The Effect of Maternal College Education and Maternal Marital Status at a Child’s Birth on Test Scores

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Abstract: This article examines if a mother's education and social status affect her child's test scores. This work uses the linear regression model to obtain the T-test and F test from over 8,000 experimental participants. To assess if there is a correlation between the mother's history and the child's test scores and if the mother's impact is significant, the White Test for Heteroskedasticity is applied to the data to determine if the variance of the errors in a regression model is constant. Finally, the mother's education and social standing affect the child's test scores.

Keywords: Test Score; Maternal College Education; Marital Status; Effect

1. Introduction and Literature Review

This paper examines how maternal traits affect children's test scores. Up to 42% of people born into the lowest socioeconomic quartile in the US remain in that income category (Jantti et al., 2006). In a country where social mobility is a growing political issue, many policymakers aim to increase mobility. Educational attainment and accessibility are vital to social mobility, therefore understanding the elements that affect it is crucial to extending it. While many factors affect students' school success, like teacher quality and class numbers, many researchers explore the impact of family characteristics on academic accomplishment. We examine how moms' marital status and college attendance affect children's test scores.

Dunifon et al. analyze how a mother's employment influences their child's academic achievement (2013). Researchers studied 135,000 Danish children from birth to 9th grade and found that a mother's working status improves their academic achievement. When a child is 0-3, each additional hour of mother's labor per week can boost their GPA by.015 points. If a mother works part time (approximately 15 hours per week) for the first 15 years of her child's life, their high school GPA will be 6.2% higher than a child with same features whose mother did not work. These findings help contextualize our paper in previous mother-child research.

In "The Impact of Parental Income and Education on the Schooling of Their Children," Chevalier et al. examine the relationship between parental education and children's academic attainment (2010). They analyze the association between UK children's school-leaving age and parental background. Researchers observed that maternal education affects children's educational attainment more than their fathers. Increasing maternal education by one year boosted daughters' likelihood of staying in school an extra year by 20%.

The literature shows a statistically significant association between moms' education and family structure and children's accomplishments. This report explains how these characteristics affect academic success.

2. Data Description

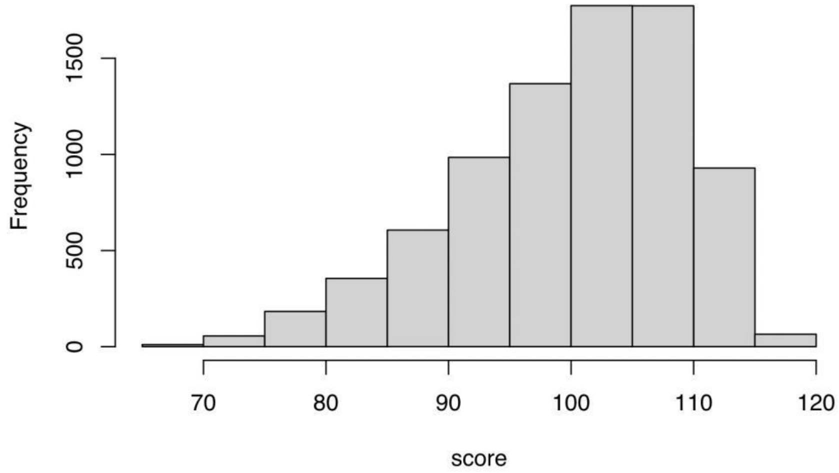

Figure 1: Average Score Distribution

Early Childhood Longitudinal Study, 1998-99 Kindergarten Class (ECLS-K). The data follow the same nationally representative group of students from kindergarten through 8th grade, with information collected via interviews and questionnaires in the spring of kindergarten(1998-99), the fall and spring of 1st grade (1999-2000), the spring of 3rd grade (2002), the spring of 5th grade (2004), and the spring of 8th grade (2007). Our data originates from the fourth round of data collecting in 2004 during the 5th grade spring semester of the selected pupils. We average math, reading, and science scores from standardized examinations with mean scores of 100 and sample standard deviations of 10. This average test score measures academic performance.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
score	8,105	100.000	9.113	67.840	94.393	106.969	117.442

Figure 1 shows the left-skewed score distribution. This means fewer children fared worse than the mean. Table 1 shows test scores. The middle 50% of average scores range from 94.39 to 106.97 out of 120, with a mean of 100.00. There are no perfect scores between 67.84 and 117.44. This table shows average student performance on all three assessments.

We want to know how a mother's marital status and degree of education affect 5th graders' scores. We employ students' gender, race, education type (public vs. nonpublic), and socioeconomic background as control variables to isolate maternal effects. We estimate socioeconomic background by family income.

Table 2: Correlation Matrix for Variables of Interest

	score	college	mom married at birth
score	1	0.361	0.305
college	0.361	1	0.252
mom married at birth	0.305	0.252	1

Table 2 gives us the correlation matrix for the non-control variables of interest. Fromthe table, we can determine that our variables have some correlation, which makes sense given that college graduates have a divorce rate of about 27 percent, as opposed to about 36 percent for those who just graduated high school (Aughinbaugh, Robles, and Sun 2013).The result of this slight multicolinearity is larger standard errors for the coefficients than we would have if the variables were uncorrelated.

3. Regression Analysis

3.1 The Regression Model

Based on our variables of interest, we constructed the following regression model:

score = β0+β1col+β2mar+β3mar∗ col+β4pub+β5fem+β6inc+β7bla+β8whi+β9his+ϵ.

Response Variable:

(a) score: average of math, science, and reading.

Independent variables:

(a) col: Dummy variable for mom's education level, 1 if she has a bachelor's degree, 0 otherwise.

(b) mar: Dummy variable for mom's marital status at birth, 1 if married, 0 otherwise.

Variables:

(a) pub: Dummy variable for student's school type, 1 if public, 0 otherwise.

(b) fem = 1 if student is female, 0 otherwise.

(c) bla, whi, his: Dummy variables for student's race, 1 if black/white/hispanic, 0 otherwise.

Table 3's first column shows our regression results.

3.2 t Test

Under MLR.1 through MLR.6, the t-statistic is the ratio of the estimated value of a parameter to its hypothesized value.

Table 3: Main Regression

	Dependentvariable:	
	score	
	OLS	*felm*
	(1)	(2)
college	6.324***	6.324***
	(0.791)	(0.753)
mom _married at birth	2.904* * *	2.904* * *
	(0.243)	(0.271)
I(mom _married _at birth ∗ college)	−2.030* *	−2.030* *
	(0.815)	(0.773)
public	−1.000* * *	−1.000* * *
	(0.224)	(0.204)
female	−1.007* * *	−1.007* * *
	(0.174)	(0.174)
family income	0.00002* * *	0.00002* * *
	(0.00000)	(0.00000)
black	−4.506* * *	−4.506* * *

	(0.407)	(0.443)
white	1.912^{***}	1.912^{***}
	(0.293)	(0.304)
hispanic	-2.743^{***}	-2.743^{***}
	(0.342)	(0.369)
Constant	96.387^{***}	96.387^{***}
	(0.404)	(0.432)

Observations	8,105	8,105
R^2	0.264	0.264
Adjusted R^2	0.263	0.263
Residual Std. Error (df = 8095)	7.825	7.825
F Statistic	321.886^{***} (df = 9; 8095)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

its standard error:

$$t_{\hat{\beta}_j} = \frac{\hat{\beta}_j}{\sqrt{v\hat{a}r(\hat{\beta}_j|X)}} \sim t_{n-k-1}$$

Where k+1 is the number of unknown parameters in the population model and $n - k - 1$ represents the degree of freedom. A t-test with $H_0 : \beta_i = 0$ and $H_1 : \beta_i \neq 0$ can be used to determine whether each variable is statistically significant. R automatically finds p-values for t-statistics. Table 3 shows that all of our measured factors are statistically significant at 1% level, except for mom-married-at-birth and college interaction, which is significant at 5% level.

3.3 F Test

The F statistic gives us a measure of the impact of excluding a group of variables to test their joint significance. The F statistic is defined by:

$$\frac{SSR_r - SSR_{ur}/q}{SSR_{ur}/(n-k-1)}$$

SSR_r is the sum of squared residuals from the restricted model, and SSR_{ur} is the sum of squared residuals from the unrestricted model. q represents the number of independent variables are dropped, and n-k-1 is the degrees of freedom.

We ran an F test with $H_0 : \beta_{col} = \beta_{mar} = \beta_{mar*\ col} = 0$ as our null hypothesis and H_1 : H_0 *is not true* as our alternative hypothesis. The resulting F-statistic is 214.2237, which is larger than the critical value of 2.61 we get from the corresponding F-distribution (with $df1 = 3$ and $df2 = 8095$) at the 0.05 significant level. This suggest that the two variables and their interaction are jointly significant.

3.4 Results and Interpretation

According to Table 3, the mother's marital status at birth, college attendance, and their interaction all have a significant impact on 5th graders' average test results (p-values are all less than 0.05). We previously determined that these two factors and their interaction impact are significant.

The coefficients are 2.904 for the mother's marital status, 6.324 for the mother's college attendance, and -2.030 for their interaction term, which means that holding all other factors constant, we expect that: on average, the mean test score across the three chosen subjects of a 5^{th}-grade student whose mother is a college graduate and was married at the student's birth will be 7.198 points higher than a 5^{th}-grade student whose mother does not have a college degree and was never married.

The R2 value is merely 0.26, showing that our model explains only a small part of 5th graders' average scores (including controls).

4. Robustness

4.1 Omitted Variable Bias

Omitted variables bias occurs when nonzero regression coefficients are omitted. Rita Subba's research shows that race, gender, school type, and socioeconomic background affect and correlate with kids' grades. Mother's marital status and degree of education link with school type and socioeconomic status, since college graduates and two-parent families have higher incomes (Chetty and Hendren 4). A child's ability to attend private school depends on family income. Given that the coefficients between our control variables and the dependent variable are nonzero and significant at the 1% level, omitted variable bias may occur. Including control variables reduces bias. We examine some potential omitted variables due to study constraints in the discussion section.

4.2 Heteroskedasticity

The OLS assumes linear independence and homoskedasticity. OLS isn't the best linear unbiased estimator if $var(u|x)$ isn't constant. To confirm our model's reliability, we utilize a White Test to check the assumption. Assumption not met, we substitute OLS standard error with robust standard error.

4.2.1 The White Test for Heteroskedasticity

The White Test determines if the variance of errors in a regression model is constant. Wooldridge says (2020):

1. Estimate model using OLS. Square OLS residuals, u2.
2. Run residual u2 regression. Keep regression's R-squared.
3. Compute the p-value and F or LM statistic. If the p-value is smaller than the selected significance level, we reject the null hypothesis of homoskedasticity.

Our model's White Test p-value is 2.404334e-34, substantially smaller than 0.05. This indicates heteroskedasticity.

4.2.2 Robust standard error

Following the results of the White Test, we calculate heteroskedasticity-robust standard errors to correct our statistical inference using the formula:

$$v\hat{a}r(\hat{\beta}_j|X) = \sum_i \frac{\hat{r}_{ij}^2 \hat{u}_i^2}{SSR_{x_j^2}}$$

Where $\hat{}r_{ij}$ denotes the i^{th} residual from regression X_j on all other independent variables, and SSR_j is the sum of squared residuals from this regression. In class, we showed that this is a valid estimator of $var(\beta_j)$, under assumptions MLR1 through MLR 4. Once heteroskedasticity-robust standard errors are obtained, once can construct heteroskedasticity robust t-statistics as follows:

$$T = (Estimate - Hypothesized\ value)/standard\ error.$$

We apply this new standard error in t-statistics. Table 3's second column shows the results and p-values. All variables keep the same level of significance when we employ robust standard errors, therefore our results do not change.

5. Conclusion and Discussion

Our data suggest that a mother's college education affects her child's test scores. Being married at birth also boosts test scores, though not as much as college attendance. If a mother went to college and was married when the child was born, the child scores much higher. Our experiment has some drawbacks, including measuring educational "success" for children by test scores and potential concerns with confounding variables outside our control, including regional characteristics. We suggest fixes for these issues.

First, we measure academic progress by combined test scores. As Jacob and Rothstein remark in "The Measurement of Student Ability in Modern Assessment Systems," test scores are not the best indication of a child's intellect or academic aptitude. Many standardized tests are biased toward specific ethnic and socioeconomic groups and have considerable measurement mistakes (2016). In a more extensive, resource-rich study, we could create a combined indicator for student educational performance based on weighted test scores, GPA, high school GPA and graduation, and college attendance and placement. Such a rating would better reflect a student's intellectual progress, but it could be biased.

Idealy, we'd control for a child's state and county of origin. The location a child grew up in is a confounding variable in this regression, but the data set doesn't include it. According to Chetty and Hendren, state and city of origin affect whether adults (mothers) get a college degree or marry (2018). Chetty and Hendren find that children's county of origin affects their future educational attainment (2018). Adding indicator variables to account for county-level (and thus state-level) variances in education programs, school budget, marriage rate, college completion rate for mothers, and other state policies like school curricula would eliminate much of this inaccuracy. To perform a regression like this, a bigger sample size is needed so each county has more children.

Despite these constraints, our results meet our expectations. The favorable effects of a mother attending college, being married at birth, and their contact were all significant. The comparatively strong positive coefficient on mother's college attainment shows that maternal education positively affects a child's growth (2010). Similarly, our data show a positive association between parents' marital status and their child's test scores, however, we used parents' marital status at the child's birth rather than when the child took the test (2012). The interaction variable between mother's college education and mother's marriage status at birth was negative, but it was minor enough that the total was greater than either of the first two factors alone. Having a married, college-educated mother at the child's birth also boosts test scores, according to Subba and Chevalier et al (2012; 2010). Our results add to child development understanding.

References

[1] Aughinbaugh, Alison, Omar Robles, and Hugette Sun. “Marriage and divorce: patterns by gender, race, and educational attainment” (2013).

[2] Chetty, Raj, and Nathaniel Hendren. “The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates”. *Quarterly Journal of Economics* 133, no. 3 (2018): 1107–1162.

[3] “The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates”. *Quarterly Journal of Economics* 133, no. 3 (2018): 1163–1228.

[4] Chevalier, Arnaud, et al. “The Impact of Parental Income and Education on the Schooling of Their Children”. *Lancaster University Management School Working Paper* 36 (2010).

[5] Dunifon, Rachel, et al. “The Effect of Maternal Employment on Children’s Academic Performance”. *NBER Working Paper Series* (2013).

[6] Jacob, Brian, and Jesse Rothstein. “The Measurement of Student Ability in Modern Assessment Systems”. *NBER Working Paper Series* (2016).

[7] Ja¨ntti, Markus, et al. “American Exceptionalism in a New Light: A Comparison of Intergenerational Earnings Mobility in the Nordic Countries, the United Kingdom and the United States”. *IZA Discussion Paper Series* (2006).

[8] Subba, Rita. “The Influence of Family Structure on The Test Scores of Students”. *Rita Subba* (2012).

[9] Wooldridge, Jeffrey. *Introductory Econometric: A Modern Approach*. 7th ed. Cengage Learning, 2020.

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