**Rural home-grown school feeding program in Nyanda**

The analysis of the 2023-2025 education dataset of students in grade 1-6 in Nyanda shows that there are particularly persistent gaps among students in education attainment based on households’ incomes, rural residence, attendance, and to certain extent basic parental education. Additionally, variation in students’ performance seems to derive from within schools and not between schools or between districts variation.

A home-grown school feeding program targeting rural communities in Nyanda is an effective educational reform aiming at reducing learning inequalities associated with households’ income, rural residence, and attendance.

Evidence shows[[1]](#footnote-1) that HGSFP by improving child nutrition and supporting local food systems can directly enhance learning equity by creating stronger incentives for higher attendance. At first, providing regular nutritious meals based on the national diet impact student concentration, cognitive development and overall ability to learn. These benefits are particularly important for children from poor and food insecure households. Second, school meals have been shown to increase school attendance and reduce dropout rates, because school meals provide a tangible incentive for parents to send their kids to school. Third, by sourcing food from the local community it favors the development of the local economy, strengthening rural livelihoods by channeling important resources to local communities. Finally, targeting rural communities often translates in low-income communities, ensuring that intervention reach the most vulnerable groups, where gains in inequities are higher.

The available education data for Nyanda allows us to predict the expected test scores results for both reading and mathematics and for any income group given an increase in attendance. Currently test scores for the last two income groups are between approximately -0.3 and – 0.1 standard deviations the national mean for the lowest two income quantiles. A meta-analysis of the impact of school feeding on children health, nutrition, and educational outcome, shows that school feeding results in a significant increase in the percentage of school days attended (2.6%; 95% CI = 1.2%, 3.9%; *P* < 0.001) (Dongging, et al. 2021). Therefore, given our data, it is realistic to assume a 0.3 standard deviation increase in attendance due to the introduction of school feeding, which translates into a 2.2% increase in attendance, or 4.2 days in a school year. This prediction is in line with the literature and therefore plausible to be expected. If this was to be realized, the student in the second to lowest income group would pass the national average, while the student in the lowest income group would benefit enormously but still be approximately -0.18 standard deviation below the national average.

This conclusion was drawn from a predictive analysis performed with the education data for Nyanda. The prediction was made from a multilevel model that included a random intercept for school, district, and student-level variance, for both reading and math test scores.

In the second step, the dataset was modified to simulate an improvement in attendance by 0.3 standard deviation, applied only to students in the lower income quantile (1 and 2) and living in rural settings. Third, the updated dataset was used to predict the new reading and math outcomes.

In the final stage, the results were aggregated by income quantile to showcase how reading and math outcomes would change based on an increase in attendance. The percentage increase in attendance was obtained multiplying the standard deviation of attendance rate by the expected standard deviation improvement in attendance thanks to the introduction of the school feeding program. While the increase in attendance days was derived by multiplying this percentage by an approximate number of school days per year (190).

# **Bibliography**

Barro, D., C. Bogaards, P. Christian, E. Kelley, R. Khincha, F. Kondylis, M.P La, et al. 2025. "Impact Evaluation of the Home-Grown School Meals Programme in The Gambia. World Food Programme Office of Evaluation." OEV/2022/038.

Dongging, Wang, Shinde Sachin, Young Tara, and Fawzi Wafaie W. 2021. "Impacts of school feeding on educational and health outcomes of school-age children and adolescents in low- and middle-income countries: A systematic review and meta-analysis." *Journal of Global Health* doi: 10.7189/jogh.11.04051.

**Appendix**

#\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
# b) Multilevel model with random intercept for school, district, and student-level variance  
#\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
# Running this multilevel model to account for:  
# 1. school variance - differences between schools  
# 2. district variance - differences between districts   
# 3. student-level variance - differences between students withing schools  
  
# load the data  
merged\_centered = file.path(out\_data\_fld,"df\_merged\_centered.xlsx")  
df\_merged\_centered = read\_excel(merged\_centered)   
  
# transform the data in numeric  
df\_merged\_centered <- df\_merged\_centered %>%  
 mutate(  
 reading\_z = as.numeric(reading\_z),  
 math\_z = as.numeric(math\_z)  
 )  
  
# Multilevel model on reading z-scores  
mixed\_reading <- lmer(  
 reading\_z ~ factor(household\_income\_quintile) + female + rural +  
 disability\_status + parent\_education\_level + attendance\_centered +  
 (1 | school\_id) + (1 | district\_id) + factor(year),  
 data = df\_merged\_centered,  
 weights = weight  
)

## boundary (singular) fit: see help('isSingular')

# Summarize the results -READING  
summary(mixed\_reading)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']  
## Formula: reading\_z ~ factor(household\_income\_quintile) + female + rural + disability\_status + parent\_education\_level + attendance\_centered + (1 | school\_id) + (1 | district\_id) + factor(year)  
## Data: df\_merged\_centered  
## Weights: weight  
##   
## REML criterion at convergence: 522823.4  
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.7497 -0.6529 0.0008 0.6487 4.5279   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## school\_id (Intercept) 0.0991 0.3148   
## district\_id (Intercept) 0.0000 0.0000   
## Residual 0.9124 0.9552   
## Number of obs: 192000, groups: school\_id, 9993; district\_id, 25  
##   
## Fixed effects:  
## Estimate Std. Error df t value Pr(>|t|)   
## (Intercept) -0.267441 0.007122 73340.893518 -37.551 <0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)2 0.168922 0.005463 191981.314551 30.919 <0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)3 0.351070 0.006383 191819.831515 54.997 <0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)4 0.532559 0.007972 191081.130834 66.800 <0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)5 0.713616 0.012081 189548.308506 59.071 <0.0000000000000002 \*\*\*  
## female 0.006998 0.004324 191976.994578 1.619 0.106   
## rural -0.255341 0.004534 191704.428750 -56.318 <0.0000000000000002 \*\*\*  
## disability\_statusYes 0.017494 0.010723 191982.153351 1.631 0.103   
## parent\_education\_levelPrimary 0.006538 0.005186 191985.797204 1.261 0.207   
## parent\_education\_levelSecondary -0.004582 0.005653 191984.542600 -0.811 0.418   
## parent\_education\_levelTertiary -0.009528 0.010074 191985.435938 -0.946 0.344   
## attendance\_centered 0.817648 0.034595 187438.999391 23.635 <0.0000000000000002 \*\*\*  
## factor(year)2024 0.119088 0.005010 181880.435243 23.772 <0.0000000000000002 \*\*\*  
## factor(year)2025 0.239488 0.005016 182182.250749 47.747 <0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

##   
## Correlation matrix not shown by default, as p = 14 > 12.  
## Use print(x, correlation=TRUE) or  
## vcov(x) if you need it

## optimizer (nloptwrap) convergence code: 0 (OK)  
## boundary (singular) fit: see help('isSingular')

# Multilevel model on math z-scores  
mixed\_math <- lmer(  
 math\_z ~ factor(household\_income\_quintile) + female + rural +  
 disability\_status + parent\_education\_level + attendance\_centered +  
 (1 | school\_id) + (1 | district\_id) + factor(year),  
 data = df\_merged\_centered,  
 weights = weight  
)

## boundary (singular) fit: see help('isSingular')

# summarize the results - MATH  
summary(mixed\_math)

## Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']  
## Formula: math\_z ~ factor(household\_income\_quintile) + female + rural + disability\_status + parent\_education\_level + attendance\_centered + (1 | school\_id) + (1 | district\_id) + factor(year)  
## Data: df\_merged\_centered  
## Weights: weight  
##   
## REML criterion at convergence: 523501.9  
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -3.4622 -0.6491 0.0014 0.6541 4.6891   
##   
## Random effects:  
## Groups Name Variance Std.Dev.   
## school\_id (Intercept) 0.103281091581 0.32137376  
## district\_id (Intercept) 0.000000000325 0.00001803  
## Residual 0.914315170047 0.95619829  
## Number of obs: 192000, groups: school\_id, 9993; district\_id, 25  
##   
## Fixed effects:  
## Estimate Std. Error df t value Pr(>|t|)   
## (Intercept) -0.276347 0.007161 71899.513146 -38.590 < 0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)2 0.185627 0.005473 191964.362041 33.918 < 0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)3 0.354298 0.006394 191759.017935 55.409 < 0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)4 0.541457 0.007985 190974.746546 67.810 < 0.0000000000000002 \*\*\*  
## factor(household\_income\_quintile)5 0.718476 0.012098 189429.337429 59.388 < 0.0000000000000002 \*\*\*  
## female -0.002273 0.004331 191985.817593 -0.525 0.59979   
## rural -0.256621 0.004542 191793.490351 -56.495 < 0.0000000000000002 \*\*\*  
## disability\_statusYes 0.018136 0.010742 191985.656262 1.688 0.09135 .   
## parent\_education\_levelPrimary 0.016739 0.005195 191981.722363 3.222 0.00127 \*\*   
## parent\_education\_levelSecondary 0.002512 0.005663 191984.245778 0.444 0.65731   
## parent\_education\_levelTertiary -0.009176 0.010091 191983.014325 -0.909 0.36321   
## attendance\_centered 0.816741 0.034640 187320.249197 23.578 < 0.0000000000000002 \*\*\*  
## factor(year)2024 0.121560 0.005015 181873.319700 24.239 < 0.0000000000000002 \*\*\*  
## factor(year)2025 0.244321 0.005021 182168.696707 48.658 < 0.0000000000000002 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

##   
## Correlation matrix not shown by default, as p = 14 > 12.  
## Use print(x, correlation=TRUE) or  
## vcov(x) if you need it

## optimizer (nloptwrap) convergence code: 0 (OK)  
## boundary (singular) fit: see help('isSingular')

#\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
# c) Prediction math and reading score given an increase in attendance due to the proposed intervention  
#\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_  
# Define values for prediction  
sd\_increase = 0.3  
nbr\_school\_days = 190  
  
# Simulate an increase of 0.3 for low-income students living in rural settings  
df\_sim <- df\_merged\_centered %>%  
 mutate(attendance\_centered = if\_else(low\_income == 1 & rural == 1, # low income represents households in the first and second quantale  
 attendance\_centered + sd\_increase,  
 attendance\_centered))  
  
# Predict outcomes using the mixed model  
df\_sim$reading\_pred <- predict(mixed\_reading, newdata = df\_sim, re.form = NA)  
df\_sim$math\_pred <- predict(mixed\_math, newdata = df\_sim, re.form = NA)  
  
# Aggregate predicted outcomes by income quantile  
sim\_summary <- df\_sim %>%  
 group\_by(household\_income\_quintile) %>%  
 summarise(mean\_reading\_pred = mean(reading\_pred),  
 mean\_math\_pred = mean(math\_pred))  
  
print(sim\_summary)

## # A tibble: 5 × 3  
## household\_income\_quintile mean\_reading\_pred mean\_math\_pred  
## <dbl> <dbl> <dbl>  
## 1 1 -0.182 -0.188   
## 2 2 0.00862 0.0189  
## 3 3 0.0984 0.0952  
## 4 4 0.303 0.305   
## 5 5 0.512 0.510

# mean and standard deviation of attendance  
mean(df\_merged\_centered$attendance\_rate, na.rm = TRUE)

## [1] 0.686

sd(df\_merged\_centered$attendance\_rate, na.rm = TRUE)

## [1] 0.07350024

# presents results on school attendance  
  
# % increase in attendance:  
sd(df\_merged\_centered$attendance\_rate, na.rm = TRUE)\*sd\_increase

## [1] 0.02205007

# Increase in attendance days thanks to school feeding. Assuming 190 days of school:  
sd(df\_merged\_centered$attendance\_rate, na.rm = TRUE)\*sd\_increase\*nbr\_school\_days

## [1] 4.189514

1. WFP [**School-based Programmes Impact Evaluation Window**](https://www.wfp.org/publications/school-based-programmes-impact-evaluation-window-brief) [↑](#footnote-ref-1)