Effect of Free Lunch Qualification on Math Test Scores for High School Students

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Introduction

Various socioeconomic factors may affect student academic performance. One factor that may contribute to academic performance is family income level. Previous studies have shown that income level has a significant influence on academic performance. For example, one study in Botswana measured math test scores in secondary school students and found that students that come from families with higher incomes tend to perform better. They also found that students of low socioeconomic status scored about 10% lower than students of high socioeconomic status (Baylian, Rao, and Baylian, 2012). One measure of income level is whether or not a student qualifies for free or reduced lunch. Students with family incomes under 130% of the federal poverty line are eligible for free meals, and students with family incomes between 130% and 185% of the poverty line are eligible for reduced meals (Danielson, 2021).This project aims to determine if free/reduced lunch qualification is correlated with student academic performance.

Data

The data is from Kaggle (Ofosu 2018), taken from the IBM SPSS Statistics V25.0 package (IBM 2021). Pre-test and post-test scores for math were recorded for students from 27 schools. Pre-test scores were recorded at the beginning of the school year, and post-test scores were recorded at the end of the school year. Overall, there were 97 classrooms and 2209 students. The variables included are school, school setting (urban, suburban, rural), school type (public, non-public), classroom, teaching method (standard, experimental), number of students per classroom, gender (male, female), reduced/free lunch (qualifies, does not qualify), pre-test score, and post-test score.

Exploratory Data Analysis

We did a preliminary analysis to determine the relationship between different covariates and the post-test scores. We created density plots of post-test scores by school setting, school type, teaching method, gender, and free/reduced lunch qualification (Figure 2). All of these variables had different test score distributions for each category, except gender. For school setting, the students in suburban schools had the highest mean of 76.04. The mean post test score in rural settings was 64.05, and the mean post test score in urban settings was 61.75. For school type, the mean of post test scores is equal to 75.96 in non-public schools, which is higher than the mean of post test scores in public schools, which is 64.02. For teaching method, the mean post test score of students that were taught with the standard teaching method was 63.85, which is lower than the mean test score of students taught with the experimental teaching method, which was 72.98. For gender, there was no difference in means, with a mean post test score of 68.2 in males and 68 in females. For free/reduced lunch qualification, the mean post test score of students that qualified for free/reduced lunch was 57.48, which was lower than the mean post test score of students that did not qualify, which was 74.38 (Table 1).

We also looked at the distribution of post-test scores for each school type, teaching method, and lunch qualification within the school settings (Figure 3). For suburban schools, the mean post test score was 75.09 for public schools and 78.61 for non-public schools. The mean post test score for standard teaching method was 72.85 and for experimental teaching method the mean was

80.9. The mean post test score for students that qualified for free/reduced lunch was 67.78 and the mean for those that did not qualify was 80.35 For urban schools, the mean post test score was 56.26 in public schools and 75.32 in non-public schools. For the standard teaching method, the mean post test score was 60.4 and for the experimental teaching method, the mean was 64.84. For students that qualified for reduced/free lunch, the mean post test score was 51.42, and for those that did not qualify, the mean was 71.16. For rural schools, the mean post test score was 62.08 in public schools and 72.42 in non-public schools. For the standard teaching method, the mean post test score was 58.28 and for the experimental teaching method, the mean was 73.93. For students that qualified for reduced/free lunch, the mean post test score was 57.81, and for students that did not qualify, the mean was 69.60 (Table 2).

Hierarchical Model

We decided to build our hierarchy with the school setting variable, which includes Rural, Suburban, and Urban as categories (Figure 1). Based on our exploratory data analysis, we found that the distribution of post test scores had different distributions for each setting. Additionally, we cannot assume exchangeability for students in each school setting because academic outcomes may vary significantly between suburban, urban, and rural settings. According to a study done on the racial-ethnic segregation and educational inequality across the urban-suburban divide, suburban schools had lower poverty rates and higher test scores than urban schools (Owens and Rich, 2023).

We fit a linear regression model using Stan with school setting as a level to predict post-test scores. Our covariates were free lunch, school type, gender, and teaching method. School type was included in the model because it affects both test scores and free lunch qualification, making it a confounder variable. Studies have shown that students in private schools tend to perform better on tests than public schools (School and Student Services, 2023). Since private schools cost more than public schools, we assume that students are less likely to qualify for free lunch at private schools compared to public schools. Teaching method is a precision variable because it affects post-test scores directly. Based on our exploratory analysis, students who had the experimental teaching method had a higher average post-test score average than those who had the standard teaching method. Pre-test score was not included since it is a mediating variable. We assume that free lunch qualification has an effect on pre-test score and pre-test score has an effect on post-test score.

For the lunch variable, we coded “Qualifies for free lunch” as 0 for the base, and “Doesn’t qualify” as 1. For school type, we coded “Non-public” as 0 for the base, and “Public” as 1. For gender, we coded “Male” as 0 for the base, and “Female” as 1. For the teaching method, we coded “Experimental” as 0 for the base, and “Standard” as 1. The slope coefficients for these variables would be interpreted as the change in post-test score when going from the category 0 to category 1.

For our hierarchical model, we used a normal distribution with mean 0 and standard deviation 10 as the prior for the mean μ of the coefficients for each predictor variable. For the individual setting intercepts (α_j), where j = urban, suburban, and rural, we used a normal distribution with mean 0 and standard deviation 10 as the prior. For the school setting level standard deviation (σ_j), we used a Cauchy distribution with parameters 0 and 2.5. For the setting-specific slope coefficients ($ß_{j,d}$), where d is each covariate, we used a normal distribution with mean μ and standard deviation σ_j. For the residual standard deviation (σ_Y), we used a Cauchy distribution with parameters 0 and 2.5. The likelihood, Y, follows a normal distribution with mean α_j+X*$ß_{j,d}$ and standard deviation σ_Y. The prior distributions and likelihood are shown below.

$$\mu_d \sim Normal(0, 10)$$
$$\alpha_j \sim Normal(0, 10)$$
$$\sigma_j \sim Cauchy(0,\ 2.5)$$
$$\beta_{j,d} \sim Normal(\mu_d, \sigma_j)$$
$$\sigma_Y \sim Cauchy(0,\ 2.5)$$
$$y_{ij} \sim Normal(\alpha_j + X\beta_j, \sigma_Y)$$

Results

After running MCMC, we can see that the distributions for each of the parameters have converged, shown in the trace plots in Figure 4.

The regression model for each setting is shown below. X_1 is lunch qualification, X_2 is school type, X_3 is gender, and X_4 is teaching method.

$$y_{rural} = 53.087 + 11.768X_1 - 5.373X_2 + 0.152X_3 - 5.992X_4$$
$$y_{suburban} = 57.271 + 12.989X_1 - 1.583X_2 - 0.117X_3 - 1.348X_4$$
$$y_{urban} = 49.464 + 15.590X_1 - 12.200X_2 + 0.476X_3 + 0.958X_4$$

The distributions of the coefficients are shown in Figure 5.

Analysis

Analysis of Free Lunch Qualification Coefficient

Free lunch qualification affected test scores in urban areas the most, with those that do not qualify for free/reduced lunch having an expected post test score that is 15.590 points higher than those who qualify. In suburban settings, those that do not qualify for free/reduced lunch have an expected post test score that is 12.989 points higher than those that qualify. In rural settings, those that do not qualify have an expected post test score that is 11.768 points higher than those that qualify.

The standard deviation of the coefficient for lunch qualification, $ß_1$, is 0.597 for the urban setting, 0.662 for the suburban setting, and 0.709 for the rural setting. These values are relatively small compared to the means, which means that the model is relatively certain on the values of $ß_1$ for each setting. The 95% prediction interval for urban setting is [14.4, 16.71], suburban is [11.64, 14.29], and rural is [10.38, 13.14]. Additionally, all the simulated samples of $ß_1$ for every setting were positive. This tells us that when going from qualifying for free/reduced lunch to not qualifying, the post-test score is expected to increase.

Analysis of other coefficients

Looking at school type, those in urban public schools have an expected post test score that is 12.2 points lower than those in urban non-public schools. In suburban settings, those who are in public schools have an expected post test score that is 1.583 points lower than those in non-public schools. In rural settings, those in public schools have an expected post test score that is 5.373 points lower than those in non-public schools. The standard deviation of the coefficient for school type, $ß_2$, is 0.646 for urban, 0.694 for suburban, and 1.001 for rural. These values are relatively small compared to the mean, which means the models are relatively certain on the value of $ß_2$. The 99% prediction interval for urban setting is [-13.46, -10.93], suburban is [-2.9, -0.22], and rural is [-7.33, -3.44]. Additionally, the simulated samples of $ß_2$ were all negative for urban and rural settings, and were negative 98.78% of the time for suburban. This tells us that when going from non-public schools to public schools, the post-test score is expected to decrease.

Looking at gender, in urban settings, females have an expected post test score that is 0.476 points higher than males. In suburban settings, females have an expected post test score that is 0.117 points lower than males. In rural settings, females have an expected post test score that is 0.152 points higher than males. The standard deviation of the coefficient for gender, $ß_3$, is 0.488 for urban, 0.527 for suburban, and 0.555 for rural. These values are relatively large compared to the mean, which means the models are not very certain on the value of $ß_3$. The 99% prediction interval for urban setting is [-0.41, 1.5], suburban is [-1.21, 0.82], and rural is [-0.98, 1.27]. Additionally, the simulated samples of $ß_3$ were positive 83.28% and 61.52% of the time for urban and rural settings, respectively. The simulated samples were negative 57% of the time for suburban settings. This means that we cannot conclude that going from female to male leads to an increase in post-test scores for rural and urban schools and we cannot conclude that going from female to male leads to a decrease in post-test scores for suburban schools.

Looking at teaching methods, those who were exposed to a standard teaching method have an expected post test score that is 0.958 points higher than those who were exposed to an experimental teaching method. In suburban settings, those who were exposed to a standard method have an expected post test score that is -1.34 points lower than those who were exposed to an experimental teaching method. In rural settings, those who were exposed to a standard method have an expected post test score that is -5.99 points lower than those who were exposed to an experimental teaching method. The standard deviation of the coefficient for teaching method, $ß_4$, is 0.581 for urban, 0.64 for suburban, and 0.812 for rural. These values are relatively small compared to the mean, which means the models are relatively certain on the value of $ß_4$. The 99% prediction interval for urban setting is [-0.131, 2.088], suburban is [-2.57, -0.12], and rural is [-7.54, -4.36]. Additionally, the simulated samples of $ß_4$ were all negative for rural, negative 98.5% of the time for suburban, and positive 95.73% of the time for urban. This tells us that for rural and suburban settings, going from experimental teaching methods to standard teaching methods leads to a decrease in post-test scores. For urban settings, going from experimental methods to standard teaching methods leads to an increase in post-test scores.

Conclusion

Students that qualified for free/reduced lunch tended to have lower post test scores compared to those that did not qualify. Since this is a measure of income, it shows that those with lower household income are expected to have lower test scores. There could be several factors contributing to this. Those with lower incomes may not be able to afford private tutoring. In addition, students of lower income may have to help their families financially, and may not prioritize academics.

In addition, test scores tended to be higher for students in suburban areas compared to urban and rural areas. This could also be related to income, as higher income families tend to live in suburban areas. Interestingly, those that qualified for free/reduced lunch in suburban areas also tended to score higher than those that qualified in urban and rural areas. Studies have shown that schools with a more negative school climate, which is defined as an excess of disciplinary issues, may have lower academic achievement. It has also been shown that suburban schools tend to have more positive school climate than urban schools (Sulak 2016). The difference in school climate may be one factor that contributes to the difference. Other factors that may be further explored could be the surrounding environment, such as the crime rate.

The dataset that we used had limitations, and did not include many covariates. One study has found that parents' education level is related to income, so this may be a confounding variable that we should add into the model in the future (NCCP 2007). Further research on other socioeconomic factors can be done for improvement of our model.

We conclude that free/reduced lunch qualification has a significant effect on post test scores in math for high school students.

Appendix
Figures

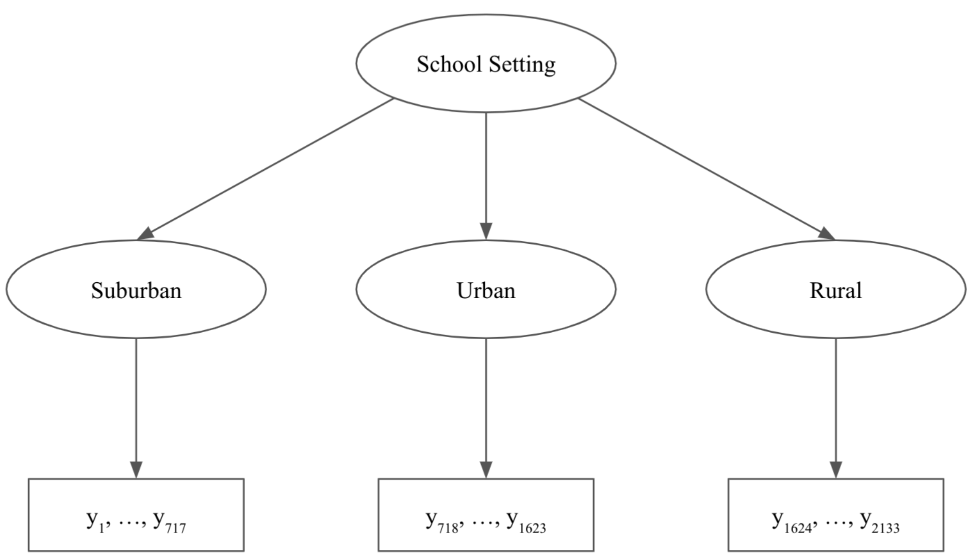

Figure 1. Hierarchy of the model

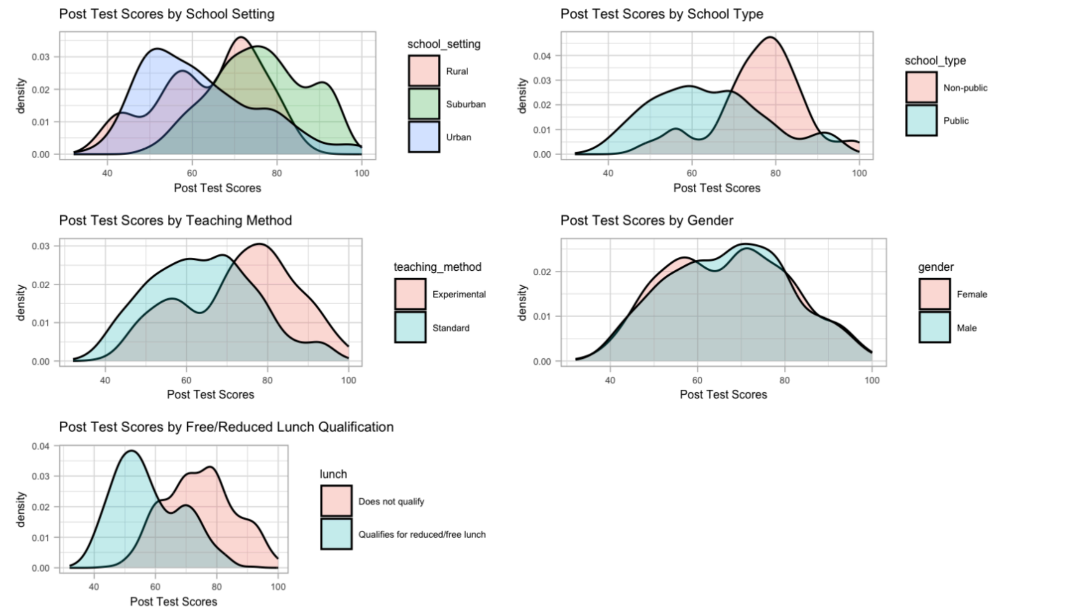

Figure 2. Density plots of post test scores for school setting, school type, teaching method, gender, and free/reduced lunch qualification

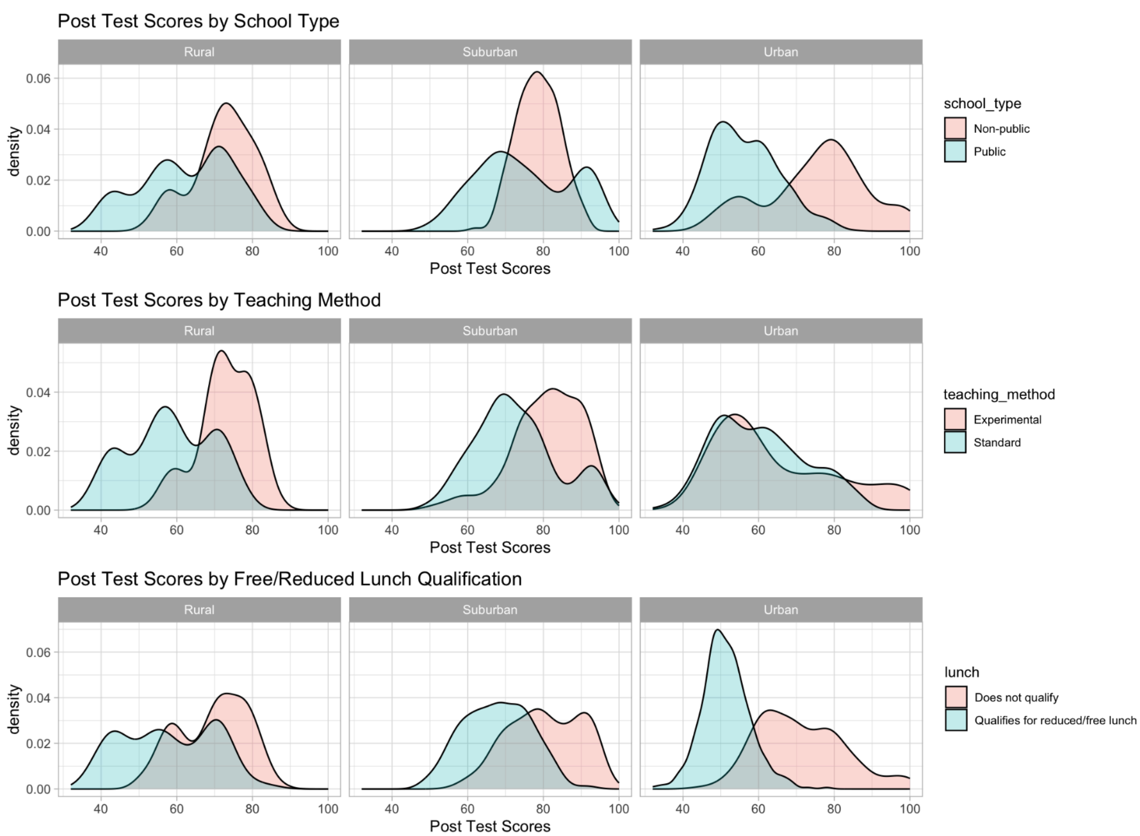

Figure 3. Density plots of post test scores for school type, teaching method, and free/reduced lunch qualification for each school setting

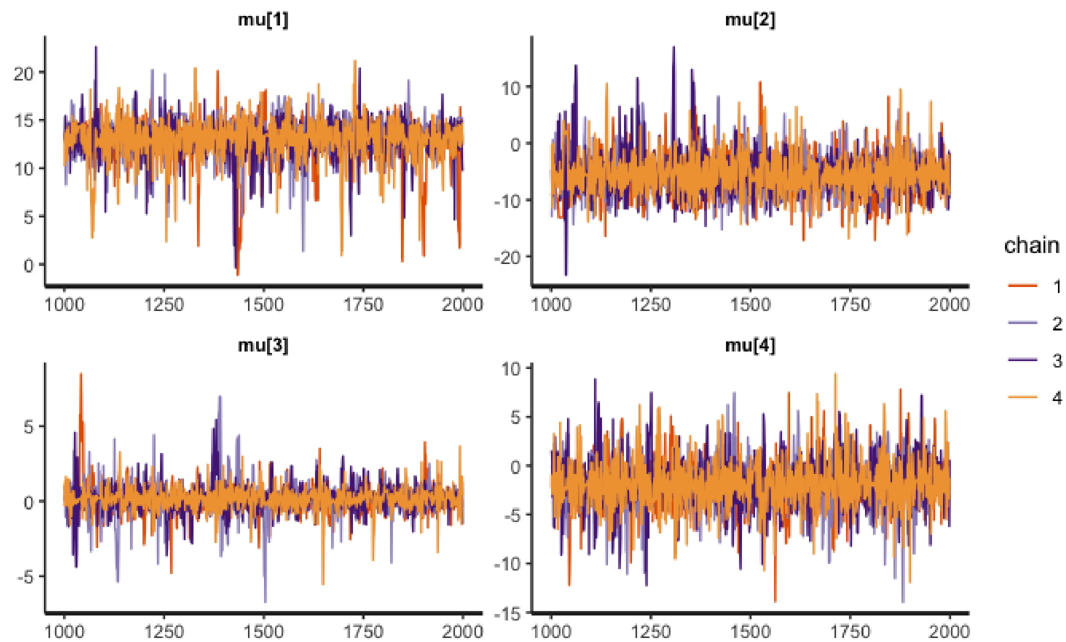

Figure 4a. Traceplots of the mean of the ß coefficients

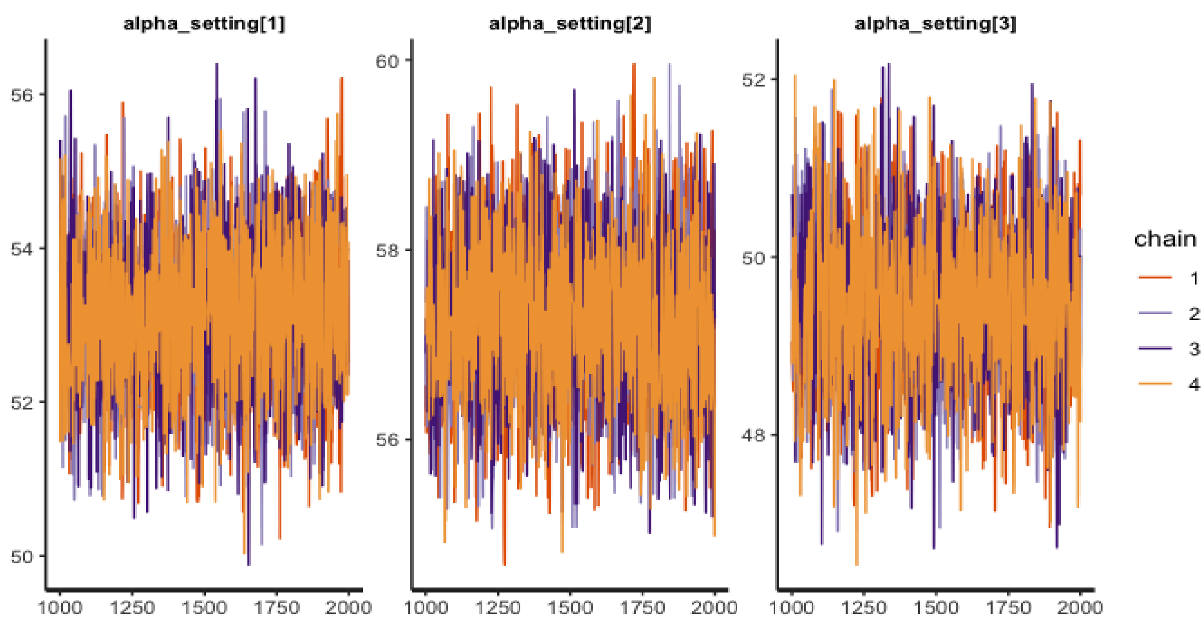

Figure 4b. Traceplots of the individual settings' intercept terms

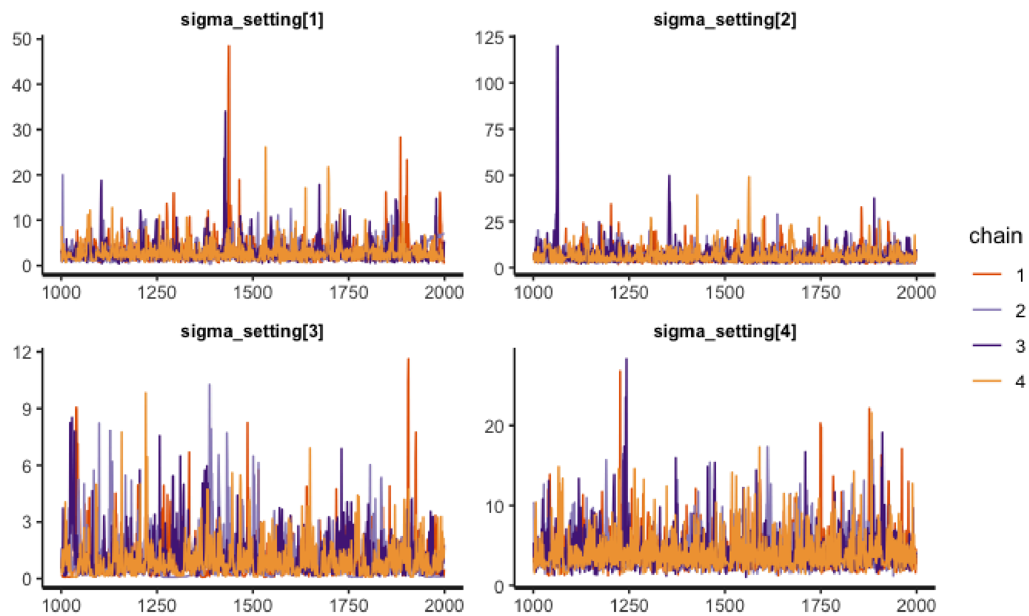

Figure 4c. Traceplots of the standard deviation of each coefficient

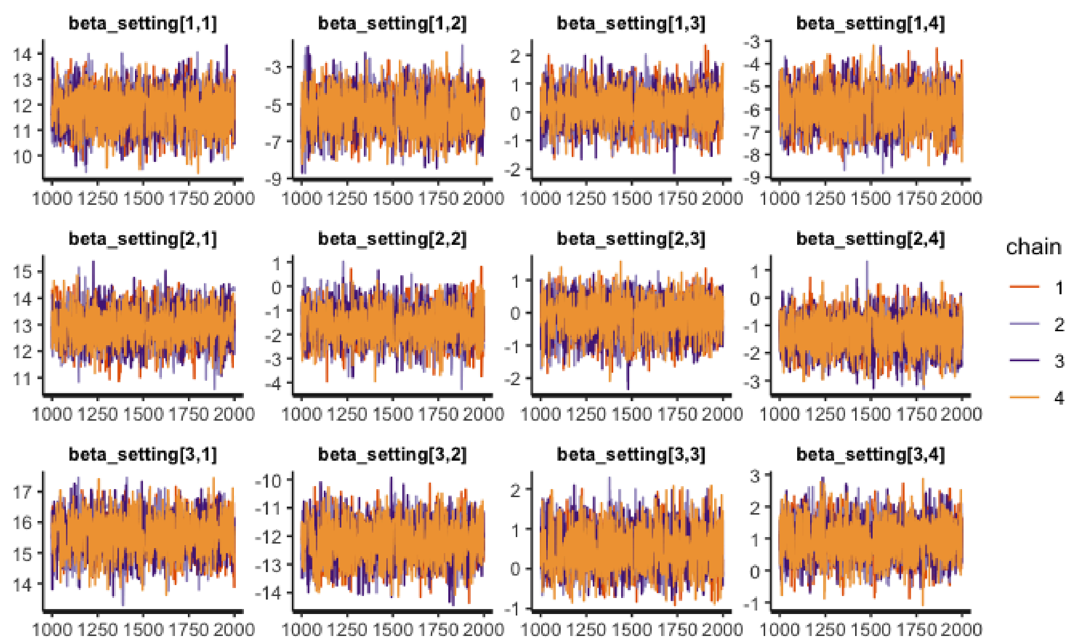

Figure 4d. Traceplots of every ß coefficient for each school setting

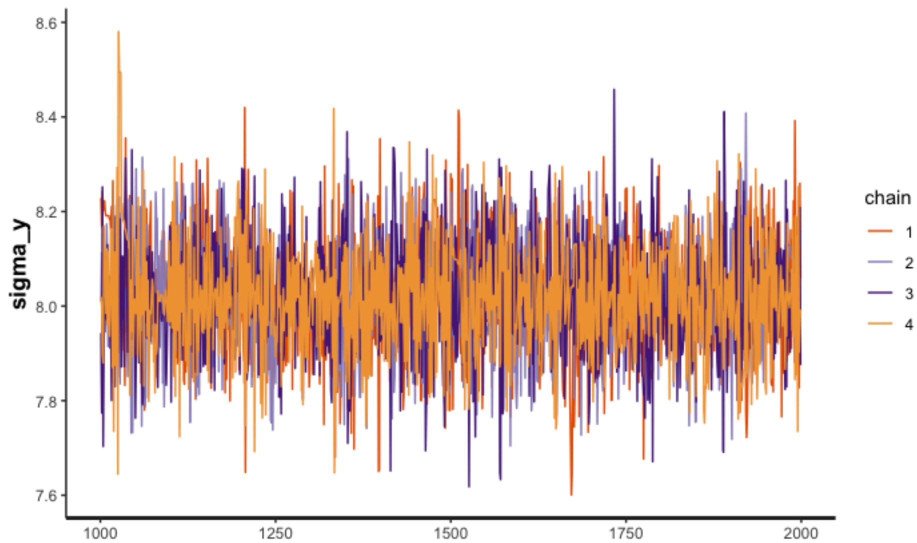

Figure 4e. Traceplot of residual standard deviation

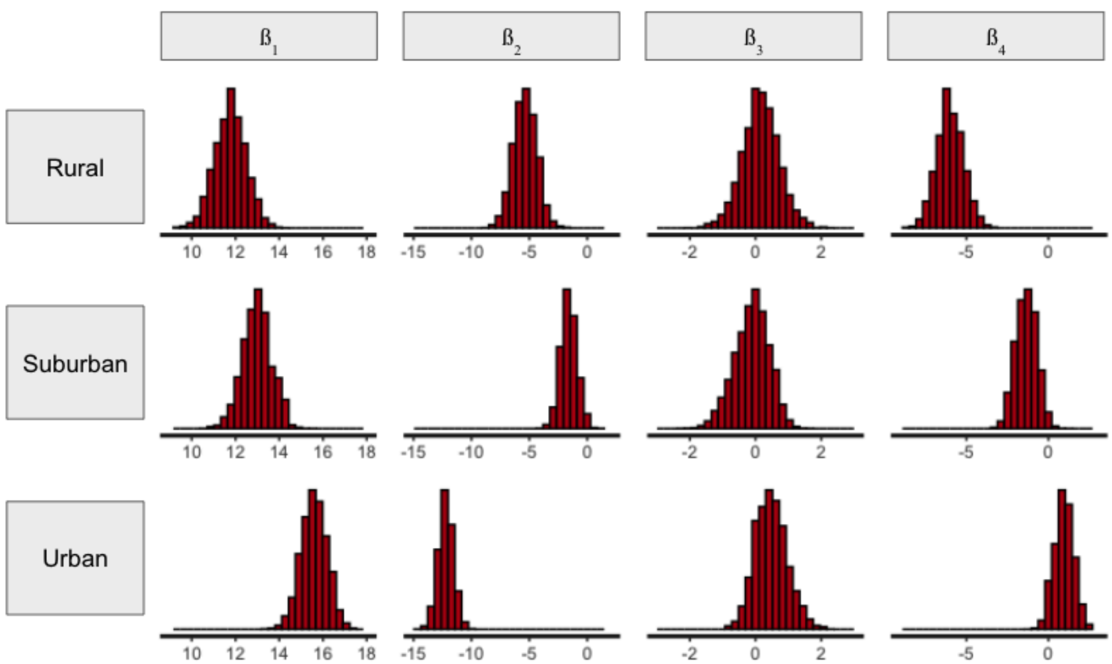

Figure 5. Posterior distributions of every ß coefficient for each school setting

Tables

		Mean Post Test Score
School setting	*Urban*	61.75
	Suburban	76.04
	Rural	64.05
School Type	*Public*	64.02
	Non-public	75.96
Teaching Method	*Standard*	63.85
	Experiemental	72.98
Gender	*Male*	68.2
	Female	68
Lunch Qualification	*Qualifies*	57.48
	Does not Qualify	74.38

Table 1. Mean post test score for each category of school setting, school type, teaching method, gender and lunch qualification covariates

			Mean Post Test Score
Urban	**School Type**	*Public*	56.26
		Non-public	75.32
	Teaching Method	*Standard*	60.4
		Experimental	64.84
	Lunch Qualification	*Qualifies*	51.42
		Does not Qualify	71.16
Suburban	**School Type**	*Public*	75.09
		Non-public	78.61
	Teaching Method	*Standard*	72.85
		Experimental	80.9
	Lunch Qualification	*Qualifies*	67.78
		Does not Qualify	80.35
Rural	**School Type**	*Public*	62.08
		Non-public	72.42
	Teaching Method	*Standard*	58.28
		Experimental	73.93
	Lunch Qualification	*Qualifies*	57.81
		Does not Qualify	69.6

Table 2. Mean post test score for school type, teaching method, and lunch qualification categories for each school setting

		Mean	Standard Deviation	95% Prediction Intervals
Rural	$ß_1$	11.768	0.709	[10.382, 13.138]
	$ß_2$	-5.373	1.001	[-7.329, -3.442]
	$ß_3$	0.152	0.556	[-0.98, 1.272]
	$ß_4$	-5.992	0.812	[-7.548, -4.362]
Suburban	$ß_1$	11.768	0.709	[10.382, 13.138]
	$ß_2$	-1.583	0.695	[-2.915, -0.225]
	$ß_3$	-0.117	0.527	[-1.209, 0.821]
	$ß_4$	-1.348	0.640	[-2.57, -0.119]
Urban	$ß_1$	15.590	0.597	[14.401, 16.711]
	$ß_2$	-12.200	0.646	[-13.456, -10.932]
	$ß_3$	0.476	0.488	[-0.409, 1.496]
	$ß_4$	0.958	0.582	[-0.131, 2.089]

Table 3. Mean, standard deviation, and 95% prediction intervals for every ß coefficient for each school setting

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