The Impacts of Household Income on Kindergarten Education Outcomes

By: Bonnie Yam

Introduction

Even though kindergarten programs are not mandatory for children, this play-based learning curriculum is a strong start in school. Not only does it provide an opportunity for children to build their socialization, but it also improves their early reading and math skills. There are findings that poverty can negatively affect a student's academic performance due to limited resources, chronic stress, and the risk of poor health (Engle and Black, 2008). The rise of income inequality leads to an investigation of the impacts of household income on kindergarten education outcomes. The *INF2178_A3_data.csv* dataset is analyzed to address the fundamental research question: does household income have an impact on kindergarten students' reading and math scores after accounting for their scores from the previous evaluation?

Data Features

The scores of 11,933 kindergarten students were analyzed in the 1998-1999 early child longitudinal study. Columns were renamed in the dataset to be more clear. The following features have no missing values and are notable for this research project:

- `Fall_Reading_Score`: The reading score in fall 1998.
- `Fall_Math_Score`: The math score in fall 1998.
- `Spring_Reading_Score`: The reading score in spring 1999.
- `Spring_Math_Score`: The math score in spring 1999.
- `Household_Income`: The amount of household income.
- `Income_Group`: Based on the household income, each child is assigned into one of the three income groups: low (i.e. less than $40,000), middle (i.e. between $40,000 and $69,999), and high (i.e. at least $70,000).

Exploratory Data Analysis

The low-income group has the largest sample size with 4,729 children. The middle-income group has 3,726 children, whereas the high-income group has 3,478 children. For each income group, the math median score is lower than the reading median score, which implies that reading is their academic strength (see Table 1 and Table 2). The high-income group has the highest reading median score (i.e. 37.58 in the fall and 48.74 in the spring), and the highest math median score (i.e. 29.09 in the fall and 41.03 in the spring). The low-income group has the lowest reading median score (i.e. 31.66 in the fall and 41.97 in the spring), and the lowest math median score (i.e. 22.79 in the fall and 32.27 in the spring). This meets the prediction that children from a high-income family achieve better marks than the other two income groups. After comparing the median scores between fall 1998 and spring 1999, it appears that the children's reading and math scores improved regardless of the income group they belonged to. Within the same season for each subject, there are minor differences in the interquartile range (IQR) between income groups (i.e. approximately 1-3 points difference). However, all income groups have a long trail of outliers as shown in Figure 1 and Figure 2. The highest reading score 156.85 was achieved by a child from the high-income class in spring 1999. A student from the same income group achieved the highest math score 115.65, but in fall 1998.

Season	Fall 1998			Spring 1999		
Income Group	High	Middle	Low	High	Middle	Low
Min	23.01	22.19	21.01	24.54	23.93	22.35
Max	133.56	138.51	118.29	156.85	142.49	142.49
25th percentile	32.78	30.27	27.10	42.78	39.87	36.10
Median	37.58	34.53	31.66	48.74	46.07	41.97
75th percentile	44.23	40	36.05	56.24	52.17	48.53
IQR	11.45	9.73	8.95	13.46	12.30	12.43

Table 1. Summary statistics for reading scores.

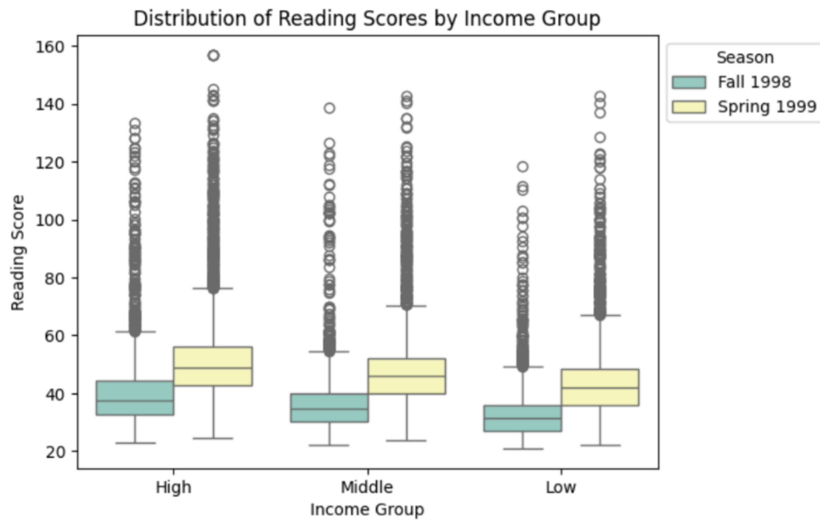

Figure 1. Boxplot of reading scores by season and income group

Season	Fall 1998			Spring 1999		
Income Group	High	Middle	Low	High	Middle	Low
Min	10.90	11.59	10.51	12.70	13.14	11.90
Max	115.65	83.42	86.33	113.80	110.33	105.06
25th percentile	24.37	21.52	18.61	33.85	30.39	26.41
Median	29.09	26.14	22.79	41.03	37.04	32.27
75th percentile	35.67	31.78	25.57	48.46	44.70	40.10
IQR	11.30	10.26	8.96	14.62	14.31	13.69

Table 2. Summary statistics for math scores.

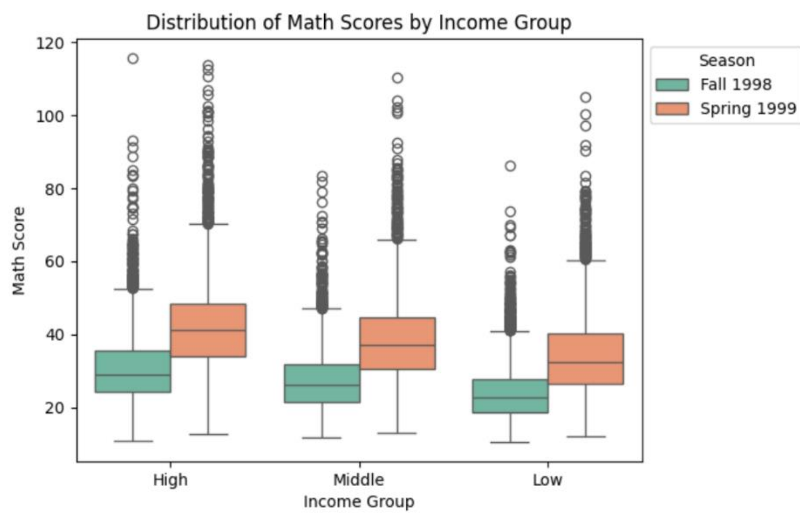

Figure 2. Boxplot of math scores by season and income group

Quantitative Analysis

For each subject, one-way ANCOVA was performed to determine whether there was a statistically significant difference in scores between three groups of household income. The assumptions of ANCOVA are normality, homoscedasticity, and linearity between the control variable and outcome.

Impacts of Household Income on Reading Scores

According to the Shapiro-Wilk test shown in Table 3, the null hypothesis is rejected with p-value < 0.001 at a significance level of $\alpha = 0.05$. Due to this violation of normality, Levene's test was used to check the homogeneity of variances (see Table 4). The p-value < 0.001, thus the null hypothesis of equal variances between income groups is rejected as well at a critical threshold of $\alpha = 0.05$. In the scatterplot shown in Figure 3, each income group has a positive linear relationship between the fall reading score (covariate variable) and the spring reading score (dependent variable). Therefore, the assumption of linearity is satisfied. Although the slopes of the three regression lines are approximately close in Figure 3, it seems that there is an intersection where the fall reading score is 40 and the spring reading score is 50. This suggests that there may be an interaction between income group and fall reading scores. However, it is difficult to determine whether there is an actual intersection in the scatterplot since the points are heavily concentrated in the bottom left corner of the graph. This can be tested by adding an interaction term in the ANCOVA fitted model (see Table 6).

Test Statistic	P-value
0.912	$p < 0.001$

Table 3. Shapiro-Wilk test to check normality of residuals in reading scores.

Test Statistic	df	P-value
39.553	2	$p < 0.001$

Table 4. Levene's test to check homogeneity of variances in reading scores.

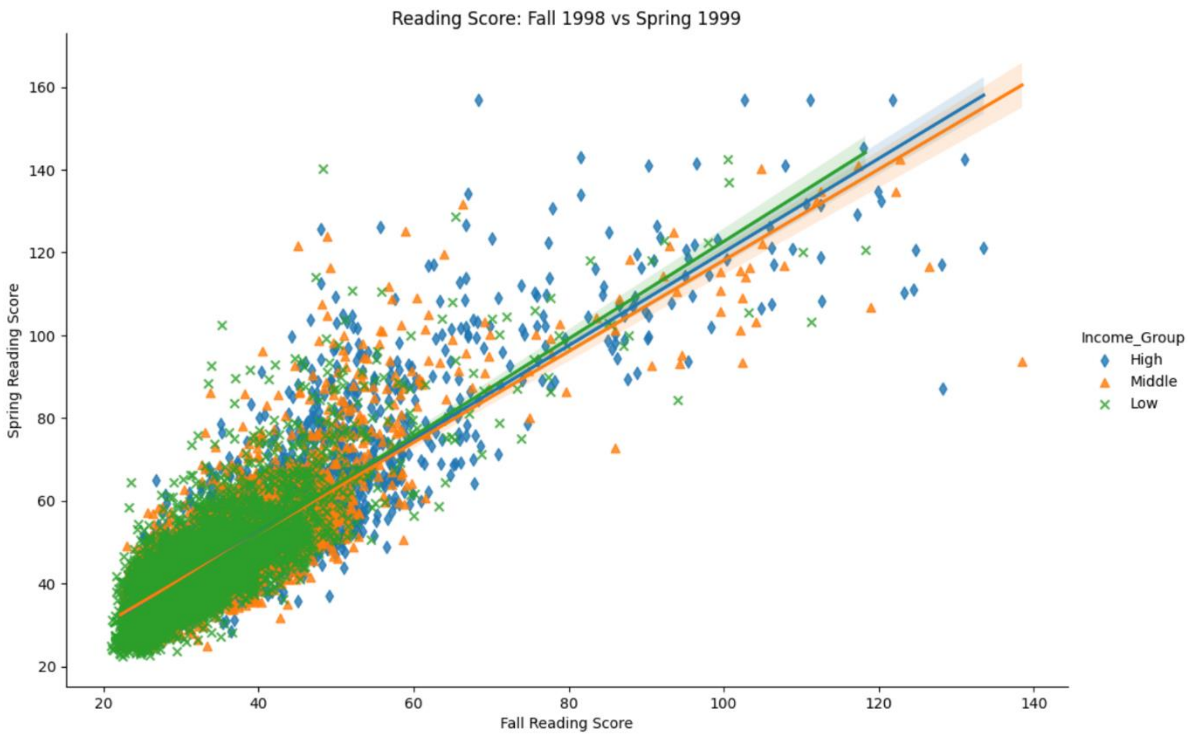

Figure 3. Scatterplot of fall reading scores vs spring reading scores for each income group.

Source	df	Sum of Squares	F-value	P-value
Income Group	2	513.120	4.056	0.017
Fall Reading Score	1	1.547×10^6	24455.398	$p < 0.001$
Residual	11929	7.546×10^5		

Table 5. One-way ANCOVA summary table for reading scores.

	Coefficient	Standard Error	t	P-value
Intercept	7.135	0.458	15.579	$p < 0.001$
Low-income	-1.999	0.665	-3.006	0.003
Middle-income	0.950	0.671	1.416	0.157
Fall Reading Score	1.130	0.011	102.980	$p < 0.001$
Low-income * Fall Reading Score	0.046	0.018	2.526	0.012
Middle-income * Fall Reading Score	-0.030	0.017	-1.737	0.082

Table 6. Regression results for reading scores.

As indicated in the one-way ANCOVA summary in Table 5, the F-value for the fall reading score is 24455.398 and it yields a p-value < 0.001, thus this covariate is statistically significant. For the income group, the F-value is 4.056 and the p-value is 0.017, which is less than the critical threshold of $\alpha = 0.05$. There is strong evidence that there is a statistical difference in the spring reading scores between income groups while adjusting the effect of the fall reading score.

The multiple linear regression model in Table 6 considers the high-income group as the base category. Both the middle-income group (t = 1.416, p-value = 0.157) and the interaction between this group and the fall reading score (t = -1.737, p-value = 0.082) are not strong predictors of the spring reading score. In other words, the middle-income group's spring reading score is not statistically different from the high-income group after controlling the effect of the covariate. On the contrary, the low-income group is a strong predictor of the spring reading score. Its negative coefficient (-1.999) suggests their spring reading score is lower than the high-income group's reading score. The slope of the fall reading score for the low-income group is statistically different from that of the high-income group (t = 2.526, p-value = 0.012). For 1 score increase in reading during fall, the mean change in the spring reading score is about 0.05 points higher for the low-income group than the high-income group. This is supported by the observation in Figure 3 that the slope of the low-income group regression line is remarkably a bit steeper than the high-income group.

Impacts of Household Income on Math Scores

Both the Shapiro-Wilk test and Levene's test reveal the p-value < 0.001, hence the assumptions of normality and homoscedasticity are violated (see Table 7 and Table 8). However, there is no violation against the assumption of linearity between the fall math score (covariate variable) and the spring math score (dependent variable). According to the scatterplot in Figure 4, the spring math score increases as the fall math score increases, which depicts a positive linear relationship. It appears that the regression line of the middle-income group intersects with the regression line of the high-income group when the fall math score is 50 and the spring reading score is 60. Also, the regression line of the low-income group intersects with the other two regression lines when the fall math score is 35 and the spring math score is 45. Once again, the points are clustered close together, which makes it hard to recognize whether an interaction effect exists.

Test Statistic	P-value
0.965	p < 0.001

Table 7. Shapiro-Wilk test to check normality of residuals in math scores.

Test Statistic	df	P-value
18.90	2	p < 0.001

Table 8. Levene's test to check homogeneity of variances in math scores.

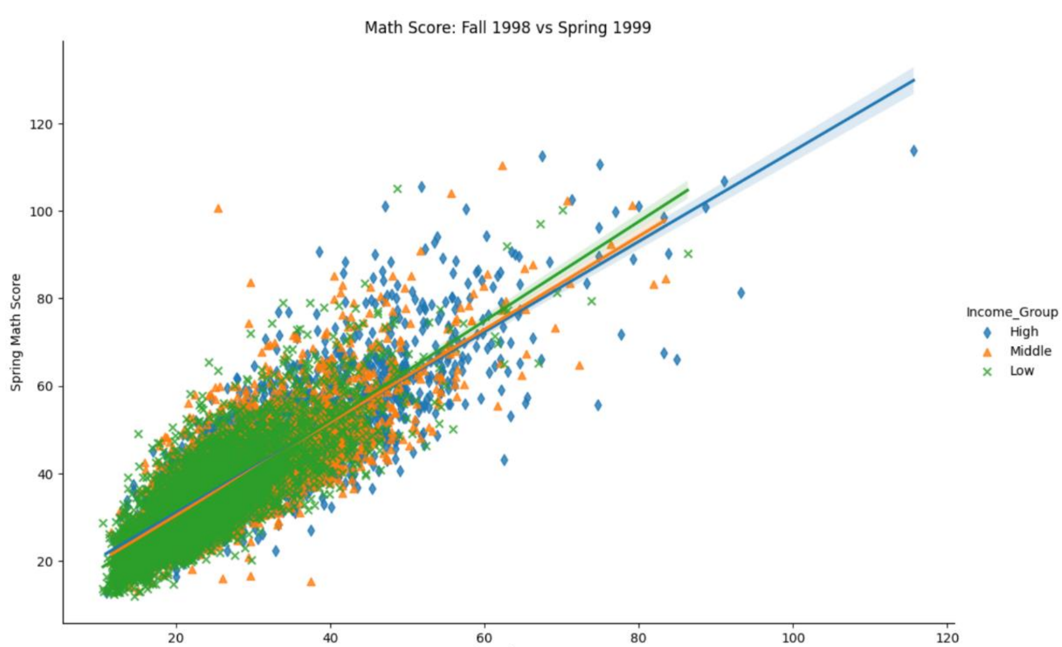

Figure 4. Scatterplot of fall math scores vs spring math scores for each income group.

Source	df	Sum of Squares	F-value	P-value
Income Group	2	1712.758	18.524	$p < 0.001$
Fall Math Score	1	1.026×10^6	22203.081	$p < 0.001$
Residual	11929	5.515×10^5		

Table 9. One-way ANCOVA summary table for math scores.

	Coefficient	Standard Error	t	P-value
Intercept	10.390	0.378	27.518	$p < 0.001$
Low-income	-3.664	0.498	-7.359	$p < 0.001$
Middle-income	-1.215	0.533	-2.280	0.023
Fall Math Score	1.033	0.012	89.053	$p < 0.001$
Low-income * Fall Math Score	0.103	0.017	5.908	$p < 0.001$
Middle-income * Fall Math Score	0.030	0.017	1.714	0.087

Table 10. Regression results for math scores.

The one-way ANCOVA summary in Table 9 presents the fall math score as statistically significant (F-value = 22203.081, p-value < 0.001). While adjusting the effect of the fall math score, there is a statistical difference in the spring math scores between income groups (F-value = 18.524, p-value < 0.001). This can be further explored in the regression model from Table 10. Not only that the low-income group (t = -7.359, p < 0.001) and the middle-income group (t = -2.280, p = 0.023) are strong predictors of the spring math score, but also their projected intercepts are lower than the high-income group. Given the low-income group, the effect of the fall math score on the spring math score is about 0.10 points higher than the effect of those given the high-income group. Similar manner to the reading scores scatterplot in Figure 3, the slope of the low-income group regression line is steeper than the high-income group in the math scores scatterplot in Figure 4. The only variable in the model that is not statistically significant is the interaction term between the middle-income group and the fall math score. This finding is also visible in Figure 4, such that the slope of the middle-income group regression line is almost the same as the slope of the high-income group regression line.

Discussion

The main similarity in the analytical results between the reading and math scores is that the children's academic performance in spring was roughly the same or better than their scores recorded back in the fall, regardless of their socioeconomic status. Therefore, the teaching methods at their school seem sufficient to help improve or maintain the students' marks without the need for private tutoring, which is often pursued in strict high or middle-income families to help their child excel, even at a young age. However, those extra lessons might explain why the children from the low-income group got lower spring reading and math scores than those from the high-income group after controlling the effect of the fall scores. The low-income group's outcome may not be as high as the wealthy, but they achieved a greater mean change in academic outcome. This shows their motivation to learn is probably more than the high-income group. The mean difference in the spring scores between the middle-income and high-income groups is statistically significant in math, but not for reading. This is a sign that math is the middle-income group's weakest subject.

Limitations

Although the assumption of linearity between the control variable and outcome was met, the other two assumptions of normality and homoscedasticity were violated in the one-way ANCOVA. Therefore, it hinders our confidence in the validity of the results. The total sample size is over 5000. This huge sample size and the presence of outliers may be the reasons behind these two violations. Since median is more resistant to outliers, the Kruskal-Wallis test can be considered.

Conclusion

The quantitative analysis from the one-way ANCOVA concludes that household income has a significant impact on kindergarten students' reading and math scores in spring 1999 after accounting for their scores from fall 1998. In both essential subjects, the academic outcomes of children in low-income families are statistically different from children in high-income families. To minimize these differences, offering educational resources to unprivileged students can help create opportunities for learning growth. Additionally, more community support is needed to reduce the interference of their daily struggles in their studies. For future work, we can extend our research by investigating whether the gap in academic success is larger for high school students from different socioeconomic backgrounds.

Reference

Engle, P. L., & Black, M. M. (2008). The Effect of Poverty on Child Development and Educational Outcomes. *Annals of the New York Academy of Sciences, 1136*(1), 243–256. https://doi.org/10.1196/annals.1425.023