to show that only a few of them are small negative numbers in the case of the UFLP. Third, I present the DID_M^{pl} estimator to ensure that the common trend assumption holds. The common trend

[27] More detailed discussion regarding de Chaisemartin and D'Haultfoeuille (2020) can be found in appendix section G.

assumption allows the DID_M estimator to have an interpretation of the average treatment effect.

Table A.26 reports the DID_M estimators, which are similar to the coefficients found in table 3.[28] In general, the DID_M estimates are slightly larger than the ones reported in table 3, implying that the sign of bias is negative. Appendix figure A.4 shows that the very few weights are negative, and the magnitudes of the negative weights for Korean standardized scores.[29] Table A.26 also reports the placebo estimates ($DID_M^{pl,1}$ and $DID_M^{pl,2}$). These estimates act as a falsification test and determine whether there were differential trends one year before the treatment ($DID_M^{pl,1}$) or two years before the year of treatment ($DID_M^{pl,2}$). Finding that the placebo estimates are not significantly different from zero supports the common trend assumption, which allows DID_M estimates to have an interpretation of the average treatment effect.

6.2 Heterogeneous Effects by Baseline Participation

In this subsection, I use the information regarding the share of students receiving meal subsidies ($Share_{sdt}$) before the UFLP implementation and investigate the possible heterogeneous effects by a school's baseline participation in the pre-existing means-tested lunch subsidies. The UFLP directly affects the share of students on meal subsidy, so it is not a suitable proxy for the baseline participation after a school implements the UFLP.

Among the observations that are treated after the first year of the sample[30], I calculate the mean of the share within the pre-treated periods. If a school is already treated before the first year of the sample, there is no available information to calculate the pre-treated period share.[31] I define the schools as having higher baseline participation if the schools have the average share of participation to the means-tested lunch subsidies greater than equal

[28] I include the same types of controls as in table 3 for comparison.

[29] Using other academic achievement outcomes does not change the general implication.

[30] The first year would be 2013 for middle schools, and 2009 for high schools.

[31] For the schools that have pre-treated period information, the estimated effects of the UFLP on academic achievements are qualitatively the same with the full sample results.

to the 67th percentile of the distribution of mean of the shares as having higher baseline participation. I define the schools as having lower baseline participation if the average share is lower than the 33rd percentile, and rest of the schools as having middle baseline participation. Using these definitions provides a way to investigate the heterogeneity of the UFLP's impacts across baseline participation, while there are no official poverty estimates for small geographic units.[32]

I run the same difference-in-differences regression for each of these three subsamples of schools. Figure 5 summarizes the estimates and standard errors by a school's baseline participation. The exact estimates can be found in column (3) of Appendix tables A.27 through A.29 for the standaridzed score outcomes, and tables A.30 to A.32 for the percentage of underachieving students. To summarize, I find general improvement in both of the academic achievement outcomes in all subsamples. I also use triple-differences regression, which fully interacts the difference-in-differences model with an indicator for each subsample of schools. Appendix tables A.33 to A.35 show that the magnitude of reduction in the percentage of underachieving students in each subsample is not statistically significantly different from zero.[33] [34] Previous studies also found similar patterns when the universal meal provision replaced the means-tested school meal subsidy. Notably, Ruffini (2020) also finds that students' math performance improves in districts with low baseline free meal eligibility. Schwartz and Rothbart (2020) also finds that the Universal Free Meals program in New York City middle schools improved the test scores of both poor and non-poor students.

Depending on the eligibility for and participation in the means-tested subsidy before the UFLP, potential benefits are different. First, students with household income low enough to qualify for and who participated in the means-tested lunch subsidy will benefit from reduced stigma but there will be no change in incomes. Stigma is a well-known factor

[32]Only the national yearly series of relative poverty rates are available at KOSIS (Korean Statistical Information Service).

[33]The regression results using the same triple-differences model for the standardized score outcomes also lead to the same conclusion.

[34]These results are robust to using either the median or the 25th and 75th percentiles to define higher and lower baseline participation (appendix tables A.36 and A.37)

that hinders the take-up of means-tested school meal subsidies (Glantz and Long 1994; Mirtcheva and Powell 2009; Sandman 2016; Yu, Lim, and Kelly 2019). Second, students who were eligible for but did not participate in the means-tested subsidy would experience reduced stigma with increased incomes by saving lunch fees. Third, students who were not eligible for the means-tested subsidy will benefit from increased income by saving lunch fees. On average, less than 30 percent of students participated in the means-tested school meal subsidies before the UFLP, which leaves roughly 70 percent of students' families experiencing increased disposable incomes. These benefits differ by household level, but the school-level data (EDSS) does not have information that I can use to calculate how many students are from each of the three types of households. In addition, the magnitude of the benefit can also differ by household income, which is also not detectable.

7 Underlying Mechanisms

In this section, I discuss various potential mechanisms that can contribute to the UFLP's positive impact on students' academic achievement. In subsections 7.1 and 7.2, I provide suggestive evidence that the UFLP increased educational expenditures.

Previous literature suggests that students react to the expanded access to school meals in two main ways. First, students participate more in school lunches programs, leading to better nutrition and cognitive ability (Figlio and Winicki 2005; Hinrichs, 2010; Bartfeld and Ahn 2011; Frisvold, 2015). This mechanism is particularly effective if the school lunches are better alternatives (Belot and James 2011; Anderson, Gallagher, and Ritchie 2017; Schwartz and Rothbardt 2020). Second, students attend school more often, as expanded access to school lunches can create an additional incentive for students to come to school (Leos-Urbel et al. 2013; Jayaraman and Simroth 2015; Ruffini 2020).

I find that these two previously emphasized mechanisms are unlikely to operate in South Korea. First, I show with the EDSS data in panel (a) of figure 1 that the share of students who receive lunch from their schools has been stable and close to one both before and after the UFLP implementation. This suggests that it is not likely that the UFLP increased participation in school lunch programs in South Korea.[35] In addition, I find that the per-student school meal expenditure, which can be a proxy for meal quality, did not change significantly (table 2 and figure 2).[36] Second, South Korea is one of the countries that do not face a severe truancy problem (OECD 2019), implying that the margin for an improvement in attendance is small. I support this argument by showing that there is no change in the proportion of students who have taken the national standardized test (table A.39). Since there is no attendance information in the EDSS data, this is indirect evidence that the UFLP did not seem to change attendance.[37]

Notably, the UFLP might reduce stigma by decreasing family income salience since it does not require means-testing. The findings of Gennetian et al. (2004) and Clark-Kaufman, Duncan, and Morris (2003) suggest that the reduced stigma could improve students' academic performance. However, EDSS data is not fit for the task of investigating the change in stigma due to the implementation of the UFLP.

7.1 After-School Program Participation Change using EduData Service System (EDSS) data

In this subsection, I focus on the effect of the UFLP on after-school program participation using the information in the EDSS data. As discussed in section 2, the UFLP increased disposable income for students' families by saving lunch fees. In addition to the income effect, mental accounting framework (Thaler 1990, 1998, and 1999) suggests an increase in

[35] The first quartile of the share of students who received lunches from their school is 0.98.

[36] If schools increased the caloric content or the glucose level to boost the students' cognitive function on the test day or the few days around it as found in Figlio and Winicky (2005), this change is unlikely to be captured in the yearly frequency of the EDSS data.

[37] Table A.39 also addresses the concern that schools at risk of accountability sanctions will manipulate the testing pool (Figlio and Winicki 2005). Specifically, studies have documented that schools intentionally misclassify the low-performing students as disabled or absent on the day of the test (Cullen and Reback 2002; Figlio and Getzler, 2002; Jacob, 2002).

expenditures in educational investment. Since the parents would have paid the after-school program fees using the same designated banking account for the lunch fees before the UFLP, this institutional detail also could contribute to mental accounting.

I use the same difference-in-differences framework in section 4 and find that average after-school program participation increased by 0.03 programs on average, as shown in table 5. I focus on the average number of after-school programs in which the students participate in each school, which is obtained by dividing the total number of programs offered by the total number of participants. The EDSS data has information on academic and non-academic programs separately, and the regression results suggest that the academic after-school program participation is the source of increased overall participation in after-school programs.[38] Typical academic after-school programs include math, English, and writing, which can help the students with exam scores and course materials. The estimated effect corresponds to a 16 percent increase in average participation in the after-school programs, and a 22 percent increase in average academic after-school program participation. This result is directly comparable to Hener (2017)'s findings that child benefit expansion in Germany increased education expenditures by 18 percent, and child-assignable expenditures by 37 percent. Notably, average participation in non-academic after-school programs does not show a statistically significant change due to the UFLP.

The back-of-the-envelope calculation suggests that the parents spend approximately 20 percent of the saved lunch expenses on academic after-school program participation. These programs are generally not free, and the average fee to participate in an after-school program on average is 20 USD to 30 USD per month, which has been stable over time (National Assembly Budget Office 2009; Lee and Hwang 2016; OECD 2012). Using the estimated increase in academic after-school program participation (0.4 more programs) and assuming this increase remained through the whole year, the back-of-the-envelope calculation gives a 144 USD increase in after-school program expenses per year (12 months $\times$ 0.4 programs

[38] Increased academic after-school program participation is robust to sparser or more saturated models (table A.40).

$\times$ 30 dollars = 144 dollars). Comparing this amount to the saved lunch expense for the parents implies that the parents are spending approximately 20 percent of the saved expense on academic after-school program participation.

7.2 Household after-school Program Expenditure Change using the Private Education Expenditure Survey

This subsection uses another data source to supplement the findings in section 7.1, to corroborate the increased after-school program participation. Using Private Education Expenditures Survey (PES) data, I estimate the impacts of the UFLP rollout on after-school program participation and expenditures.

I use a regression model similar to the difference-in-differences model described in section 4, but there are adjustments due to the different data structure. PES data is student-level repeated cross-section data and does not have detailed enough geographic information to define the treatment intensity as the share of students affected by the UFLP in each school. Instead, I define the treatment intensity using the share of schools in each year for every province using the EDSS data. Since the geographical information in the PES data has less detail, the treatment definition of the PES data is bound to have a larger measurement error than that of the EDSS data. Table A.43 reports the summary statistics for the PES data. For the PES data, I use the following regression equation:

$$Y_{ihdt} = \beta UFLPshare_{dt}^{PES} + \Phi X_{iht}^{PES} + \mu_d + \mu_d \times t + \mu_t + e_{ihdt}, \tag{4}$$

where Y_{ihdt} is the after-school program participation or expenditure of student i in household h in province d in year t. D_{dt}^{PES} ranges from 0 to 1 and represents the probability that students in province d in year t are in a school with universal free lunch provision due to the UFLP. Unlike the case of the school-level regression using the EDSS data, the value of D_{dt}^{PES} does not differ in the same province. To accentuate the different definition of the treatment and the additional controls in the regression model for the Private Education Expenditure Survey compared to the regression in section 4, I use superscript PES notation on the treatment (D_{dt}^{PES}) and the controls (X_{iht}^{PES}). I consider both the log and the inverse hyperbolic sine transformation of the after-school programs' expenditure since there are outliers.[39]

X_{iht}^{PES} stands for student-level controls such as students' gender, school-level indicator (middle or high school) and students' previous achievement categories (the top 10 percent, 11 to 30 percent, 31 to 60 percent, 61 to 80 percent, the lowest 20 percent in class, reported by the homeroom teacher of each student). μ_d represents geographic fixed effects including province and urban fixed effects, and μ_t represents the year fixed effects. To closely follow the preferred specification, I also include the province-specific linear time trends, denoted by $\mu_d \times t$. The standard errors are clustered at each province by each school level by urban or rural indicator by year (17×2×2×8=544 clusters).

The results from the PES data suggest a statistically significant and economically meaningful increase in participation, which corroborates the findings from the EDSS data. Column (1) of table A.44 reports that the participation rate increased by 10 percentage points, which implies a 14 percent increase with high statistical significance.[40] Moreover, the results in columns (2) and (3) of table A.44 suggest that the average expenditures on the after-school programs also increased. The coefficients reported in columns (2) and (3) show the treatment effect on the growth rate of the expenditures on after-school programs. The estimated effects of the implementation of the UFLP suggest an approximately 20 percent increase in expenditures on after-school programs, which can be translated into a 4.5 USD increase per month on average. Putting this result into yearly expenditures implies an approximately 53 (=4.5 × 12) USD increase in expenditures on after-school programs.

This increased expense consists of 8 to 10 percent of the increased disposable income

[39]The inverse hyperbolic sine transformation approximates the log transformation but accommodates zeros since the domain of the inverse hyperbolic sine function contains zero.

[40]The mean participation rate is 70 percent throughout the sample. Among the observations with treatment equal to zero (which means that no school in the province in that year is treated), 73 percent of students participate in the after-school programs.

by saving the lunch fees due to the UFLP, which supports the back-of-the-envelope calculation using the increased participation in the after-school programs from the EDSS data. Specifically, the back-of-the-envelope calculation of the increase in the after-school program expenditures found in the EDSS data is greater than the increase found from utilizing the PES data. But the after-school program participation and expenditure information in the PES data combines both academic and non-academic programs, unlike the EDSS. Moreover, the PES is a survey and the EDSS is administrative data, not to mention the different data structure. Given these innate differences between the two data sets, it is unlikely that the estimates will be the same.

Using the family income information in the PES data, figure A.5 plots the coefficients and the standard errors for different income groups separately (monthly income 3,000 USD or below, between 3,000 and 6,000, and 6,000 or above). Note that the eligibility threshold for the means-tested school lunch subsidies is approximately 2,500 USD: thus the majority of the first income group is eligible.[41] According to panel (a) of figure A.5, all three subsamples show a statistically significant increase in after-school program participation. Panel (b) shows that the expenditures on the after-school programs also increased statistically significantly for the families with monthly incomes of 3,000 USD or below. Middle and higher income groups do not show statistically significant increases in log of expenditures, but the level values show similar magnitude of increases. Transforming the log increase in panel B of figure A. 5 into the level amount, the estimates suggest that the expenditures increased by 13 USD (7 percent) for the lower income group, and approximately by 11 USD (5 percent) for the middle and higher income groups. To summarize, the results from the PES data also suggest that the households respond to the UFLP by increasing the after-school program participation, even though the increase in expenditures on the after-school program participation varies across

[41] For families with three members, the eligibility threshold is approximately $2,050, and for families with four members, the eligibility threshold is approximately $2,500. Average family size during the sample period is approximately 2.7 (Statistics Korea 2021) Still, there can be misreporting of income groups since this is survey data.

different income groups.[42] Still, there is a possibility that the UFLP improves students' academic achievement through a channel that is not discussed in this paper, and parents increase the education investment as a response to the higher return on the investment.

8 Conclusion

This paper examines the Universal Free Lunch Program's effect on students' academic achievement in South Korea. By utilizing administrative school-level data and the program rollout information, I implement difference-in-differences and IV frameworks to estimate the Universal Free Lunch Program's causal effect. I find strong evidence of a reduction in the percentage of underachieving students, and an increase in standardized scores, which was comparable to the effects found in other contexts.

I find that the UFLP's beneficial impact prevails universally in schools with different income levels. I provide empirical and anecdotal evidence that the UFLP acted as an in-kind transfer to relatively higher income families. By examining numerous potential underlying mechanisms, I show that the South Korean context does not harm the generalizability of the results, but provides a setting where a new mechanism can be highlighted. This paper provides suggestive evidence of an underlying mechanism that highlights parents' educational investment. Even though the higher income families are less income constrained, the mental accounting of parents can lead to an economically meaningful increase in educational investment. It is likely that the saved lunch fees are perceived as an increased budget for educational expenditures but not for other categories of consumption.

There are government budgetary concerns regarding the universal provision of school meals, as it does not target the neediest population and thus uses the resource inefficiently. One approach to analyze the efficiency is to derive the cost-effectiveness of the UFLP. I follow Dhaliwal et al. (2013) to claculate the cost-effectiveness of the UFLP using the estimates

[42] I find neither economically meaningful nor statistically significant results for the intensive margin (by using only the observations with nonzero expenditures on after-school programs). I also do not find any distinct pattern across income groups by investigating the intensive margin of after-school program spending.

provided in section 5.[43] The effectiveness-cost ratio estimate suggests that per-student annual expenditures on the UFLP increases standardized test scores by 0.07SD for Korean, 0.05SD for math, and 0.04 SD for English. These magnitudes are comparable to several programs in the US setting (Yeh 2010), including Summer school, a 10 percent increase in spending, and class size reduction (Nye et al. 2001; Finn et al. 2001). This leads to the conclusion that the UFLP is relatively cost-effective even though it does not explicitly aim to raise student achievement.[44]

The empirical evidence the UFLP's impacts in South Korea sheds light on the program's impact in other countries with similar contexts, such as high stigma and high take-up of pre-existing means-tested school meal subsidies. As many countries have means-tested school meal subsidies as part of their redistribution measures, the benefit of the UFLP provides evidence that seemingly misaligned in-kind transfers can nudge parents' consumption towards children's educational investment.

[43] I provide detailed explanation on the implementation of Dhaliwal et al. (2013) in appendix section F.

[44] However, including the measurement error issues regarding the cost, the cost-effectiveness of the UFLP can have limited generalizability. For example, if other countries were to adopt the program, depending on the institutional context, the cost to implement this program can be much higher than the cost in South Korea. Since the early 1990s, almost 100 percent of students in South Korea have received lunch through their schools, and thus the essential equipment and staffs to provide lunch to all students were already in place. If this is not the case in other settings, the program's cost increases and thus reduces the cost-effectiveness of the program.

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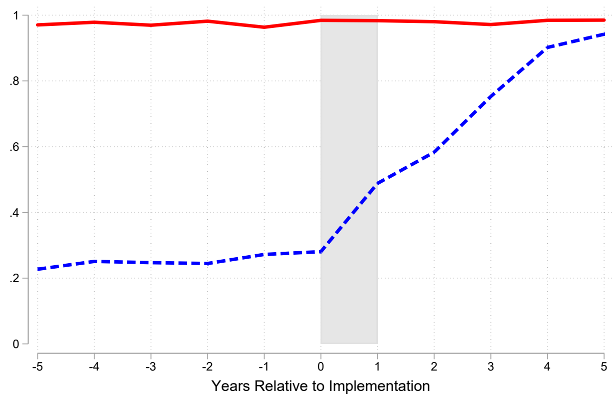
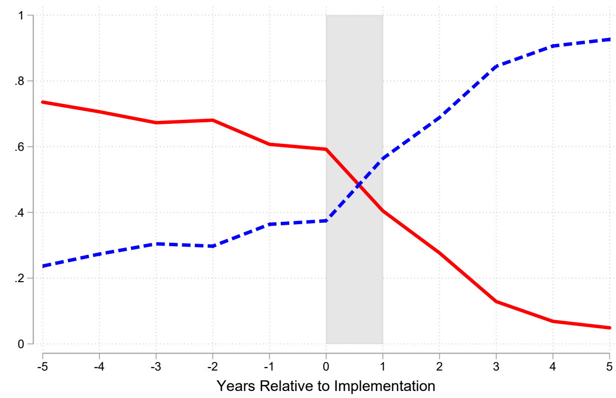
Figures and Tables



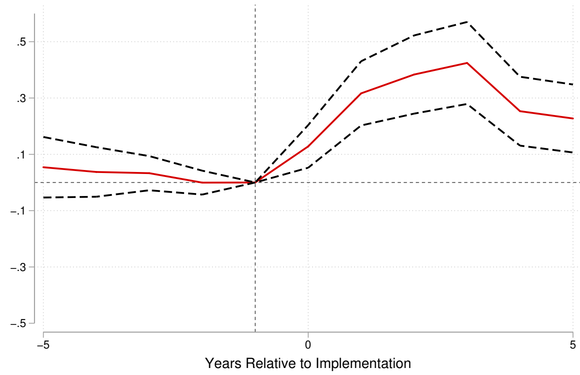
(a) Share of students receiving lunch from school and share of students on meal subsidy



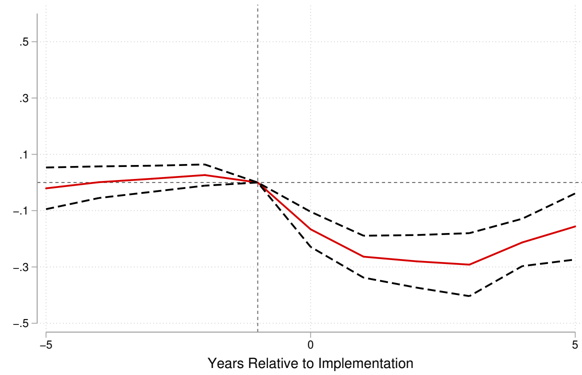
(b) Shares of parents and government contribution

Figure 1. Change in shares over the years relative to the UFLP implementation

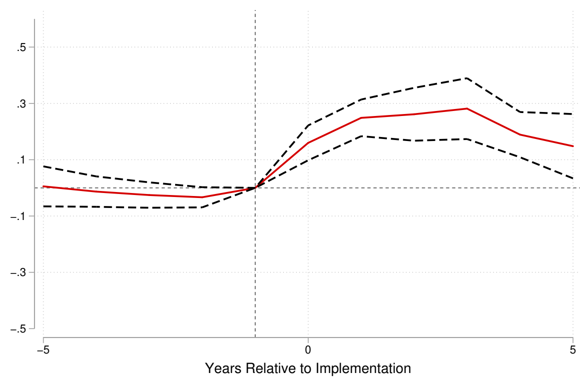
Notes: Panel (a) shows the average share of students receiving lunch from school (red solid line) and the average share of students on meal subsidy (blue dashed line) across the years relative to implementation of the UFLP. Panel (b) shows the share of parents' contribution (red solid line), and the government's contribution (blue dashed line) relative to the total yearly budget for school meals across the years relative to implementation of the UFLP. The shaded areas on both panel highlights the changes due to the UFLP implementation in the initial adoption year. I use the information from the EDSS data to calculate these shares. Average values of shares are calculated separately in each year relative to the first year of the UFLP implementation in each school.



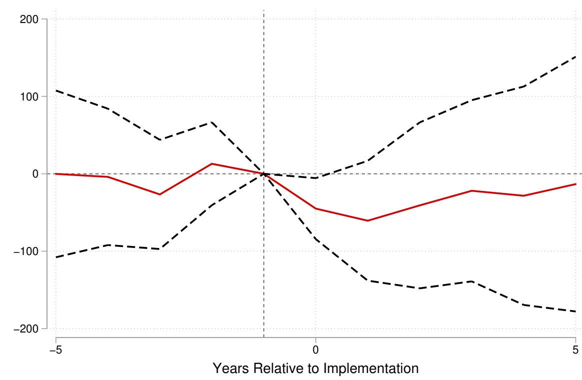
(a) Share of students on meal subsidy



(b) Share of parents' contribution



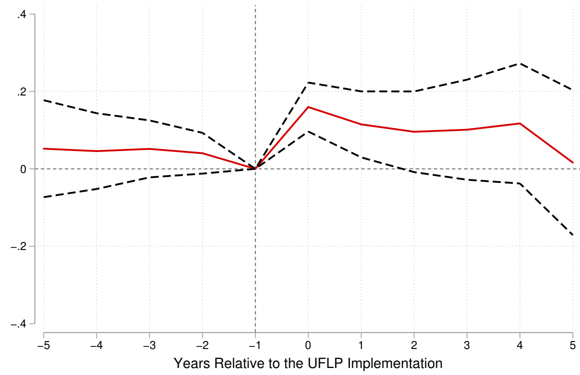
(c) Share of government's contribution



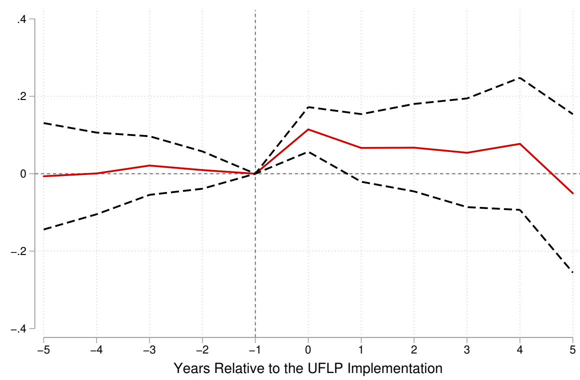
(d) Per student yearly school meal cost ($)

Figure 2. Event Study of Share of Students On Meal Subsidy, Share of Parents' Contribution, Share of Government Contribution, and Per Student Yearly Expenditure on School Meals

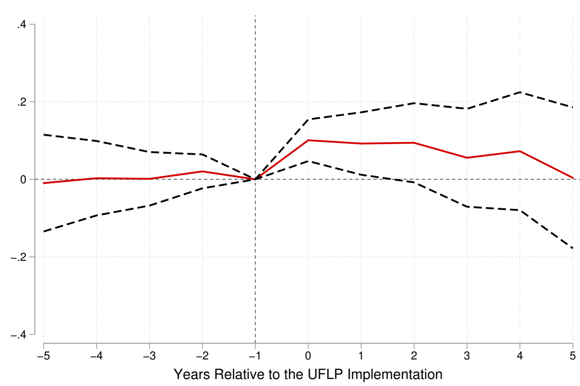
Notes: I use the information from the EDSS data for these figures. Panel (a) presents the event study results of the share of students on meal subsidy, panel (b) reports the event study results of the share of parents' contribution relative to the total expenditure, and Panel (c) shows the event study results of the share of government contribution. Panel (d) is presenting the event study results of per student yearly expenditure, thus the unit of the outcome is USD. All these event study design in which I estimate treatment effects yearly, I include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province-specific controls (superintendents' support for the UFLP, two financial capacity measures of the provincial government). The red solid line depict point estimates, and the black dashed lines depict 95% confidence intervals, using the standard errors clustered at each school using school identifier.



(a) Standardized Korean Scores



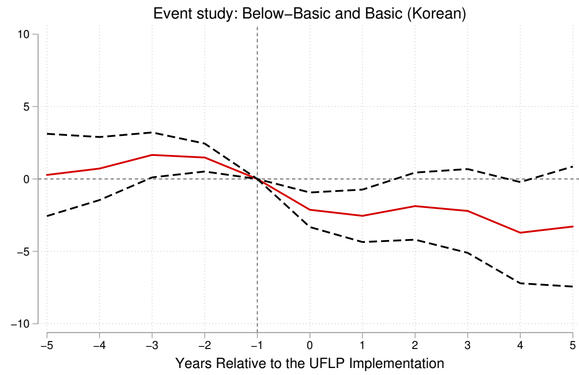
(b) Standardized Math Scores



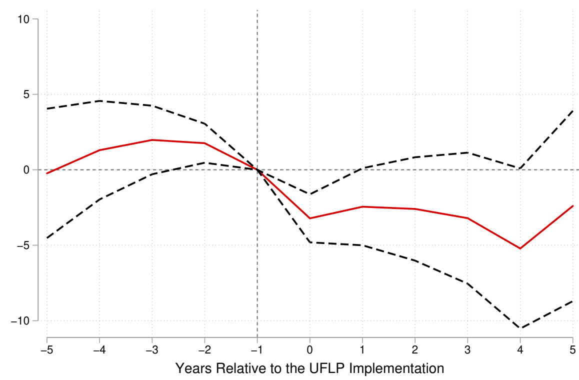
(c) Standardized English Scores

Figure 3. Event Study Results for Standardized Score Outcomes

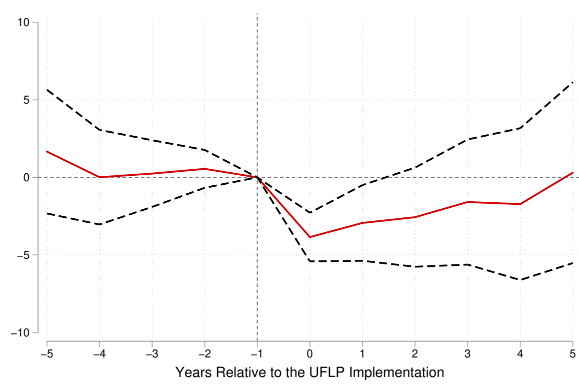
Notes: All score outcomes are standardized as explained in section 4. I use event study design to estimate treatment effects for all years relative to the ULFP implementation. I include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province-specific controls (superintendents' support for the UFLP, two financial capacity measures of the provincial government). The red solid line plots the estimated coefficients of each years-relative-to-implementation indicators, and the black dashed lines depict 95% confidence intervals, using the standard errors clustered at each school using school identifier. During the sample period, time to treat spans from -11 to +9, which are all estimated.



(a) Percentage of Underachieving Students (Korean)



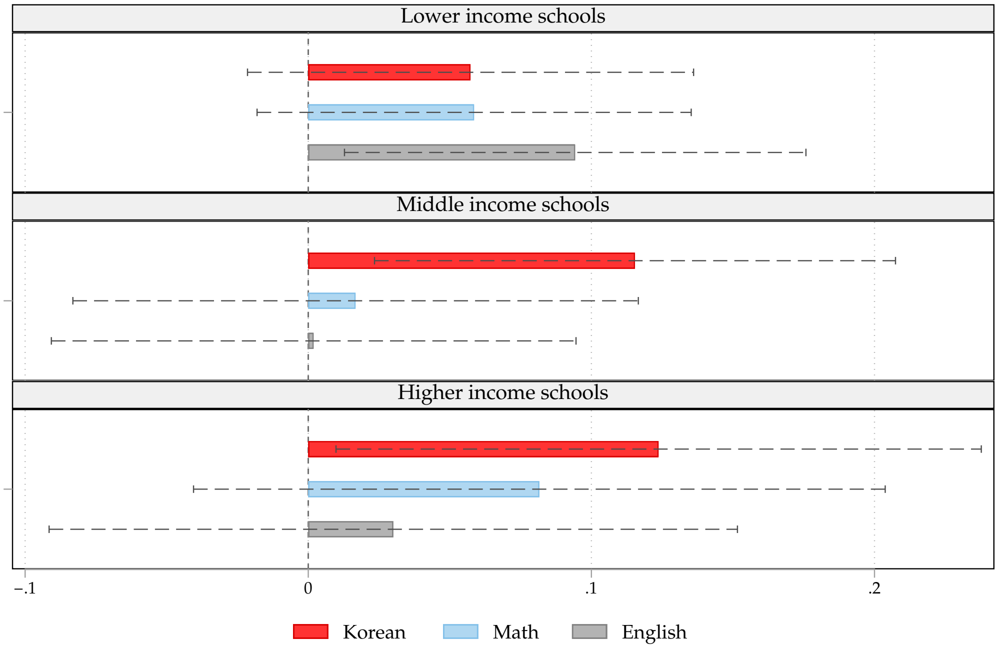
(b) Percentage of Underachieving Students (Math)



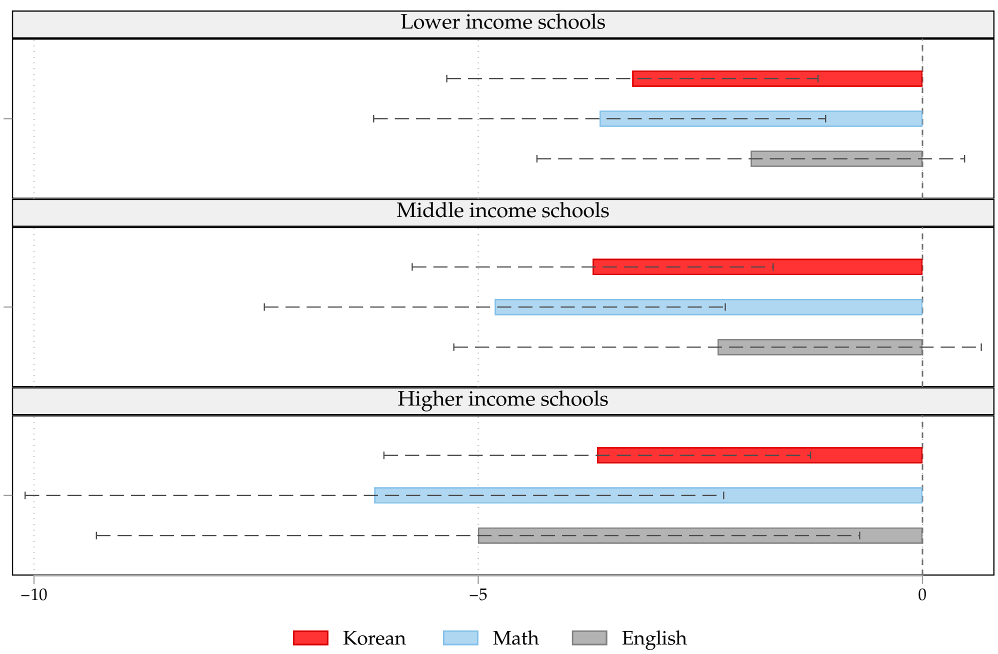
(c) Percentage of Underachieving Students (English)

Figure 4. Event Study Results for the Percentage of Underachieving Students

Notes: I use the information from the EDSS data for these figures. I define the percentage of underachieving students as the share of students who are at the basic level of achievement or below. All event study regressions include school fixed effects, year fixed effects, school-level variables, and province-level variables. The red solid line plots the estimated coefficients of each years-relative-to-implementation indicators, and the navy dashed line plots the standard errors clustered at the school level. During the sample period, time to treat spans from -11 to +9, which are all estimated.



(a) Standardized scores



(b) Percent of underachieving students

Figure 5. The effect of the UFLP standardized scores and Percentage of underachieving students: by baseline participation in the means-tested lunch subsidy.

Notes: These graphs report the coefficient on the treatment (ULFP implementation) by using three different subsamples: "lower income schools (red)" are the schools with the baseline participation lower than 33rd percentile, "middle income schools (blue)" with the baseline participation higher than the 33rd percentile but lower than the 67th percentile, and "higher income schools (grey) with the baseline participation higher than the 67th percentile." Panel (a) shows the estimated effects of the UFLP rollout on the standardized score for Korean, and panel (b) shows them for Math, and panel (c) reports them for English. Point estimates are specified as boxes, and 95% confidence interval using the standard errors (clustered by using school identifier) are plotted with the spiked lines behind the boxes.

Table 1. Descriptive Statistics

	(1) All	(2) post-treated	(3) pre-treated	(4) coeff.
Standardized Scores				
Korean	0.01	-0.13	0.10	0.10***
	(1.00)	(1.03)	(0.97)	(0.03)
Math	0.00	-0.15	0.11	0.05**
	(1.00)	(1.04)	(0.96)	(0.02)
English	0.01	-0.12	0.10	0.04
	(1.00)	(1.04)	(0.96)	(0.04)
% underachieving				
Korean	19.55	16.83	21.44	-2.7***
	(18.30)	(12.94)	(21.04)	(0.56)
Math	34.80	40.17	31.06	-3.87***
	(23.46)	(18.44)	(25.74)	(0.70)
English	30.16	31.96	28.90	-4.21***
	(23.33)	(17.60)	(26.53)	(0.72)
School Characteristics				
No. of teachers	49.18	34.09	59.68	-0.16
	(25.55)	(19.69)	(23.84)	(0.21)
No. of students	710.33	468.59	878.63	10.60**
	(449.42)	(363.79)	(425.97)	(4.35)
No. of students transferred in	12.65	12.50	12.74	-0.37
	(11.81)	(11.80)	(11.82)	(0.41)
No. of students transferred out	13.50	13.43	13.54	-0.98***
	(10.98)	(11.50)	(10.60)	(0.34)
Male-female student ratio	0.53	0.53	0.52	-0.01**
	(0.31)	(0.26)	(0.34)	(<0.003)
Student-teacher ratio	13.07	11.57	14.12	0.08
	(4.27)	(4.94)	(3.36)	(0.07)
Variables Related to School Meal Provision				
Proportion of students on school meals	0.97	0.98	0.97	0.04***
	(0.11)	(0.13)	(0.10)	(0.01)
Proportion of students on school meal subsidies	0.24	0.45	0.22	0.29***
	(0.20)	(0.34)	(0.16)	(0.01)
Per student meal expenditures (yearly, $)	935.97	973.51	910.01	29.69
	(476.59)	(489.55)	(465.68)	(21.26)
Parent's contribution (%)	0.48	0.14	0.71	-0.19***
	(0.36)	(0.22)	(0.22)	(0.01)
Government's contribution (%)	0.49	0.82	0.26	0.20***
	(0.35)	(0.22)	(0.21)	(0.01)
Province Characteristics				
Educational Superintendent supporting the UFLP	0.67	0.85	0.55	-0.04**
	(0.47)	(0.36)	(0.50)	(0.02)
Financial independence index 1	52.19	47.09	55.75	-0.06
	(21.32)	(22.39)	(19.78)	(0.12)
Financial independence index 2	75.41	74.09	76.33	0.02
	(6.50)	(6.46)	(6.37)	(0.08)
Unemployment rate	3.28	3.42	3.08	0.17***
	(0.80)	(0.82)	(0.72)	(0.02)
Observations (School-by-year)	20310	8336	11974	20310

Notes: Descriptive statistics are the mean and standard deviation in the parentheses using the EDSS (EduData Service System) data, Ministry of Education, South Korea. Sample period covers 2009 to 2016. The first column shows the characteristics of all observations. The second column show characteristics of already-treated observations (observation year is after the first year of the ULFP rollout). The third column show characteristics of not-yet-treated observations (observation year is before the first year of the ULFP rollout).

Table 2. The Effect of the UFLP on Students' Participation and Food Spending

	(1) Share on meal subsidy	(2) Parents' contribution	(3) Government's contribution	(4) Per student meal cost/yr ($)
$UFLPShare_{sdt}$	0.291***	-0.187***	0.199***	6.296
	[0.015]	[0.011]	[0.011]	[22.126]
Mean of Outcome in pre-UFLP	0.178	0.715	0.252	911.0
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School-level Controls	Yes	Yes	Yes	Yes
Province specific time trend	Yes	Yes	Yes	Yes
Observations	20310	20256	20256	20016

Notes: I use the information from the EDSS data. Panel (a) presents the results of the share of students on meal subsidy, panel (b) reports the results of the share of parents' contribution relative to the total expenditure, and Panel (c) shows the estimation results of the share of government contribution. Panel (d) reports the regression results for per student yearly expenditure, thus the unit of the outcome is the US Dollar. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. Significant at *10%, **5%, and ***1% levels.

Table 3. The Effects of the UFLP on Academic Achievement Outcomes

	(1) Korean	(2) Math	(3) English
	A. Standardized Scores		
$UFLPshare_{sdt}$	0.107***	0.063***	0.053***
	[0.026]	[0.024]	[0.024]
	B. Percent of underachieving students		
$UFLPshare_{sdt}$	-2.868***	-4.087***	-4.267***
	[0.520]	[0.678]	[0.683]
Mean of Outcome	19.55	34.80	30.16
School FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
School-level Controls	Yes	Yes	Yes
Province-level Controls	No	No	No
Province-specific time trend	Yes	Yes	Yes
Observations		20310	

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the square brackets are clustered at the school level. Significant at *10%, **5%, and ***1% levels.

Table 4. The Effects of the UFLP on an Alternative Measure of the Percentage of Underachieving Students

	(1) Korean	(2) English	(3) Math
	A. All school levels		
$UFLPshare_{sdt}$	-0.954***	-1.488***	-1.845***
	[0.255]	[0.286]	[0.683]
Mean of Outcome	3.169	7.028	5.282
Observations		20310	
	B. Middle school subsample		
$UFLPshare_{sdt}$	-0.676**	-0.613***	-0.355
	[0.305]	[0.338]	[0.272]
Mean of Outcome	2.065	5.681	3.695
Observations		9828	
	C. High school subsample		
$UFLPshare_{sdt}$	-1.342***	-2.054***	-2.559***
	[0.430]	[0.478]	[0.702]
Mean of Outcome	4.204	8.290	6.770
Observations		10482	
School FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
School-level Controls	Yes	Yes	Yes
Province-specific time trend	No	No	Yes

Notes: I use the information from the EDSS data for these estimates. For this table, I use an alternative measure of the percent of underachieving students as the share of students who are at "below-basic" level, which is the lowest achievement level, not the sum of the two lower levels (below-basic and basic level). $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the square brackets are clustered at the school level. Significant at *10%, **5%, and ***1% levels.

Table 5. The effects of the UFLP on after-school program participation

	(1) Average number of programs participated	(2) Average number of academic programs	(3) Average number of non-academic programs
D_{sdt}	0.331**	0.354***	-0.024
	(0.131)	(0.128)	(0.025)
Mean of Outcome	2.029	1.606	0.424
Observations		20295	
School FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
School-level Controls	Yes	Yes	Yes
Province-specific time trend	Yes	Yes	Yes

Notes: I use the information from the EDSS data for the estimates above. The average number of after-school programs that the students participate in each school, which is obtained by dividing the total number of programs offered with the total number of participants. The EDSS data has information for academic and non-academic programs separately. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the parentheses are clustered at the school level. Significant at *10%, **5%, and ***1% levels.

Appendices

A Literature Review

A considerable body of literature investigated the relationship between nutrition and academic achievement, especially in developing countries where malnutrition is a prevalent problem. Earlier studies that established this nutrition-learning channel are summarized in Glewwe and Miguel (2007) and in Alderman and Bundy (2012). Some of these studies use exogenous shocks such as policy interventions to provide better access to food, civil war, and drought to examine the differences in educational outcomes such as enrollment, high school graduation rate, and years of schooling.

A strand of studies found that changes in school meal nutrition can be linked to students' academic achievement in developed countries. For example, there were policy changes in the US and UK that provided healthier school meals to students, and studies have found that healthier school meals improve academic achievement outcomes (Andersen, Gallagher, and Ritchie 2017; Belot and James 2011). Regarding the impact of caloric content, Figlio and Winicki (2005) find that increased caloric content is linked to increased standardized test scores in the US, but McEwan (2013) finds no such link in Chile.

Several studies examined the effects of the expanded access to school meals on educational outcomes, and general findings suggest that expanded access to school meals leads to more school lunch participation, better nutrition and better academic achievement. Many countries provide subsidized school meals for students with lower family incomes (OECD 2012) to assist students from lower income families. Bartfield and Ahn (2011), Frisvold (2015), and Schwartz and Rothbart (2020), Ruffini (2020) points out that improved nutrition is a key factor behind the improvement found in academic achievement. Still, not all of these studies can rule out the effects of increased incentives for students to attend school. Many studies point out increased attendance and enrollment (Hindrich 2010; Leos-Urbel et al. 2013; Imberman and Kugler 2014; Jayaraman and Simroth 2015; Chakraborty and Jayaraman 2019).

Since many countries provide means-tested subsidies for school lunches, there are concerns regarding the association between free lunch status and stigma. There exists abundant anecdotal evidence and correlation between stigma and take-up of the means-tested subsidy (Glantz and Long 1994; Pogash 2008; Mirtcheva and Powell 2009; Sandman 2016). Notably, Yu, Lim and Kelly (2019) find suggestive evidence that the stigma associated with the means-tested lunch subsidy in Seoul, South Korea, is more notable in schools with a low percentage of students on lunch subsidy.

This paper provides suggestive evidence that the improved educational outcomes are associated with the increased spending on educational inputs, specifically by increased participation in academic after-school programs. In the South Korean context, where most students receive lunch from their schools, expanded access to school meals create increased disposable income for parents. These results can be linked to the "mental accounting" in behavioral economics, where they focus on the evidence against the complete fungibility of money. People often allocate funds for specific purposes (such as housing, food, or children's education), and the categorized budget often restricts money to move across different purposes of expenditure. People can experience disutility by exceeding the categorical budget, and Thaler (1990, 1998, and 1999)'s work provides pertinent examples. On top of the income effect, mental accounting provides grounds for expecting an even greater impacts on education expenditure, especially because parents clearly knew that the increased disposable income (if they were not participating in the means-tested lunch subsidy) was the school lunch fee saved due to the UFLP. Gouldner (1960) documented that the benefit recipients are likely to be nudged towards the suggested uses of the benefit. These findings suggest that the saved lunch fees would be spent more on children's education.

Large body of empirical literature supports the incomplete fungiblility of money. Lundberg, Pollak, and Wales (1997) find evidence that benefits labeled for children in the UK had greater tendency to be spent on children.[45] More recently, Jones et al. (2019) and Hener (2017)'s results suggest that the benefits earmarked for children leads to increased household expenses on direct education inputs and day-to-day items that are likely to be for the children.

There are two other studies which studies the effect of the UFLP. As the UFLP increases the share of students on meal subsidy, Altindag et al. (2020) examine the impacts of the increased share on school misbehavior outcomes, and Baek et al. (2019) investigate how it affects the physical ability of students. Altindag et al. (2020) find reduction in misbehavior, but Baek et al. (2019) do not find changes in students' physical aptitude.[46] [47]

B South Korean School System

In this subsection, I briefly describe the school system in South Korea. Students spend six years in elementary school, three years in middle school, and three years in high school. This 6-3-3 system is kept regardless of the school type or regions, and skipping a grade rarely happens. Elementary school is from grade 1 (age 7) to grade 6 (age 12). Starting from the first grade, students have lunch at school. Elementary school education has been compulsory since 1952, and all students are admitted to schools by lottery system within the school districts.

After graduating from elementary school, students go to middle school. Middle school education became compulsory by law in 1984, and in 1999, the middle school enrollment rate was 99.9 percent. More than 99 percent of the middle schools are general middle schools, which are subject to the admission by lottery within the school district. Less than one percent of middle schools are for students with specialties in art, music, or physical ability (to be professional athletes). These schools have their own entrance exams to measure the

[45] Lundberg, Pollak and Wales (1997) and Kenney (2008) also points out that this phenomenon is prone to be greater if the child benefits are controlled by the mother. Before the UFLP, school lunch fees were generally paid by mothers as anecdotal evidence (Ryu et al. 2011) and research on household financial management (Lee et al. 2008).

[46] In order to show that there was no selection of schools based on the scores into the program, Altindag et al. (2020) used the standardized scores as outcomes and conclude that the UFLP has no effects on the standardized scores. The main difference from this paper's approach to Altindag et al. (2020)'s approach is the identifying variation. This paper utilizes the UFLP rollout information, and Altindag et al. (2020) uses the share of students on school meal subsidy, which is affected by the UFLP rollout. The share of students on school meal subsidy increased due to the UFLP, and Altindag et al. (2020) defined the schools as treated by the UFLP if this share is greater than 0.9 in each school. See section 4 for more detail.

[47] Replication results of these two papers are summarized in appendix section E.

students' artistic or physical ability but not their academic achievement.

The high school enrollment rate is over 99 percent since 2002 (OECD 2021). High schools can be categorized into three types. Roughly 88 percent of the schools are for the students who pursue post-secondary education, including general high schools, foreign language high schools, and science high schools. General high schools consist of approximately 80 percent of all high schools. Foreign language and science high schools select students among the applicants by their own exams or interviews, but the difficulty and the evaluation procedure of the exam are also subject to a centralized guideline. Arts and physical high schools consist of less than 2 percent of the total high schools, and they also admit a selected group of students who passed their exams. The rest are vocational high schools, including technical high schools, commercial high schools, fishery high schools, and agricultural high schools. The University enrollment rate is less than 40 percent among these vocational schools, counting for both technical and university degrees.

One feature to note is that South Korea has a very centralized education system regardless of the school type. Almost all school types share common regulations regarding the curriculum, textbooks, school facilities, and teacher quality.[48] Foreign language high schools and science high schools have entrance exams, and average achievement in these schools can be higher than the general public. Still, these schools were not treated differently in terms of the universal free lunch program rollout.[49]

Between 2009 and 2016, all the third grade of middle school students and second grade of high school students took the NAEA exam. Every elementary school student in sixth grade took this test from 2009, but the government stopped this elementary school assessment procedure in 2013 and the only available outcome for elementary schools is the percentage of underachieving students. For the comparability of the regression results, I focus on the middle schools and high schools, which have both the scores and the percentage information. The data availability for each school level is summarized in figure A.2.

Province-level unemployment rate is obtained from Korean Statistical Information Service (KOSIS), and is generally higher among the post-treated observations.[50]

[48]Public school teachers need to pass the national teaching license exam as the first class, but private schools can hire teachers with a second-class teaching license. Teachers with second class teaching licenses must satisfy two requirements (at least three years of teaching experience and passing a training program) to obtain the first-class license. All public school teachers are subject to the rotation to another public school after five years.

[49]Private elementary schools in Seoul and Busan were treated later than the public elementary schools, but these are less than 1 percent of the total elementary schools in each city.

[50]See `https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=INH_1DA7104S&conn_path=I3` for more information.

C Instrumental Variables Regression

In this subsection, I discuss the instrumental variable regression model. The Universal Free Lunch Program is intended to increase the share of the students on lunch subsidy ultimately to one hundred percent. However, the share might be increasing or decreasing due to other factors such as neighborhood characteristics and regional business cycle. Previous studies such as Altindag et al. (2020) and Baek et al. (2019) used the share of the students on meal subsidy as the treatment variable, and thus subject to the bias originated from the variations other than the UFLP.[51] EDSS data do not provide the information of each school being treated by the Universal Free Lunch Program or not, but it provides the share of students receiving a subsidized meal. I use the Universal Free Lunch Program rollout information ($UFLPShare_{sdt}$) to instrument the share of students on a subsidized meal, denoted as $Share_{sdt}$. The value of $Share_{sdt}$ also ranges from 0 to 1 as $UFLPShare_{sdt}$. If this measurement error is pervasive in $Share_{sdt}$, using only the variation of $Share_{sdt}$ that was originated from the program rollout information would measure the causal effect of the program.

Two-stage least squares (2SLS) regression captures the variation in $Share_{sdt}$ that is associated with the variation of the program rollout. This first stage regression of regressing $Share_{sdt}$ on the program rollout information measured by $UFLPShare_{sdt}$ prevents the potential endogeneity or omitted variable bias issues. The two-stage least squares regression equations can be described as follows:

$$Y_{sdt} = \alpha \widehat{Share}_{sdt} + \Gamma X_{sdt} + \Pi Z_{dt} + \mu_s + \mu_t + \omega_{sdt} \tag{5}$$

$$Share_{sdt} = \rho UFLPShare_{sdt} + \Theta X_{sdt} + \Upsilon Z_{dt} + \eta_s + \eta_t + \nu_{sdt} \tag{6}$$

where Y_{sdt} is the academic achievement outcome of school s in province d in year t. X_{sdt} includes school-level controls, and Z_{dt} includes provincial level controls as in the baseline specification. μ_s is school fixed effects, μ_t is year fixed effects. ω_{sdt} is the error term. $\widehat{Share}_{sdt}$ is the fitted value of $Share_{sdt}$ derived from equation (4). Equation (4) is the first stage regression equation that captures the relationship between the Universal Free Lunch Program rollout ($UFLPShare_{sdt}$) and the share of students on meal subsidy ($Share_{sdt}$). The fitted value of this first stage regression is the treatment variable of interest, and α has a different interpretation compared to the interpretation of β in the baseline regression. By increasing the share of students who are on meal subsidy by 10 percentage points, it results in the $10 \times \alpha$ percentage point increase of the outcome of interest. η_s is school fixed effects,

[51] There is one more possibility that the schools are reporting other information than the share of the lunch subsidy. According to several provincial offices of the Ministry of education, if schools that are supposed to be fully treated (when $D_{sdt} = 1$) are not reporting almost one hundred percent of the $Share_{sdt}$, they might be reporting the share of students on subsidized snacks or dinner. It is common for high schools in South Korea to provide dinner since the students are likely to remain in school to study more after the regular class time. Snacks are relatively more prevalent, and the most common form is fresh white milk. This white milk snack started in 1981 and was mandatory in the 1980s but gradually changed towards providing it to only the ones who subscribe to this. Even after the lunch meal became free, subsidy for milk and other snacks is still based on the means-tested procedure. In the late 2010s, roughly 50 percent of students were participating in the milk snack program. In 2017, fruit snack programs were implemented, but not as broadly or frequently as milk snack program.

η_t is year fixed effects. ν_{sdt} is the error term.

Instrumental Variable Regression Results. The Universal Free Lunch Program intends to increase the share of students who are getting the meal subsidy. Due to the provincial budget issues, the program was partially rolled out in many schools and provinces. There is also a possibility of measurement error in the share since the schools might report the students who are on subsidized dinner or snack after the school is fully treated.[52] To measure the correlation between the share of the students on the subsidized meal and the Universal Free Lunch Program rollout, I separately report the first stage regression in appendix table A.20. Then I move on to the regression results from the two-stage least squares (2SLS) model.

The estimation result from appendix table A.20 reports the effect of the Universal Lunch Program Rollout on the Share of the Students on Meal Subsidy, which implies that the implementation of the Universal Free Lunch Program will increase the share of the students on meal subsidy by approximately 27 to 29 percentage points on average. A frequently used cutoff for the relevance condition is to have an F statistic greater than or equal to 10, and all four models exceed this cutoff with large margins. However, Lee et al. (2020) pointed out that this cutoff can be too lax ("anti-conservative") for testing the first-stage relationships. Among the alternative measures discussed in Lee et al. (2020), I use a threshold of F statistic greater than or equal to 104.7. The estimation results from appendix table A.20 suggest that province by school level clustering of the standard errors would not satisfy this criterion unless we include the province specific linear time trend. In contrast, clustering the standard errors at each school provides F statistic values larger than 104.7 across all four specifications and satisfies a conservative test proposed by Lee et al. (2020).

Appendix table A.21 presents the 2SLS estimation results for the standardized scores. According to the result, a 10 percentage point increase in the share of students on meal subsidy due to the Universal Free Lunch Program implementation increases the Korean score by 0.03SD. Average increase of the share of the students who are on subsidized meals found in the first-stage is roughly 30 percentage points, and combining these two results implies that the increase in Korean score is 0.09SD, which is the similar to the reduced form estimate. This coefficient also closely matches the ratio of the reduced form estimate to the first stage estimate ($0.093/0.277 = 0.336$). The impact of increasing the share is smaller and statistically insignificant for math and English scores, but the relationship between the coefficients still holds.[53]

Appendix table A.22 and table A.23 shows the estimation results for the percentage at different achievement levels. According to the estimated effect on the percentage of students who are either at the below-basic level or the basic level of achievement (appendix table A. 22), ten percentage point increase of the share of the students on meal subsidy (due to the Universal Free Lunch Program) contributes to approximately one to 1.5 percentage points decrease in the percentage of students who are below the adequate level of achievement.

[52] Many of the provincial offices of Ministry of Education suspected this measurement error is highly probable if the share is not close to one when the school should be treated completely. In the data, the share was 0.8 on average among the fully treated school-by-year observations.

[53] For standardized math scores, the ratio of the reduced form estimate (0.049) to the first stage estimate (0.28) was 0.175. This also applies to the English scores, where the ratio of the reduced form estimate (0.042) to the first stage estimate (0.28) is 0.15.

These effects span from 40 to 50 percent decrease compared to the mean. The estimated effect of UFLP in terms of decreasing the percentage of students who falls behind exhibits larger impact in decreasing the percentage of students at the below-basic level of achievement, which are presented in appendix table A.23.

D Other Outcomes

This section investigates the effect of the UFLP on other outcomes. I examine two other outcomes. First, I estimate the causal impact of UFLP on school misbehavior and investigate the potential channel of the UFLP, providing a better school environment for students. Second, I attempt to indirectly test the hypothesis that the UFLP promoted better health of the students.

The implementation of UFLP might have decreased school violence, which might have reduced the negative externalities of disturbing behaviors. Numerous studies provided empirical evidence that peer effects exist. Carrell and Hoekstra (2010) found that children from troubled families posed negative externalities. They also found that having troubled children in class increases misbehavior in the classroom. Carrell and Hoekstra (2012) were able to identify the within-classroom externalities using data that matched domestic violence cases and school records.

EDSS data is school-level data, which does not allow the researchers to investigate within-classroom externalities. Still, I utilize the school level yearly misbehavior information and examine whether there was a reduction in the reported school level misbehavior due to the implementation of UFLP. I use the number of reported school violence cases per 100 students, the number of reported victims throughout the year per 100 students, and the number of perpetrators of reported cases per 100 students as outcomes. Using the same regression methods that I presented in section 4, I report the estimation results for the main sample, and I also break out the sample into each school level and investigate whether there were heterogeneous effects across school level.

Appendix table A.45 shows the regression results for the main sample. The estimates imply that UFLP contributed to approximately 20 percent more reported school violence incidents, measured by increasing the number of cases reported, the number of victims, and the number of perpetrators reported per 100 students. Subsample result provides a clearer picture. Appendix table A.46 presents the regression results for the middle school subsample, and appendix table A.47 presents the regression results for the high school subsample. Both subsamples show an increase in the school violence outcomes, but the high school subsample exhibits a steeper increase. The mean of the outcome is generally higher in the middle school subsample. A possible reason is that middle school students are more likely to report these incidents to the teachers than high school students, making the under-reporting problem less severe. Since the mean of the outcomes is relatively smaller, and the increase in the reported occurrence is relatively larger, the high school subsample exhibits a greater effect relative to the mean. Specifically, the high school subsample shows at least a 40 percent increase of all three outcomes relative to the mean, while the middle school subsample shows less than a 20 percent increase relative to the mean.

Altindag et al. (2020) used data from 2009 to 2014 (except 2011) across all three school levels and drew the conclusion that UFLP decreased the occurrence of students' misbehaviors.[54] These results imply that the reduction in student misbehavior comes from the

[54] I replicate the results of Altindag et al. (2020) in the appendix, but there are possible reasons for not being able to match the results. Firstly, EDSS extracts 70 percent of all schools for each of the data requests, so each research team has a slightly different dataset. Still, 70 percent of the total schools is a large enough proportion to get similar results. However, Altindag et al. (2020) declare that their data extract does not

elementary schools, which I confirm by running the same sets of regressions using the elementary school subsample. Some of these reported misbehavior cases are categorized into more specific behaviors, and these categories include physical fights, ostracising, insulting, threatening, and cyber-bullying. Across all these specific misbehavior types, I find a statistically significant increase only in physical fights for both middle school and high schools. The regression results suggest reductions in insulting, threatening, and cyber-bullying, but these effects are statistically insignificant. However, these specific misbehavior types are subsets of the reported cases and with sporadic occurrences.

In sum, it is unlikely that within-school externalities of having less school violence can be contributed to the improvements in academic outcomes. As explained in section 2, compared to the US setting, there is less scope for the UFLP to reduce the salience of family income since the parents used to submit lunch payments to schools on monthly basis before the implementation of the program. In addition, explaining why the UFLP reduces school violence in elementary schools and aggravates the school violence in higher school levels is out of the scope of this paper. As discussed before, these results cannot be interpreted as contradicting evidence to Carrell and Hoekstra (2010). By definition, within-school peer effects are less likely to exist and to be captured than the within-classroom peer effects since it requires a more considerable extent of effects.

Next, I examine whether there were changes in students' physical fitness due to the rollout of the UFLP. The relationship between physical fitness and academic performance in youth has not been studied in depth in the economics literature. Some studies in medicine and pediatrics found a positive association between physical fitness and academic performance (Santana et al., 2017). Ministry of Education in South Korea provides a centralized Physical Activity Promotion System (PAPS) guideline for testing students' physical fitness. Since 2010 for middle schools and 2011 for high schools, the guideline has changed, and since then all schools were following the same guidelines. Schools can choose five types of tests among 12 types, and the guideline provides thresholds for each type of tests to divide students into five levels of physical fitness.[55]

I focus on the percentage of students at the top two levels of physical fitness and utilize the same regression models to examine the impact of UFLP on the percentage of physically fitted students, since the schools choose the type of tests that students take. EDSS data provides the total number of students in each level of physical aptitude for each school by testing types. To summarize, I did not find any statistically significant changes in the percentage, but the magnitude of increase in the top two levels ranged from 10 percentage points compared to the mean. Given the lack of evidence of changes in school meal quality, these results are not surprising. Again, since schools can choose which tests to determine

have school-level misbehavior information for 2011. This same issue occurred in this paper's data extract but with the year 2010 and only with middle schools. Thus, the main sample would not be affected since the main sample contains middle-school observations from 2013. Secondly, EDSS changed the school misbehavior variables after 2011. Regarding the variables that are less likely to be subject to this definition change, this change should not matter. In sum, due to the potential definition change and the data availability at the time of research, the choices that Altindag et al.(2020) made might be different from what I made.

[55] The 12 tests include measuring records of push-ups, running (short-distance and long-distance), standing long jump, grip strength, flexibility. `https://index.go.kr/potal/stts/idxMain/selectPoSttsIdxMainPrint.do?idx_cd=1540&board_cd=INDX_001`

these aptitude levels, this measure's comparability across schools is unclear.

E Replication of Altindag et al. (2020) and Baek et al. (2019)

There are two possible reasons for my results to be different from the results of Altindag et al. (2020) and Baek et al. (2019) who investigated the effects of the UFLP on various school-level outcomes. Specifically, Altindag et al. (2020) reports that they find no statistically significant increase in standardized scores. The first reason is the longer sample period that I am using (I have two more years than Altindag et al. (2020), and 4 or 5 more years than Baek et al. (2019)). The second reason is due to the different definition of treatment. Still, even though the value of the treatment is different, if the both treatment definition is determined by the same underlying variation, then the treatment effects should be similarly estimated. This purpose of this subsection is to provide evidence to determine which one of these two reasons is more likely to be the cause of the different results that I am finding. I closely follow the sample restrictions that these two papers make, and see if the regression results are similar.

Replication of Altindag et al. (2020). Altindag et al. (2020) examined the effect of the UFLP on student misbehavior outcomes, mainly number of the cases reported, number of offenders, number of victims. They found that the UFLP contributed to large reduction (largely 50 percent of the mean) in student misbehavior. They used the data from 2009 to 2014 except for 2011 since the information was all missing for year 2011. I find that summary statistics such as school characteristics and number of cases are very close to what they are reporting. I follow their regression specification use two treatment definitions, following Altindag et al. (2020), and using the UFLP rollout information. When I use the treatment definition of Altindag et al. (2020), the regression results are similar to those reported in Altindag et al. (2020). In contrast, when I use the UFLP rollout information as treatment, the results differ in terms of magnitude, statistical significance, and the signs of the coefficients.

Replication of Baek et al. (2019). Baek et al.(2019) investigated the effects of the UFLP on students' physical fitness. Students are classified into 5 levels of physical fitness, which is measured with physical performance on various types of exercises, including push-ups, 100-meter running, etc. Their outcome measure is the share of students who are classified as level 1 and 2 per 100 students, which represents the share of students with high fitness in each school in each year. They found no significant impact on the share of students with high physical aptitude due to the implementation of the universal free lunch program. Again, I find that the summary statistics of dependent and control variables are very similar. I also find similar results with that of Baek et al. (2019) when I use the treatment definition of theirs. However, using the UFLP implementation information as treatment, the regression estimates contradicts to those reported in Baek et al. (2019) in terms of magnitude, statistical significance, and the signs of the coefficients.

This replication exercise cannot perfectly match the regression results of these two other studies, as the EDSS creates different extract for each of the projects. Still, using the same sample resulted in contradicting results depending on which treatment definition that I use. This suggests that the UFLP implementation information and the treatment definition of Altindag et al. (2020) and Baek et al. (2019) are determined by different underlying variations.

F Cost-Effectiveness of the UFLP

In this section, I discuss the cost-effectiveness of the UFLP using the estimated impact on the standardized scores following Dhaliwal et al. (2013). Cost-effectiveness can be described as effects that a program brings relative to the cost incurred. One advantage of the cost-effectiveness analysis is that the program's estimated impacts are easily comparable across different countries and years. Moreover, the unit of the effect is the same as the outcome of interest. Thus, the cost-effectiveness analysis does not require an assumption to be made about the benefits' monetary value (which can differ across readers and policymakers) induced by the effect. Compared to the case of cost-benefit analysis, this is a convenient advantage. However, due to this program's nature (since it is not a field experiment), information on many types of costs are not available. I summarize the procedure to calculate the cost and the effectiveness of the UFLP while providing the limitations and assumptions that are made to calculate the cost-effectiveness estimates that I find.

Dhaliwal et al. (2013) provide detailed steps to calculate the cost-effectiveness of a program. In terms of the program's effect, they advise considering only the statistically significant effects at 10 percent level or better. The suggested calculation of the total impact of a program differs slightly by the design of the program. In terms of the Intent-to-Treat effects (ITT), the program's total impact can be derived by multiplying the estimated Intent-To-Treat effect by the corresponding sample size. For the estimated Intent-to-treat effects, I use the estimates obtained by using the preferred specification (which includes school and year fixed effects, time-varying school-level characteristics, and province-specific linear time trend). The estimated impacts using this specification are statistically significant at a 10 percent level or better across all three subjects. For the sample size, I use the affected population by using the treatment intensity ($UFLPShare_{sdt}$) in each school across the years available in the sample.[56] I use a 10 percent social discount rate of the effects to aggregate the effects of the UFLP over the years to reflect the social opportunity cost of capital and convert the effect in the value of the year 2020.[57]

Due to the data limitation, quantifying the cost of the UFLP requires more assumptions. I use the governmentsâ contribution for school lunches as the cost of the UFLP (which is also utilized to derive the share of governments' contribution for school lunches). Ideally, the cost calculation would take only the cost additionally incurred by implementing the program ("cost at the margin"). But the EDSS data do not have information on how these funds are spent. Thus, this cost might include the costs that are not ideally included in cost calculation (such as cost for equipment that would already be present without the UFLP) and might not include the costs that should be included (such as administrative costs). The universal provision would not require means-testing to determine eligibility, which would likely decrease the administrative cost. However, since almost all students are already getting lunch from their schools before the initiation of the UFLP (with some portion of students

[56] According to Dhaliwal et al. (2013), the program duration should also be multiplied. Nevertheless, since this paper estimates the intent-to-treat effect over the post-treatment period, multiplying the duration seems more appropriate for the Treatment on the Treated (ToT).

[57] According to Zhuang et al. (2007), the applicable social discount rate for several European countries (including Germany, Norway, UK, France) is 4 percent. For the US, it is 7 percent and a 10 percent rate for Canada. Asian Development Bank utilizes a 10 to 12 percent discount rate (Zhuang et al. 2007; Dhaliwal et al., 2013).

on the means-tested lunch subsidy), this cost estimate is likely to be an overestimation. To make the cost into the US dollar unit in 2020, I use a 10 percent discount rate, average annual inflation rate, and average annual exchange rate.[58]

The effectiveness-cost ratio is obtained by dividing the total impact by the total cost estimates.[59] The results suggest that per annual cost per student (approximately 600 to 720 US dollars), the effect size spans from 0.075 SD to 0.091 SD for Korean, 0.044 SD to 0.053 SD for Math, and 0.037 SD to 0.045 SD for English scores. According to Yeh (2010), the effectiveness-cost ratio estimates (converted to US dollar unit in 2020 with 10 percent discount rate) of various programs span from 0.000004 to 0.098 SD increase for reading and math scores.[60] This leads to the conclusion that the UFLP is relatively cost-effective even though it does not explicitly aim to raise student achievement. However, including the measurement error issues regarding the cost, the cost-effectiveness of the UFLP can have limited generalizability. For example, if other countries were to adopt the program, depending on the institutional context, the cost to implement this program can be much higher than in South Korea. Since early 1990, almost 100 percent of students in South Korea received lunch through their schools, and thus the essential equipment and staffs to provide lunch to all students were already in place. If this is not the case in other settings, the program's cost increases and thus reduces the cost-effectiveness of the program.

[58]The annual inflation rate series is obtained from the US Bureau of Economic Analysis (2021), and the annual exchange rate is obtained from the University of Groningen and the University of California, Davis (2021). Both series are obtained via Federal Reserve Economic Data (FRED).

[59]One can also divide the total cost by the total impact to obtain the cost per additional unit of improvement of the outcome of interest, but for better comparability with other programs, I use the effect relative to the cost measure.

[60]Table 1 of Yeh (2010) summarizes the effectiveness-cost ratios measured in 2006 USD. For these ratios to be directly comparable with the cost-effectiveness of the UFLP, I used a 10 percent discount rate and an annual inflation rate of the US to convert these values. However, this still is not an accurate conversion into 2020 US dollars since I do not have information on the program's cost stream or effect stream over the years.

G Difference-in-Differences with Different Treatment Timing

To consider the potential bias originated from the heterogeneous treatment effect, I implement the estimator proposed by de Chaisemartin and D'Haultfoeuille (2020). This estimator is one of the recent innovations in difference-in-differences that allow the researchers to reflect heterogeneous effect and staggered adoption of treatment in the real setting. I use the same main sample, a panel data of 70 percent stratified sample of middle schools from 2013 to 2016 and high schools from 2009 to 2016, and apply de Chaisemartin and D'Haultfoeuille (2020)'s estimator (DID_M). The estimator of de Chaisemartin and D'Haultfoeuille (2020) allows control variables to be included and extends to nonbinary treatment. I present results for two different cases in terms of the treatment definition. First is binary treatment, where the school is considered treated if a year of observation is equal to or greater than the first year that school is treated. This definition is comparable to the definition used in the event study analyses. Second is the continuous treatment spanning from zero to one, with shares of students affected by the UFLP as the value of treatment. This definition is the same as the one used in the regression analyses.

Two way fixed effects estimated with OLS ($\hat{\beta}_{fe}$) can be decomposed into the weighted sums of the average treatment effects (ATE) in each group and each period (Borusyak and Jaravel, 2017; de Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2020; Goodman-Bacon, 2020; Sun and Abraham, 2020). To establish the extent of the bias coming from the negative weights, I report how many of these group-period combinations receive negative weights and how much the negative weights are. Moreover, following the proof in de Chaisemartin and D'Haultfoeuille (2020), I test whether the homogenous treatment effect assumption holds or not by using the difference of the two-way fixed effect estimator ($\hat{\beta}_{fe}$) and the first difference estimator ($\hat{\beta}_{fd}$). Then I move on to the DID_M estimates and discuss the plausibility of a common trend assumption by using the placebo estimator (DID_M^{pl}) proposed by de Chaisemartin and D'Haultfoeuille (2020).

These placebo estimators are used as a criterion to select one among the four specifications that were utilized throughout the paper's main analysis. This specification includes school and year fixed effects, region-specific linear time trend, and school-specific control variables.[61] This specification passes the common trend assumption test with two placebo estimates, which allows DID_M estimates to have causal interpretation across all three subjects. Thus, I focus on the results using this specification and report the estimates related to the Chaisemartin and D'Haultfoeuille (2020)'s method in appendix table A.26.

First I present the results with the binary treatment definition. According to the two-way fixed effect estimation result using the controls as specified above, 4019 among the 8172 total group-period combinations have strictly negative weights. The sum of these negative weights is equal to -0.231. Using the first difference, 3963 among the 8095 of all combinations of ATT have strictly negative weights. This comprises roughly a half of all combinations, and the sum of all negative weights is equal to -0.443. These sums of negative weights are applied to all three subjects, but the difference comes from the different group-period ATTs. Since the group-period ATTs are different across the subjects, this leads to different DID_M estimates.

[61] This specification is reported in the third column of the regression result tables, in general.

Even if the weights associated with group-period combinations for $\hat{\beta}_{fe}$ are negative, if the weights are uncorrelated with the ATEs conditional on the treatment, $\hat{\beta}_{fe}$ can still be robust to heterogeneous treatment effects across group and periods. Similar logic also applies to $\hat{\beta}_{fd}$ as well. However, if the common trend assumption is true, these two assumptions (one for $\hat{\beta}_{fe}$ and one for $\hat{\beta}_{fd}$) cannot be satisfied jointly[62]. Thus, one can test whether $\hat{\beta}_{fe}$ and $\hat{\beta}_{fd}$ significantly differ and test the plausibility of the common trend assumption. First, t-statistics for each of the bootstrap sample in each cluster (by dividing the difference of the two estimates, $\hat{\beta_{fe}} - \hat{\beta_{fd}}$, with the standard deviation of the difference) is calculated, and by using the average value of these statistics is used to determine the statistical significance.[63] The numerical test result for Korea score suggests that (t-statistic = -0.680) the $\hat{\beta}_{fe}$ (=0.082 with s.e. of 0.025, clustered at school id level) and $\hat{\beta}_{fd}$ (=0.090 with s.e. of 0.033, clustered at school id level) are not statistically significantly different, which does not casts doubt on the homogenous treatment effect. Largely the same conclusion can be drawn with math and English scores as well. For math scores, $\hat{\beta}_{fe}$ (=0.041 with s.e. of 0.022, clustered at school id level) and $\hat{\beta}_{fd}$ (=0.024 with s.e. of 0.027, clustered at school id level) were not statistically significantly different from zero with t-test statistic equal to -0.319. Similarly for English scores, $\hat{\beta}_{fe}$ (=0.038 with s.e. of 0.022, clustered at school id level) and $\hat{\beta}_{fd}$ (=0.019 with s.e. of 0.025, clustered at school id level) were not statistically significantly different from zero with t-test statistic equal to 1.014. All $\hat{\beta}_{fe}$ and $\hat{\beta}_{fd}$ estimates are summarized in panel A of appendix table A.26.[64]

Next, I move on to calculating the proposed estimator of de Chaisemartin and D'Haultfoeuille (2020), which is denoted by DID_M. In general, the DID_M estimates have a greater magnitude than the two-way fixed effects estimates ($\hat{\beta}_{fe}$), which suggests that the two-way fixed effect estimates are affected by modest negative bias. I use model specification with the school fixed effects, year fixed effects and school level controls and all estimates are reported in panel A of appendix table A.26. The estimated DID_M for Korean score is equal to 0.010 which suggest 0.10 SD increase in Korean test scores with a standard error of 0.041. DID_M estimates for math and English score implies the improvement of 0.052 SD and 0.045 SD, respectively. In sum, the bias of the two-way fixed effect estimators originated from the heterogeneous treatment effect is not severe to neither flip the sign nor severely underestimate the treatment effect of interest. This is also corroborated with the t-test results of the differences between FE estimates ($\hat{\beta}_{fe}$) and FD estimates ($\hat{\beta}_{fd}$).

The assumption that DID_M relies on to have a causal interpretation is a common trend assumption. The plausibility of this assumption can be tested by using the placebo estimator, DID_M^{pl}. This placebo estimator compares the change of the mean outcome from $t-2$ to $t-1$ in two sets of groups: those untreated at $t-2$ and $t-1$ but treated at t, referred as the switchers, and those untreated from $t-2$ to t. If the assumptions that make DID_M viable are satisfied, the expected value of DID_M^{pl} is zero. In other words, finding the estimate of DID_M^{pl} significantly different from zero implies that the switchers experienced different trends

[62] This is proved in de Chaisemartin and D'Haultfoeuille (2020).

[63] This procedure was executed 200 times, which is the same as the number of repetition specified in the code provided by de Chaisemartin and D'Haultfoeuille (2020).

[64] None of these t-statistics are statistically significant when the just school and year fixed effects are included in the model.

before the switch than the groups that were used to construct the counterfactual trends. The estimated DID_M^{pl} and the standard errors associated to the estimate are reported in panel A of appendix table A.26. As briefly mentioned above, the model specification that is chosen shows the best performing placebo estimates: across all subjects, placebo estimates are not significantly different from zero. This condition is critical for the DID_M to have causal implication, which makes the model choice viable.

The placebo estimator (DID_M^{pl}) compares the switchers to the stable groups one period before the switch, according to the definition of switchers above. Researchers can adjust the timing of comparison so that the placebo estimator would compare these two groups two or three periods before the switch, or even far before if the data allows. Here, I report the placebo estimator comparing these two groups two periods before ($DID_M^{pl,2}$) the switch[65]. The estimates are reported in panel A of appendix table A.26, and the confidence intervals of the placebo estimates comparing the switchers and stable groups two periods before the switch contains zero across all subjects, suggesting that the common trend assumption is appropriate.

Results using the fuzzy treatment which allows the treatment to take values between zero and one according to the share of students who are treated by the UFLP is also reported in panel B of appendix table A.26 in panel B. Slightly smaller sum of negative weights with fewer number of negative weights are found for both FE and FD estimates. Overall, the placebo estimates are not statistically significantly different from zero, and the DID_M estimates are slightly greater than but not drastically different from the estimates derived from the model with binary treatment. This suggests that fortunately in the case of the UFLP, bias from the heterogeneous treatment effects is not substantially crucial to consider. But this cannot be generalized to other programs without scrutiny.

[65]The placebo estimator comparing the two groups three periods before ($DID_M^{pl,3}$) have very few numbers of observation, but the confidence interval contains zero.

Appendix Figures and Tables

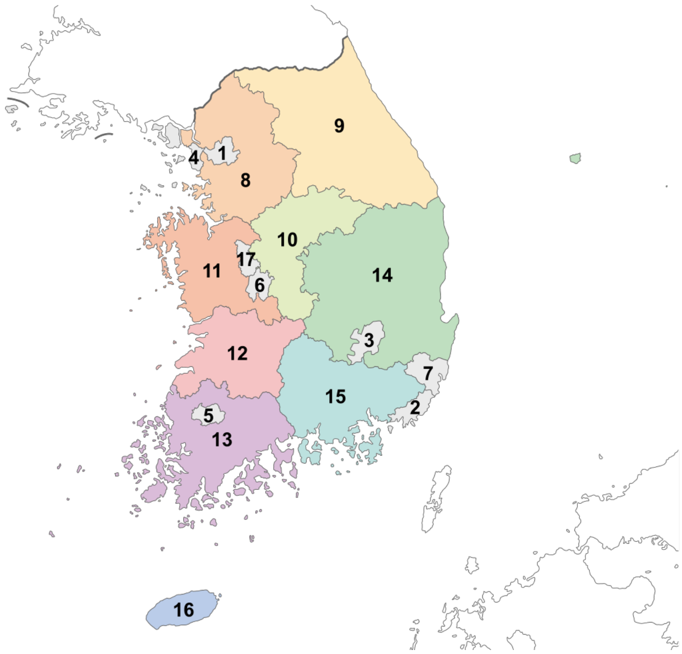


Figure A.1. Provinces of South Korea
Notes: The number written in each province matches the number in table A.1 through table A.4

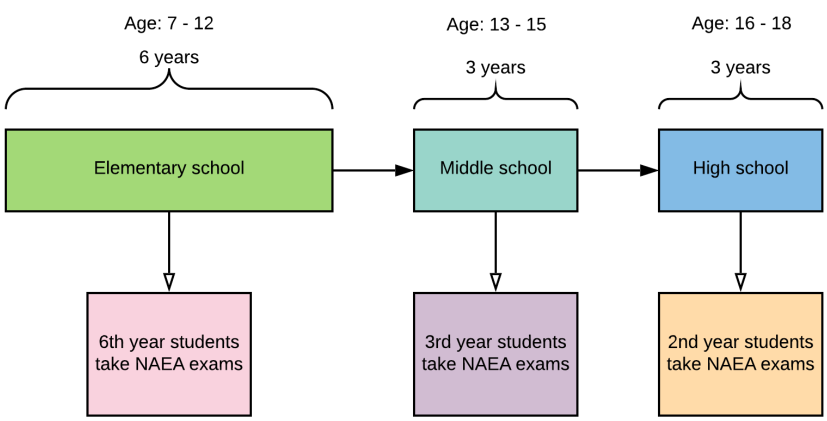


Figure A.2. National Assessment of Educational Achievement (NAEA) exam summary.
Notes: Between 2009 and 2016, all the third grade of middle school students and second grade of high school students took the National Assessment of Educational Achievement (NAEA) exam. After 2016, only one percent of the students take the NAEA exam which makes the data lacks the comparability to the previous years. Also, the EDSS data is not available to the researchers after 2016.

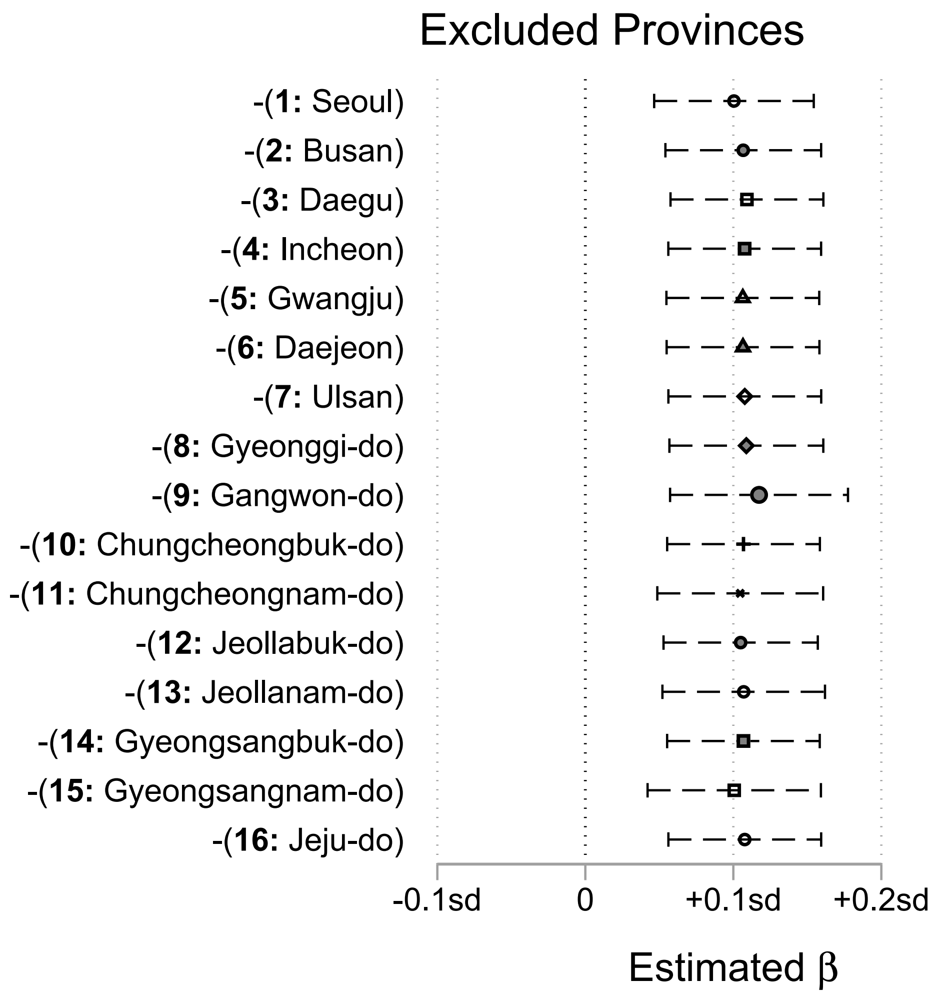


Figure A.3. The effects of the UFLP on Korean standardized scores: exclude one province from each regression.

Notes: I use the information from the EDSS data. This figure reports the estimated effects of the UFLP and the confidence intervals using the standard errors clustered at school level using school identifiers (dashed lines) of the UFLP implementation on standardize Korean scores. Each of these 16 regression excluded one province each, which is shown in the left side of the graph with the format "-(number: province name)," where the number identifies each province's location in figure A.1.

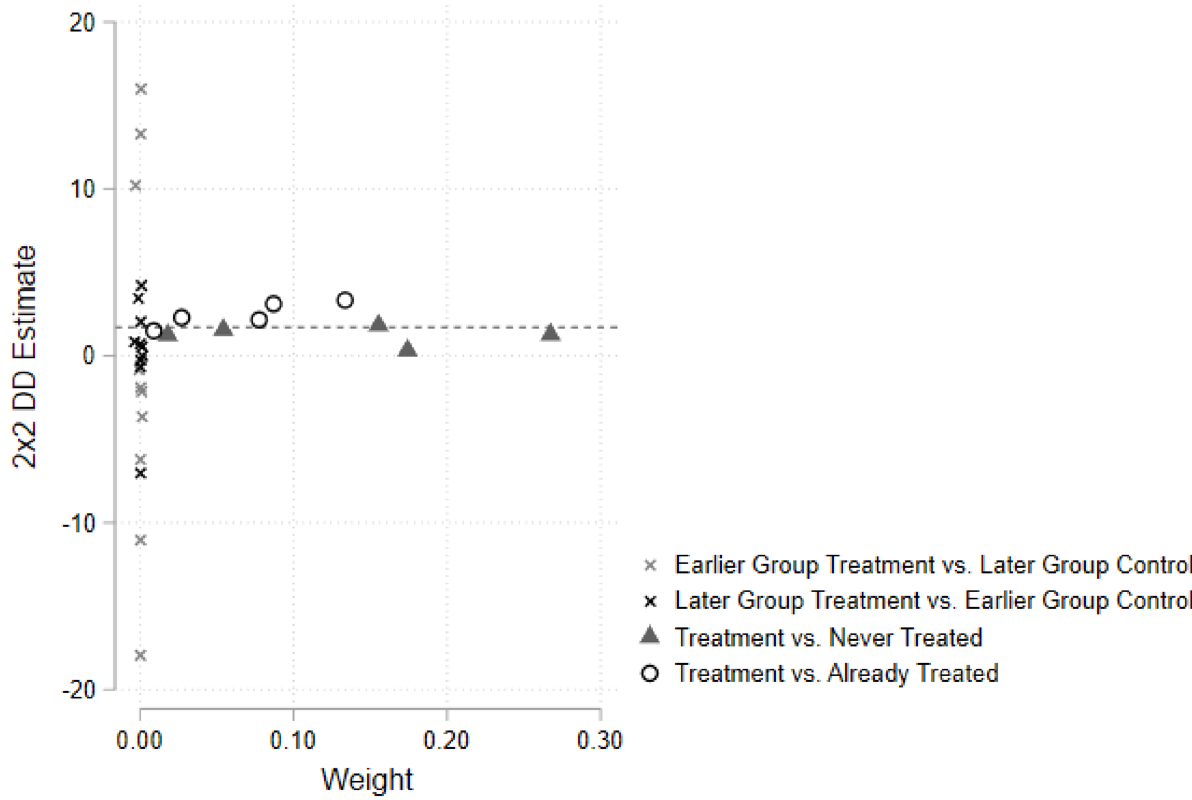
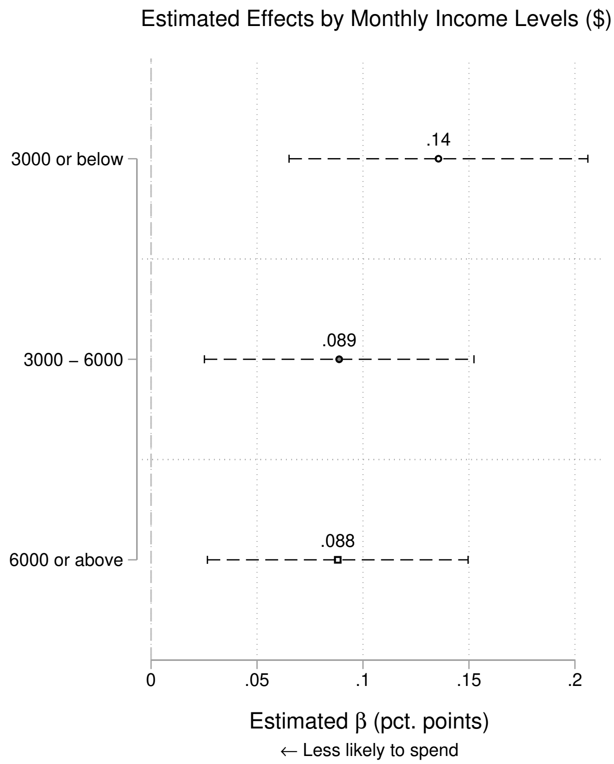
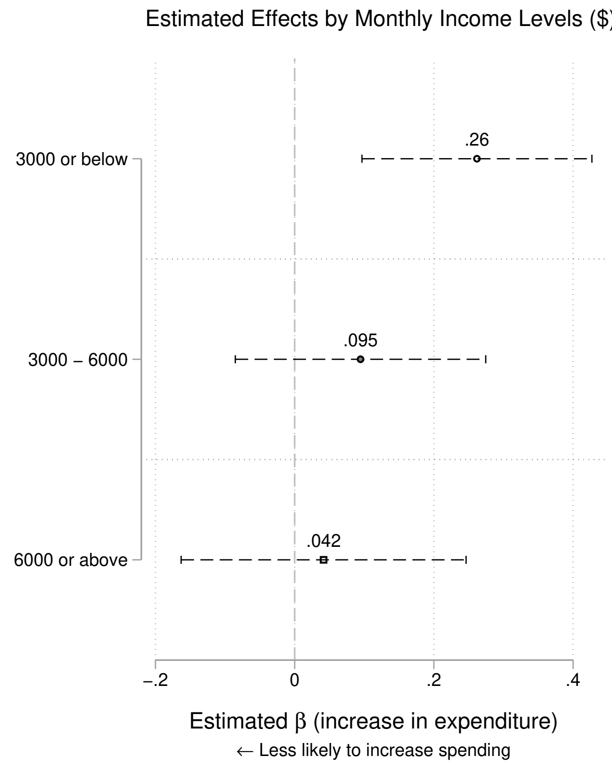


Figure A.4. Weights of the 2-by-2 Average Treatment Effects.
Notes: This figure plots the 2-by-2 average treatment effects (average treatment effects in each group and each period) by the weights associated to them. This graph was generated by following the Goodman-Bacon's stata package, `eventdd`, using the first year each school got treated to assign a binary treatment.



(a) Participation



(b) Log(Expenditure)

Figure A.5. After-School Program Participation and Expenditure by Income Groups.

Notes: I use the information from the PES data for these estimates. Panel (a) shows the estimated effects of the UFLP rollout on after-school program participation and panel (b) shows the estimated effects of the UFLP rollout on log of the after-school program expenditures. Point estimates are specified in the graph and standard errors clustered at province by urban indicators by year by school levels are depicted in dash lines to represent 95% confidence intervals.

Table A.1. The Universal Free Lunch Program Rollout Information

City (# on the map)	School Level	Detail of expansion
Seoul (1)	Elementary	March 2011: Public school 1-4th grade (21 districts), public school 1-3th grade (4 districts) November 2011: public school, extended to 4th grade (4 districts) 2012: public school full provision (extended to 5-6th grades in 4 districts) 2019: extended to private schools
	Middle	2012: 1st grade 2013: extended to 2nd grade 2014: extended to 3rd grade (full provision)
	High	2019: 3rd grade 2020: extended to 2nd grade 2021: will extend to 1st grade
Busan (2)	Elementary	2011: public school, 1st grade 2012: extended to public school 2-3 grades 2013: extended to public school 4-5 grades 2014: extended to public school 6th grade (public school full provision) 2018: extended to private schools (full provision)
	Middle	2016: 1st grade 2017: extended to 2-3 grades (full provision)
	High	2017: Gijang-gun, all grades 2019: 1st grade 2020: extended to 2nd grade 2021: will extend to 3rd grade
Daegu (3)	Elementary	2017: 4-6th grades 2018: extended to 1-3 grades
	Middle	2019: full provision
	High	2020: 3rd grade Will be extended to 2nd and 1st grade sequentially.
Incheon (4)	Elementary	March 2011: grade 3-6 September 2011: extended to grade 1-2
	Middle	2017: full provision
	High	2018: full provision
Gwanju (5)	Elementary	2010: full provision
	Middle	2012: full provision
	High	2017: 3rd grade 2018: extended to 2nd grade 2019: extended to 1st grade
Daejeon (6)	Elementary	2011: 1-2 grade 2012: extended to 3-4 grade 2013: extended to 5th grade 2014: extended to 6th grade
	Middle	2018: full provision
	High	2019: full provision

Notes: I gathered the UFLP rollout information by contacting each provincial offices of Ministry of Education. I use this information to determine the treatment intensity ($UFLPshare_{sdt}$), which is the share of students treated by the UFLP in each school.

Table A.2. The Universal Free Lunch Program Rollout Information (continued)

City (# on the map)	School Level	Detail of expansion
Ulsan (7)	Elementary	2012: schools in Ulju county (Ulju-gun) town area with less than 1000 students, 6th grade in Dong-gu and Buk-gu 2013: extended to all schools in Ulju county, 5th grade in Dong-gu and Buk-gu 2017: full provision
	Middle	2012: schools in Ulju county township area 2018: full provision
	High	2019: full provision
Gyeonggi-do (8)	Elementary	2010: town area 2010: urban area grade 5-6 2011: extended to grade 1-4 in urban area, full provision
	Middle	2012: grade 2-3 2013: extended to grade1, full provision
	High	2019: full provision
Gangwon-do (9)	Elementary	2011: small schools, region1 2012: extended to all schools, except Chuncheon 2014: extended to Chuncheon, full provision
	Middle	2011: small schools, region2 2013: extended to all schools, except Chuncheon 2014: 7.23: extended to Chuncheon, full provision
	High	2011: vocational schools, small schools, region 3 2015: reduced to region 4 (except vocational schools) 2017: returned back to region 3 2018: extended to full provision
Chungcheongbuk-do (10)	Elementary	2011: full provision
	Middle	2011: full provision
	High	2018: Boeun county, Okcheon county 2019: extended to full provision
Chungcheongnam-do (11)	Elementary	2004: township area 2010: extended to town area 2011: extended to all schools, full provision
	Middle	2012: township area 2013: town area 2014: extended to city area, full provision
	High	2019: full provision
Jeollabuk-do (12)	Elementary	2007-2008: remoted area 2011: extended to elsewhere, full provision
	Middle	2007-2008: remoted area 2011: extended to city area with 50% subsidy 2012: full subsidy to all schools
	High	2007-2008: remoted area 2014: Jeongeup provided 50 % subsidy 2018: extended to city area, full provision

Notes: I gathered the UFLP rollout information by contacting each provincial offices of Ministry of Education. I use this information to determine the treatment intensity ($UFLPshare_{sdt}$), which is the share of students treated by the UFLP in each school.

Table A.3. The Universal Free Lunch Program Rollout Information (continued)

City (# on the map)	School Level	Detail of expansion
Jeollanam-do (13)	Elementary	2011: town area 2011: extended to Mokpo, Naju, Gwangyang town area 2012: extended to the rest of the schools, full provision
	Middle	2011: town area 2011: Naju, Gwangyang town area 2012: extended to the rest of the schools, full provision
	High	2011: schools with less than 100 students 2011: Gurye, Yeongam, Jindo schools with 100 or mor students (Gurye, Yeongam, Jindo â full provision) 2012: extended to Goheung, Yeonggwang, Wando 2013: extended to all schools in town area 2017: extended to Gwangyang city area 2018: extended to Mokpo, Yeosu, Suncheon, Naju city area 2019: extended to all other city are, full provision
Gyeongsangbuk-do (14)	Elementary	2007: schools with less than 50 students 2008: extended to Ulleung county, schools in remote area with less than 100 students 2011: Andong, Gumi, Gunwi, Uljin 2012: extended to Pohang, Sangju, Cheongsong, Goryeong 2013: town area of the rest of the region 2018: city area of the rest of the region
	Middle	2008: Ulleng township level 2009: schools with less than 50 students 2011: Andong, Gumi, Gunwi, Uljin 2012: extended to Pohang, Sangju, Cheongsong, Goryeong 2013: town area of the rest of the region 2019: city area of the rest of the region
	High	2008: Ulleng township level 2020: grade 3

Notes: I gathered the UFLP rollout information by contacting each provincial offices of Ministry of Education. I use this information to determine the treatment intensity ($UFLPshare_{sdt}$), which is the share of students treated by the UFLP in each school.

Table A.4. The Universal Free Lunch Program Rollout Information (continued)

City (# on the map)	School Level	Detail of expansion
Gyeongsangnam-do (15)	Elementary	2007: Geochang township area 2010: Geochang city area 2010: extended to Tongyeong, Haman, Sancheong, Changneong, Goseong, Hamyang, Uiryeong, Namhae, Hadong, Hapcheon 2013: extended to the rest of the regions, full provision 2015: Stopped due to the Provincial governmentâs budget issue, full provision was continued only in the schools with less than 100 students 2016: Back to full provision
	Middle	2007: Geochang township area 2010: Geochang city area 2010: extended to Tongyeong, Haman, Sancheong, Changneong, Goseong, Hamyang, Uiryeong, Namhae, Hadong, Hapcheon 2013: extended to the town area of rest of the regions, full provision 2015: Stopped due to the Provincial government's budget issue, full provision was continued only in the schools with less than 100 students 2016: back to the full provision in town area 2017: extended to the urban area, full provision
	High	2007: Geochang township area 2010: extended to Geochang city area 2010: extended to Uiryeong, Namhae, Hadong, Hapcheon 2013: extended to all other town areas 2015: Stopped due to the Provincial government's budget issue, full provision was continued only in the schools with less than 100 students 2016: back to full provision in town area 2019: extended to the urban area, full provision
Jeju-do (16)	Elementary	2010: town area 2011: city area
	Middle	2010: town area 2012: grade 3 in city area 2013: grade 1-2 in city area
	High	2018: full provision
Sejong (17)	Elementary	2012: full provision
	Middle	2012: full provision
	High	2015: town area 2018: extended to city area (full provision)

Notes: I gathered the UFLP rollout information by contacting each provincial offices of Ministry of Education. I use this information to determine the treatment intensity ($UFLPshare_{sdt}$), which is the share of students treated by the UFLP in each school.

Table A.5. The Effect of the UFLP on Students' Participation and Food Spending

	(1)	(2)	(3)	(4)
	A. Share of students on meal subsidy			
$UFLPshare_{sdt}$	0.296 (0.083)*** [0.015] ***	0.292 (0.080)*** [0.015] ***	0.291 (0.075)*** [0.015] ***	0.277 (0.069)*** [0.015] ***
Mean of Outcome in pre-treatment periods	0.178			
Observations	20310			
	B. Share of parents' contribution			
$UFLPshare_{sdt}$	-0.192 (0.068)*** [0.011] ***	-0.190 (0.067)*** [0.011] ***	-0.187 (0.065)*** [0.011] ***	-0.178 (0.060)*** [0.011] ***
Mean of Outcome in pre-treatment periods	0.715			
Observations	20256			
	C. Share of government's contribution			
$UFLPshare_{sdt}$	0.204 (0.072)*** [0.011] ***	0.202 (0.070)*** [0.011] ***	0.199 (0.068)*** [0.011] ***	0.189 (0.062)*** [0.011] ***
Mean of Outcome in pre-treatment periods	0.252			
Observations	20256			
	D. Per student yearly expenditure on school meals ($)			
$UFLPshare_{sdt}$	28.163 (34.244) [21.742]	29.383 (31.543) [21.636]	6.296 (28.520) [22.126]	2.149 (29.863) [22.129]
Mean of Outcome in pre-treatment periods	911.0			
Observations	20016			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes

Notes: I use the information from the EDSS data. Panel (a) presents the results of the share of students on meal subsidy, panel (b) reports the results of the share of parents' contribution relative to the total expenditure, and Panel (c) shows the estimation results of the share of government contribution. Panel (d) reports the regression results for per student yearly expenditure, thus the unit of the outcome is the US Dollar. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province-specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific linear time trends added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.6. The Effect of the UFLP on Standardized Scores

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
	0.086	0.081	0.107	0.093
$UFLPshare_{sdt}$	(0.021)***	(0.021)***	(0.013)***	(0.015)***
	[0.026] * **	[0.026] * **	[0.026] * **	[0.026] * **
	B. Standardized Math Score			
	0.049	0.045	0.063	0.049
$UFLPshare_{sdt}$	(0.030)	(0.031)	(0.030)**	(0.032)
	[0.023]	[0.023] * *	[0.024] * **	[0.024] * **
	C. Standardized English Score			
	0.036	0.032	0.053	0.042
$UFLPshare_{sdt}$	(0.030)	(0.035)	(0.031)*	(0.034)
	[0.023]	[0.023]	[0.024] * **	[0.024] *
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province-specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific linear time trends added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.7. Results for the Percentage of underachieving (students at basic level of achievement or below)

	(1)	(2)	(3)	(4)
	A. Percentage at below-basic and basic level (Korean)			
$UFLPshare_{sdt}$	-2.462 (0.726)*** [0.538] * **	-2.389 (0.839)*** [0.540] * **	-2.868 (0.642)*** [0.520] * **	-2.742 (0.690)*** [0.524] * **
Mean of Outcome	19.55			
	B. Percentage at below-basic and basic level (Math)			
$UFLPshare_{sdt}$	-3.663 (1.514)** [0.693] * **	-3.579 (1.594)** [0.696] * **	-4.087 (1.687)** [0.678] * **	-3.974 (1.699)** [0.684] * **
Mean of Outcome	34.80			
	C. Percentage at below-basic and basic level (English)			
$UFLPshare_{sdt}$	-3.916 (0.832)*** [0.708] * **	-3.835 (0.892)*** [0.710] * **	-4.267 (0.650)*** [0.683] * **	-4.050 (0.673)*** [0.690] * **
Mean of Outcome	30.16			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province-specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.8. The Effect of the UFLP on Standardized Scores (Middle School Subsample)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.106	0.070	0.098	0.099
	[0.041] $***$	[0.042] $*$	[0.047] $**$	[0.049] $**$
Mean of Outcome	0.0002			
SD of Outcome	1.0002			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.031	-0.013	-0.002	-0.008
	[0.035]	[0.036]	[0.039]	[0.040]
Mean of Outcome	0.0005			
SD of Outcome	0.99999			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.021	-0.018	0.007	-0.008
	[0.032]	[0.033]	[0.034]	[0.035]
Mean of Outcome	0.003			
SD of Outcome	1.0002			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	9828			

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province level controls. Significant at *10%, **5%, and ***1% levels.

Table A.9. The Effect of the UFLP on Standardized Scores (High School Subsample)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.073	0.086	0.119	0.117
	[0.033] $**$	[0.033] $***$	[0.033] $***$	[0.033] $***$
Mean of Outcome	0.0096			
SD of Outcome	0.9943			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.075	0.082	0.123	0.124
	[0.032] $**$	[0.032] $**$	[0.033] $***$	[0.033] $***$
Mean of Outcome	0.0057			
SD of Outcome	0.9966			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.064	0.069	0.101	0.100
	[0.033] $*$	[0.033] $**$	[0.034] $***$	[0.034] $***$
Mean of Outcome	0.0102			
SD of Outcome	0.9965			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	10482			

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province level controls. Significant at *10%, **5%, and ***1% levels.

Table A.10. Results for the Percentage of students at the bottom two levels (below-basic level and basic level combined): Middle School Subsample

	(1)	(2)	(3)	(4)
	A. Percentage of underachieving students (Korean)			
	-0.340	0.042	-0.576	-0.262
$UFLPshare_{sdt}$	(0.805)	(0.857)	(0.786)	(0.743)***
	[0.536]	[0.543]	[0.614]	[0.629] * **
Mean of Outcome	14.72			
	B. Percentage of underachieving students (Math)			
	-0.302	0.291	0.243	-0.224
$UFLPshare_{sdt}$	(0.903)	(0.951)	(0.855)	(0.824)
	[0.697]	[0.711]	[0.776]	[0.809]
Mean of Outcome	38.46			
	C. Percentage of underachieving students (English)			
	-1.597	-0.873	-1.587	-1.287
$UFLPshare_{sdt}$	(0.877)*	(0.783)	(0.729)**	(0.927)
	[0.717] * *	[0.732] * **	[0.792] * *	[0.821]
Mean of Outcome	30.14			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	9828			

Notes: I use the information from the EDSS data for these figures. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province level controls. Significant at *10%, **5%, and ***1% levels.

Table A.11. Results for the Percentage of students at the bottom two levels (below-basic level and basic level combined): High School Subsample

	(1)	(2)	(3)	(4)
	A. Percentage of underachieving students (Korean)			
$UFLPshare_{sdt}$	-3.345 (0.774)*** [0.884] $***$	-3.739 (0.498) *** [0.883] $***$	-4.260 (0.232)*** [0.863] $***$	-4.235 (0.211)*** [0.866] $***$
Mean of Outcome	24.07			
	B. Percentage of underachieving students (Math)			
$UFLPshare_{sdt}$	-4.444 (0.853)*** [1.132] $***$	-4.718 (0.514)*** [1.127] $***$	-5.248 (0.296)*** [1.098] $***$	-5.299 (0.257)*** [1.101] $***$
Mean of Outcome	31.37			
	C. Percentage of underachieving students (English)			
$UFLPshare_{sdt}$	-5.979 (0.835)*** [0.1.174] $***$	-6.112 (0.541)*** [1.170] $***$	-5.873 (0.295)*** [1.120] $***$	-5.901 (0.234)*** [1.122] $***$
Mean of Outcome	30.14			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	10482			

Notes: I use the information from the EDSS data. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.12. The effect of the Universal Lunch Program rollout on the number of dropouts per 100 students

	(1)	(2)	(3)	(4)
	A. All high schools			
$UFLPshare_{sdt}$	-0.047	-0.087	-0.099	-0.107
	[0.107]	[0.106]	[0.106]	[0.106]
Mean of Outcome	1.755			
Observations	10184			
	B. High schools in high poverty area			
$UFLPshare_{sdt}$	0.080	0.031	-0.091	-0.094
	[0.180]	[0.179]	[0.179]	[0.178]
Mean of Outcome	2.904			
Observations	2440			
	C. High schools in low poverty area			
$UFLPshare_{sdt}$	0.058	0.004	0.017	-0.001
	[0.134]	[0.131]	[0.138]	[0.138]
Mean of Outcome	1.176			
Observations	2833			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes

Notes: I utilize the dropout information in EDSS data. I focus on the dropout per 100 students among the high school subsample, since middle school is compulsory education. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.13. Results for the Proportion of students at the below-basic level

	(1)	(2)	(3)	(4)
	A. Percentage at below-basic level (Korean)			
	-0.715	-0.691	-0.954	-0.936
$UFLPshare_{sdt}$	(0.490)	(0.512)	(0.337)***	(0.323)***
	[0.267] * **	[0.267] * **	[0.255] * **	[0.256] * **
Mean of Outcome	3.169			
	B. Percentage at below-basic level (Math)			
	-1.294	-1.276	-1.488	-1.485
$UFLPshare_{sdt}$	(0.502)**	(0.521)**	(0.505)***	(0.513)***
	[0.292] * **	[0.293] * **	[0.286] * **	[0.288] * **
Mean of Outcome	7.028			
	C. Percentage at below-basic level (English)			
	-1.592	-1.584	-1.845	-1.934
$UFLPshare_{sdt}$	(0.379)**	(0.609)**	(0.375)***	(0.633)***
	[0.379] * **	[0.710] * **	[0.683] * **	[0.380] * **
Mean of Outcome	5.282			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. I use an alternative measure of the percent of underachieving students as the share of students who are at "below-basic" level, which is the lowest achievement level, not the sum of the two lower levels (below-basic and basic level). $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.14. Results for the percentage of students at the below-basic level (Middle School Subsample)

	(1)	(2)	(3)	(4)
	A. Percentage at below-basic level (Korean)			
$UFLPshare_{sdt}$	-0.399	-0.360	-0.676	-0.554
	(0.428)	(0.431)	(0.327)*	(0.279)*
	[0.268]	[0.271]	[0.305] $**$	[0.310] $*$
Mean of Outcome		2.065		
	B. Percentage at below-basic level (Math)			
$UFLPshare_{sdt}$	-0.257	-0.062	-0.613	-0.430
	(0.205)	(0.228)	(0.176)***	(0.206)*
	[0.295]	[0.302]	[0.338] $***$ $**$	[0.348]
Mean of Outcome		5.681		
	C. Percentage at below-basic level (English)			
$UFLPshare_{sdt}$	-0.130	0.025	-0.355	-0.161
	(0.226)	(0.291)	(0.189)*	(0.133)
	[0.244]	[0.250]	[0.272]	[0.277]
Mean of Outcome		3.695		
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations		9828		

Notes: I use the information from the EDSS data for these estimates. I use an alternative measure of the percent of underachieving students as the share of students who are at "below-basic" level, which is the lowest achievement level, not the sum of the two lower levels (below-basic and basic level). $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.15. Results for the percentage of students at the below-basic level (High School Subsample)

	(1)	(2)	(3)	(4)
	A. Percentage at below-basic level (Korean)			
$UFLPshare_{sdt}$	-1.009 (0.680) [0.437] **	-1.118 (0.679) [0.438] **	-1.342 (0.496)** [0.430] ***	-1.335 (0.541)** [0.429] ***
Mean of Outcome	4.204			
	B. Percentage at below-basic level (Math)			
$UFLPshare_{sdt}$	-1.727 (0.395)*** [0.479] ***	-1.817 (0.249)*** [0.478] ***	-2.054 (0.202)*** [0.478] ***	-2.109 (0.186)*** [0.479] ***
Mean of Outcome	8.290			
	C. Percentage at below-basic level (English)			
$UFLPshare_{sdt}$	-2.243 (0.873)** [0.676] ***	-2.243 (0.812)** [0.678] ***** **	-2.559 (0.189)*** [0.702] ***	-2.624 (0.799)*** [0.702] ***
Mean of Outcome	6.770			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	10482			

Notes: I use the information from the EDSS data for these estimates. I use an alternative measure of the percent of underachieving students as the share of students who are at "below-basic" level, which is the lowest achievement level, not the sum of the two lower levels (below-basic and basic level). $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier, and the standard errors in the parenthesis are clustered at the province-by-year-by-school levels (middle or high school). In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.16. Robustness Check: Including sub-province-specific linear time trends

	(1)	(2)	(3)	(4)
	Korean			
	A1. Standardized Score		A2. Percent underachieving	
$UFLPshare_{sdt}$	0.099	0.091	-2.603	-2.504
	[0.027] $***$	[0.027] $***$	[0.519] $***$	[0.522] $***$
Mean of Outcome	0.005		19.55	
	Math			
	B1. Standardized Score		B2. Percent underachieving	
$UFLPshare_{sdt}$	0.061	0.055	-3.937	-3.886
	[0.024] $**$	[0.024] $**$	[0.669] $***$	[0.691] $***$
Mean of Outcome	0.003		34.80	
	English			
	C1. Standardized Score		C2. Percent underachieving	
$UFLPshare_{sdt}$	0.051	0.045	-4.353	-4.232
	[0.024] $**$	[0.024] $*$	[0.682] $***$	[0.686] $***$
Mean of Outcome	0.005		30.16	
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Sub-province specific time trend	Yes	Yes	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, and school-specific controls (total number of students, male to female student ratio, student-teacher ratio). The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (3) present the estimation results adding sub-province-specific linear time trend. In addition, column (2) and (4) adds provincial level controls. using the school fixed effects and year fixed effects. Significant at *10%, **5%, and ***1% levels.

Table A.17. Robustness Check: Excluding the schools that were treated before the sample period (Standardized score outcomes)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.085	0.099	0.117	0.117
	[0.027] $***$	[0.027] $***$	[0.028] $***$	[0.028] $***$
Mean of Outcome	0.066			
SD of Outcome	0.967			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.041	0.051	0.069	0.069
	[0.026]	[0.026] $**$	[0.026] $***$	[0.026] $***$
Mean of Outcome	0.060			
SD of Outcome	0.960			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.051	0.059	0.073	0.073
	[0.026] $**$	[0.025] $**$	[0.026] $***$	[0.026] $***$
Mean of Outcome	0.048			
SD of Outcome	0.952			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	13945			

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.18. Robustness Check: Excluding the schools that were treated before the sample period (percentage of underachieving students)

	(1)	(2)	(3)	(4)
	A. Percentage of underachieving students (Korean)			
$UFLPshare_{sdt}$	-3.241	-3.587	-3.849	-3.848
	[0.643] $***$	[0.641] $***$	[0.622] $***$	[0.623] $***$
Mean of Outcome	20.84			
	B. Percentage of underachieving students (Math)			
$UFLPshare_{sdt}$	-4.008	-4.157	-4.403	-4.438
	[0.821] $***$	[0.820] $***$	[0.800] $***$	[0.802] $***$
Mean of Outcome	32.05			
	C. Percentage of underachieving students (English)			
$UFLPshare_{sdt}$	-4.581	-4.792	-4.481	-4.473
	[0.836] $***$	[0.831] $***$	[0.796] $***$	[0.796] $***$
Mean of Outcome	29.14			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	13945			

Notes: I use the information from the EDSS data for these estimates. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.19. Robustness Check: Excluding the schools that were treated before the sample period (Re-standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.097	0.110	0.129	0.129
	[0.029] $***$	[0.029] $***$	[0.029] $***$	[0.029] $***$
Mean of Outcome	0.005			
SD of Outcome	0.997			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.048	0.056	0.076	0.076
	[0.027] $*$	[0.027] $**$	[0.028] $***$	[0.028] $***$
Mean of Outcome	0.002			
SD of Outcome	0.997			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.056	0.063	0.079	0.079
	[0.027] $**$	[0.027] $**$	[0.028] $***$	[0.028] $***$
Mean of Outcome	0.005			
SD of Outcome	0.998			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	13945			

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. This table uses the standardized scores that are standardized after the exclusion of the early treated schools. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.20. The effect of the Universal Lunch Program Rollout on the Share of the Students on Meal Subsidy

	(1)	(2)	(3)	(4)
$UFLPShare_{sdt}$	0.296	0.292	0.291	0.277
	(0.083) ***	(0.080) ***	(0.075)***	(0.069) ***
	[0.015] $***$	[0.015] $***$	[0.015] $***$	[0.015] $***$
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
F Statistic (province by school level)	27.90	10.85	291.3	595.5
F statistic (clustering at each school)	249.9	191.7	128.4	123.6
Mean of Outcome		0.453		
Observations		20310		

Notes: I use the information from the EDSS data for these estimates. This estimates shows how the implementation of the UFLP affects the actual share of the subsidized students, and the column (3) reports the same estimates as in column (1) of table 2. $SubsidyShare_{sdt}$ is different from $UFLPshare_{sdt}$, since the $UFLPshare_{sdt}$ uses the UFLP rollout information, and $SubsidyShare_{sdt}$ is the actual percentage of the subsidized students which can be driven by the $UFLPshare_{sdt}$. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the square brackets are clustered at school level. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A. 21. The effect of the Share of the Students on Meal Subsidy on Standardized Score Outcomes (2SLS)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
	0.291	0.277	0.367	0.336
$SubsidyShare_{sdt}$	(0.103)***	(0.021)***	(0.080)***	(0.087)***
	[0.089] * **	[0.090] * **	[0.093] * **	[0.097] * **
Mean of Outcome	0.005			
SD of Outcome	0.997			
	B. Standardized Math Score			
	0.167	0.154	0.217	0.177
$SubsidyShare_{sdt}$	(0.094)*	(0.101)***	(0.095)**	(0.110)
	[0.079] * *	[0.080] *	[0.082] * **	[0.087] * *
Mean of Outcome	0.003			
SD of Outcome	0.998			
	C. Standardized English Score			
	0.121	0.110	0.183	0.152
$SubsidyShare_{sdt}$	(0.104)	(0.122)	(0.103)*	(0.120)
	[0.078]	[0.079]	[0.081] * *	[0.086] *
Mean of Outcome	0.005			
SD of Outcome	0.998			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. This estimates shows how the variation in $SubsidyShare_{sdt}$ driven by the UFLP rollout ($UFLPshare_{sdt}$) affects the standardized score outcomes. $SubsidyShare_{sdt}$ is different from $UFLPshare_{sdt}$, since the $UFLPshare_{sdt}$ uses the UFLP rollout information, and $SubsidyShare_{sdt}$ is the actual percentage of the subsidized students which can be driven by the $UFLPshare_{sdt}$. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the square brackets are clustered at school level. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A. 22. The effect of the Share of the Students on Meal Subsidy on the Percentage of underachieving students (2SLS)

	(1)	(2)	(3)	(4)
	A. Percentage at below-basic and basic level (Korean)			
	-8.328	-8.193	-9.846	-9.883
$SubsidyShare_{sdt}$	(3.873)**	(4.108)**	(3.628)***	(3.688)***
	[1.880] * **	[1.907] * **	[1.863] * **	[1.966] * **
Mean of Outcome	19.55			
	B. Percentage at below-basic and basic level (Math)			
	-12.390	-12.270	-14.029	-14.323
$SubsidyShare_{sdt}$	(4.970)**	(5.218)**	(5.119)***	(5.438)***
	[2.392] * **	[2.425] * **	[2.376] * **	[2.516] * **
Mean of Outcome	34.80			
	C. Percentage at below-basic and basic level (English)			
	-13.243	-13.148	-14.648	-14.599
$SubsidyShare_{sdt}$	(4.319)***	(4.430)***	(3.283)***	(3.464)***
	[2.477] * **	[2.511] * **	[2.445] * **	[2.588] * **
Mean of Outcome	30.16			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. This estimates shows how the variation in $SubsidyShare_{sdt}$ driven by the UFLP rollout ($UFLPshare_{sdt}$) affects the percent of underachieving students. $SubsidyShare_{sdt}$ is different from $UFLPshare_{sdt}$, since the $UFLPshare_{sdt}$ uses the UFLP rollout information, and $SubsidyShare_{sdt}$ is the actual percentage of the subsidized students which can be driven by the $UFLPshare_{sdt}$. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the square brackets are clustered at school level. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table 23. The effect of the Share of the Students on Meal Subsidy on the alternative measure of the percentage of underachieving students, or percentage at "below-basic" level (2SLS)

	(1)	(2)	(3)	(4)
	A. Percentage at below-basic level (Korean)			
	-2.419	-2.368	-3.273	-3.375
$SubsidyShare_{sdt}$	(2.076)	(2.413)	(1.723)*	(1.695)**
	[0.929] * **	[0.940] * *	[0.916] * **	[0.964] * **
Mean of Outcome	3.169			
	B. Percentage at below-basic level (Math)			
	-4.377	-4.373	-5.108	-5.353
$SubsidyShare_{sdt}$	(1.992)**	(2.053)**	(1.821)***	(1.998)***
	[1.014] * **	[1.028] * **	[1.011] * **	[1.072] * **
Mean of Outcome	7.028			
	C. Percentage at below-basic level (English)			
	-5.383	-5.430	-6.332	-6.971
$SubsidyShare_{sdt}$	(2.585)**	(2.541)**	(2.535)**	(2.501)***
	[1.324] * **	[1.345] * **	[1.340] * **	[1.432] * **
Mean of Outcome	5.282			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. I use an alternative measure of the percent of underachieving students as the share of students who are at "below-basic" level, which is the lowest achievement level, not the sum of the two lower levels (below-basic and basic level). This estimates shows how the variation in $SubsidyShare_{sdt}$ driven by the UFLP rollout ($UFLPshare_{sdt}$) affects the percent of underachieving students. $SubsidyShare_{sdt}$ is different from $UFLPshare_{sdt}$, since the $UFLPshare_{sdt}$ uses the UFLP rollout information, and $SubsidyShare_{sdt}$ is the actual percentage of the subsidized students which can be driven by the $UFLPshare_{sdt}$. All specifications include school fixed effects using school id, year fixed effects, and school-level controls (total number of students, male-to-female student ratio, and student-to-teacher ratio), and province-specific linear time trend. The standard errors in the square brackets are clustered at school level. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.24. Robustness Check: weighted regression using the total number of students as weights (standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.126	0.129	0.164	0.150
	[0.027] $***$	[0.027] $***$	[0.028] $***$	[0.028] $***$
Mean of Outcome	0.158			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.068	0.070	0.098	0.084
	[0.027] $**$	[0.027] $***$	[0.028] $***$	[0.028] $***$
Mean of Outcome	0.188			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.049	0.050	0.077	0.066
	[0.027] $*$	[0.027] $*$	[0.028] $***$	[0.028] $**$
Mean of Outcome	0.207			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. I assign the total number of students in each school as weights to obtain weighted estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.25. Robustness Check 3: weighted regression using the total number of students as weights (Percentage of underachieving students)

	(1)	(2)	(3)	(4)
	A. Percentage of underachieving students (Korean)			
$UFLPshare_{sdt}$	-2.542	-2.582	-3.254	-3.152
	[0.605] $***$	[0.603] $***$	[0.584] $***$	[0.582] $***$
Mean of Outcome	18.53			
	B. Percentage of underachieving students (Math)			
$UFLPshare_{sdt}$	-3.488	-3.536	-4.090	-3.944
	[0.885] $***$	[0.881] $***$	[0.850] $***$	[0.852] $***$
Mean of Outcome	26.70			
	C. Percentage of underachieving students (English)			
$UFLPshare_{sdt}$	-4.581	-4.792	-4.481	-4.473
	[0.836] $***$	[0.831] $***$	[0.796] $***$	[0.796] $***$
Mean of Outcome	29.14			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the information from the EDSS data for these estimates. I assign the total number of students in each school as weights to obtain weighted estimates. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.26. Robustness Check: DID_M estimator of de Chaisemartin and D'haultfoeuille (2020)

	A. Binary Treatment			B. Fuzzy Treatment		
	Korean Score	Math Score	English Score	Korean Score	Math Score	English Score
$\hat{\beta}_{fd}$	0.100	0.024	0.019	0.100	0.027	0.017
	(0.033)	(0.027)	(0.025)	(0.028)	(0.029)	(0.027)
$\hat{\beta}_{fe}$	0.107	0.063	0.053	0.091	0.059	0.047
	(0.026)	(0.024)	(0.024)	(0.036)	(0.025)	(0.025)
DID_M	0.010	0.045	0.052	0.011	0.060	0.052
	(0.041)	(0.028)	(0.033)	(0.046)	(0.038)	(0.035)
$DID_M^{pl,1}$	-0.047	-0.032	-0.0005	-0.064	-0.0007	-0.043
	(0.028)	(0.019)	(0.033)	(0.033)	(0.025)	(0.027)
$DID_M^{pl,2}$	-0.002	0.002	-0.034	-0.006	-0.090	0.005
	(0.045)	(0.030)	(0.031)	(0.117)	(0.089)	(0.084)

Notes: I use the information from the EDSS data for these estimates. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. I utilize the new estimator (DID_M) proposed by de Chaisemartin and D'Haultfoeuille (2020). I also report the placebo estimators (DID_M^{pl}) which is a criterion to determine the common trend assumption. I also report first difference estimates and the two-way fixed effects estimates, which are also utilized for the statistical test to determine the existence of heterogeneous treatment effects over time within units. Regression includes school fixed effects using school identifiers, year fixed effects, province-specific linear time trend and school-level controls. The standard errors in the parentheses are clustered at each school level using school identifiers. Significant at *10%, **5%, and ***1% levels.

Table A.27. The effects of the UFLP among the schools with high baseline participation in the means-tested lunch subsidy (Standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.059	0.069	0.057	0.050
	[0.043]	[0.042]	[0.040]	[0.040]
Mean of Outcome	-0.352			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.048	0.054	0.059	0.051
	[0.041]	[0.040]	[0.039]	[0.039]
Mean of Outcome	-0.362			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.095**	0.101**	0.094**	0.085**
	[]0.044]	[.043]	[0.042]	[0.042]
Mean of Outcome	-0.418			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	4380			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools with the baseline participation in the means-tested subsidy higher than the 67th percentile before the ULFP. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.28. The effects of the UFLP among the schools with middle baseline participation in the means-tested lunch subsidy (Standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.087**	0.106**	0.115**	0.126***
	[0.042]	[0.043]	[0.047]	[0.047]
Mean of Outcome	0.298			
	C. Standardized Math Score			
$UFLPshare_{sdt}$	0.010	0.018	0.017	0.028
	[0.049]	[0.049]	[0.051]	[0.051]
Mean of Outcome	0.0202			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.016	0.008	0.002	0.002
	[0.043]	[0.043]	[0.047]	[0.048]
Mean of Outcome	0.010			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	4297	4297	4297	4297

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools with the baseline participation in the means-tested subsidy higher than the 33rd percentile but lower than the 67th percentile before the ULFP. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.29. The effects of the UFLP among the schools with low baseline participation in the means-tested lunch subsidy (Standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.047	0.097	0.124**	0.139**
	[0.058]	[0.059]	[0.058]	[0.058]
Mean of Outcome	0.598			
	A. Standardized Math Score			
$UFLPshare_{sdt}$	0.007	0.043	0.082	0.096
	[0.056]	[0.056]	[0.062]	[0.062]
Mean of Outcome	0.663			
	A. Standardized English Score			
$UFLPshare_{sdt}$	-0.040	-0.005	0.030	0.045
	[0.056]	[0.057]	[0.062]	[0.062]
Mean of Outcome	0.698			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	4168			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools with the baseline participation in the means-tested subsidy lower than the 33rd percentile before the ULFP. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.30. The effects of the UFLP among the schools with high baseline participation in the means-tested lunch subsidy (percentage of underachieving students)

	Percentage of Underachieving students			
	(1)	(2)	(3)	(4)
	A. Korean			
$UFLPshare_{sdt}$	-2.192*	-2.415**	-3.265***	-3.027***
	[1.136]	[1.125]	[1.065]	[1.078]
Mean of Outcome	30.26			
	B. Math			
$UFLPshare_{sdt}$	-2.597***	-2.615*	-3.634***	-3.407***
	[1.345]	[1.338]	[1.296]	[1.295]
Mean of Outcome	44.75			
	C. English			
$UFLPshare_{sdt}$	-1.580	-1.727	-1.933	-1.637
	[1.325]	[1.313]	[1.226]	[1.235]
Mean of Outcome	42.19			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	4297			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools with the baseline participation in the means-tested subsidy higher than the 67th percentile before the ULFP. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.31. The effects of the UFLP among the schools with middle baseline participation in the means-tested lunch subsidy (percentage of underachieving students)

	Percentage of Underachieving students			
	(1)	(2)	(3)	(4)
	A. Korean			
$UFLPshare_{sdt}$	-2.991***	-3.547***	-3.712***	-3.756***
	[0.973]	[0.993]	[1.035]	[1.050]
Mean of Outcome	20.37			
	B. Math			
$UFLPshare_{sdt}$	-4.339***	-4.404***	-4.814***	-4.834***
	[1.237]	[1.274]	[1.321]	[1.355]
Mean of Outcome	29.96			
	C. English			
$UFLPshare_{sdt}$	-2.712*	-2.974**	-2.306	-2.546*
	[1.447]	[1.477]	[1.512]	[1.537]
Mean of Outcome	27.75			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	4297			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools with the baseline participation in the means-tested subsidy higher than the 33rd percentile but lower than the 67th percentile before the ULFP. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.32. The effects of the UFLP among the schools with low baseline participation in the means-tested lunch subsidy (percentage of underachieving students)

	Percentage of Underachieving students			
	(1)	(2)	(3)	(4)
	A. Korean			
$UFLPshare_{sdt}$	-2.277 *	-3.294**	-3.661***	-3.979***
	[1.314]	[1.336]	[1.223]	[1.229]
Mean of Outcome	12.59			
	B. Math			
$UFLPshare_{sdt}$	-4.477**	-5.274**	-6.169 ***	-6.459***
	[2.151]	[2.152]	[2.002]	[2.000]
Mean of Outcome	18.01			
	C. English			
$UFLPshare_{sdt}$	-4.736 **	-5.444**	-5.002 **	-5.533**
	[2.341]	[2.343]	[2.187]	[2.186]
Mean of Outcome	15.41			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	4168			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools with the baseline participation in the means-tested subsidy lower than the 33rd percentile before the ULFP. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.33. Triple differences: The effects of the UFLP among the schools with high baseline participation in the means-tested lunch subsidy (Percentage of underachieving students)

	Percentage at basic level or below			
	(1)	(2)	(3)	(4)
	A. Korean			
$UFLPshare_{sdt}$	-2.690***	-3.476***	-3.673***	-3.816***
	(0.788)	(0.802)	(0.786)	(0.796)
$LowerIncome \times UFLPshare_{sdt}$	0.499	1.061	0.408	0.789
	(1.382)	(1.381)	(1.322)	(1.339)
Mean of Outcome	21.22			
	B. Math			
$UFLPshare_{sdt}$	-4.424***	-4.850***	-5.513***	-5.614***
	(1.177)	(1.185)	(1.115)	(1.128)
$LowerIncome \times UFLPshare_{sdt}$	1.846	2.236	1.879	2.207
	(1.786)	(1.787)	(1.708)	(1.716)
Mean of Outcome	31.02			
	C. English			
$UFLPshare_{sdt}$	-3.716***	-4.212***	-3.486***	-3.816***
	(1.323)	(1.332)	(1.266)	(1.275)
$LowerIncome \times UFLPshare_{sdt}$	2.136	2.484	1.554	2.179
	(1.872)	(1.870)	(1.761)	(1.774)
Mean of Outcome	28.67			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	12845			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools that has information of the baseline participation in the means-tested subsidy. $LowerIncome$ is an indicator with value one if the school has baseline participation higher than the 67th percentile before the ULFP. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the parentheses are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.34. Triple differences: The effects of the UFLP among the schools with middle baseline participation in the means-tested lunch subsidy (Percentage of underachieving students)

	Percentage at basic level or below			
	(1)	(2)	(3)	(4)
	A. Korean			
$UFLPshare_{sdt}$	-3.119***	-3.590***	-4.051***	-4.017***
	(0.889)	(0.886)	(0.827)	(0.829)
$MiddleIncome \times UFLPshare_{sdt}$	0.128	0.044	0.339	0.261
	(1.317)	(1.330)	(1.323)	(1.337)
Mean of Outcome	21.22			
	B. Math			
$UFLPshare_{sdt}$	-5.187***	-5.440***	-5.777***	-5.762***
	(1.144)	(1.139)	(1.101)	(1.099)
$MiddleIncome \times UFLPshare_{sdt}$	0.849	1.036	0.963	0.928
	(1.684)	(1.708)	(1.718)	(1.743)
Mean of Outcome	31.02			
	C. English			
$UFLPshare_{sdt}$	-5.047***	-5.310***	-4.510***	-4.494***
	(1.169)	(1.163)	(1.082)	(1.083)
$MiddleIncome \times UFLPshare_{sdt}$	2.335	2.337	2.204	1.948
	(1.860)	(1.879)	(1.857)	(1.878)
Mean of Outcome	28.67			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	12845			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools that has information of the baseline participation in the means-tested subsidy. $MiddleIncome$ is an indicator with value one if the school has baseline participation higher than the 33rd percentile but lower than the 67th percentile before the ULFP. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the parentheses are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.35. Triple differences: The effects of the UFLP among schools with low baseline participation in the means-tested lunch subsidy (Percentage of underachieving students)

	Percentage at basic level or below			
	(1)	(2)	(3)	(4)
	A. Korean			
$UFLPshare_{sdt}$	-3.069***	-3.423***	-3.735***	-3.732***
	(0.825)	(0.820)	(0.785)	(0.786)
$HigherIncome \times UFLPshare_{sdt}$	0.792	0.130	0.074	-0.248
	(1.550)	(1.566)	(1.451)	(1.457)
Mean of Outcome	21.22			
	B. Math			
$UFLPshare_{sdt}$	-4.173***	-4.222***	-4.690***	-4.677***
	(0.989)	(0.992)	(0.971)	(0.971)
$HigherIncome \times UFLPshare_{sdt}$	-0.304	-1.051	-1.478	-1.817
	(2.366)	(2.367)	(2.222)	(2.220)
Mean of Outcome	31.02			
	C. English			
$UFLPshare_{sdt}$	-3.046***	-3.235***	-2.899***	-2.894***
	(1.005)	(1.001)	(0.954)	(0.953)
$HigherIncome \times UFLPshare_{sdt}$	-1.690	-2.209	-2.103	-2.659
	(2.546)	(2.545)	(2.383)	(2.381)
Mean of Outcome	28.67			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	12845			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools that has information of the baseline participation in the means-tested subsidy. $HigherIncome$ is an indicator with value one if the school has baseline participation lower than the 33rd percentile before the ULFP. Percent of underachieving students are sum of the two lower levels (below-basic and basic level), which are lower than the adequate level of achievement. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the parentheses are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.36. The effects of the UFLP among the schools with alternative cutoff for high baseline participation in the means-tested lunch subsidy: higher than 75th percentile (Standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
$UFLPshare_{sdt}$	0.056	0.045	0.062	0.053
	[0.044]	[0.044]	[0.044]	[0.044]
Mean of Outcome	-0.422			
	B. Standardized Math Score			
$UFLPshare_{sdt}$	0.034	0.027	0.035	0.029
	[0.038]	[0.039]	[0.038]	[0.038]
Mean of Outcome	-0.416			
	C. Standardized English Score			
$UFLPshare_{sdt}$	0.066	0.054	0.066	0.047
	[0.040]	[0.041]	[0.040] $*$	[0.041]
Mean of Outcome	-0.486			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	3478			

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools that has information of the baseline participation higher than the 75th percentile before the ULFP. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.37. The effects of the UFLP among the schools with alternative cutoff for low baseline participation in the means-tested lunch subsidy: lower than 25th percentile (Standardized scores)

	(1)	(2)	(3)	(4)
	A. Standardized Korean Score			
D_{sdt}	0.039	0.080	0.133	0.137
	[0.055]	[0.056]	[0.049] $***$	[0.049] $***$
Mean of Outcome			0.699	
	B. Standardized Math Score			
D_{sdt}	0.034	0.068	0.127	0.134
	[0.051]	[0.051]	[0.052] $**$	[0.053] $**$
Mean of Outcome			0.782	
	C. Standardized English Score			
D_{sdt}	-0.037	-0.008	0.044	0.052
	[0.053]	[0.053]	[0.056]	[0.056]
Mean of Outcome			0.824	
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations			3231	

Notes: I use the information from the EDSS data for these estimates. For this table, I use a subsample of schools that has information of the baseline participation lower than the 25th percentile before the ULFP. All score outcomes are standardized as explained in section 4. Mean and standard deviation of standardized scores are mechanically 0 and 1, respectively, due to the standardization process. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. Difference-in-differences specifications include year and school fixed effects, school-specific controls (total number of students, male to female student ratio, student-teacher ratio), and province- specific linear time trends. The standard errors in the square brackets are clustered at each school using school identifier. In each panel, column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province-level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.38. The effect of the Universal Lunch Program rollout on the number of dropouts

	(1)	(2)	(3)	(4)
		A. All high schools		
$UFLPshare_{sdt}$	-0.157	-0.538	-1.095	-1.097
	[0.416]	[0.403]	[0.396] $***$	[0.395] $***$
Mean of Outcome			13.81	
Observations			10184	
		B. High schools in high poverty area		
$UFLPshare_{sdt}$	-0.030	-0.222	-1.304	-1.261
	[0.523]	[0.504]	[0.526] $**$	[0.515] $**$
Mean of Outcome			15.66	
Observations			2440	
		C. High schools in low poverty area		
$UFLPshare_{sdt}$	1.039	0.348	0.282	0.173
	[1.098]	[1.092]	[1.222]	[1.231]
Mean of Outcome			12.50	
Observations			2833	
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes

Notes: I utilize the dropout information in EDSS data. I focus on the total number of dropouts among the high school subsample, since middle school is compulsory education. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.39. The effect of the Universal Lunch Program rollout on the test taking share

	(1)	(2)	(3)	(4)
	A. Main sample			
$UFLPshare_{sdt}$	-0.009	-0.008	-0.012	-0.010
	[0.009]	[0.009]	[0.008]	[0.009]
Mean of Outcome	0.975			
Observations	20281			
	B. Middle school subsample			
$UFLPshare_{sdt}$	-0.003	-0.003	-0.005	-0.004
	[0.003]	[0.003]	[0.004]	[0.004]
Mean of Outcome	0.981			
Observations	9828			
	C. High school subsample			
$UFLPshare_{sdt}$	-0.001	-0.003	-0.011	-0.010
	[0.020]	[0.019]	[0.015]	[0.016]
Mean of Outcome	0.970			
Observations	10453			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes

Notes: I utilize the number of students who are supposed to be taking the NAEA exam, and the number of students who actually took the test. I take the share of actual number of test takers to the total number of students and see if the UFLP changed the test taking share. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.40. The effects of the UFLP on after-school program participation

	(1)	(2)	(3)	(4)
	A. Average number of after school programs			
$UFLPshare_{sdt}$	0.463	0.452	0.331	0.271
	[0.146] $***$	[0.145] $***$	[0.131] $**$	[0.133] $**$
Mean of Outcome	2.029			
	B. Average number of academic programs			
$UFLPshare_{sdt}$	0.478	0.468	0.354	0.298
	[0.142] $***$	[0.140] $***$	[0.128] $***$	[0.130] $**$
Mean of Outcome	1.606			
	C. Average number of non-academic programs			
$UFLPshare_{sdt}$	-0.016	-0.015	-0.024	-0.026
	[0.025]	[0.025]	[0.025]	[0.025]
Mean of Outcome	0.424			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20295			

Notes: I use the information from the EDSS data for the estimates above. The average number of after-school programs that the students participate in each school, which is obtained by dividing the total number of programs offered with the total number of participants. The EDSS data has information for academic and non-academic programs separately. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.41. The effects of the UFLP on after-school program participation (middle school subsample)

	(1)	(2)	(3)	(4)
	A. Average number of after school programs			
$UFLPshare_{sdt}$	0.331	0.314	0.237	0.319
	[0.107] $***$	[0.108] $***$	[0.105] $**$	[0.110] $***$
Mean of Outcome	1.542			
	B. Average number of academic programs			
$UFLPshare_{sdt}$	0.334	0.305	0.250	0.308
	[0.105] $***$	[0.105] $***$	[0.099] $**$	[0.105] $***$
Mean of Outcome	1.606			
	C. Average number of non-academic programs			
$UFLPshare_{sdt}$	-0.004	0.009	-0.013	0.011
	[0.031]	[0.031]	[0.035]	[0.036]
Mean of Outcome	0.637			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	9826			

Notes: I use the information from the EDSS data for the estimates above and focus on the middle school subsample. The average number of after-school programs that the students participate in each school, which is obtained by dividing the total number of programs offered with the total number of participants. The EDSS data has information for academic and non-academic programs separately. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.42. The effects of the UFLP on after-school program participation (high school subsample)

	(1)	(2)	(3)	(4)
	A. Average number of after school programs			
$UFLPshare_{sdt}$	0.623	0.504	0.056	0.001
	[0.262] ∗∗	[0.259] ∗	[0.242]	[0.245]
Mean of Outcome	2.487			
	B. Average number of academic programs			
$UFLPshare_{sdt}$	0.643	0.536	0.082	0.030
	[0.253] ∗∗	[0.250] ∗∗	[0.238]	[0.242]
Mean of Outcome	2.263			
	C. Average number of non-academic programs			
$UFLPshare_{sdt}$	-0.020	-0.033	-0.025	-0.029
	[0.040]	[0.040]	[0.037]	[0.038]
Mean of Outcome	0.224			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	10469			

Notes: I use the information from the EDSS data for the estimates above and focus on the high school subsample. The average number of after-school programs that the students participate in each school, which is obtained by dividing the total number of programs offered with the total number of participants. The EDSS data has information for academic and non-academic programs separately. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.43. Private Education Expenditures Survey (PES) Descriptive Statistics

	(1) All	(2) post-treated	(3) pre-treated
After school program participation and expenditures			
Participation (0 or 1)	0.70	0.65	0.73
	(0.46)	(0.48)	(0.45)
Expenditures (monthly, USD)	21.70	15.45	24.96
	(28.15)	(24.06)	(29.49)
Students' gender and school levels			
Female	0.48	0.47	0.48
	(0.50)	(0.50)	(0.50)
Attending high school	0.62	0.42	0.72
	(0.49)	(0.49)	(0.45)
Student's academic achievement levels			
Top 10% in class	0.10	0.10	0.10
	(0.30)	(0.31)	(0.30)
11-30%	0.20	0.20	0.20
	(0.40)	(0.40)	(0.40)
31-60%	0.30	0.30	0.30
	(0.46)	(0.46)	(0.46)
61-80%	0.20	0.20	0.20
	(0.40)	(0.40)	(0.40)
Bottom 20%	0.19	0.19	0.19
	(0.39)	(0.40)	(0.39)
Family income (monthly, USD)			
less than 3000	0.36	0.36	0.36
	(0.48)	(0.48)	(0.48)
3000-5999	0.48	0.48	0.47
	(0.50)	(0.50)	(0.50)
6000 or above	0.16	0.16	0.17
	(0.37)	(0.36)	(0.37)
Observations (student-by-year)	460352	157660	302692

Notes: Descriptive statistics are the mean and standard deviation in the parentheses. These are calculated using Private Education Expenditure Survey data, Statistics Korea. Sample period covers 2009 to 2016. The first column shows the characteristics of all observations. The second column show characteristics of already-treated observations (observation year is after the first year of the ULFP rollout). The third column show characteristics of not-yet-treated observations (observation year is before the first year of the ULFP rollout).

Table A.44. The effect of the Universal Lunch Program rollout on after-school program participation and expenditures

	(1) After School Program Participation	(2) log(expenditure)	(3) IHS(expenditure)
$UFLPshare_{dt}^{PES}$	0.097***	0.170**	0.210**
	(0.031)	(0.083)	(0.100)
Mean of Outcome	0.699	2.061	2.456
		(Mean of monthly expenditure = 22.17 USD)	
Observations		460,352	
Province FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Province specific time trend	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes

Notes: I use the information from the PES data for the estimates above. After-school program participation ins an indicator variable with value one if a student participated in the after school program in a given year. I use the expenditure on after-school programs and take log and inverse hyperbolic sine transformation to accomodate the outliers. $UFLPshare_{dt}^{PES}$ is the probability that each student is attending the school that initiated the UFLP in each year (y) in each province (d), which can be interpreted as the treatment intensity. All specifications include Province fixed effects, year fixed effects, province-specific linear time trends, and student level observables including gender, school levels, and previous achievement level (5 categories). The standard errors in the parentheses are clustered at school level by province by year. Significant at *10%, **5%, and ***1% levels.

Table A.45. The effect of the Universal Lunch Program Rollout on School Misbehavior

	(1)	(2)	(3)	(4)
	A. Number of Cases Reported per 100 Student			
$UFLPshare_{sdt}$	0.062 (0.045) [0.026] **	0.062 (0.046) [0.026] **	0.060 (0.049) [0.028] **	0.062 (0.050) [0.028] **
Mean of Outcome	0.296			
	B. Number of Victims Reported per 100 Student			
$UFLPshare_{sdt}$	0.174 (0.099)* [0.064] ***	0.175 (0.100)* [0.064] ***	0.157 (0.102) [0.065] ***	0.165 (0.105) [0.066] **
Mean of Outcome	0.431			
	C. Number of Perpetrators Reported per 100 Student			
$UFLPshare_{sdt}$	0.126 (0.106) [0.073] *	0.129 (0.105) [0.073] *	0.123 (0.118) [0.074] *	0.138 (0.118) [0.075] *
Mean of Outcome	0.455			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	20310			

Notes: I use the school misbehavior information from the EDSS data for the estimates above. EDSS data provides yearly total misbehavior cases reported to the school, number of victims, and number of perpetrators. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.46. The effect of the Universal Lunch Program Rollout on School Misbehavior (Middle School Subsample)

	(1)	(2)	(3)	(4)
	A. Number of Cases Reported per 100 Student			
$UFLPshare_{sdt}$	-0.005	0.013	0.035	0.043
	(0.057)	(0.041)	(0.026)	(0.035)
	[0.033]	[0.035]	[0.039]	[0.045]
Mean of Outcome	0.410			
	B. Number of Victims Reported per 100 Student			
$UFLPshare_{sdt}$	0.051	0.067	0.147	0.138
	(0.123)	(0.110)	(0.083)*	(0.094)
	[0.086]	[0.091]	[0.097]	[0.116]
Mean of Outcome	0.652			
	C. Number of Perpetrators Reported per 100 Student			
$UFLPshare_{sdt}$	-0.018	0.002	0.072	0.114
	(0.039)	(0.044)	(0.077)	(0.086)
	[0.065]	[0.069]	[0.075]	[0.088]
Mean of Outcome	0.638			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	9828			

Notes: I use the school misbehavior information from the EDSS data and focus on the middle school subsample for the estimates above. EDSS data provides yearly total misbehavior cases reported to the school, number of victims, and number of perpetrators. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.

Table A.47. The effect of the Universal Lunch Program Rollout on School Misbehavior (High School Subsample)

	(1)	(2)	(3)	(4)
	A. Number of Cases Reported per 100 Student			
$UFLPshare_{sdt}$	0.109	0.097	0.107	0.108
	(0.077)	(0.078)	(0.098)	(0.091)
	[0.040] $***$	[0.041] $**$	[0.045] $**$	[0.045] $**$
Mean of Outcome	0.189			
	B. Number of Victims Reported per 100 Student			
$UFLPshare_{sdt}$	0.275	0.261	0.272	0.279
	(0.181)	(0.180)	(0.211)	(0.204)
	[0.094] $**$	[0.094] $***$	[0.099] $***$	[0.099] $***$
Mean of Outcome	0.225			
	C. Number of Perpetrators Reported per 100 Student			
$UFLPshare_{sdt}$	0.262	0.246	0.271	0.281
	(0.191)	(0.191)	(0.234)	(0.222)
	[0.124] $**$	[0.124] $**$	[0.135] $**$	[0.134] $**$
Mean of Outcome	0.283			
School FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
School level Controls	Yes	Yes	Yes	Yes
Province level Controls	No	Yes	No	Yes
Province specific time trend	No	No	Yes	Yes
Observations	10482			

Notes: I use the school misbehavior information from the EDSS data and focus on the high school subsample for the estimates above. EDSS data provides yearly total misbehavior cases reported to the school, number of victims, and number of perpetrators. $UFLPshare_{sdt}$ is the share of students treated by the UFLP rollout in each school in each year, which can be interpreted as the treatment intensity. All specifications include school fixed effects using school id, year fixed effects, and school-level controls. The standard errors in the parentheses are clustered at school level by province, and the standard errors in the square brackets are clustered at school level. Column (1) and (2) present the estimation result using the school fixed effects and year fixed effects. Column (1) shows the results using a sparse model, which excludes the province characteristics from the baseline model, and column (2) shows the results using the baseline model. Column (3) and (4) present the estimation results using the province-specific trend added to the spares model and baseline model, respectively. Column (3) is comparable to column (1) since this model does not contain the province level controls, and column (4) is comparable to column (2) since it contains the province-level controls. Significant at *10%, **5%, and ***1% levels.