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The Effect of School Feeding on Education Outcomes: A Non-parametric Bounds Analysis

Innocent Akampurira

Building Tomorrow and Makerere University, Uganda

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Abstract

This paper estimates the causal effect of school feeding programs on primary-school attendance, English and local-language literacy, and numeracy using Manski-style non-parametric bounds from the 2024 Uwezo Uganda learning assessment. The findings are twofold: (i) the binary "feeding vs no feeding" comparison under the MTS+MIV assumption yields upper bounds that lie below zero for all education outcomes except attendance, but this reflects the concentration of feeding programs in more deprived schools rather than a harmful effect of feeding; (ii) exploiting feeding intensity shows non-negative upper bounds lower than the OLS point estimates for attendance, English literacy, and numeracy (but not local language literacy) when comparing schools with the highest feeding intensity to those with no feeding and the lowest intensity under the MTS+MIV assumption. These findings show that in contexts where school feeding is overwhelmingly parent-led and unevenly covered, the binary 'has-a-program-or-not' distinction is uninformative; what matters is the share of children who are actually fed.

Keywords: Partial identification, bounds, school feeding, attendance, foundational literacy, foundational numeracy

* Building Tomorrow / Makerere University, Uganda. Email: innocentakampurira57@gmail.com

1 Introduction

Education and health are the most important investments in human capital (Hahn & Truman, 2015). Becker, (1964) and Schultz (1961) define human capital as the stock of productive knowledge, skills, health, and abilities embodied in individuals, acquired through investment in education, training, and health, which enhances productivity and generates economic returns. The dynamic interaction between health and education is one of the driving forces for developing human capital, which in turn drives national economies, with over 70 percent of the wealth of high-income countries attributed to human capital compared to 40 percent in low-income countries (Research Consortium for School Health & Nutrition & Sustainable Financing Initiative, 2022).

Educational interventions targeting child hunger and nutrition are widely promoted as a means of improving educational outcomes. This is because the condition and well-being of children largely determine school participation and learning (Research Consortium for School Health & Nutrition & Sustainable Financing Initiative, 2022). Hungry children or those who suffer from protein-energy malnutrition do not have the same potential for learning as healthy and well-nourished children. Even temporary hunger, common among children who are not fed before going to school or during school, can adversely affect learning, as children have more difficulty concentrating and performing complex tasks, even if otherwise well-nourished (Del Rosso, 1999). In low and lower-middle-income countries, approximately 300 million school children have iron-deficiency anemia, causing them to lose some six IQ points per child (WFP, 2022). The Cost of Hunger report estimates that up to 18 percent of grade repetitions in Africa are associated with stunting (African Union & WFP, 2013), which increases costs for the education system and families. With that, on average, only 18 percent of school children in low-income countries receive school meals, compared to 39 percent in lower middle-income countries, 48 percent in upper middle-income countries, and 61 percent in high-income countries (WFP, 2022). This pattern is correlated with the educational outcomes of school enrollment, completion, and learning gains in the respective regions.

Significant progress has been made in global education over the past few decades, particularly in achieving universal primary education (UNESCO, 2016). Despite significant progress in expanding access to education globally over the past few decades, the number of children not in school has decreased by only 1% since 2015 and now stands at 251 million. For those in school, the education they receive is often substandard, with approximately three out of four children in developing countries unable to read and comprehend a simple text by age 10 (UNESCO, 2023). Without foundational skills, children are less likely to advance to the next grade level and more prone to dropping out of school, thereby compromising their future academic success and job prospects (World Bank, 2018).

To identify causal effects of school feeding, several studies have used quasi-experimental methods such as the Difference-in-Differences (DiD) and Instrumental Variable approaches. Evidence from Mali and Burkina Faso on school enrollment and attendance outcomes, estimated with a DiD estimator, shows positive effects. In Mali, the emergency school feeding program led to increases in the probability of enrolment by 10 percentage points and to around an additional half-year of completed schooling among treatment children relative to children in households in the comparison group (Aurino et al., 2019). In Burkina Faso, the DiD results suggest that, on average, the school feeding program that took on the modality of Take-Home Ratios (THR) had a positive impact on pupils' attendance rate of 8.4 percentage points for both girls and boys (Nikiema, 2019). Regarding learning outcomes, evaluation of the Rwanda Home Grown School Feeding (HGSF) program using a difference-in-differences approach shows that each additional month of exposure increases student test scores in math, science, and social studies by 0.015, 0.026, and 0.025 standard deviations, respectively (Nsabimana & Mensah, 2025). Evidence from India using the same method finds that nearly five years of exposure to midday meals increased test scores by 18% (0.17σ) in reading and 9% (0.09σ) in math relative to children with less than one year of exposure (Chakraborty & Jayaraman, 2019). In Colombia, school feeding improved educational achievement by 0.1 standard deviation (Zárate et al., 2024). A study on school feeding that uses an instrumental variable approach finds that school feeding causes a significant increase of around 2 percentage points in the retention rate and attendance of students in food-insecure areas in Malawi (Manea, 2020).

While there are numerous studies on the effects of school feeding programs across education-related indicators, it is difficult to generalize the significance of these outcomes, given the breadth and variation in program design and the rigor of each evaluation (African Union, 2018). Even more, in some cases, findings are mixed, like when examining attendance as an outcome (Cohen et al., 2021). These diverse and mixed findings could also be attributed to the failure to account for endogeneity arising from both omitted variable bias and reverse causality. Omitted variable bias arises from other factors that are correlated with both school feeding and educational outcomes. Specifically, educational outcomes can be influenced by classroom infrastructure, availability of resources, quality of school leadership, parental and community commitment, and teaching staff, including their qualifications, experience, and effectiveness (Glewwe & Kremer, 2006; Grantham-McGregor et al., 2007; Hammond, 2000). Reverse causality, on the other hand, could occur when low(high) attendance rates or low(high) learning gains worsen(improve) School Feeding Programs (SFPs). Generally, the presence of feeding programs in a school can be correlated with (un)observed school and pupil characteristics, including strong parent and community commitment to school governance and the district's food security situation (Budget Monitoring and Accountability Unit, 2019).

In addition to endogeneity problems, there is no exogenous variation to exploit in the context of school feeding in Uganda; therefore, obtaining a credible point estimate of the causal effect is difficult. The Ministry of Education provides guidelines to schools and parents and stipulates the role of parents and communities in feeding children at school; therefore, the implementation of school feeding programs is left to parents and schools. Thus, the non-parametric bounds approach, a partial identification approach that employs relatively weak but plausible assumptions on selection and response to school feeding, is used to deal with this identification problem brought on by endogeneity and a lack of exogenous variation (Manski, 1990, 1997; Manski & Pepper, 2000). The estimated bounds obtained via this approach are informative and show the effect of school feeding on attendance and learning. The treatment effect of school feeding can be bound because the outcomes themselves are bounded (Manski, 1990).

This study, therefore, aims to answer the question of the effects of school feeding programs on primary school students' educational outcomes, measured by school attendance and reading and numeracy scores, using a non-parametric bounds approach. The analysis starts with investigating what can be concluded about the effect without imposing assumptions, followed by cases when plausible non-parametric assumptions are layered to tighten the bounds. The major contribution of this paper is the use of a non-parametric bounds approach to bound the effect of school feeding on education outcomes, which, to the best of my knowledge, has not been used to analyze school feeding effects on education.[1] This study also contributes to the literature on the differential program effects of varying levels of school feeding intensity. Additionally, particularly for Uganda, this study will contribute to understanding the effects of school feeding on learning outcomes in early years, basic literacy, and numeracy. Finally, most existing evidence comes from large-scale donor- or government-funded programs (Mali emergency feeding, Burkina Faso THR, India MDM). Uganda's predominantly parent-led feeding model, where 76% of funding comes from household contributions, has not been studied at this scale. This Uwezo data, therefore, offers a unique window into the effects of decentralized, unstructured feeding programs. Through these analyses, this study aims to inform future policy decisions, especially as the Ugandan government and other low-income countries work to formalize feeding programs through national policies and contribute to the broader discourse on improving child learning outcomes through meals.

The study uses cross-sectional data from the 2024 Uwezo survey on schools and children aged 4 to 17 years, with basic literacy and numeracy competencies assessed. School feeding programs and attendance data are collected at the school level. With the non-parametric bounds approach, the monotone treatment selection assumption (MTS) that is made in this case is that

[1] Some notable previous applications of the Manski-style non-parametric bounds to education measurement include: an application to measure the effects of additional resources for low-ability pupils (de Haan, 2014), effects of parents' schooling on child's schooling (de Haan, 2011) and effects of private tutoring (Hof, 2014). Gundersen & Kreider (2009) bound the effects of food security on children's health.

"Pupils who select to be in a school with a feeding program have weakly higher scores in foundation skills than those who do not choose to participate in a school with a feeding program". Under the MTR assumption, school attendance rises with the presence of a school feeding program, and, for foundational skills, proficiency rises with school feeding. In addition to the MTS and MTR assumptions, the reliability of the type of water source in the school is used as a monotone instrumental variable (MIV), thereby assuming that schools/pupils in schools with low water reliability, on average, do not have better potential educational outcomes than schools with more water reliability.

In the binary comparison of feeding versus non-feeding schools, the MTS+MTR assumption rules out negative effects on attendance and English literacy, but with the additional MIV, the bounds become non-identifying. Stratifying by intensity reveals a different picture: comparing schools where 75% of pupils receive meals (Q4) to schools with completely no feeding program, the MTS+MTR+MIV bounds place the effect on attendance at [0, 8.3%] (vs. an OLS estimate of 9.6%), on English literacy at [0, 7.7%] (vs. 9.4%), and numeracy at [0, 9.5] percentage points (vs. 10% for OLS). A similar pattern is observed when comparing schools where 75% of pupils receive meals (Q4) to schools where <25% do (Q1), the MTS+MTR+MIV bounds place the effect on English literacy at [0, 12.8%] (vs. an OLS estimate of 13.9%), on numeracy at [0, 18.5%] (vs. 18.9%), on attendance at [0, 11.1%] percentage points (vs. 11.8) and lastly on local language reading at [0, 6.8] (vs an OLS estimate of 5.1%). The pattern suggests that the binary 'has a program or not' distinction is uninformative in a context where parent-led programs are unevenly covered; what matters for measurable learning gains is the share of pupils actually fed.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on the evaluation of the effects of school feeding. Section 3 sets the Ugandan context. Section 4 describes the data. Section 5 presents the empirical strategy. Section 6 reports the results. Section 7 concludes.

2 Literature Review

Research on school feeding programs and their education outcomes across various modalities and contexts, as well as different evaluation methods, is abundant in the literature. First, looking at school feeding's effects on attendance, this synthesis of available evidence on school feeding's effects on educational outcomes begins with an evaluation of a Food for Education program operated by the World Food Program in Northern Uganda that employed two modalities: in-school meals and take-home rations. Evidence from this prospective, clustered, randomized controlled field experiment between 2005 and 2007 by Alderman et al. (2012) showed statistically significant effects of 8 to 12 percentage points for both modalities on the morning attendance of older children, aged 10-17, based on unannounced attendance data. Specifically, with respect to

children's gender, the in-school meals program had a positive impact on the morning attendance of girls of all ages, and the take-home rations program had a significant positive impact on the attendance of boys aged 10-17.

Aurino et al. (2019) also examine the educational impacts of school feeding, which takes the form of emergency school feeding and generalized food distribution, in a context of conflict and substantial food insecurity in Mali. They utilize a difference-in-differences weighted estimator on pre-intervention baseline and five-year follow-up data and find that children in households receiving school meals had completed, on average, nearly an additional half-year of education relative to children in the comparison group. Similarly, Nikiema (2019) uses difference-in-differences (DiD) estimation on data from a humanitarian school feeding intervention in Burkina Faso and finds that, on average, the take-home rations program has a positive impact of 8.4 percentage points on pupils' attendance rate.

Further looking at national feeding programs, Afridi et al. (2020) find 3 percentage-point increases in average monthly attendance with large effects in early grades when using DiD estimation on staggered implementation and child-level panel data from India's school midday meal program. Kyzy (2021) for a study on Kyrgyzstan's primary schools' free meals program, use panel regression models and find that students participating in the program have lower odds and lower rates of missing school in later years.

Cohen et al. (2021) in their meta-analysis of evidence on the effects of universal school feeding across 47 studies in economically developed countries reveals that nearly all studies examining universal free school meals found positive associations with school meal participation. Additionally, in most studies examining universal free school meals that included free lunch, positive associations with academic performance were found, whereas findings from studies examining only universal free breakfast were mixed. Research findings were similarly mixed when examining attendance as an outcome.

For school feeding effects on learning outcomes, Nsabimana & Mensah (2025)'s study of the impact of Rwanda's Home-Grown School Feeding (HGSF) program on students' cognitive performance uses the DiD method to exploit plausibly exogenous variation in exposure induced by the program's staggered implementation across schools and students' grades. They find a positive impact of the program on student test scores of 0.02, 0.025, and 0.029 standard deviations in math, science, and social studies, respectively, for an additional month of exposure to school feeding, with the impact accruing over time. The effect of exposure to school feeding on English and Kinyarwanda test scores is also positive, with 0.028 and 0.023 standard deviations, respectively.

Regarding the effects of large-scale, government-led interventions on education and human capital in resource-constrained settings, Aurino et al. (2023) provide evidence from a randomized trial of Ghana's government school feeding program. They find that, after almost two years,

the school feeding program led to moderate average increases in math and literacy standardized scores among pupils in treatment communities by about 0.15 standard deviations, and to larger achievement gains for girls, disadvantaged children, and regions. For learning outcomes effects with India's midday program, Chakraborty & Jayaraman (2019) find, using DiD estimation, that exposure to midday meals for a nearly five-year duration of primary school increased test scores by 18% (0.17σ) for reading and 9% (0.09σ) for math relative to children with less than a year of exposure (School feeding and learning achievement. Still, with India's Midday meals program, a study that uses a phased-in research design provides experimental evidence on the impacts of early versus late initiation of iron fortification in school lunch programs on children's health and cognitive outcomes in India. This study by Grafenstein et al. (2023) found that individuals in the early treatment group, who received four years of treatment, experienced health benefits, including higher hemoglobin levels and a lower likelihood of anemia, compared with those in the late treatment group, who received only one and a half years of treatment. However, there was no evidence of any treatment effects on cognitive or educational outcomes.

Several studies have also been done on China's Student Nutrition Improvement Plan (SNIP). SNIP covers 40.6 million students in the compulsory education stage, accounting for 42% of all students enrolled in rural compulsory education in 2021(Duan et al., 2024). Duan et al. (2024) utilize the county-by-county rollout of the SNIP and DiD estimation and find that SNIP increases math test scores (0.39 standard deviations) but has a statistically insignificant effect on verbal achievement (0.08 standard deviations). The effect is greater for middle school students and children from disadvantaged families. Zhou et al. (2024) also examine the impacts of childhood exposure to China's Nutrition Improvement Program (SNIP) using data from the China Family Panel Studies. They employ a cohort difference-in-differences (DID) design to identify the SNIP's long-term effects and find that early-life exposure to the SNIP yields lasting benefits in adult education attainment, cognitive and non-cognitive skills, and health and health behaviors. These long-term effects are realized in the increased probability of adult employment (6.5 percentage points) and a 10.3% average increase in annual income. Zheng et al. (2022) still examine China's Nutrition Improvement plan, but this time assess the programs' spillover effects on children's noncognitive skills. Using the China Education Panel Survey (CEPS), this study finds that the school feeding program significantly improves children's noncognitive outcomes, suggesting that school feeding should be treated not only as a nutrition or education scheme but also as a transfer program that fosters children's development beyond health and academic outcomes.

Finally, for looking at evaluations of national feeding programs, McEwan (2013) evaluates the impact of higher-calorie meals on educational outcomes for public rural schools and their students in Chile. This study applies a regression-discontinuity design to administrative data on

educational outcomes and finds no evidence, across a range of specifications and samples, that additional calories affect school attendance and fourth-grade scores.

Beyond experimental RCT, DiD, and regression discontinuity evidence, there is also evidence using the Instrumental Variable (IV) quasi-experimental technique. Mostert (2021) applies the two-stage least squares (2SLS) model to quantify the impact of the school feeding program (SFP) on the education and health outcomes of South African children. The results show that the SFP has a significant effect on school attendance and academic achievement. Specifically, illness-linked absenteeism is reduced by between 0.5 and 1.2 percentage points, which is significant at the 5 percent level. The impact of this SFP is higher in rural regions than in urban settings and larger in boys than in girls.

Lastly, the effects of school feeding on learning outcomes have been documented not only in low- to middle-income contexts but also in developed economies. Frisvold (2015) estimates the impact of the availability of School Breakfast Programs in U.S. schools on cognitive achievement using multiple data sets: the National Assessment of Educational Progress (NAEP) and the Early Childhood Longitudinal Study, Kindergarten Cohort of 1998–99 (ECLS-K). This study finds that the availability of the School Breakfast Programs increases math achievement by at least 23 percent of a standard deviation in the NAEP data and at least 29 percent of a standard deviation in the ECLS-K data. These results suggest that food assistance programs and nutrition interventions can influence cognitive achievement not only in developing countries but also in higher-income countries, such as the United States.

From a qualitative evidence perspective, there is a consensus on the benefits of having school feeding programs. Studies in Ethiopia and Rwanda found that the home-grown school feeding program was successful in improving class attendance and academic performance among schoolchildren, according to teachers and school directors. Specifically, the observation was that before the SFP was launched in their schools, many children did not attend school because they engaged in various household activities to help their parents, especially female students (Desalegn et al., 2022; Munyangeri et al., 2024).

The evidence reviewed above establishes a credible body of findings linking school feeding programs to improved attendance and learning outcomes across diverse contexts, from emergency interventions in Mali and Burkina Faso to large national programs in India, China, Ghana, and Rwanda, with effect sizes ranging from modest attendance gains to meaningful improvements in test scores, often larger for girls and disadvantaged children. Despite this breadth, endogeneity and reverse causality remain persistent interpretive challenges, and the studies that most credibly address them do so by exploiting plausibly exogenous, policy-induced variation: staggered rollouts, randomized assignments, or sharp eligibility cutoffs. Uganda's school feeding landscape does not offer such a natural experiment in the data available for this study, which forecloses the point-identification strategies that dominate this literature. This paper, therefore,

turns to partial identification methods, which yield informative bounds on the effect of school feeding on learning outcomes under a set of weak, theoretically grounded assumptions, an approach that trades point precision for robustness, and that remains valid precisely where the conditions for conventional causal identification cannot be met.

3 Context

3.1 Uganda's Education System

According to the Uganda Education Act of 2008, the Ministry of Education and Sports (MoES) is responsible for providing quality education and sports services on behalf of the government of Uganda. Uganda's education system comprises seven years of primary education, typically serving children aged 6 to 12 years. This is followed by a six-year secondary cycle, and later students can pursue a university education (lasting 3 to 5 years), attend a technical or vocational institute, or enroll in another government-sanctioned study program. Primary education is the first level of formal education, and it is universal, with all pupils following a common basic curriculum. Furthermore, the government made primary education free in 1997 through the Universal Primary Education (UPE) program (Government of Uganda, 2008). The implementation of the Universal Primary Education (UPE) program has increased enrollment from 7.53 million children in 2007 to 8.6 million in 2024, with projections suggesting it will reach 11.7 million by 2025 (MoES, 2025).

In Uganda's case, significant challenges persist in ensuring enrollment, school attendance, completion, and learning outcomes for primary school children, particularly in rural areas (UBOS, 2021). One in four children of school-going age (6 to 12 years) remains out of school (UBOS, 2024). And only 6 out of 10 children complete primary school on time (UNESCO, 2024). In a 2023 assessment of educational progress in Uganda, approximately 60% of primary three (P.3) learners were rated proficient in numeracy, while about 53.9% were rated proficient in English literacy. For grade 6, around 2 in 3 learners were rated proficient in numeracy, and about 2 in 5 learners assessed were proficient in literacy in English (UNEB, 2024).

In terms of funding, the Ministry of Education and Sports (MoES) receives a portion of the national budget to support its operations and programs. These funds cover teaching and learning materials, co-curricular activities, school maintenance and operations, and administrative costs, but do not include school feeding expenses. Private schools are independently funded. Regarding school ownership, education is provided through both government (public) and private institutions. Private schools include community-founded schools, those owned by entrepreneurs, faith-based schools, and schools operated by non-governmental organizations, as well as non-formal learning centers that are either government-led or community-led (MoES,

2017). According to the Education Management Information System (EMIS), there were a total of 45,164 primary schools, of which 12,544 (27.8%) were government-owned, while the remaining 32,620 were privately owned (MoES, 2025).

3.2 Description of school feeding in Uganda

School feeding programs in Uganda date back to 1979 and initially covered all schools. However, due to economic challenges in the 1980s, the quality of education declined, rendering large-scale feeding initiatives unfeasible. Recognizing that Karamoja, a sub-region in the northeast characterized by a semi-arid climate, had the worst social indicators in the country, the government partnered with the United Nations World Food Programme (WFP) to launch a school feeding initiative in 1983 (Kibenge, 2005). As of 2024, the WFP provides a daily hot meal to at least 78 percent of schools in the Karamoja region and has collaborated with the Ugandan government to join the School Meals Coalition and develop the first National School Feeding Policy. The Karamoja program also has a component of take-home rations targeted towards girls with attendance rates above 80% at the end of the school term (WFP, 2022).

Beyond Karamoja, several complementary feeding initiatives operate across the country. These include a school milk programme in parts of the Southwestern region supported by the Netherlands Development Organization (SNV), Cotton On Foundation-funded school meals, the Kakira Sugar Limited Corporate Social Responsibility Meals Programme serving schools near the Kakira Sugar Estate in Jinja district, and the parent-led Gulu feeding Programme targeting schools in Northern Uganda (Global Child Nutrition Foundation (GCNF), 2024). The Government of Uganda has broadly advocated for parent-led school feeding as a viable and sustainable approach, and most school feeding programs across the country are indeed parent-driven, funded through cash contributions or in-kind food provision. However, the absence of a guiding policy instrument has kept overall school feeding coverage low and raised persistent concerns about the adequacy and quality of meals provided.

The introduction of Universal Primary Education (UPE) in 1997 significantly increased school enrollment, underscoring the need for school feeding programs to keep children in school. In response, the Ministry of Education and Sports (MoES) issued guidelines to provide a framework for school feeding across Universal Primary Schools. These guidelines emphasized the role of school feeding in reducing short-term hunger and promoting enrolment, attendance, concentration, cognitive development, and the overall nutritional and health status of school-going children (MoES, 2013). These guidelines aligned with the Education Act, which designated parents as responsible for providing food, shelter, medical care, and transportation (Government of Uganda, 2008). Additionally, the guidelines aimed to operationalize a Cabinet directive outlining the different modes of financing for school feeding programs in rural and urban settings, targeting School Governing Bodies (School Management Committees and Boards of Governors)

and Local Authorities (sub-county and district levels). According to these Ministry of Education and Sports (MoES) guidelines, School Governing Bodies have the authority to determine the quantities of food staples to be contributed each term, based on the recommended daily calorie allowance. They also decide on the cash equivalent for parents who prefer that option. To implement the school feeding programs, School Feeding Committees (SFCs) are formed and tasked with collecting and managing contributions in both in-kind and cash forms.

School feeding practices vary between rural and urban contexts. In urban schools, the School Feeding Committees, upon receiving approval from the school governing body and relevant local authorities, decide on the types of food to procure or contribute, the nature and number of meals (solid or semi-solid), and grade-based variations. For instance, mid-morning porridge may be provided for Primary One and Two students, along with lunch, or both. In rural schools, contributions are tailored to accommodate parents' convenience. The MoES guidelines recommend that contributions take the form of an agreed quantity of quality beans and seed maize, or a cash equivalent of the agreed food staples, depending on the parents' preferences (MoES, 2013).

Despite the availability of this school feeding framework, coverage remains limited and uneven. A 2021 national survey found that 84% of government primary schools reported learners having access to some form of meal, whether at school, packed from home, or by returning home for lunch, while 16% reported students going without lunch entirely. Table 1 shows significant disparities across locations and sub-regions. Urban schools were more likely to provide in-school meals (60%) than rural schools (44%), while one in five rural schools reported that learners received no lunch at all, compared to just 8% in urban areas. At the sub-regional level, Kampala recorded 100% in-school meal provision, and regions such as Buganda, Busoga, and Karamoja also reported high rates, partly attributable to WFP support. By contrast, home-packed lunches were predominant in Bunyoro, Ankole, Kigezi, and Tooro, while West Nile and Lango had high proportions of children going home for lunch. Bukedi and Teso stood out for the large share of children receiving no lunch whatsoever (UBOS, 2021).

These gaps are further reflected in national coverage data. Of the over 8.8 million children enrolled in Uganda's primary school system in 2022, only approximately 1.2 million (14%) were receiving food at school. Funding for school feeding is heavily fragmented: international donors contribute 18%, domestic NGOs 3%, the government 2%, and the private sector 1%, while the remaining 76% comes from other sources, primarily parents' own financial contributions (Global Child Nutrition Foundation (GCNF), 2024).

Table 1: Distribution of Government Primary Schools by provision of lunch to Learners (UBOS, 2021)

Background Characteristics Residence	Lunch at School	Packed from Home	Go Back Home	No Lunch	Total
Rural	43.9	14.8	21.5	19.8	100
Urban	60.1	21.8	10	8.1	100
Sub-region					
Kampala	100	0	0	0	100
Buganda South	88.2	2.7	0	9.1	100
Buganda North	85.2	4.3	0	10.5	100
Busoga	95.4	0	0	4.6	100
Bukedi	39.9	5.4	2.8	51.9	100
Elgon	55.4	0	20.1	24.5	100
Teso	36.1	3.4	14.9	45.7	100
Karamoja	90.9	0	9.1	0	100
Lango	44.6	0	40.4	15	100
Acholi	59.4	2.8	23.9	13.8	100
West Nile	38.6	0	52.5	9	100
Bunyoro	22	71.9	0	6.2	100
Tooro	21.7	59.8	5.2	13.3	100
Ankole	13.7	81.5	4.8	0	100
Kigezi	4	68.8	23.5	3.6	100
National	49.2	17.1	17.8	16	100

Notes: Rows may not sum exactly to 100 due to rounding.

4 Data

This study utilizes school and child-level data from the 2024 Uwezo National Learning Assessment survey conducted in July–August 2024 (Uwezo Uganda, 2024). Uwezo Uganda, a program of Twaweza East Africa, a non-governmental organization, conducts regular citizen-led assessments of the learning situation at the individual child, household, school, and community levels.

In the 2024 Uwezo survey, data were collected on school attendance on the day of the survey and learning competencies in literacy and numeracy. Children were evaluated for their literacy skills in both English and local languages. The literacy assessment focused on basic skills such as recognizing letters, reading words and paragraphs, story reading, and comprehension. The numeracy assessment included tasks related to number recognition, addition, subtraction, multiplication, division, and fundamental ethno-mathematical skills. The Uwezo survey was designed to gather data from schools with seven grades (Primary One to Seven) that serve the local community the most. The survey covered 4 regions, 15 sub-regions, 29 districts and cities

from a national total of 147, and 435 schools. Twenty households were sampled from each village/enumeration area, and all children aged 4–16 years in each household were asked about school attendance and assessed in foundational skills. The sampling procedure used the framework of the 2014 Uganda Population and Housing Census, and units were drawn from all 15 statistical sub-regions of Uganda. Within each district, 15 Enumeration Areas (EAs) were selected by Probability Proportional to Size (PPS), using the number of households as the measure of size. Twenty households per EA were then targeted for child assessment.

Data were also gathered on whether schools had feeding programs. At the household level, children were asked if they attended the surveyed school, which is relevant for analyzing the relationship between feeding programs and educational outcomes.

For the assessment of reading in local languages, the sample was limited to 12 of the 29 selected districts and cities. This assessment was conducted in four languages that are widely used: Leblango in two districts (Alebtong and Oyam), Luganda in three districts (Kassanda, Mukono, and Mpigi), Lusoga in three districts (Bugiri, Kamuli, and Namutumba), and Runyankore/Rukiga in four districts (Kabale, Isingiro, Mbarara, and Rubirizi). The effective sample of primary schools with complete data was 410 schools out of the expected 435. The Uganda Primary 2 curriculum was referenced in the development of these foundational skills tests (Uwezo Uganda, 2024).

The Uwezo 2024 survey yielded a main sample of 21,057 children (10,742 boys and 10,315 girls) across 8,608 households out of the targeted 8,707. All these children were assessed in both English language literacy and numeracy. From the data, a sub-sample of 8,707 children (4,365 boys and 4,342 girls) enrolled in Primary Grades 3 to 7 (P3–P7) is eligible for analysis of English reading and numeracy levels by grade. For reading in local languages, a sub-sample of 3,513 children (1,737 boys and 1,776 girls) drawn from 12 districts is eligible for analysis of grade-level performance in P3–P7. Because children were assessed at households, the data were further filtered to include only children attending the surveyed school, for which school feeding data were collected. Since data were collected at the child, household, and school levels, the datasets were merged to link surveyed children to their corresponding surveyed schools.

For this study, data cleaning involved standardizing the spellings of school names to ensure consistency for merging the school and learner-household datasets. The data were further filtered to retain only learners attending the surveyed school for which feeding program status was captured, yielding a total of 4,163 child records for analysis of English and numeracy competencies across 410 schools. The merging and filtering processes yielded a total of 1,602 learners eligible for local language competency analysis.

Attendance for each school by grade was recorded on the survey date. The overall school attendance headcount was then divided by the total school enrollment, as recorded in the headteacher's official school records, to produce the attendance rate as a percentage. In cases where

the percentage exceeded 100, these records (for 37 schools) were winsorized to a maximum value of 100%.

For learning competencies, the competency variables available in the data were used directly. All variables were already available for local language, English literacy, and numeracy, with 0 representing no competence on the Grade 2 assessment and 1 representing that the child could complete the Grade 2 test. Proficiency in literacy is defined, for children in Grades 3 to 7, as the ability to read a Grade 2-level English story; similarly, proficiency in numeracy is defined as the ability to complete a Grade 2-level division task. Children are marked as either proficient or not.

The MIV used was water reliability, derived from the variable "main source of water for other purposes." Water reliability data were available for 409 of the 410 schools with school feeding data; 1 school was removed. In the data, this was measured by source type, with categories including: borehole, piped, covered well/spring, open well/spring, rainwater, river/lake/stream, dam, trucked water, and none. These categories were recoded into high-reliability (piped) and low-reliability (borehole, covered well/spring, open well/spring, rainwater, river/lake/stream, dam, and trucked water). Boreholes are coded under low-reliability sources because, while they are improved compared to surface water, they are not always dependable on a day-to-day basis for purposes such as school feeding, as they are prone to high breakdown rates, lengthy repair delays, and seasonal groundwater variability (MacAllister et al., 2022). This recoding yields 294 schools with low reliability and 115 with high reliability. The one school recorded as having no water source for other purposes was dropped at the point of applying the MIV.

Table 2 presents summary statistics, showing that about 71% of schools have a feeding program in place. From Table 3, the average attendance rate is 73.439% for schools with feeding programs, compared with 71.178% for schools without formal feeding programs. The difference in attendance rates between the two treatments is not statistically significant. For learning outcomes, local language literacy, and learner competencies, averages are higher in the no-school-feeding program treatment (23.3%) than in school-feeding schools (16.4%). A similar trend is observed in Numeracy. For English language literacy, a slightly higher average competency is observed in feeding schools (23%) compared to 22% in learners in no school feeding.

Table 2: Summary Statistics

Variable	n (schools)	mean	SD	min	max
Attendance rate	410	72.782	23.896	6.507	100
School feeding	410	0.710	0.454	0	1
No (0)	119	0.290			
Yes (1)	291	0.710			
Coverage of the School Feeding program (School Feeding = 1)	291	2.137	1.301	1	4
Q1 - (0–25%)	147	0.505	0.501		
Q2 - (26–50%)	38	0.131	0.338		
Q3 - (51–75%)	25	0.086	0.281		
Q4 - (76–100%)	81	0.278	0.449		
Reliability of the water source	409	1.281	0.450	1	2
Low	294	0.719			
High	115	0.281			

Table 3: Descriptive Statistics for Attendance rates and Learning outcomes in Literacy and Numeracy (Primary Three to Seven) by status of school feeding

	Feeding Program					**No Feeding Program**				
	n	**Mean**	**SD**	**min**	**max**	**n**	**Mean**	**SD**	**min**	**max**
Attendance rates	291	73.439	23.135	6.507	100	119	71.178	25.694	8.130	100
English Literacy	2,723	0.230	0.421	0	1	1,440	0.222	0.415	0	1
Local Language Literacy	1,040	0.164	0.371	0	1	562	0.233	0.423	0	1
Numeracy	2,723	0.518	0.500	0	1	1,440	0.544	0.498	0	1

Notes: Attendance rates are expressed as percentages, measured at the school level, and cover all grades. Learning competencies are at the learner level, cover grades 3 to 7, and range from 0 (no competence) to 1 (required competence).

5 Empirical Strategy

Consider a population, J, of schools or learners. Each school/learner, j of the population, J has observable covariates $x_j \, \epsilon \, X$ and a response function $y_j(.) : T \rightarrow Y$, mapping the mutually exclusive and exhaustive treatments, $t \, \epsilon \, T$ of school feeding into real-valued education outcomes $y_j(t) \, \epsilon \, Y$. Treatment T is participation in a school feeding program, thus assumed to be an ordered set. Learner or school, j has a realized treatment $z_j \, \epsilon \, T$ when they belong to a school with a feeding program or have a feeding program for the case of schools, and a realized learning or attendance outcome $y_j \; = \; y_j(z_j)$, both of which are observable. The latent outcomes $y_j(t)$ when $t \neq \; z_j$ are not observable.

The key education outcome variables include the likelihood that a school achieves optimal attendance and the likelihood that a student is proficient in literacy or numeracy. To measure the effect of school feeding, school attendance rates and learning proficiency in either literacy or numeracy are taken as the outcome variable (y). The attendance rate education outcome is calculated as the percentage of learners present on the day of the survey, divided by the school's total enrollment. The treatment variable $(t)$for education outcomes on learning is whether the learner attended a school with a feeding program ($t = 1$ for "yes" and $t = 0$ for "no"), whereas for the case of the attendance outcome, the treatment (t) is whether the school had a feeding program $(t = 1)$ or not $(t = 0)$. For potential outcomes, $y(t = 1)$ represents the outcome for school attendance rates if the school had a feeding program, or for the case of literacy or numeracy proficiency, if a learner was in a school with a feeding program, and $y(t = 0)$ represents the outcome if a learner was not in such a school.

Empirically, the average treatment effect of school feeding can be expressed as follows:

$$\Delta = E\left[y(t = 1)\right] - E\left[y(t = 0)\right] \tag{1}$$

where:

- y represents the treatment outcome,

- t is the treatment variable, which equals 1 to indicate receiving a school meal and 0 otherwise.

This average treatment effect is the difference between the two mean potential outcomes of the cases of the education outcomes if all the children or schools participated in a feeding program $y(t = 1)$ and the case if all children/schools had no access to a feeding program $y(t = 0)$. Both $y(t = 1)$ and $y(t = 0)$ for the same learner and school are never observed. Manski's approach helps bound the effect without requiring strong assumptions (Manski, 1990). Using the law of iterated expectations, the identification problem with the effect is highlighted here in equation (2).

$$E[y(t = 1)] = E[y(t = 1)|z = 1] * P(z = 1) + E[y(t = 1)|\, z = 0] * P(z = 0) \tag{2}$$

The sampling process identifies each of the quantities on the right side of equation (2) except for the term $E[y(t = 1)|\, z = 0]$, the unobserved counterfactual.

Firstly, this study investigates what can be concluded about the school feeding effect without imposing assumptions by computing the worst-case bounds on the treatment effect. According to Manski (1990), bounds can be placed on the mean outcomes to account for the mean outcomes from unobserved scenarios. It is plausible to assume that the outcome space, y of attendance or learning outcomes, is bounded and has the greatest lower bound, $y_{\min}$ and the least upper bound,

$y_{\max}$. In this case, $y_{\min}$ and $y_{\max}$ take on the values 6.5 and 100 percent, respectively, when the education outcome under consideration is school attendance rates, and then 0 and 1, respectively, as well when the outcomes are competencies in literacy or numeracy. The unobserved term may thus take any value in the interval $[y_{\min},\ y_{\max}]$. Equation (2) can be obtained for the term $E\,[y(t=0)]$ as well. The values $y_{\max}$ and $y_{\min}$, the maximum and minimum values of the outcome on attendance and literacy or numeracy proficiency, are utilized in computing the upper and lower bounds for the terms $E[y(t=1)]$ and $E[y(t=0)]$. The following equation (3) summarizes this substitution.

$$\begin{aligned} E[y|z=1]*P(z=1)+\ y_{\min}*P(z=0) \\ \leq\ E[y(t=1)]\leq \\ E\,[y|z=1]*P(z=1)]+y_{\max}*P(z=0) \end{aligned}$$

(3)

$$\begin{aligned} E\,[y|z\ =\ 0]*\ P(z\ =\ 0)+\ y_{\min}*\ P(z\ =\ 1) \\ \leq\ E\,[y(t=0)]\leq \\ E\,[y|z\ =\ 0]*\ P(z\ =\ 0)+\ y_{\max}\ *\ P(z\ =\ 1) \end{aligned}$$

To then obtain the lower bound on the treatment, Δ, the upper bound on $E\,[y(t=0)]$ is subtracted from the lower bound on $E[y(t=1)]$, and for the treatment upper bound, the lower bound on $E\,[y(t=0)]$ is subtracted from the upper bound of $E\,[y(t=1)]$. This treatment effect lower bound assumes the worst-case scenario in which all proficient learners in non-feeding schools would also have been proficient in feeding schools. The upper bound assumes the best-case scenario in which all learners in feeding schools would have failed if they had been in non-feeding schools. These bounds tend to be wide and include zero, but can rule out large positive or negative bounds.

Because these bounds provide the most conservative estimate of impact, relatively weak, plausible non-parametric assumptions about the selection process, treatment response, and the instrumental variable are made to obtain tight bounds on the treatment effect. Non-parametric bounds assumptions are weaker but credible.

5.1 Monotone Treatment Selection

The Monotone Treatment Selection (MTS) assumption is added to tighten the bounds around the two mean potential outcomes $E\,[y(t=1]$ and $E\,[y(t=0)]$. The positive MTS assumption in this case asserts that, "Pupils who select to be in a school with a feeding program have weakly higher

scores in foundation skills than those who do not choose to participate in a school with a feeding program" or for the case of the attendance rate, "schools that choose to have feeding programs have weakly higher attendance rates than for those that select not to have feeding programs".

To define the MTS assumption, if T is an ordered set of treatments and z is the realized treatment based on the status of school feeding. For each treatment, $t \epsilon T$, and if u_2 *and* u_1 are levels of treatment which, in the case of learner competency in literacy or numeracy, take on the values 1 and 0 respectively,

$$u_2 \geq u_1,\ E[y(t)|z = u_2]\ \geq E[y(t)|z = u_1]\, for\ all\ u_2,\ u_1\ in\ T$$

(4)

Rewriting $E[y(t)]$ using the law of total probability gives,

$$E[y(t)]\ = E[y(t)|z < t] * P(z < t) + E[y(t)|z = t] * P(z = t) + E[y(t)|z > t] * P(z > t)] \quad (5)$$

Letting the MTS assumption in equation (4) hold, the term $E[y(t)|z < t]$ in (5) will be no less than $y_{\min}$ and no greater than $E[y(t)|z = t)]$, which is the mean outcome of the observed treatment. For the term $E[y(t)|z > t]$, factoring in the MTS assumption in equation (4) implies that $E[y(t)|z > t]$ will be no less than the mean outcome of the observed treatment, $E[y(t)|z = t]$ and will be no greater than $y_{\max}$. Substituting for $E[y(t)|z < t]$ and $E[y(t)|z > t]$ as a result of the MTS assumption yields the following bounds on $E[y(t)]$,

$$\begin{aligned} y_{\min} * P(z < t) + E\left(y|z = t\right) * P(z \geq t) \\ \leq E\left[y(t)\right] \leq \\ y_{\max} * P(z > t) + E(y|z = t) * P(z \leq t) \end{aligned}$$

(6)

Upper (lower) bounds on the average treatment effect are obtained by subtracting the lower (upper) bound on $E\left[y(t = 0)\right]$ from the upper (lower) bound on $E\left[y(t = 1)\right]$.

For this study, the MTS assumption is plausible as there is vast evidence of the positive effects of school feeding on children's health, cognitive well-being, and academic performance (Alderman et al., 2012; Mostert, 2021; Nikiema, 2019; Wang et al., 2021)[2]. To further explore

[2] The positive MTS assumption asserts that schools selecting into feeding programs have weakly higher latent outcomes than those that do not. While school-level characteristics support this direction, feeding schools are more likely to be private, have lower pupil-to-teacher ratios, and have electricity. Regional allocation patterns complicate the picture. School feeding in Uganda is disproportionately concentrated in sub-regions characterized by lower household food security and, on average, weaker learning outcomes, suggesting a degree of negative selection on regional disadvantage. The net direction of selection at the binary participation margin is there-

the plausibility of the MTS assumption, I compute the average characteristics for both treatment groups: schools/students with feeding programs and those without. Intuitively, one would expect to see schools/learners with school feeding programs to show traits correlated with better education outcomes. Table 4 provides averages for some observed characteristics by the presence of school feeding.

Table 4: Average characteristics

Variable	**School Feeding**	**No School Feeding**
Type of school		
Government Aided	81.10 (0.023)	94.12 (0.022)
Private	17.18 (0.022)	2.52 (0.014)
Community	1.72 (0 .008)	3.36 (0.017)
School enrollment	750.172 (30.860)	796.773 (51.280)
Pupil Teacher Ratio (PTR)	50.908(1.713)	62.070 (3.669)
Pupil Classroom Ratio (PCR)	92.161 (3.663)	104.451 (8.183)
Percentage of Teachers paid from collected fees	27.762 (2.169)	13.394 (2.008)
Does the school have electricity?		
Yes	0.653 (0.0280)	0.412 (0.045)
No	0.347 (0.0280)	0.588 (0.045)
Sub-region		
Buganda North	0.127 (0.020)	0.042 (0.019)
Buganda South	0.138 (0.020)	0.017 (0.012)
Kampala	0.048 (0.013)	0 (no observations)
Bugisu	0.100 (0.018)	0.084 (0.023)
Bukedi	0.045 (0.012)	0.008 (0.008)
Busoga	0.148 (0.021)	0.008 (0 .008)
Teso	0.041 (0.012)	0.025 (0.014)
Acholi	0.017 (0.008)	0.084 (0 .026)
Karamoja	0.048 (0.013)	0.008 (0.008)
Lango	0.055 (0.013)	0.101 (0.028)
West Nile	0.048 (0 .013)	0.134 (0.031)
Ankole	0.079 (0 .016)	0.168 (0.034)
Bunyoro	0.045 (0.012)	0 .013 (0.031)
Kigezi	0 .017 (0.008)	0.076 (0.024)
Tooro	0.045 (0.012)	0.109 (0 .029)

Notes: Standard errors are shown in parentheses

fore ambiguous. The positive MTS assumption is more defensible within the intensity margin among schools that already operate a program where higher-intensity delivery plausibly reflects stronger school capacity and community support. This distinction is discussed further in Section 6.

A significantly larger proportion of private schools (17.18% versus 2.52%) have school feeding programs than those without. More government schools (94.12%) do not have feeding programs than those that do (81.10%). Evidence shows that the proportion of primary three learners rated proficient in numeracy in private schools (86.5%) is significantly higher than that in government schools (51.5%) (p=0.000) (UNEB, 2024). Additionally, schools with lower Pupil to Teacher and Pupil to Classroom Ratios, all characteristics associated with better education outcomes, were associated with having a school feeding program. Other variables of interest that are associated with better outcomes displayed here include the percentage of teachers paid from fees (an indicator of school revenues and parental/community financial support), amenities such as electricity, and sub-region, which differ significantly between treatments with and without school feeding. In the Kampala sub-region, the most urban, all sample schools provide meals.

In Table 2, the MTS and MTR assumptions are violated for the learning outcomes on reading in the local language and numeracy. Even for school attendance rates, the higher average attendance in schools with feeding programs is not statistically significant. This can be explained by the fact that sub-regions are generally correlated with household food security, as shown in Figure 1(UBOS, 2024), which in turn is significantly associated with the presence of school feeding, as shown in Figure 2, a plot of lunch at school against Primary 3 (P3/Grade 3) foundational literacy competencies.

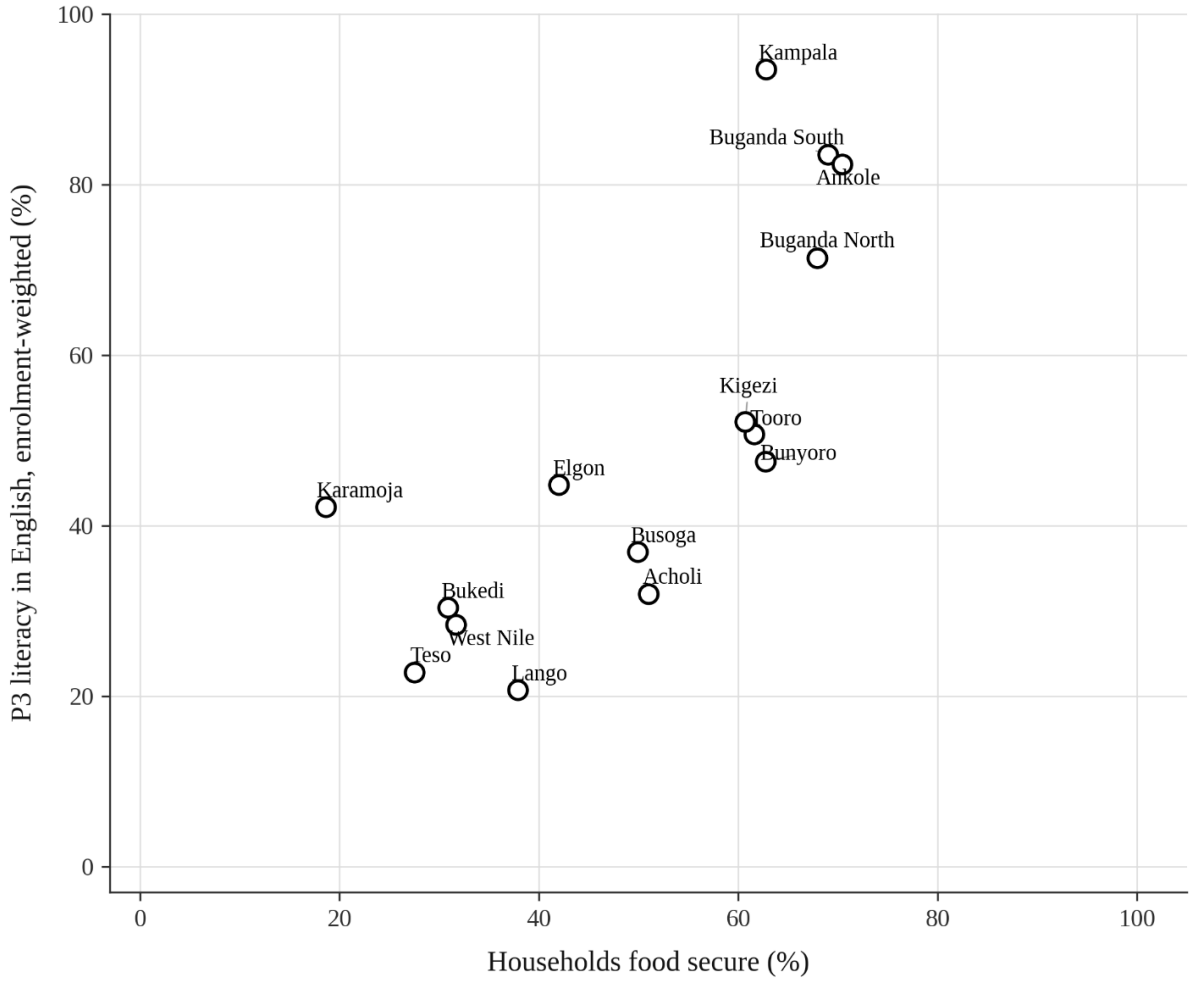
Each point on Figures 1 and 2 represents one of 15 Uganda Bureau of Statistics (UBOS) sub-regions. The vertical axes show the percentage of Primary 3 learners rated proficient in English literacy (2023 NAPE assessment) (UNEB, 2024), aggregated to the sub-region using district-level enrolment weights. The horizontal axis in Figure 1 shows the percentage of households classified as food secure (neither moderately nor severely food insecure), based on the Food Insecurity Experience Scale (FIES) module of the Uganda National Population and Housing Census 2024 (UBOS, 2024). The two variables are strongly positively correlated (r = 0.76). Karamoja is a notable outlier, combining the lowest household food security of any sub-region (18.6%) with a moderate literacy rate (42.2%), consistent with its distinct agro-pastoral context and semi-arid climate.

The horizontal axis in Figure 2 shows the percentage of government primary school learners receiving lunch at school, from the UBOS 2021 national service delivery survey(UBOS, 2021). The two variables are weakly positively correlated (r = 0.28), with notable outliers: Karamoja and Busoga report high lunch provision alongside low literacy, while Ankole and Kigezi report high literacy with near-zero formal lunch provision.

5.2 Monotone Treatment Response

The Monotone Treatment Response (MTR) assumption, taking the case of a school and attendance rates, posits that attendance rates of a school rise as a function of the presence of a school

Figure 1: P3 literacy proficiency and household food security, by sub-region



feeding program, and in the case of foundational skills, proficiency rises as a function of school feeding (Manski, 1997).

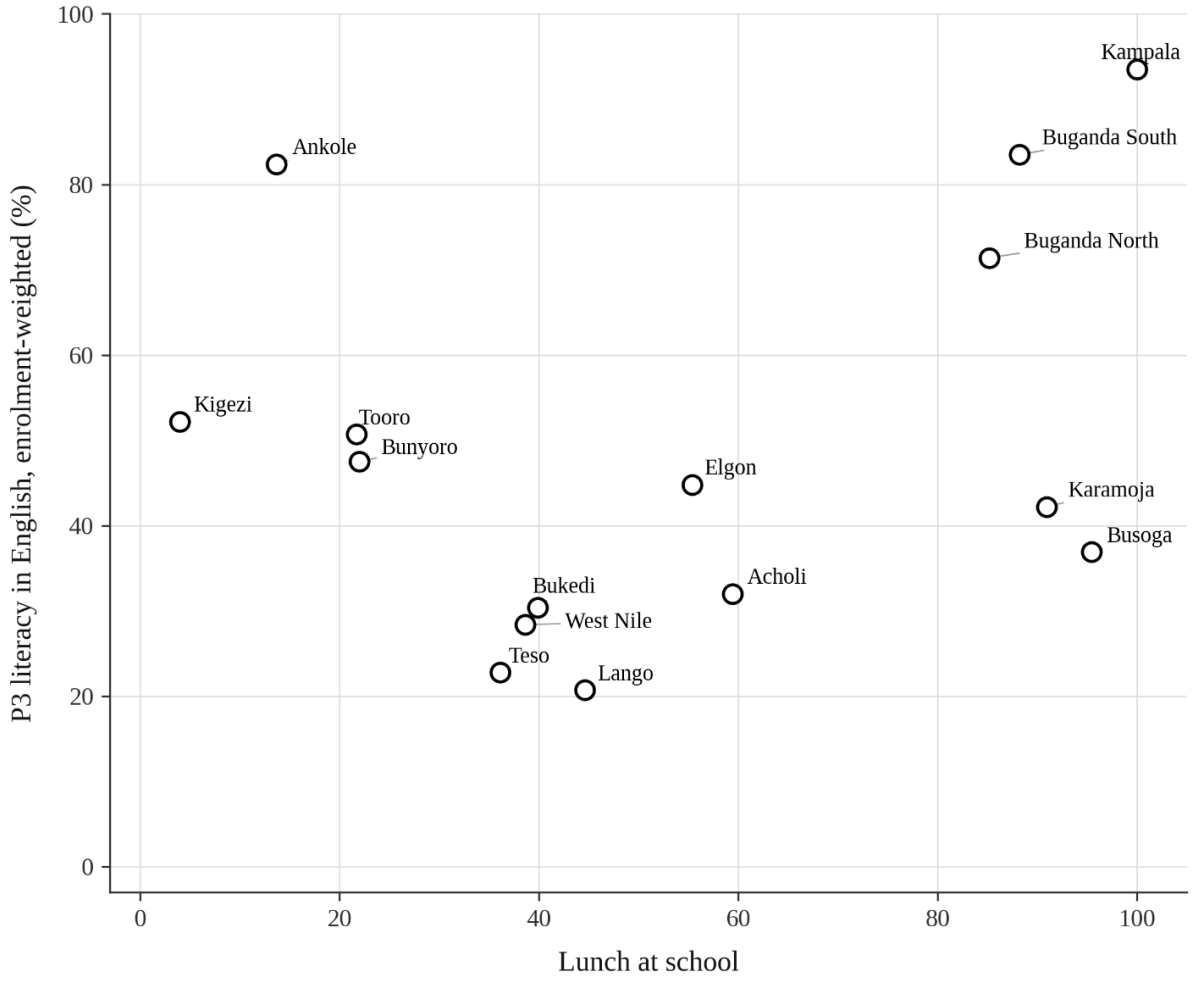
To define the MTR assumption, let T be an ordered set. For each learner j in J and t_2 *and* $t_1$treatment levels corresponding to 1 and 0 for school feeding,

$$t_2 \geq t_1,\ y\left(t_2\right) \geq y\left(t_1\right)\ \ where\ t_2\ ,\ t_1 in\ T$$

(7)

Layering the MTR assumption would imply that for any $t_2 \geq t_1$, the conditional mean $E\left(y|(t_2)|z=t\right)$ will be no less than $E\left(y|(t)|z=t\right)$. For the case of $t \geq t_2$, the mean $E\left(y|(t_2)|z=t\right)$ will not be greater than $E\left(y|(t)|z=t\right)$. The tightened bounds on $E[y(t)]$ are therefore as follows.

Figure 2: P3 literacy proficiency and lunch-at-school provision, by sub-region



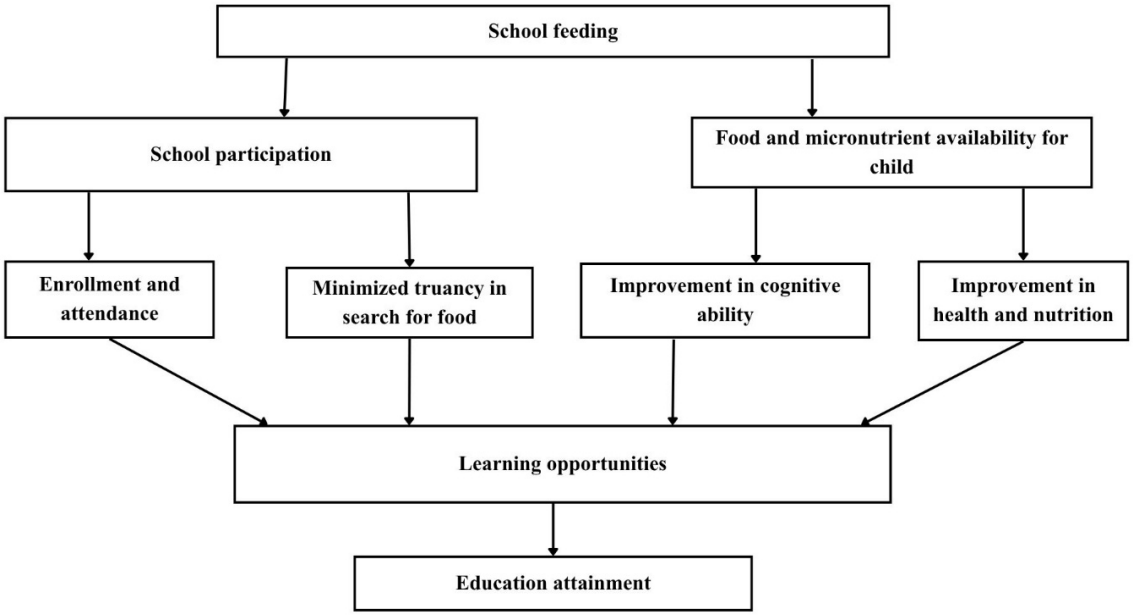
$$E\left(y|t \geq z\right) * P(t \geq z) + y_{\min} * P(t < z) \leq E\left[y(t)\right] \leq E\left(y|\, t \leq z\right) * P(t \leq z) + y_{\max} * P(t > z) \tag{8}$$

Subsequently, I compute the bounds for the cases, $E[y(t = 1)]$ and $E[y(t = 0)]$, and similarly, I obtain the upper (lower) bounds on the average treatment effect by subtracting the lower (upper) bound on $E\left[y(t = 0)\right]$ from the upper (lower) bound on $E\left[y(t = 1)\right]$.

Extensive evidence in the literature renders the MTR assumption plausible. Adelman et al. (2008) theorize the pathways in which school feeding affects education, as shown in Figure 3:

In addition to the pathways spelled out in the conceptual framework in Figure 3, Del Rosso (1999) documents that children with diminished cognitive abilities and sensory impairments naturally perform less well and are more likely to repeat grades and to drop out of school than

Figure 3: The pathways linking school feeding programs to educational outcomes. Source: Adapted from Adelman et al. (2008), Figure 3.1, International Food Policy Research Institute (IFPRI)



children who are not impaired; they also enroll in school at a later age, if at all, and finish fewer years of schooling. The irregular school attendance of malnourished and unhealthy children is one of the key factors in poor performance. Given these pathways, several studies link a school feeding treatment to positive education outcomes. School feeding resulted in a significant increase in the percentage of school days attended (2.6%; 95% CI = 1.2%, 3.9%; P < 0.001) (Wang et al., 2021).

Again, as observed in the summary statistics in Table 2, schools with feeding programs have better learning outcomes than those without. This violates the MTR assumption. However, when I further account for heterogeneity in the percentage of children covered by feeding programs, the trend of better learning outcomes in non-treatment schools is reversed. School feeding programs generally have positive effects on children's nutrition, attendance, and sometimes learning. However, some studies note documented or possible detrimental effects. For example, school feeding sometimes reduces a child's food intake at home, which might diminish the nutritional gains from the school meal (Adelman et al., 2008; Alderman et al., 2012). Rather than being harmful, some research finds little to no effect on certain outcomes, particularly reading achievement and school attendance, even though positive effects may be observed for enrollment and mathematics performance (Kristjansson et al., 2025). Poor-quality food provision, inadequate funding, weak implementation systems, and short program duration can substantially limit the effectiveness of school feeding interventions, leading to mixed or inconclusive results across settings (Adelman et al., 2008; Kristjansson et al., 2025; WFP, 2022). Thus, when negative or

negligible effects are observed, they are often attributable to challenges in program design and implementation rather than to school feeding itself. The simple cross-tabular violation of MTR for local-language literacy and numeracy is consistent with selection effects; feeding programs are concentrated in regions like Karamoja, where baseline learning outcomes are weaker, rather than reflecting a true negative response to feeding. The intensity-stratified analysis (Section 6.2), in which MTR is held constant across coverage quartiles within feeding schools, supports this interpretation.

For local language literacy, a key contributing factor to lower competencies compared to English language and numeracy is that they are inherently disadvantaged by many factors, including weaker instructional ecosystems, limited materials and standardization, lower teacher preparedness, rapid transition to English, and high-stakes dominance of English in assessment and progression (Akello & Timmerman, 2017). Mother-tongue instruction is generally more feasible and consistently implemented in rural areas due to greater linguistic homogeneity, whereas urban multilingual classrooms often encourage greater reliance on English (Altinyelken et al., 2014). The districts sampled for local language assessments in this survey by Uwezo Uganda, used in this study, do not include any cities and reflect a significant rural component.

5.3 MTS-MTR

Layering and combining MTS and MTR assumptions make distinct contributions to identifying the effect of school feeding on learning outcomes (Manski & Pepper, 2000). I further combine the MTS and MTR assumptions. Combining the MTS and MTR in equations (4) and (7), respectively, implies that the bounds on $E\left[y(t)\right]$ under the MTS-MTR assumption become.

$$\begin{aligned} E\left(y|z<t\right)*P(z<t)+E\left(y|z=t\right)*P(z\geq t) \\ \leq E\left[y(t)\right]\leq \\ E\left(y|z=t\right)*P(z\leq t)+E(y|z>t)*P(z>t) \end{aligned}$$

(9)

5.4 Monotone Instrumental Variable (MIV)

I further layer a Monotone Instrumental Variable (MIV) assumption, which holds that the mean response varies weakly monotonically across specified subpopulations. It is a variation of the instrumental variable (IV) assumption in which the mean response is constant across the specified subpopulations of the population of interest. The MIV assumption relaxes the strict IV assumption by replacing the equality in the mean independence assumptions with an inequal-

ity, yielding a mean-monotonicity condition (Manski & Pepper, 2000). The MIV assumption requires only that mean potential outcomes E[y(t) | v] be weakly monotonic in v; it does not require that v be excluded from the outcome equation.

The variable "main source of water for other purposes" is used as the monotone instrumental variable. The variable is further categorized according to water availability for each water source type. This recoding of the variable generated two categories: sources with high and low water reliability. Water reliability is plausibly an MIV in this setting because schools with more reliable water sources are systematically located in wealthier districts, urban areas, and better-resourced administrative units, characteristics that are positively associated with learning outcomes regardless of whether the school has a feeding program. Direct channels through which water reliability may affect outcomes (for example, reduced absenteeism due to improved hygiene and less time spent fetching water) reinforce rather than threaten the monotonicity assumption. Table 5 presents the average values for each education outcome across the MIV levels by treatment, showing the monotonic relationship between the MIV and school feeding for these outcomes.

Table 5: Average education outcomes across water reliability (MIV) by School Feeding Program (SFP)

	Attendance rates		**English Language**		**Local Language**		**Numeracy**	
Water Reliability	SFP	No SFP	SFP	No SFP	SFP	No SFP	SFP	No SFP
Low	70.645	70.295	0.200	0.195	0.133	0.193	0.502	0.533
High	79.385	74.444	0.321	0.355	0.308	0.414	0.569	0.597

To combine the MIV and MTS assumptions, the sample is divided into sub-samples based on MIV values, and I compute the MTS bounds within each sub-sample. But first, to define an MIV, a covariate v is a monotone instrumental variable if, for each $t \epsilon T$, and all $(u_1, u_2) \in (V * V)$ which correspond to the sub-samples of v such that $u_2 \geq u_1$;

$$u_1 \leq u \leq u_2 \Rightarrow E[y(t)|\, v = u_1] \leq E\,[y(t)|v = u] \leq E[y(t)|\, v = u_2], \quad \text{for} \quad t = 0, 1$$

(10)

5.4.1 MTS-MIV

Specifically, combining the MTS and MIV bounds on the conditional mean, $E\,[y(t)|v = u]$ can be presented as shown in the equation below.

$$\sup_{u_1 \leq u} [E(y|v = u_1,\ z\ = t)\ *\ P(z \geq t|v = u_1) +\ y_{\min}\ *\ P(z < t|v = u_1)]$$
$$\leq E\,[y(t)|v = u] \leq$$
$$\inf_{u_2 \geq u} [E(y|v = u_2,\ z = t)\ *\ P(z \leq t|v = u_2) +\ y_{\max}\ *\ P(z > t|v = u_2)$$

(11)

I then obtain the marginal mean for each treatment t from equation (11) above, as shown below.

$$\sum_{u \in V} P(v = u)\{\sup_{u_1 \leq u} [E(y|v = u_1,\ z\ = t)\ *\ P(z \geq t|v = u_1) +\ y_{\min}\ *\ P(z < t|v = u_1)\}$$
$$\leq E\,[y(t)] \leq$$
$$\sum_{u \in V} P(v = u)\{\inf_{u_2 \geq u} [E(y|v = u_2,\ z = t)\ *\ P(z \leq t|v = u_2) +\ y_{\max}\ *\ P(z > t|v = u_2)\}$$

(12)

5.4.2 MTR-MIV

I also combine the MTR assumption with the MIV. To combine the MIV and MTR assumptions, the sample is divided into sub-samples based on MIV values, and I compute the MTR bounds within each sub-sample.

The marginal mean for each treatment t is then obtained from the equation above, as shown below.

$$\sum_{u \in V} P(v = u)\{\sup_{u_1 \leq u} [E(y|v = u_1,\ t \geq z)\ *\ P(t \geq z|v = u_1) +\ y_{\min}\ *\ P(t < z|v = u_1)\}$$
$$\leq E\,[y(t)] \leq$$
$$\sum_{u \in V} P(v = u)\{\inf_{u_2 \geq u} [E(y|v = u_2,\ t \leq z)\ *\ P(t \leq z|v = u_2) +\ y_{\max}\ *\ P(t > z|v = u_2)\}$$

(13)

5.4.3 MTS-MTR-MIV

To combine the MIV and MTS-MTR assumptions, the sample is divided into sub-samples based on the MIV, water reliability, and I compute the MTR + MTS bounds within each sub-sample. Hence, in this case of layering the MTS-MTR assumption, the mean potential outcome

$E\,[y(t)|v = u]$ is no smaller than the MTS-MTR lower bound on $E[y(t)|\,v = u_1\,]$ provided $u_1 \leq u$ and no larger than the MTS-MTR upper bound on $E[y(t)|\,v = u_2\,]$ provided $u \leq u_2$.

The lower bound for each case of treatment, $y(t)$ is the largest MTS-MTR lower bound across all the sub-samples of the MIV provided $u_1 \leq u$, and the upper bound is the smallest upper bound across the sub-samples provided $u \leq u_2$.

The law of iterated expectations is used to define the marginal mean outcome as shown in equation (12),

$$E\,[y(t)\,] = \sum P(v = u) \;*\; E[y(t)|v = u]\, for\ all\ u$$

(14)

The bounds on $E\,[y(t)\,]$ given the combination of assumptions, MIV-MTS-MTR are thus shown below in equation (13);

$$\sum_{u\in V} P(v = u) * [max_{u_1 \leq u} LB_{E}[y(t)|v = u_1]]$$
$$\leq E[y(t)] \leq$$
$$\sum_{u\in V} P(v = u) * [min_{u_2 \geq u} UB_{E}[y(t)|v = u_2]]$$

(15)

Replacing for $y(t = 0)$ and $y(t = 1)$ gives the lower and upper bounds on each treatment case. Thus, if the MIV-MTS-MTR assumption is imposed, the sharp upper (lower) bound on the treatment effect Δ is obtained by subtracting the upper (lower) bound on $E[y(t = 0)\,]$ from the lower (upper) bound on $E[y(t = 1)\,]$.

5.5 Estimation and inference

I obtain the bounds for the different assumptions from the worst case, MTS, MTR, MTS-MTR, MTS-MIV, MTR-MIV, and MTS-MTR-MIV, by plugging in the mean potential outcomes and probabilities for each treatment case of school feeding. I bootstrapped the confidence intervals with 1000 replications and conducted cluster analysis at the district level, where schools are the units of analysis, and at school clusters, where learners are the units of analysis, for learning outcomes in literacy and numeracy.

For the special case of assumptions that include the MIV, because lower/upper bound estimates are obtained by taking supremum and infimum operators of collections of nonparametric regression estimates, these bounds may have non-negligible positive or negative finite-sample biases. In particular, sampling variation can cause estimated lower bounds to be biased upward and estimated upper bounds to be biased downward, leading to bounds that are artificially nar-

row relative to the true population identification region (Manski & Pepper, 2000). This concern does not arise in the special case of MTS-MTR bounds, which do not require taking sups and infs (Manski & Pepper, 2000).

To address this issue, I implemented the bootstrap bias-correction procedure proposed by Kreider & Pepper, (2007). Let θ_e denote an estimated bound and let θ_b denote the average estimate obtained from B bootstrap replications. The bootstrap estimate of bias is given by:

$\text{Bias}(\theta) = \theta_b - \theta_e$

The bias-corrected estimator is then computed as:

$\theta_{BC} = \theta_e - \text{Bias}(\theta)$

In each replication, the MTS+MTR+MIV bounds were re-estimated, and the average bootstrap estimate was used to calculate the finite-sample bias. The final row in Tables 6-11 reports the resulting bias-corrected bounds. Comparing the corrected and uncorrected estimates indicates the extent to which finite-sample bias affects the informativeness of the estimated identification regions.

6 Results and Discussion

6.1 Effects of school feeding programs on education outcomes (School feeding programs Versus no school feeding programs)

This section presents the bounds on the average treatment effect of school feeding programs on schools' attendance rates and children's learning outcomes under varying assumptions about selection and treatment response, as proposed by Manski (1990) and Manski & Pepper (2000).

Using the non-parametric bounds technique, this study employed various assumptions about the presence of school feeding to ascertain the bounds within which the effect falls. It also estimates the effect without the partial identification technique, which is here described as the Ordinary Least Squares (OLS) estimate. First, as shown in Table 6, the study examines the average treatment effect for the binary case of school feeding programs $(t = 1)$ versus no school feeding programs $(t = 0)$. These OLS point estimates are positive for education outcomes: attendance rates (2.37%), English language reading literacy (0.7%), and negative for local language literacy and numeracy competency.

Considering the Manski assumptions, the bounds on average treatment effects are wide for the worst-case scenario of no assumptions across all education outcomes covered in this study. As for the attendance rate, the worst-case scenario bounds range from -37.525 to 55.968 percent. In practice, the no-assumption bounds are typically wide and contain zero by construction. They can, however, potentially rule out large positive or large negative values of the treatment effect. Further layering the MTS and MTR assumptions for all education outcomes under investigation, respectively, narrows the no-assumption bounds. Layering the combination, MTS+MTR, further

narrows the bounds on education outcomes, ruling out a negative effect. The average treatment effects under the MTS+MTR assumptions are bounded between 0 and 2.370% for attendance and between 0 and 0.7% for English literacy. Notably, the MTS+MTR assumption combination is non-identifying for the treatment effects for the outcomes of local language and numeracy, as indicated by the italicized results in Table 6. These empty set findings are consistent with the MTR assumption being falsified for the local language and numeracy outcomes, as shown in Table 3.

I still compare the layering of the MTS and MTR assumptions alongside the MIV, water reliability. For all outcomes, the MTS+MIV assumption narrows the bounds produced by the MTS assumption alone. The same applies to the MTR+MIV assumption combination. For instance, based on attendance rates, the MTS+MIV assumptions place bounds on average treatment effect between -37.525 and 1.641 percent, compared to the MTS-identified bounds of [-37.525, 2.370]. The upper bound (1.641 percent) for attendance rates under the MTS+MIV assumption is lower than the OLS point estimate of 2.370%. A similar pattern of narrower bounds than in the MTS case is observed across all other outcomes, except local language literacy, when the MIV is layered with the MTS and MTR bounds, respectively.

Applying MTS+MTR+MIV is informative when the identified set is non-empty, yielding tighter bounds under the additional assumption of monotone treatment response. Where the identified set is empty, as in the English language, local language, and numeracy outcomes in Table 6, the data are incompatible with the joint assumptions, which, following Kreider & Pepper (2007), constitute a refutation of MTR for those outcomes. MTS+MIV therefore serves as the primary specification here, with MTS+MTR+MIV reported as a sensitivity layer that tightens bounds where MTR holds and signals its violation where it does not.

6.2 Effects of school feeding programs on education outcomes when comparing high-intensity feeding programs (75 to 100%) to no formal school feeding program

This study goes on to compare school feeding in programs with high coverage (75 to 100%) to schools/learners with no school feeding program. Here, the point estimates are 9.557% for attendance rates, 9.4% for English Language literacy, and 10% for Numeracy. The OLS estimate remains negative (-5.4%) for local language literacy. The MTS+MTR bounds yield non-negative bounds for attendance, English literacy, and numeracy competency, and the upper bounds are equal to the point estimates for each respective outcome. The MTS+MTR bounds produced for the local language remain empty in this binary case of high-coverage feeding programs versus no feeding programs. Layering the MIV on the MTS and MTR bounds narrows the bounds for all outcomes except local language literacy. Particularly, the MTS+MIV layering yields the bounds [-46.169, 8.306] for attendance, [-0.350, 0.077] for English language, [-0.419, -0.036] for local language, and the bounds [-0.492, 0.095] for numeracy. These upper bounds for attendance (8.306%), English Literacy (7.7%), and Numeracy (9.5%) under MTS+MIV (and, where MTR

Table 6: OLS point estimates and non-parametric bounds estimates of school feeding effects on education outcomes (binary case of school feeding program versus no school feeding program)

Assumption	Attendance Rate	English Literacy	Local Language Literacy	Numeracy
OLS	2.370	0.007	-0.075	-0.026
	(-6.309, 11.048)	(-0.038, 0.052)	(-0.142, -0.009)	(-0.077, 0.026)
Worst case	[-37.525, 55.968]	[-0.582, 0.418]	[-0.630, 0.370]	[-0.503, 0.497]
	(-41.196, 59.639)	(-0.610, 0.446)	(-0.675, 0.415)	(-0.522, 0.515)
MTS	[-37.525, 2.370]	[-0.582, 0.007]	[-0.630, -0.075]	[-0.503, -0.026]
	(-41.196, 9.132)	(-0.610, 0.042)	(-0.675, -0.023)	(-0.522, 0.014)
MTR	[0, 55.968]	[-0.014, 0.392]	[0, 0.370]	[0, 0.497]
	(0, 59.639)	(-0.018, 0.417)	(0, 0.415)	(0, 0.515)
MTS + MTR	[0, 2.370]	[0, 0.007]	*[0, -0.075]*	*[0, -0.026]*
	(0, 10.080)	(0, 0.049)	*(0, 0.562)*	*(0, 0.043)*
MTS + MIV	[-37.525, 1.641]	[-0.582, -0.003]	[-0.630, -0.068]	[-0.503, -0.030]
	(-41.194, 8.120)	(-0.610, 0.030)	(-0.682, -0.022))	(-0.522, 0.010)
MTR + MIV	[0, 53.766]	[0, 0.418]	[0, 0.370]	[0, 0.490]
	(-0.132, 57.847)	(0, 0.452)	(0, 0.416)	(-0.003, 0.525)
MTS + MTR + MIV	[0, 1.641]	*[0, -0.003]*	*[0, -0.069]*	*[0, -0.030]*
	(0, 9.246)	*(0, 0.041)*	*(0, 0.599)*	*(-0.006, 0.043)*
MTS + MTR + MIV – bias corrected	[-0.006, 1.776]	*[0, -0.003]*	*[0, -0.070]*	*[0, -0.029]*
	(-0.169, 9.769)	*(0, 0.041)*	*(0, 0)*	*(-0.006, 0.043)*

Notes: Italicized empty-set entries indicate that the assumption combination has no identifying power for the comparison; bias-corrected estimates may still be informative when reported. Binary participation bounds in Table 6 assume positive MTS (feeding schools have weakly higher latent outcomes). Given evidence of negative regional selection (Figures 1-2), these bounds are reported for completeness; intensity comparisons (sections 6.2 and 6.3) carry the primary identification claims.

holds, MTS+MTR+MIV) are lower than the OLS estimate. This points to an overestimation in the OLS part of the effects of school feeding.

6.1 Treatment effects of school feeding by intensity of feeding program

The treatment effect of school feeding is initially small or even negative for schools with feeding programs compared to those without. This indicates better performance in schools without feeding programs than in those with them, before adjusting for program intensity.

Considering the intensity of school feeding programs reveals considerable differences in their effects. Tables 8 to 11 show the worst-case bounds up to the MTS+MTR+MIV assumptions for selected levels of feeding coverage. Comparing schools with the least-intensive feeding programs (Q1) versus those with the most-intensive feeding programs (Q4) reveals that the

Table 7: OLS Point estimates and non-parametric bounds estimates of school feeding effects on education outcomes (binary case of highest intensity schools (Q4) versus no feeding schools)

Assumption	Attendance Rate	English Literacy	Local Language Literacy	Numeracy
OLS	9.557	0.094	-0.054	0.100
	(-0.317, 19.430)	(0.017, 0.171)	(-0.151, 0.043)	(0.027, 0.172)
Worst case	[-46.169, 47.324]	[-0.350, 0.650]	[-0.419, 0.581]	[-0.492, 0.508]
	(-52.794, 53.949)	(-0.385, 0.154)	(-0.479, 0.641)	(-0.521, 0.538)
MTS	[-46.169, 9.557]	[-0.350, 0.094]	[-0.419, -0.054]	[-0.492, 0.100]
	(-52.794, 17.249)	(-0.385, 0.154)	(-0.479, 0.022)	(-0.521, 0.156)
MTR	[0, 47.324]	[0, 0.650]	[0, 0.581]	[0, 0.508]
	(0, 53.949)	(0, 0.684)	(0, 0.641)	(0, 0.538)
MTS + MTR	[0, 9.557]	[0, 0.094]	*[0, -0.054]*	[0, 0.100]
	(0, 17.317)	(0, 0.154)	*(0, 0.080)*	(0, 0.156)
MTS + MIV	[-46.169, 8.306]	[-0.350, 0.077]	[-0.419, -0.036]	[-0.492, 0.095]
	(-52.661, 16.406)	(-0.385, 0.135)	(-0.480, -0.038))	(-0.523, 0.153)
MTR + MIV	[0, 41.724]	[0, 0.636]	[0, 0.581]	[0, 0.481]
	(-1.300, 48.827)	(0, 0.690)	(-0.002, 0.643)	(-0.011, 0.532)
MTS + MTR + MIV	[0, 8.306]	[0, 0.077]	*[0, -0.036]*	[0, 0.095]
	(-1.326, 16.567)	(0, 0.136)	*(-0.004, 0.081)*	(-0.011, 0.153)
MTS + MTR + MIV – bias corrected	[-0.243, 9.277]	[0, 0.077]	*[0, -0.034]*	[-0.002, 0.103]
	(-1.557, 17.470)	(0, 0.135)	*(-0.003, 0.081)*	(-0.013, 0.161)

Notes: Italicized empty-set entries indicate that the assumption combination has no identifying power for the comparison; bias-corrected estimates may still be informative when reported.

worst-case bounds for attendance rates range from -57.109% to 56.625%. The MTS and MTR assumptions further narrow this no-assumption case, and the combined MTS+MTR assumption specifically places the effects for attendance rates between 0 and 11.810. MTS+MIV yields the bounds [-57.109, 11.065], with the upper bound below the OLS estimate of 11.81%.

The MTS+MTR+MIV restriction in this case yields bounds between 0 and 11.065% for attendance rates in the lowest-intensity school-feeding program schools, compared with high-intensity schools. Similar patterns are observed in the Q4 versus Q1 comparison of school feeding program coverage for English and numeracy competency, where the tightest assumptions bound the estimates: MTS+MTR+MIV yield upper bounds below the OLS point estimate, as shown in Tables 9 and 11. However, for local language literacy, the (Q4, Q1) comparison yields narrower bounds as you layer in more assumptions, except for the MTS+MTR+MIV case, where the upper bound (0.068) exceeds the OLS estimate (0.051).

Table 8: Non-parametric bounds estimates of levels of school feeding intensity effects on Attendance rates

Assumption	**(Q2, Q1)**	**(Q3, Q2)**	**(Q4, Q3)**	**(Q4, Q1)**
OLS	7.174	-2.527	7.163	11.810
	(0.698, 13.650)	(-12.981, 7.927)	(-2.378, 16.704)	(6.960, 16.661)
Worst Case	[-68.666,	[-84.605,	[-70.582,	[-57.109,
	58.882]	82.140]	82.348]	56.625]
	(-72.752,	(-86.594,	(-77.241,	(-62.172,
	64.562)	84.912)	85.101)	61.367)
MTS	[−43.357,	[−53.839,	[−53.711,	[−57.109,
	15.920]	39.960]	49.729]	11.810]
	(-47.485,	(-59.532,	(-60.330,	(-62.172,
	21.104)	47.164)	56.955)	18.503)
MTR	[−26.383,	[−36.384,	[−18.889,	[0, 56.625]
	55.804]	45.272]	41.799]	(0, 61.367)
	(-33.422,	(-41.448,	(-22.484,	
	55.804)	50.167)	46.394)	
MTS + MTR	[-1.073, 8.247]	[−5.618,	[-2.018, 9.181]	[0, 11.810]
	(-3.130, 14.068)	03.091]	(-7.500, 14.095)	(0, 18.509)
		(-9.454, 9.779)		
MTS + MIV	[-42.946,	[-53.180,	[-54.193,	[-57.109,
	15.785]	40.030]	48.460]	11.065]
	(-47.002,	(-58,830,	(-60.856,	(-61.913,
	20.495)	47.255)	56.268)	18.948)
MTR + MIV	[-26.188,	[-35.853,	[-18.889,	[0, 56.190]
	50.849]	45.077]	41.195]	(-0.179, 61.182)
	(-32.649,	(-40.180,	(-22.486,	
	55.078)	49.694)	45.521)	
MTS + MTR +	[-0.663, 8.112]	[-4.959, 3.162]	[-2.500, 7.911]	[0, 11.065]
MIV	(-2.330, 13.435)	(-8.089, 9.704)	(-8.040, 13.860)	(-0.180, 18.983)
MTS + MTR +	[-0.682, 8.173]	[-4.926, 3.193]	[-2.517, 9.012]	[-0.006, 12.259]
MIV	(-2.349, 13.495)	(-8.056, 9.735)	(-8.054, 14.956)	(-0.186, 20.160)
(bias-corrected)				

Table 9: Non-parametric bounds estimates of levels of school feeding intensity effects on English Language

Assumption	**(Q2, Q1)**	**(Q3, Q2)**	**(Q4, Q3)**	**(Q4, Q1)**
OLS	0.107	-0.133	0.165	0.139
	(0.048 0.165)	(-0.218 -0.048)	(0.066, 0.264)	(0.063, 0.215)
Worst Case	[-0.463, 0.797]	[-0.905, 0.896]	[-0.872, 0.868]	[-0.439, 0.760]
	(-0.500, 0.831)	(-0.927, 0.919)	(-0.897, 0.893)	(-0.476, 0.785)
MTS	[-0.385, 0.288]	[-0.440, 0.203]	[-0.257, 0.290]	[-0.439, 0.139]
	(-0.416, 0.336)	(-0.480, 0.255)	(-0.306, 0.347)	(-0.476, 0.198)
MTR	[-0.073, 0.610]	[-0.561, 0.656]	[-0.583, 0.711]	[0, 0.760]
	(-0.089, 0.641)	(-0.597, 0.684)	(-0.618, 0.735)	(0, 0.785)
MTS + MTR	[0.005, 0.101]	[-0.096, -0.037]	[0.032, 0.133]	[0, 0.139]
	(-010, 0.140)	(-0.128, -0.013)	(-0.010, 0.192)	(0, 0.200)
MTS + MIV	[-0.387, 0.275]	[-0.427, 0.198]	[-0.250, 0.280]	[-0.439, 0.128]
	(-0.440, 0.338)	(-0.481, 0.2750	(-0.325, 0.348)	(-0.506, 0.193)
MTR + MIV	[-0.073, 0.609]	[-0.560,0.656]	[-0.583, 0.711]	[0, 0.760]
	(-0.100, 0.671)	(-631, 0.721)	(-0.663, 0.751)	(-0.001, 0.798)
MTS + MTR +	[0.003, 0.087]	[-0.085, -0.035]	[0.031, 0.125]	[0, 0.128]
MIV	(-0.011, 0.121)	(-0.112, 0.031)	(-0.031, 0.181)	(0, 0.184)
MTS + MTR +	[0.003, 0.087]	[-0.085, -0.015]	[0.012, 0.125]	[0, 0.127]
MIV	(-0.011, 0.121)	(-0.114, 0.054)	(-0.050, 0.181)	(0, 0.183)
(bias-corrected)				

Across tables 8 to 11, the comparison (Q3, Q2), consistently shows negative OLS estimates, -2.527 percentage points for attendance, -0.133 for English literacy, -0.069 for local language, and -0.093 for numeracy, and, in some cases, bounds. This is a result of non-monotonic relationships between feeding intensity and outcomes, particularly between Q3 and Q2, as further illustrated in Table 12 in Appendix A.

Two explanations are plausible. The first is a small-sample explanation: Q3 contains only 25 sub-regions, the smallest quartile, and the confidence intervals around all Δ (Q3, Q2) estimates are wide and cross zero, consistent with imprecision rather than a true structural reversal. The second is a transition-dynamics explanation: Q3 schools may have recently scaled beyond the low-intensity baseline but not yet operated long enough to generate measurable gains, while Q4 schools have had sufficient duration to accumulate the complementary inputs, reliable supply chains, trained food handlers, and community buy-in that amplify feeding's benefits. This is consistent with Nsabimana & Mensah (2025)'s finding that the effects of Rwanda's HGSF program accrue with additional months of exposure.

Table 10: Non-parametric bounds estimates of levels of school feeding intensity effects on Local Language

Assumption	**(Q2, Q1)**	**(Q3, Q2)**	**(Q4, Q3)**	**(Q4, Q1)**
OLS	0.026	-0.069	0.093	0.051
	(-0.067, 0.120)	(-0.181, 0.044)	(-0.030, 0.216)	(-0.056, 0.157)
Worst case	[-0.454, 0.807]	[-0.900, 0.905]	[-0.890, 0.850]	[-0.438, 0.761]
	(-0.499, 0.841)	(-0.921, 0.929)	(-0.916, 0.881)	(-0.484, 0.798)
MTS	[-0.406, 0.239]	[-0.367, 0.203]	[-0.236, 0.178]	[-0.438, 0.051]
	(-0.451, 0.308)	(-0.422, 0.267)	(-0.295, 0.253)	(-0.484, 0.134)
MTR	[-0.046, 0.592]	[-0.558, 0.666]	[-0.619, 0.727]	[0.001, 0.761]
	(-0.059, 0.635)	(-0.603, 0.706)	(-0.660, 0.763)	(-0.007, 0.798)
MTS + MTR	[0.002, 0.024]	*[-0.029, -0.036]*	[0.035, 0.056]	[0.001, 0.051]
	(-0.019, 0.094)	*(-0.085, 0.049)*	(-0.024, 0.147)	(-0.007, 0.140)
MTS + MIV	[-0.517, 0.266]	[-0.392, 0.176]	[-0.211, 0.194]	[-0.552, 0.068]
	(-0.624, 0.359)	(-0.488, 0.286)	(-0.312, 0.307)	(-0.677, 0.185)
MTR + MIV	[-0.058, 0.497]	[-0.448, 0.616]	[-0.558, 0.709]	[0, 0.758]
	(-0.448, 0.603)	(-0.564, 0.723)	(-0.680, 0.804)	(-0.015, 0.844)
MTS + MTR +	[-0.013, -0.008]	*[-0.008, -0.021]*	[0.034, 0.083]	[0, 0.068]
MIV	(-0.039, 0.050)	*(-0.056, 0.085)*	(-0.034, 0.163)	(-0.004, 0.154)
MTS + MTR +	[-0.013, -0.008]	[-0.008, -0.021]	[0.034, 0.083]	[0, 0.068]
MIV	(-0.038, 0.052)	(-0.052, 0.091)	(-0.058, 0.166)	(-0.004, 0.156)
(bias-corrected)				

Notes: Italicized empty-set entries indicate that the assumption combination has no identifying power for the comparison; bias-corrected estimates may still be informative when reported.

Both explanations likely contribute. Distinguishing between them empirically requires longitudinal data tracking coverage and outcomes within sub-regions over time, and this remains a priority for future research on Uganda's school feeding landscape.

6.2 Heterogeneous effects on school quality (Pupil Teacher Ratio-PTR) and child sex

Further looking at school and child characteristics in the form of school quality, here represented by the chosen variable of pupil teacher ratio and children's gender, the paper compares the case with the most assumptions layered (MTS+MTR+MIV) in Figures 4 and 5, respectively, for school quality/Pupil Teacher Ratio and child gender. The findings show that even when the extreme case of the highest-feeding-coverage schools (Q4) is compared with the lowest-feeding-coverage schools (Q1), the effects indicated by the bounds are larger for schools within the MoES-recommended PTR of 53:1 (MoES, 2025). For child gender, the upper bound on the effect size for boys in the extreme case of (Q4 Vs Q1) is higher than for girls in English reading competency. The difference in bounds on the effects is not big for numeracy competency.

Table 11: Non-parametric bounds estimates of levels of school feeding program intensity effects on Numeracy

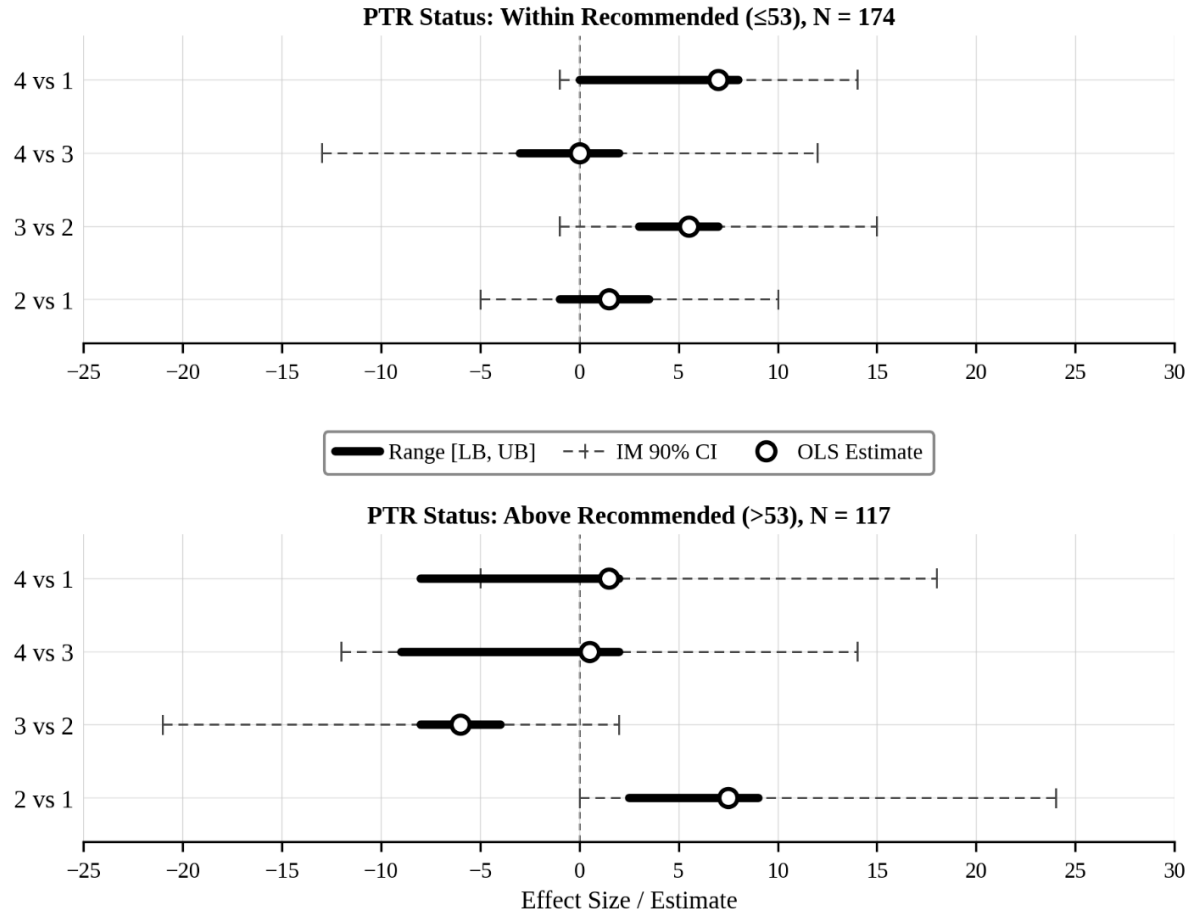
Assumption	(Q2, Q1)	(Q3, Q2)	(Q4, Q3)	(Q4, Q1)
OLS	0.095	-0.093	0.187	0.189
	(0.012, 0.178)	(-0.221, 0.034)	(0.067, 0.306)	(0.120, 0.257)
Worst Case	[-0.605, 0.655]	[-0.910, 0.890]	[-0.839, 0.901]	[-0.554, 0.645]
	(-0.634, 0.681)	(-0.930, 0.913)	(-0.866, 0.920)	(-0.582, 0.670)
MTS	[-0.457, 0.208]	[-0.557, 0.354]	[-0.451, 0.538]	[-0.554, 0.189]
	(-0.486, 0.262)	(-0.604, 0.427)	(-0.518, 0.592)	(-0.583, 0.242)
MTR	[-0.157, 0.551]	[-0.446, 0.536]	[-0.379, 0.540]	[0, 0.645]
	(-0.184, 0.573)	(-0.475, 0.557)	(-0.407, 0.562)	(0, 0.670)
MTS + MTR	[-0.009, 0.104]	[-0.092 -0.001]	[0.010, 0.177]	[0, 0.189]
	(-0.028, 0.157)	(-0.137, 0.071)	(-0.052, 0.231)	(0, 0.242)
MTS + MIV	[-0.457, 0.200]	[-0.552, 0.340]	[-0.437, 0.537]	[-0.554, 0.185]
	(-0.495, 0.280)	(-0.622, 0.442)	(-0.526, 0.617)	(-0.590, 0.248)
MTR + MIV	[-0.157, 0.521]	[-0.415, 0524]	[-0.367, 0.532]	[0, 0.637]
	(-0.206, 0.556)	(-0.460, 0.567)	(-0.428, 0.563)	(-0.004, 0.678)
MTS + MTR + MIV	[-0.008, 0.085]	[-0.076, -0.023]	[0.031, 0.177]	[0, 0.185]
	(-0.029, 0.150)	(-0.142, 0.073)	(-0.053, 0.234)	(-0.005, 0.242)
MTS + MTR + MIV (bias-corrected)	[-0.008, 0.085]	[-0.076, -0.023]	[0.031, 0.177]	[0, 0.185]
	(-0.030, 0.163)	(-0.152, 0.094)	(-0.078, 0.248)	(-0.006, 0.255)

6.3 Discussion

The results across Sections 6.1 through 6.3 reveal a broadly positive relationship between school feeding and education outcomes. In the binary case (Section 6.1), OLS estimates are positive for attendance (2.370%) and English literacy (0.7%), but negative for local language literacy and numeracy, a pattern consistent with feeding programs being disproportionately concentrated in more deprived schools. The pattern of negative regional selection is precisely what makes the positive MTS assumption contestable at the binary participation margin. If schools in disadvantaged sub-regions are disproportionately likely to have feeding programs, the assumption that feeding schools have weakly higher latent outcomes is not guaranteed to hold. It is this ambiguity that motivates shifting identification weight to intensity comparisons, where positive MTS conditional on program presence is considerably more credible.

Under the primary MTS+MIV specification, the upper bound on attendance falls to 1.641 percentage points relative to the OLS estimate (2.370%), and the upper bound on English literacy becomes negative, suggesting that the positive OLS association for English is largely attributable to selection. For local language and numeracy, MTS+MIV bounds remain negative throughout.

Figure 4: MTS+MTR+MIV bounds on the effects of school feeding by Pupil Teacher Ratio on school attendance

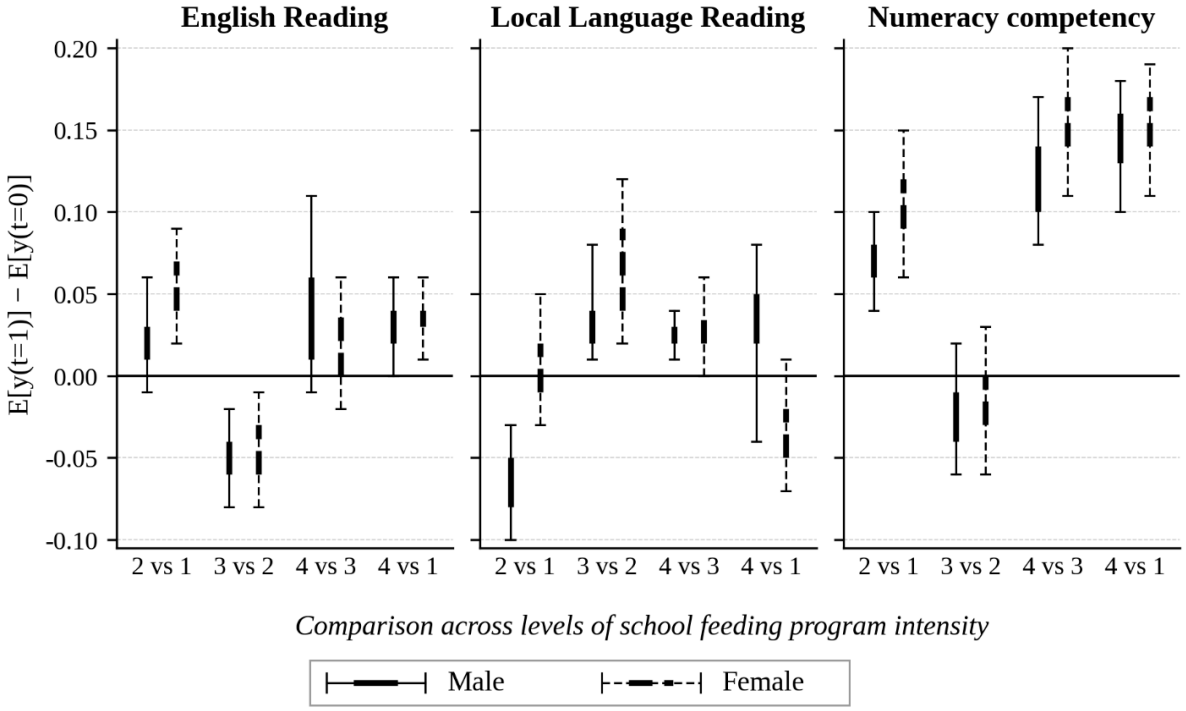


The high-intensity comparison to no school feeding (Section 6.2) sharpens this picture considerably. MTS+MIV upper bounds of 8.306% for attendance, 7.7% for English literacy, and 9.5% for numeracy are positive and non-trivial, surviving the partial identification correction in a way the binary-case bounds do not. This distinction is substantively important: the presence of a feeding program alone carries a limited, identifiable effect, whereas high-coverage programs carry a credible positive signal showing that program intensity matters.

The quartile comparisons in Section 6.3 extend this gradient, with MTS+MIV upper bounds remaining consistently below OLS across all outcomes and comparisons, confirming that OLS overstatement is a persistent feature of the data rather than a characteristic of any single comparison. Where MTR holds, MTS+MTR+MIV bounds tighten further and are reported as a sensitivity layer; where MTR is rejected, MTS+MIV remains the appropriate lens.

The binary-case MTS+MIV upper bound of 1.641 percentage points for attendance is conservative relative to the causal literature. Nikiema (2019) estimates 8.4 percentage points for Burkina Faso, and Aurino et al. (2019) find nearly half an additional school year completed in Mali, but this gap is expected. Those studies evaluated targeted emergency interventions in

Figure 5: MTS+MTR+MIV bounds on the effects of varying levels of school feeding coverage in schools across children's gender



high-deprivation settings with strong compliance, whereas the binary comparison here pools schools across the full coverage spectrum, diluting the estimated effect.

The high-intensity MTS+MIV upper bound of 8.306 percentage points for attendance is directly comparable to the prior literature and converges reassuringly with it. It falls within the 8-12 percentage-point range reported by Alderman et al., (2012) for Uganda's WFP Food for Education program, and closely matches Nikiema (2019)'s point estimate. This convergence across a randomized field experiment, a difference-in-differences estimator, and partial identification bounds lends external validity to the approach adopted here.

For learning outcomes, the MTS+MIV upper bounds of 0.077 for English literacy and 0.095 for numeracy in the high-intensity comparison are expressed as proportions on a 0-1 scale and can be interpreted, respectively, as the share of children achieving literacy and numeracy competency. These are meaningful magnitudes. Aurino et al. (2023) report standardized score gains of approximately 0.15 standard deviations for Ghana's government school feeding program after nearly two years, and Nsabimana & Mensah (2025) find per-month gains of 0.02-0.029 standard deviations for Rwanda's HGSF program. While direct comparison across metrics is not straightforward, a 7.7 percentage point gain in English literacy competency and a 9.5 percentage point gain in numeracy competency among children in high-coverage schools are broadly consistent in magnitude with what these credibly identified studies find and sit below the OLS point estimates of 9.4% and 10%, respectively, as the partial identification logic anticipates. The persistently

negative results for local language literacy across all three sections, binary, high-intensity, and quartile comparisons, warrant particular attention. No prior study in the literature review reports a consistently negative association between school feeding and local language outcomes. This may reflect the greater sensitivity of local language literacy to home-language environment and community-level factors relative to school-based nutritional inputs, or it may reflect within-region heterogeneity obscured by sub-regional aggregation. Either way, it warrants further investigation at finer levels of disaggregation.

It is also important to note that positive MTS is more defensible within the intensity margin than for the binary participation margin. Regional allocation patterns, with feeding concentrated in lower-food-security and lower-outcomes sub-regions such as Karamoja and Busoga (Figures 1–2), imply negative selection on regional disadvantage, which can partially offset school-level resource advantages (Table 4). The binary bounds in Table 6 should therefore be interpreted cautiously: they illustrate how selection on unobservables contaminates the naive participation contrast rather than providing a primary causal estimate. The intensity comparisons in sections 6.2 and 6.3, where MTS within program schools is more plausible, carry the main identification weight.

7 Conclusion

This study examined the effects of school feeding programs on attendance and learning outcomes, drawing on data from Uwezo Uganda's 2024 survey and employing a non-parametric bounds approach to address endogeneity concerns that surround much of the prior literature and also deal with the lack of exogeneity. Rather than imposing strong assumptions to obtain point estimates, this study relied on weak but plausible monotonicity conditions, Mean Treatment Selection (MTS), Monotone Treatment Response (MTR), and a Monotone Instrumental Variable (MIV) to construct informative bounds on the causal effects of attendance and foundational learning outcomes.

The findings show that when the treatment is binary, comparing schools that have a feeding program to those that do not, the evidence is mixed. In this case, under the MTS+MIV assumptions, the upper bounds are below zero for the learning outcomes in literacy and numeracy. But this reflects the concentration of feeding programs in more deprived schools rather than a harmful effect of feeding; the binary 'program-or-not' distinction therefore fails to isolate a feeding benefit. Once feeding intensity is exploited, the upper bounds under the MTS+MIV assumption turn non-negative and are lower than the OLS estimates. This suggests that simply having a school feeding program on record is not, by itself, enough for improving educational outcomes. As a sensitivity check, when the MTR assumption is not violated for attendance, English reading, and numeracy, the MTS-MTR-MIV bounds are also positive and informative, with upper

bounds that fall consistently below the corresponding OLS estimates. This pattern implies that OLS overstates the causal effect of feeding intensity, and that the data are consistent with effects ranging from zero up to those upper bounds. Together, these results suggest that what matters for educational outcomes is not the mere presence of a program, but the breadth and consistency with which it reaches learners.

Several limitations bear on how these findings should be interpreted. The school feeding indicator was reported by headteachers at the school level, while learning outcomes were measured for individual children through household surveys. This mismatch means one cannot directly observe each child's actual exposure to school meals, introducing potential measurement error in treatment assignment. More substantively, the binary treatment indicator captures only formal feeding arrangements and does not account for informal modalities, most notably, packed lunches from home. Descriptive data reveal that packed lunches are particularly prevalent in food-secure sub-regions: Ankole (81.5%), Bunyoro (71.9%), Kigezi (68.8%), and Tooro (59.8%). Where a meaningful share of the comparison group is informally fed, the binary contrast understates the true effect of receiving no school-day feeding, and the bounds should be interpreted accordingly. Finally, as is inherent to any partial identification exercise, the estimated effects are expressed as bounds rather than point estimates. This preserves honesty about what the data can and cannot establish, but it leaves some uncertainty about the precise magnitude of effects.

These findings carry clear implications for policy. The Government of Uganda should prioritize operationalizing the forthcoming National School Feeding Policy, with an emphasis on expanding the share of learners who consistently access meals, rather than merely increasing the number of schools that nominally report having a program. The intensity-based results suggest that broad, reliable coverage is the mechanism most likely to yield measurable gains in attendance and learning. From a resource-allocation standpoint, this favors deepening coverage in schools already operating programs over spreading thin resources to additional schools where participation would remain marginal. In sub-regions where informal feeding is widespread, policymakers may also wish to consider whether household-level food security interventions could complement or partly substitute for formal programs, though this remains an empirical question beyond the scope of the present analysis.

Future research should seek to address the limitations identified here on several fronts. First, individual-level administrative records linking children to actual meal receipt would sharply reduce the measurement error inherent in school-level treatment assignment. Second, direct observation or enumeration of informal feeding arrangements, including packed lunches, would allow researchers to more accurately characterize the counterfactual condition and improve the credibility of the treatment contrast. Third, data on feeding quality, dietary diversity, and program regularity would help researchers examine the mechanisms through which intensity translates

into learning gains, rather than treating coverage as a black box. Finally, replication across different country contexts and program modalities would strengthen the external validity of the intensity-based findings, which currently rest on cross-sectional variation in a single setting.

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Appendix A: Additional tables and figures

Table 12: Average Education outcomes across school feeding intensity

Coverage of the School Feeding program (School Feeding = 1)	Attendance rates	English language literacy	Local language literacy	Numeracy
Q1 - (0–25%)	68.815	0.195	0.158	0.473
Q2 - (26–50%)	75.989	0.302	0.184	0.568
Q3 - (51–75%)	73.462	0.169	0.116	0.475
Q4 - (76–100%)	80.625	0.334	0.209	0.662