Household Food Insecurity and Children's Development: A Longitudinal GEE Analysis

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1 Summary

Our study examined how household food insecurity relates to children's academic development from kindergarten to fifth grade using NHANES data and GEE models. We looked at both mathematics and science scores and considered not only children's food security at each time point but also their baseline levels and changes over time. Overall, food insecurity showed only weak associations with academic scores, and the effects were small after accounting for demographic and socioeconomic factors. However, we found clear evidence that socioeconomic status influenced this relationship. Children in the lowest SES group showed slower growth in both subjects when food insecurity increased, while children in higher SES groups were less affected. These findings suggest that the effects of food insecurity on children's learning may develop over time and depend largely on the broader resources available to families. The results underscore the importance of examining food insecurity within the full family context when assessing its impact on educational outcomes.

2 Introduction

Children's performance during the early academic years (kindergarten through early grades in elementary school) provides an important foundation for later success in academic, social, and economic domains (Boivin and Bierman, 2013). Students' academic achievements have long been linked to teaching quality, school resources, and community education levels, with existing research focusing on identifying factors that either advance or hinder reading and math achievement during this timeframe (Valiente et al., 2021). However, one critical yet often overlooked factor is household food insecurity. The U.S. Economic Research Service (2025) defines food insecurity as having reduced quality, variety, or desirability of food, or experiencing disrupted eating patterns due to limited resources. Food insecurity could undermine children's academic and socioemotional development in the early school years. Previous longitudinal work focuses on both transient and persistent food insecurity. Persistence is defined as experiencing food insecurities in multiple time points (such as both kindergarten and elementary school), whereas transition is defined as experiencing food insecurity at only one time point but not others (Slotnick et al., 2024).

2.1 Related Work

Existing cross-sectional studies have documented connections between food insufficiency and various academic and behavioral difficulties in elementary school children. Using NHANES III data, Alaimo et al. (2001) found that food insecurity was associated with lower mathematics scores, grade repetition, higher absenteeism and tardiness, psychosocial problems, school suspensions, and trouble getting along with peers among children ages 6 to 12. However, longitudinal studies offer advantages by capturing temporal relationships, establishing that outcomes stem from initial exposure rather than reverse causality, and reducing bias from unmeasured confounders Jyoti et al., 2005.

Using data from 11,400 children in the ECLS-K study, Jyoti et al. (2005) demonstrated that food insecurity in kindergarten was linked to slower growth in math scores, particularly for girls. Gallegos et al. (2021) summarized five longitudinal studies, four of which found significant negative effects of persistent food insecurity on academic and cognitive outcomes. Two studies reported that both transient and persistent food insecurity were associated with decreased approach to learning and lower reading and math scores, while another found that only persistent food insecurity predicted reduced reading scores. One study identified that children experiencing deepening food insecurity (moving from marginal to food insecure status) showed lower math and working memory scores. However, one study found no associations between food insecurity patterns and academic outcomes.

While existing longitudinal research has examined patterns and persistence of food insecurity, few studies have explored the underlying mechanisms explaining these effects. In particular, how socioeconomic status may moderate the relationship between food insecurity and academic growth over time has not yet been directly investigated in early elementary samples.

3 Data

3.1 Data Source

This study uses data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-11 (ECLS-K:2011), a nationally representative longitudinal study following approximately 18,200 children from kindergarten through fifth grade. Data were collected through direct child assessments, parent and teacher questionnaires, and school administrator surveys using a multistage probability sample design. Our analytic sample focuses on three waves where household food security data were collected: Spring of kindergarten (Wave 2), Spring of first grade (Wave 4), and Spring of fifth grade (Wave 9), yielding approximately 18,000 children contributing up to 54,000 person-wave observations.

3.2 Measures

Academic Achievement: We examined mathematics and science achievement using IRT-based scale scores standardized across waves. Mathematics assessments evaluated number sense, operations, measurement, geometry, and data analysis. Science assessments measured physical science, life science, and scientific inquiry skills. Raw scores containing negative values indicating item-level nonresponse or missing data codes were set to missing.

Food Security: Household food security was assessed using the 18-item U.S. Household Food Security Survey Module administered at each wave. The module produces raw scores (total affirmative responses, range: 0–18), IRT-based scale scores, and categorical classifications. The scale score is a continuous measure derived from IRT modeling that accounts for item severity, with higher values indicating greater food insecurity. Following ECLS-K documentation, we recoded scale scores from -6 to 1.4 to represent food secure households, while values below -6 were treated as missing. Negative raw scores were also recoded to missing. We constructed two additional variables: baseline food security (fs_baseline), defined as each child's food security scale score at Wave 2, with missing baseline values imputed from the earliest available wave for that child; and food security change (fs_change), calculated as the difference between time-varying food security and baseline food security to estimate within-child effects.

Covariates: Socioeconomic status (SES) was measured using a continuous composite variable created by NCES that combines parental education, occupational prestige, and household income at baseline (Wave 1). For moderation analyses, we created SES quartiles based on the sample distribution. Additional covariates included child sex (male or female), race/ethnicity collapsed into five categories (White, Black, Hispanic, Asian, Other), disability status (whether the child had any diagnosed disability or IEP), household size (continuous count of household members), school urbanicity (urban, suburban, rural, other), and school type (public, private, other).

3.3 Data Processing

The ECLS-K:2011 public use file is structured in wide format with approximately 2.3 GB of data. We developed a Python-based extraction pipeline to parse the raw data file using the Stata dictionary specification, identifying column positions and variable names for all required variables across the three waves. ECLS-K missing value codes (-9 to -1) were systematically converted to missing values. The data were then reshaped from wide to long format where each row represents one child at one time point. Time-invariant characteristics (sex, race, baseline SES) were replicated across all waves for each child, while time-varying measures (achievement scores, food security status, school characteristics) were matched to their corresponding wave. We created a discrete time variable coded as 0 (kindergarten), 1 (first grade), and 2 (fifth grade). All categorical variables were cleaned to remove verbose ECLS-K value labels and standardized to human-readable factor levels. Wave-specific sampling weights were incorporated to maintain national representativeness and account for differential probabilities of selection and nonresponse.

4 Methodology

4.1 Generalized Estimating Equations Framework

We employed Generalized Estimating Equations (GEE) as our primary analytic approach to model longitudinal changes in academic achievement from kindergarten through fifth grade. We chose GEE over Generalized Linear Mixed Models (GLMM) because our research questions focus on population-averaged effects rather than individual-specific trajectories. GEE provides estimates that describe average outcomes across the population, making them directly interpretable for education policy and interventions targeting specific groups of children. In contrast, GLMM requires correct specification of the random effects distribution and is better suited for questions about individual patterns and predictions.

GEE offers several additional advantages for this research. First, GEE handles the within-child correlation inherent in repeated measures data while producing valid standard errors through the sandwich (robust) variance estimator. Second, GEE yields consistent parameter estimates even when the working correlation structure is misspecified, allowing flexibility in modeling temporal dependencies, although efficiency is maximized when the working correlation approximates the true correlation. Third, GEE handles missing data efficiently by utilizing all available observations at each time point without requiring complete cases, providing valid inference under the assumption that data are missing completely at random.

All models used a Gaussian distribution with an identity link given the continuous nature of the outcome variables. Standard errors were computed using the sandwich estimator to ensure robustness to potential misspecification of the working correlation structure.

4.2 Working Correlation Structure Selection

We compared four candidate working correlation structures: independence (assuming no within-child correlation), exchangeable (assuming equal correlation between all pairs of observations), first-order autoregressive (AR(1); assuming correlations decay exponentially with time lag), and unstructured (allowing separate correlation estimates for each pair of time points).

Model selection was guided by the Quasi-likelihood under Independence Model Criterion (QIC), an extension of Akaike's Information Criterion appropriate for GEE models Pan, 2001. The correlation structure minimizing QIC was selected for subsequent analyses. Given the temporal nature of our data, we anticipated that AR(1) would provide the best fit, as observations closer in time should exhibit stronger correlation.

4.3 Model Specification

Our main effects model took the following form:

$$\begin{aligned}
E(Y_{it}) = \beta_0 &+ \beta_1(\text{TIME}_{it}) + \beta_2(\text{TIME}_{it}^2) \\
&+ \beta_3(\text{FS_SCALE}_{it}) + \beta_4(\text{TIME}_{it} \times \text{FS_SCALE}_{it}) \\
&+ \beta_5(\text{FS_BASELINE}_i) + \beta_6(\text{TIME}_{it} \times \text{FS_BASELINE}_i) \\
&+ \boldsymbol{\gamma}^\top \mathbf{X}_i
\end{aligned} \tag{1}$$

where Y_{it} is the academic outcome (mathematics or science IRT score) for child i at time t; TIME and TIME^2 capture the functional form of developmental trajectories (linear and quadratic growth); FS_SCALE$_{it}$ represents time-varying food security; FS_BASELINE$_i$ represents baseline (between-child) food security; and $\mathbf{X}_i$ is a vector of covariates including sex, race/ethnicity, disability status, SES, household size, school type, and urbanicity.

The inclusion of both time-varying food security and baseline food security allows for decomposition of effects: β_3 captures the contemporaneous (within-child) effect of food security changes, while β_5 captures the between-child effect of initial food security status. The interaction terms with time (β_4 and β_6) test whether food security influences the rate of academic growth over time.

4.4 SES Moderation Analysis

To examine whether the effects of food insecurity vary by socioeconomic status, we estimated models including three-way interactions between food security, time, and SES quartile:

$$\begin{aligned}
E(Y_{it}) = \beta_0 &+ \beta_1(\text{TIME}_{it}) + \beta_2(\text{TIME}_{it}^2) \\
&+ \beta_3(\text{FS_SCALE}_{it}) + \beta_4(\text{TIME}_{it} \times \text{FS_SCALE}_{it}) \\
&+ \beta_5(\text{FS_BASELINE}_i) + \beta_6(\text{TIME}_{it} \times \text{FS_BASELINE}_i) \\
&+ \sum_{q=2}^{4} \beta_{7q}(\text{SES_Q}_q) + \sum_{q=2}^{4} \beta_{8q}(\text{SES_Q}_q \times \text{FS_SCALE}_{it}) \\
&+ \sum_{q=2}^{4} \beta_{9q}(\text{SES_Q}_q \times \text{TIME}_{it} \times \text{FS_SCALE}_{it}) \\
&+ \boldsymbol{\gamma}^\top \mathbf{X}_i
\end{aligned} \tag{2}$$

where SES_Q$_q$ represents indicator variables for SES quartiles 2, 3, and 4 (with Q1, the lowest SES quartile, as the reference group). The coefficients β_{8q} test whether the contemporaneous effect of food security differs across SES groups, while β_{9q} test whether the effect of food security on growth rates differs by SES. Simple slopes were calculated for each SES quartile to facilitate interpretation.

4.5 Sensitivity Analyses

We conducted several sensitivity analyses to assess the robustness of our findings:

1. **Alternative correlation structures:** We re-estimated the main effects models using independence, exchangeable, and AR(1) correlation structures to verify that substantive conclusions were not sensitive to this modeling choice.

2. **Categorical food security specification:** We replaced the continuous food security scale with the three-level categorical classification (high/marginal, low, very low) to examine whether results were consistent across operationalizations.

4.6 Model Diagnostics

Model fit and assumptions were evaluated through residual diagnostics. For each model, we examined: (1) Pearson residuals versus fitted values to assess linearity and homoscedasticity; (2) normal Q-Q plots to evaluate the distributional assumption; (3) scale-location plots to check for heteroscedasticity; and (4) residuals across time to verify that the model adequately captured temporal trends. Additionally, we plotted within-child residual patterns for a random sample of 30 children to visually assess the adequacy of the correlation structure.

4.7 Software

All analyses were conducted in R version 4.x using the `geepack` package for GEE estimation Halekoh et al., 2006. The `QIC` function from `geepack` was used for correlation structure comparison.

5 Results

5.1 Correlation Structure Selection

We compared four candidate working correlation structures (independence, exchangeable, AR(1), and unstructured) using the Quasi-likelihood under the Independence Model Criterion (QIC). Lower QIC values indicate better fit for GEE models. Across both the mathematics and science models, the independence structure produced the lowest QIC (5,777,447 for math; 2,373,308 for science). Because independence minimized QIC in both cases, we selected it as the working correlation structure for all subsequent analyses.

Table 1: QIC Comparison for Math and Science GEE Models

Correlation Structure	Math Model QIC	Science Model QIC
Independence	5,777,447	2,373,308
Exchangeable	5,855,001	2,386,789
AR(1)	5,867,582	2,389,655
Unstructured	5,864,567	2,394,244

Table 2: GEE Coefficients for Mathematics and Science Models

Mathematics Model				Science Model			
Predictor	**Estimate**	**p-value**	**Sig**	**Predictor**	**Estimate**	**p-value**	**Sig**
Intercept	50.16	<0.001	***	Intercept	35.58	<0.001	***
time	10.46	<0.001	***	time	-1.17	<0.001	***
time^2	12.65	<0.001	***	time^2	11.00	<0.001	***
fs_scale	-0.07	0.761		fs_scale	0.10	0.541	
fs_baseline	0.03	0.889		fs_baseline	0.09	0.593	
ses_baseline	6.13	<0.001	***	ses_baseline	3.93	<0.001	***
sex = Female	-2.00	<0.001	***	sex = Female	-0.88	<0.001	***
race = Black	-7.67	<0.001	***	race = Black	-5.58	<0.001	***
race = Hispanic	-4.56	<0.001	***	race = Hispanic	-4.51	<0.001	***
race = Asian	1.29	0.002	**	race = Asian	-3.30	<0.001	***
race = Other	-1.03	0.036	*	race = Other	-0.54	0.065	.
disability = No	7.06	<0.001	***	disability = No	3.31	<0.001	***
household_size	-0.39	<0.001	***	household_size	-0.52	<0.001	***
urban = Suburban	-0.66	0.010	**	urban = Suburban	0.11	0.512	
urban = Rural	-0.07	0.800		urban = Rural	0.74	<0.001	***
urban = Other	-1.66	0.011	*	urban = Other	0.27	0.516	
time × fs_scale	**-0.30**	**0.072**	**.**	**time × fs_scale**	**-0.22**	**0.069**	**.**
time × fs_baseline	-0.14	0.377		time × fs_baseline	-0.18	0.120	

5.2 Main GEE Results for Mathematics and Science

Both models showed clear patterns of academic growth from kindergarten through fifth grade. In the mathematics model, scores increased as students moved from Spring kindergarten (Wave 2) to Spring first grade (Wave 4) and then to Spring fifth grade (Wave 9). The estimate for time was 10.46 ($p < 0.001$) and the estimate for time^2 was 12.65 ($p < 0.001$). The results mean that mathematics scores rose each year, and the increase between Wave 4 and Wave 9 was larger than the increase between Wave 2 and Wave 4. In the science model, the estimate for time was -1.17 ($p < 0.001$) while the squared term was 11.00 ($p < 0.001$). This pattern suggests that science scores dipped slightly from Wave 2 to Wave 4, but then rose more sharply from Wave 4 to Wave 9.

Food insecurity was not strongly related to either outcome. The food security score was not significant in mathematics ($\beta = -0.07$, $p = 0.76$) or science ($\beta = 0.10$, $p = 0.54$). Baseline food security also showed no association with either subject. The interaction terms between time and the food security scale were small and not statistically significant at the 0.05 level. The estimate for the time by food security interaction in the mathematics model was $\beta = -0.30200$ ($p = 0.072$), and the corresponding estimate in the science model was $\beta = -0.2222$ ($p = 0.069$). Both p values fall below a 0.10 threshold. These estimates point to a possible pattern where children with higher food insecurity may experience slightly slower academic score increases over time, though the evidence is not strong. This is consistent with the construction of the food security scale based on the number of affirmative responses to the USDA food security module. Most children in the sample were in the food secure or marginally secure range, which reduces variability and makes small effects more difficult to detect.

Several covariates showed consistent and statistically significant associations with mathematics and science scores. Socioeconomic status was one of the strongest predictors. In the mathematics model, the estimate for SES was 6.13 ($p < 0.001$). In the science model, the estimate for SES was 3.93 ($p < 0.001$). Children from families with higher socioeconomic status scored noticeably higher in both subjects. Clear demographic differences were also present. Girls scored lower than boys in mathematics (estimate −2.00, $p < 0.001$) and in science (estimate −0.88, $p < 0.001$). Black children scored 7.67 points lower in mathematics and 5.58 points lower in science compared with White children. Hispanic children scored 4.56 points lower in mathematics and 4.51 points lower in science. Asian children scored 1.29 points higher in mathematics ($p = 0.002$) but 3.30 points lower in science ($p < 0.001$). Children without a reported disability scored 7.06 points higher in mathematics and 3.31 points higher in science compared with children with a disability.

Household size showed small negative associations with both outcomes. Each additional household member was associated with 0.39 points lower in mathematics ($p < 0.001$) and 0.52 points lower in science ($p < 0.001$). School location showed modest differences. For mathematics, children in suburban schools scored 0.66 points lower than those in urban schools ($p = 0.010$). For science, children in rural schools scored 0.74 points higher than those in urban schools ($p < 0.001$).

Overall, the findings show that socioeconomic background, race, disability status, sex, and household size are consistently related to children's academic performance. After adjusting for these characteristics, food insecurity did not show strong associations with achievement in either subject. The small negative interaction terms suggest that children experiencing higher food insecurity may show slightly slower gains over time, though the evidence is limited and does not meet conventional significance thresholds.

5.3 SES Moderation

To examine whether the relationship between food insecurity and academic growth varied by socioeconomic status, models were constructed that included interactions between SES quartile, the food security scale, and time. This help testing whether children from different SES backgrounds showed different patterns of mathematics and science growth as food insecurity levels changed over time.

In the mathematics model, the three-way interaction terms were all statistically significant. The estimates were $\beta = 0.33$ for Quartile 2 ($p = 0.002$), $\beta = 0.53$ for Quartile 3 ($p < 0.001$), and $\beta = 0.99$ for Quartile 4 ($p < 0.001$). The negative main effect of food insecurity on growth is given by the coefficient for the interaction between time and the food security scale ($\beta = -0.53$). This means that in the lowest SES quartile, increases in food insecurity were linked to slower math growth over time. For children in the highest SES quartile, the additional three-way interaction of $\beta = 0.99$ cancels out this negative slope. In other words, while Quartile 1 children showed slower math growth when food insecurity increased, Quartile 4 children had a much flatter relationship, meaning their growth remained more stable. The overall pattern indicates that higher SES weakened the negative effect of food insecurity on mathematics progress.

The science model showed the same pattern. The three-way interaction estimates were $\beta = 0.19$ for Quartile 2 (p = 0.018), $\beta = 0.52$ for Quartile 3 (p < 0.001), and $\beta = 1.08$ for Quartile 4 (p < 0.001). The main effect of food insecurity on growth is the time-by-food insecurity coefficient ($\beta = -0.39$), which captures the slowing of science growth in the lowest SES quartile. As SES increased, the positive three-way interaction terms added back to this negative slope. The Quartile 4 estimate of $\beta = 1.08$ more than offsets the negative main effect, meaning that increases in food insecurity no longer slowed science growth for the highest SES children. Together these results show that higher SES helped maintain more stable science growth even under rising food insecurity.

These results show that socioeconomic status moderated the relationship between food insecurity and academic development. Children in the lowest SES quartile experienced slower mathematics and science growth when food insecurity increased, whereas those in higher SES quartiles were less affected. The consistent pattern across subjects suggests that socioeconomic resources may help protect children from the academic consequences of food related hardship.

Table 3: SES Moderation Coefficients: Food Security × Time × SES Quartile

Term	**Model**	**Estimate**	**p-value**	**Signif.**
Main Effect				
Time × Food Security	Math	−0.529	0.0026	**
Time × Food Security	Science	−0.387	0.0025	**
Three-Way Interaction: SES Quartile				
Time × Food Security × Q2	Math	0.328	0.0020	**
Time × Food Security × Q3	Math	0.528	< 0.001	***
Time × Food Security × Q4	Math	0.994	< 0.001	***
Time × Food Security × Q2	Science	0.187	0.0179	*
Time × Food Security × Q3	Science	0.520	< 0.001	***
Time × Food Security × Q4	Science	1.078	< 0.001	***

5.4 Model Diagnostic

The diagnostic plots showed that the models fit the data well. The residuals did not display strong curvature patterns across fitted values, and the green curves remained nearly flat, indicating the linear and quadratic time terms captured the shape of the growth trajectories. The scale-location plots suggested fairly constant variance, with some spread differences across score ranges. The Q-Q plots showed some departures from normality at the tails, which is expected with large samples, but most areas aligned with the reference line. The within child residual plots were mostly around zero with no consistent trends, confirming the accuracy our working correlation structures. Overall, these model diagnostics did not find major issues that could affect our GEE model result interpretation and suggested our models fit the data reasonably well.

5.5 Sensitivity Analyses

To check whether the main findings depended on how food insecurity was measured, our study re-estimated the mathematics model using a categorical food security variable with three levels: food secure, low food security, and very low food security. The results were similar to the continuous-scale model. Neither the low nor very low food security groups differed from the food secure group in their overall mathematics scores. Only the time by low food security interaction was significant. Overall, using categories instead of a continuous scale did not change the conclusion that food insecurity was only weakly related to mathematics growth.

The study also showed whether the food insecurity estimates depended on the choice of working correlation structure in the GEE model. The continuous-scale model was re-fit under independence, exchangeable, and AR(1) structures, and the coefficients for food insecurity were compared. The main effect of food insecurity and its interaction with time were negative across all three structures and stayed similar. The standard errors were also nearly the same. Because the direction and size of these estimates were stable, the results appear robust to different correlation assumptions.

Table 4: Sensitivity of Food Insecurity Estimates Across Working Correlation Structures

Correlation Structure	FS Effect	Time × FS	SE(FS)
Independence	−0.073	−0.302	0.240
Exchangeable	−0.049	−0.206	0.156
AR(1)	−0.029	−0.196	0.153

6 Discussion

6.1 Summary of Key Findings

First, food insecurity did not show a strong contemporaneous association with mathematics or science scores at a single time point. Across models and sensitivity checks, the main effect coefficients for both the time-varying and baseline food security measures were small and statistically insignificant. This suggests that short-term food insecurity may not have an immediate effect on children's performance in the standardized tests used in ECLS-K.

Second, food insecurity was not significantly associated with children's learning trajectories. Although the time-by-food-insecurity interaction terms were negative in both subjects, the estimated effects were small. Children experiencing higher levels of food insecurity may exhibit slightly slower academic growth, but this tendency was weak and not statistically reliable after adjusting for demographic and socioeconomic covariates. These findings differ from some prior studies emphasizing the impact of severe food insecurity, but they are consistent with the limited variation in food insecurity measures within the ECLS-K cohort and the relatively high proportion of food-secure households.

Third, socioeconomic status significantly moderated the association between food insecurity and academic growth. Food insecurity had the strongest negative effect on learning trajectories among children in the lowest SES quartile. For these children, higher levels of food insecurity were associated with noticeably slower academic growth over time. In Quartile 2, this negative association was smaller, and by Quartile 3 the food-insecurity effect was nearly eliminated. Among children in the highest SES quartile, the estimated slope turned slightly positive. This indicates that the negative impact of food insecurity on academic progress gradually weakened as socioeconomic resources increased. The significance interaction terms for Quartiles 3 and 4 reflect their substantial differences from the lowest SES group.

6.2 Interpretation of SES Moderation and Underlying Mechanisms

The observed SES moderation pattern is consistent with cumulative risk and resource-buffering frameworks, which state that children exposed to multiple environmental stressors are more susceptible to additional hardship, whereas those with greater socioeconomic resources benefit from protective buffers that mitigate the impact of adversity. Children in low SES households often experience several overlapping stressors, such as financial instability, housing difficulties, and limited access to learning materials, which heighten the academic consequences of food-related hardship. In contrast, higher SES families typically have more stable routines, supplemental educational supports, and greater parental capacity to absorb disruptions, reducing the extent to which food insecurity alters their learning trajectories. According to these frameworks, the impact of material hardship depends not only on the deprivation itself but also on the broader constellation of risks and supports that shape children's emotional, cognitive, and physiological responses to adversity (Evans et al., 2013). These mechanisms help explain why food insecurity had the strongest negative association with academic growth among children in the lowest SES quartile, while the effect diminished substantially among higher SES groups.

6.3 Implications for Educational and Social Policy

The developmental pattern observed here indicates that the consequences of food insecurity may emerge gradually rather than appearing at a single point in time. This highlights the importance of ongoing monitoring and early identification of food-related hardship, rather than relying solely on cross-sectional assessments. To counter these risks, schools and community organizations play a critical role by securing regular meals and stable learning environments that promote sustained academic progress.

The SES differences observed in our study further underscore the need to tailor interventions to family contexts, as food insecurity may disrupt learning through different pathways depending on families' baseline resources and expectations. For low SES families facing multiple stressors, targeted supports such as after-school programs, access to tutoring, and additional financial assistance can be helpful. Such efforts can help reduce disparities in academic growth associated with food insecurity and promote more equitable educational outcomes.

6.4 Limitations

Several limitations should be considered when interpreting these findings. First, as food insecurity and SES were parent-reported, the data may contain measurement error or social desirability bias, potentially weakening associations. Second, although GEE accommodates incomplete outcome data under MAR or MCAR assumptions, unobserved factors associated with missingness may still bias estimates. For example, if lower-performing children are more likely to miss testing sessions for reasons not captured in our data, the MAR assumption may be violated. Third, although our models adjusted for a range of socioeconomic and demographic characteristics, other relevant factors such as unstable employment, housing insecurity, or parental stress were not fully captured in the ECLS-K covariate set. These omitted variables may confound the relationships we estimate. Finally, standardized tests are performed only once a year, the test scores, while reliable at the population level, may be insufficiently sensitive to detect short-term or subtle fluctuations in academic performance.

7 Future Work

Future research can extend beyond SES differences to investigate the mechanisms through which food insecurity influences academic growth. Potential pathways include teacher-child relationships, children's stress responses, and levels of school engagement. Incorporating teacher reports and behavioral indicators alongside standardized test scores may help clarify whether learning trajectories are mediated through attentional, emotional, or behavioral pathways. In addition, increasing the frequency of academic assessments can help researchers better capture short-term learning fluctuations and identify sensitive developmental periods. Finally, qualitative or mixed-methods studies could reveal how families across SES strata experience and manage food-related hardship, supporting the development of interventions that are more responsive to family circumstances.

8 References

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9 Appendix

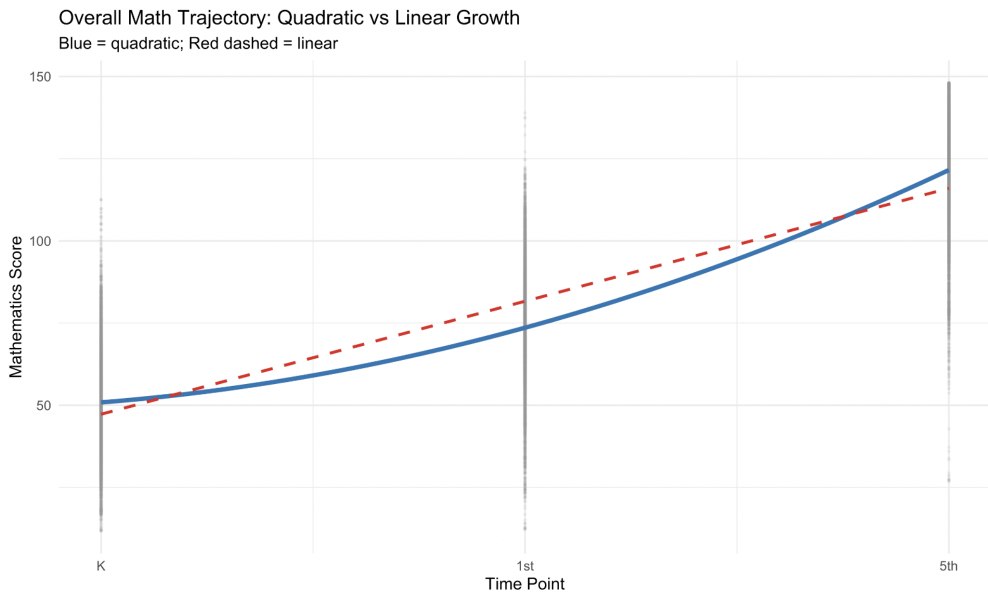

Figure 1: Comparison of quadratic (blue solid line) and linear (red dashed line) growth models for overall mathematics achievement. The quadratic model captures the deceleration in growth rates between kindergarten and first grade, followed by acceleration from first to fifth grade. The linear model systematically overestimates growth in early years and underestimates growth in later years.

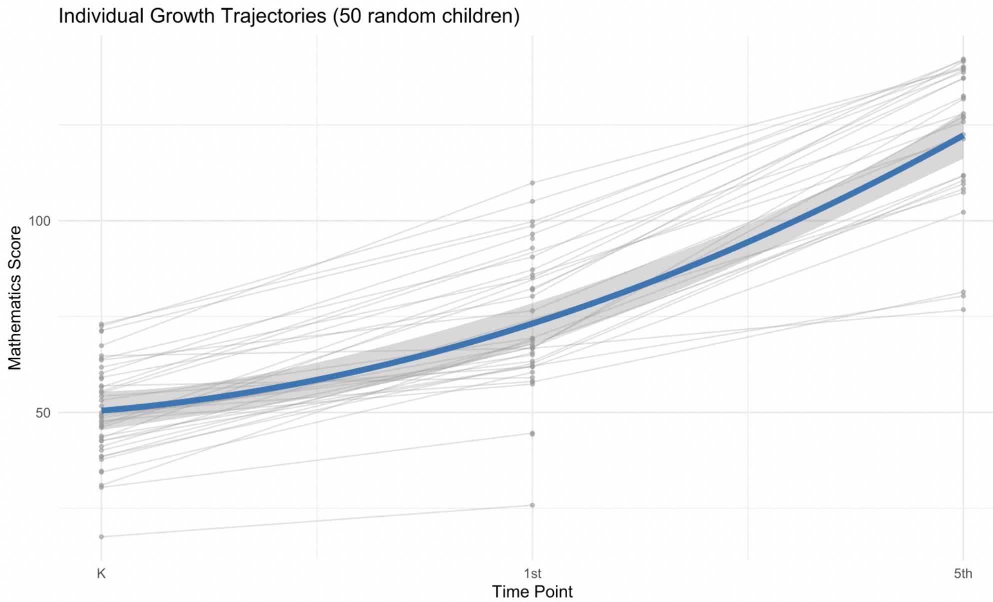

Figure 2: Individual growth trajectories for 50 randomly sampled children (gray lines) with population-averaged trajectory (blue line). Individual trajectories show varying patterns of acceleration and deceleration, with the quadratic population average capturing the typical pattern of modest early growth followed by steeper later gains. The wide variability justifies using GEE to model population-averaged effects rather than individual-specific trajectories.

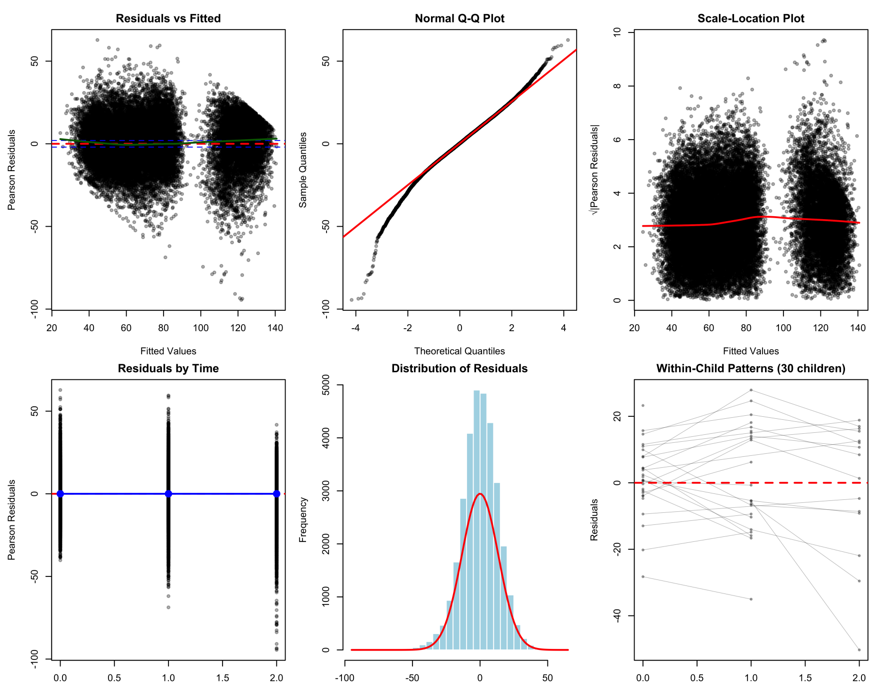

Figure 3: Diagnostic plots for the main mathematics model

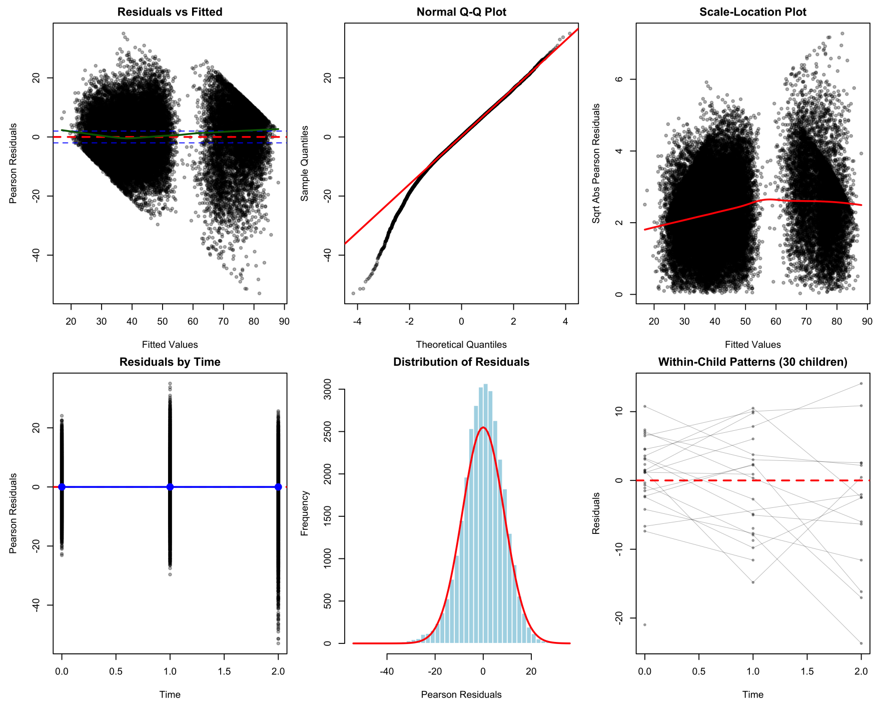

Figure 4: Diagnostic plots for the main science model

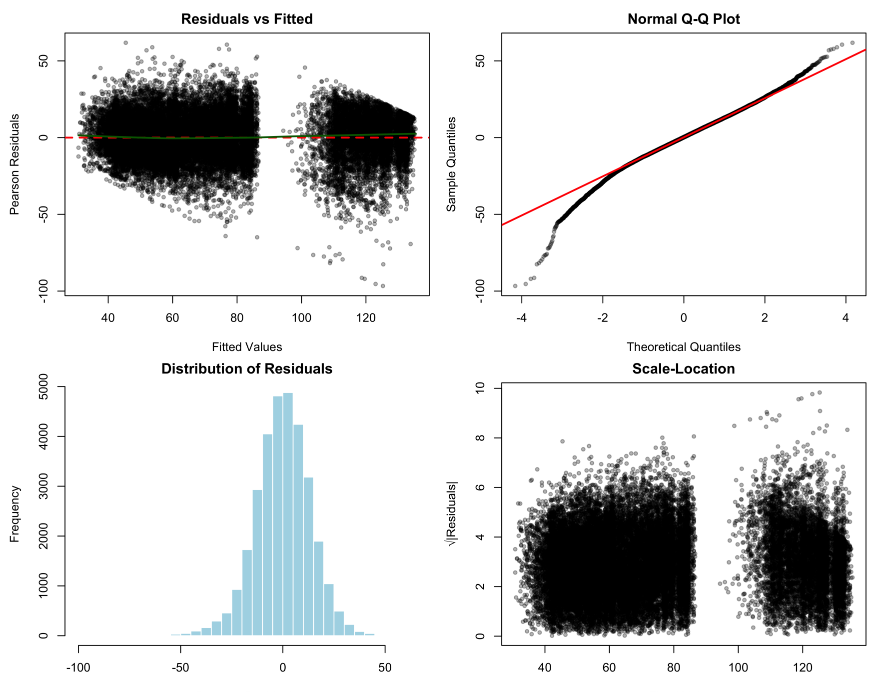

Figure 5: Diagnostic plots for the mathematics moderation model

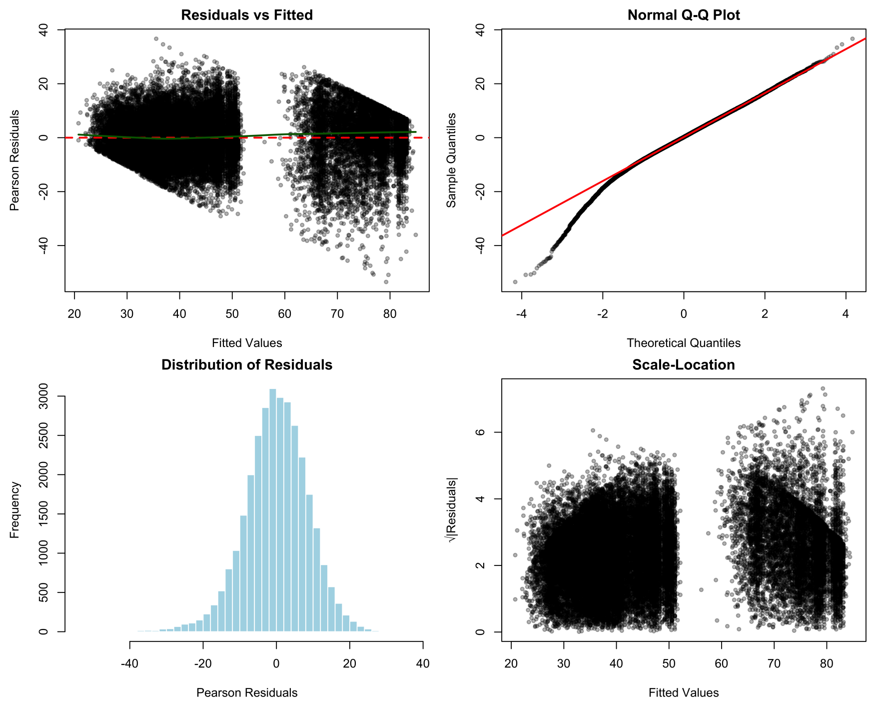

Figure 6: Diagnostic plots for the science moderation model