Impact of Household Income on Standardized Test Scores

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Abstract

The influence of socio-economic factors on standardized test scores has been long debated and studied. This paper examines the relationship between family income and state-mandated achievement test scores for students in the State of Georgia. We first use a simple linear regression model of average test score and average household income to first establish a positively correlated relationship. This relationship is further analyzed by differentiating for other community-based factors (race, household type, and educational attainment level) in three multiple variable regression models. For comparison and to evaluate any consistencies these variables may have, the regressions were run on data from both 2007 and 2014. In both cases, the final multiple regressions found that average household income was not statistically significant in impacting the average test scores of the counties studied, while household type and educational attainment level were statistically significant.

1. Introduction

The 20th century saw the rise of standardized testing in the United States. mandated and funded by the Elementary and Secondary Education Act of 1965. These tests were the measure by which the federal government could make cross-state comparisons and evaluate the public education system. In 2001, the *No Child Left Behind Act* further emphasized the use of standardized testing to measure student and school progress. However, despite decades of policy initiatives aimed at addressing test score disparities attributed to household income, race, and parent socio-economic status. Stiefel (2007) notes that the gaps have remained basically unchanged since the 1990s, and though some convergence in test scores took place during the 1970s and 80s, 'white' students score significantly higher than black or Hispanic students, students from affluent families tend to do better, and studies correlate parent's cognitive and education level with higher scores as well.

The arguments against standardized testing are numerous. Opponents frequently cite the exorbitant cost. Chingos' economic data provides context for our topic. Nationwide, six for-profit vendors taking nearly ninety percent of primary assessment contracts, a $690 million market. Annual spending on primary assessment contracts varies significantly across states, with Georgia among the lowest at $14 per student. In total, the U.S. spends approximately 1.7 billion dollars each year on standardized testing.

Research consistently correlates certain external, or community-based, factors with test performance. These factors often lead to what is considered an "achievement gap." According the U.S. Department of Education, race gaps between fourth and eighth graders are typically 20-30 points on a test ranging from 0 to 500 points (2009). The existing literature attributes score disparities to a variety of environmental conditions: socio-economic circumstances, racial demographics, and within-classroom factors such as teaching quality and volume of school resources. Closing the gaps is crucial to equalizing educational opportunities that will engender long-term success—academically as well as economically—for all of America's students.

2. Hypothesis

This paper examines several community-based factors that could have an influence on student standardized test performance, by analyzing Georgia datasets. These community-based factors include household income ethnicity, household makeup (married versus single-parents), and educational attainment levels. We hypothesize that counties with higher incomes will see higher average scores on all sections of the state standardized tests for primary schools. The economic implications for such studies hold significance, not only because disparities in test scores indicate underlying educational inequalities, but performance on standardized tests has also been repeatedly linked with outcomes later in life. Murnane's work shows that early disparities translate into disparities in college attendance and correlates

test scores with future labor market outcomes such as earnings and wages. This potential long term economic impact on the lives of Georgia's school children served as the impetus for this paper.

3. Literature Review

Popham (1999) describes that standardized tests come in two forms—*aptitude tests* (e.g., SAT) that predict a student's future success, and *achievement tests* that are used by school board's to measure a school's effectiveness. This study pertains to the latter, student achievement. Certain factors have been shown to influence student performance on such assessments, raising questions over the fairness of mandatory tests. Interpretation that fails to account for such variables is widely thought to contribute to a persistent bias that disadvantages certain subsets of children, thereby compromising the fundamental premise for standardized testing. Standardized tests in the United States have been used to draw statewide comparisons and set standards in national education programs and policies. The following studies pertain to some of the factors used in our analysis: household income, race and educational attainment. While myriad factors have been hypothesized to be at the core of the achievement, or test-score, gap, we examine topic that we found to have generated the most discourse in contemporary literature.

3.1 Impact of Family Income on Child Achievement

Abundant research has been undertaken to correlate family income with test scores. Dahl and Lochner (2012) support their hypothesis, linking test scores with household income, by using data based on five repeated measures of cognitive test scores per child. Using data derived from the U.S. government's Earned Income Tax Credit (EITC)[1] records, they identified nonlinear changes that indicated upward shifts, or expansions, in family income over twelve years (1987-1999), mainly, a twenty-percent increase of around $2,100, between 1993 and 1997. Applying an "instrumental variable strategy" they established a causal relationship between measurable expansions in family income and corresponding increases in children's math and reading scores. Testing to a variety of independent variables, they found short term score improvements of six percent, with one standard deviation for every $1,000 increase in income, for low-income families. Log total family income was used to check for robustness. Similarly, Mayer shows that 10% increase in income yields 1.1%-1.5% increase in chance of enrolling in college.

3.2 Impact of Race on Standardized Test Results - The "Black-White" Score Gap

In July 2009, the U.S. Department of Education published a statistical analysis report on the black-white achievement gap, based on outcomes of a government-mandated NAEP assessments devised

[1] The Extra Income Tax Credit (EITC), established in the mid-1990s, is one of the largest federal antipoverty programs in the US. It provides cash assistance to low-income families and individuals (Dahl, Lochner).

by the National Assessment of Educational Progress (NAEP)[2] administered to public students in grades four and eight nationwide during the period from 1992 to 2007. On average, white students score higher in all subjects, as measured by the. The report was compiled by the National Center for Education Statistics (NCES)[3]. Its state-differentiated data shows a persistent divide in test score outcomes for the State of Georgia public schools. Average scores for Black (African-American) cohorts were lower than the White (European-American) demographic, by 25 points in reading and 27 points in math. Stiefel, Schwartz and Ellen (2007) attempt to explain within-school gaps through analysis of size and distribution data across races in New York City public schools, utilizing a dataset provided by the NYC Department of Education that included socioeconomic and educational information on 70,638 fifth and 55,921 eighth graders in the 2000-2001 school year. Controlling for differences in student characteristics and academic preparation, the researchers employ regressions with race-specific school fixed effects to show that, in most schools, black and Hispanic fifth and eighth graders achieve lower test scores than their white peers. These valuable insights would be beneficial if replicated across multiple states. As such, our study aims to derive actionable insights locally, from Georgia school districts. We aim to elucidate state-specific patterns while providing localized information for educational stakeholders in Georgia.

3.3 Parents' Education and I.Q. - Intergenerational Transmission of Cognitive Abilities

Cognitive abilities factor significantly in education and income, and in terms of human capital and economic development. Hanushek and Woessmann (2008) examine the role of cognitive skills in promoting economic well-being. Data derived from their analyses of economic outcomes shows strong evidence that cognitive skills have "powerful economic effects" on individual earnings, on the distribution of income, and on economic growth. They conclude a positive correlation between strong intergenerational cognition and higher earnings, although this could negatively translate into higher persistence of the achievement gap as the strong become stronger and vice versa. Anger and Heineck (2010) analyze the correlation between the cognitive skills of individuals and the abilities of their parents. Controlling for educational attainment and family background, the researchers differentiate between mother and fathers' IQ transmission. Their findings show that parental cognitive skills, especially skills

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[2] The National Assessment of Educational Progress (NAEP), a congressionally mandated project of the U.S. Department of Education, informs the public periodically about the academic achievement of elementary and secondary students in reading, mathematics, science, writing and other subjects. Only information related to academic achievement and relevant variables is collected under this program from students representing the country.

[3] The National Center for Education Statistics (NCES) is the primary federal entity for collecting, analyzing, and reporting data related to education. It fulfills a congressional mandate to collect, collate, analyze, and report full and complete statistics on the condition of education in the United States. NCES activities are designed to address high-priority education data needs and report timely, useful, and high-quality data to the U.S. Department of Education, the Congress, the states, other education policymakers, practitioners, data users, and the general public.

based on past learning, are highly predictive of their sons' and daughters' measurements. The impact of parents' cognitive abilities on their offspring bears potential economic implications for individuals, schools, and economic development at a national scale. Anger and Heineck (2010) further note that Black et al (2009) established strong cognitive transmission between fathers and sons: a 1-point increase in the father's IQ score translates into an increase in the son's cognitive ability by about 0.3 points. High correlations for brothers (about one half) led them to deduce that up to 50 percent of the variation in IQ can be attributed to family and community background factors, a finding that holds relevance for our paper. This and similar studies served as an impetus for us to review the relationship between educational attainment level and test scores, using counties in Georgia as demographic microcosms to establish potential relationships across or among school districts.

3.4 Meritocracy in Education – Impact of Good Teaching and the Value-Added Model (VAM)

Chetty, Friedman, and Rockoff (2011) test Popham's assertion that teacher experience and ability—not achievement tests—is a better measure of education quality. Seeking to quantify the long-term impact of good teaching, they employ a value-added (VA) approach, or value-added modeling (VAM), to analyze variation in students' test scores attributable to teaching. The study concludes that good teachers create substantial economic value. Students in classes taught by "high-VA" teachers are not only more likely to attend college, they attend higher-ranked colleges. On average, one standard deviation improvement in teacher VA in a single grade raises earnings by about 1% at age 28. While teaching quality is not a community-based factor, it lends perspective to our analysis by qualifying that, within-classroom factors such as teaching quality must also be considered before drawing any broad conclusions on causation of test score gaps.

4. Data

4.1 Variables

The dependent variable in this study is the fifth grade Criterion-Referenced Competency Tests (CRCT) test scores from the 36 reported Georgia counties. This includes test scores for each of the five subject areas (Reading, English/Language Arts, Math, Science, Social Studies). In 2014, a numerical score of 800 indicates meeting standards, and 850 or higher indicates exceeding standards. In 2007, Math and Social Studies were scored on a lower scale, centered around 300. For the purpose of this study and analysis, the average score from all five subject areas was used.

The independent variables analyzed in this study are community factors that have been historically recognized as having an influential impact on standardized test scores, and thus are likely to

have an influence on the county's average CRCT scores, including: average household income, race, household type, and educational attainment level of the population aged 25 years and older.

Table 1: Defined Variables

Label	Variable	Measure	Type
score_avg	average score of all five subject areas	numerical score value	dependent
race_white	percentage of population that identified as White/Caucasian	percentage value	independent
house_married	percentage of population living in a married-couple household	percentage value	independent
edu_collegeplus	percentage of population that has attended college for some period of time, or obtained a Bachelor's, Master's, Professional school, or Doctorate degree, or any combination of the above	percentage value	independent
avgincome	average household income in the county	dollars	independent

The test score data used in this analysis is from the Georgia Department of Education. The county demographic information has been pulled from Social Explorer American Community Surveys census data. This paper will compare the regression of test scores on community factors from 2014 to an equivalent regression of 2007 data to determine if there are any significant relationships that have remained constant or changed over the seven-year period.

4.2 Regression Models

Single Variable Regression:

$$\text{score\_avg} = \beta_0 + \beta_1(\text{avgincome})$$

Regressing Georgia counties' average CRCT scores with the average household income in the county.

Multiple Variable Regression I:

$$\text{score\_avg} = \beta_0 + \beta_1(\text{avgincome}) + \beta_2(\text{race\_white}) + \beta_3(\text{house\_married})$$

Regressing Georgia counties' average CRCT scores on the average household income, controlling for the percentage of the population in the county that is white and married households.

Multiple Variable Regression II:

$$\text{score\_avg} = \beta_0 + \beta_1(\text{avgincome}) + \beta_2(\text{race\_white}) + \beta_3(\text{edu\_collegeplus})$$

Regressing Georgia counties' average CRCT scores on the average household income, controlling for the percentage of the population in the county that is white and with an educational level of some college or more.

Multiple Variable Regression III:

$$score\_avg = \beta_0 + \beta_1(avgincome) + \beta_2(race\_white) + \beta_3\ (house\_married) + \beta_4(edu\_collegeplus)$$

Regressing Georgia counties' average CRCT scores on the average household income, controlling for the percentage of the population in the county that is white, married households, and adults with an educational level of some college or more.

4.3 Descriptive Statistics

Table 2: 2014 Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
race_white	34	.615	.183	.21	.93
house_married	36	.488	.099	.29	.68
edu_collegeplus	36	.565	.088	.4	.73
unemployed	36	.088	.029	.04	.17
avgincome	36	$66,106	$15,169	$45,380	$107,088
score_avg	36	838.4	8.48	822.9	860.6

Table 3: 2007 Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
race_white	30	.639	.169	.25	.90
house_married	32	.504	.104	.31	.67
edu_collegeplus	32	.527	.098	.36	.69
unemployed	30	.068	.025	.03	.15
avgincome	32	$65,623	$14,295	$45,429	$104,721
score_avg*	32	701.1	7.19	688.4	717.0

**in 2007, Math and Social Studies tests were scored on a different scale than the 800-meets standards scale, therefore the averages in 2007 were all significantly lower.*

4.4 Gauss Markov Assumptions

Assumption 1: Linear Parameters

The model is in linear parameters, such that: Y = β_0+β_1X$_1$ + . . . + β_KX$_2$

Assumption 2: Random Sampling

An appropriately sized, random sample is used in the regression model.

Assumption 3: Zero Conditional Mean

The expected value of the error term is zero, such that: E(u) = 0

Assumption 4: No Perfect Collinearity

The error term, *u,* is independently distributed and not correlated with any of the variables. The variables are not correlated.

Table 4: Variable Matrix of Correlation (based on 2014 data)

	race_white	***house_married***	***edu_collegeplus***	***avgincome***
race_white	1.0000			
house_married	.7416	1.0000		
edu_collegeplus	-.0813	.1142	1.0000	
avgincome	.3356	.5630	.7164	1.0000

**highest levels of correlation are seen between race_white and house_married as well as avgincome and edu_collegeplus*

Assumption 5: Homoskedacity

The conditional variance of the error term, *u*, is constant given any value of the explanatory/independent variables. This implies that the model's uncertainty is constant over all observations.

5. Results

5.1 Single Variable Regression:

$$\text{score\_avg} = 813.78 + .00037(\text{avgincome})$$
$$(4.849) \quad (.0000715)$$

This simple regression takes the dependent variable as the average CRCT score in the county, a numerical score value. A level-level model is used because a scatter plot (Figure 1) between the average score and average income shows that there could be some linear relationship between the two variables—specifically a positive correlation. Based on the results from the simple regression, a $10,000 increase in the average household income of the county leads to a 3.7-point increase in the average CRCT score. This

relationship supports our hypothesis that higher incomes correspond with higher scores and was proven statistically significant at all levels, allowing the rejection of the null hypothesis.

5.2 Multiple Variable Regression:

I. score_avg = 803.68 + .00026(avgincome) + 2.23(race_white) + 32.35(house_married)
(5.3707) (.0000808) (8.3272) (17.2861)

The multiple regression models have the same dependent variable, the numerical value average score, as the simple regression. This first multiple regression model includes controls for race (specifically “White/Caucasian”) and household type (specifically “Married Couple” status). The results showed that only the average income and household type were statistically significant, rejecting the null hypotheses, and thus demonstrating that each has a positive relationship with the average score.

II. score_avg = 794.14 +.000169(avgincome) + 19.37(race_white) + 36.47(edu_collegeplus)
(8.8192) (.000115) (6.7379) (19.8102)

This multiple regression controls for race and educational attainment level of the population (the percentage of the population in the county that has attended some college or more). the results showed that race and educational attainment level were statistically significant.

III. score_avg = 784.43 +.000012(avgincome) + 6.70(race_white) + 43.05(house_married) +
(8.8617) (.0001207) (6.7026) (16.3422)
48.82(edu_collegeplus)
(18.6967)

This final multiple regression includes the same dependent variable, average score, as well as all of the potential variables identified in the beginning of the paper: average income, race, household type, and educational attainment level. The results indicate that only household type and educational attainment level were statistically significant.

Table 4 displays higher correlations between *avgincome* and *edu_collegeplus* as well as *race_white* and *house_married* —this possible multicollinearity could influence the regression analysis. The F Test was used to test the joint significance on income and education, where F = 6.206. With this F-statistic for the robustness test, we reject the null hypothesis that βavgincome = βcollegeplus = 0, and thus the variables are jointly statistically significant. This implies that they should both be included in the final model. The F Test was also used on race and household type, where F = 6.423. This F-statistic allows us to reject the null hypothesis that βrace_white = βhouse_married = 0, and thus the variables are jointly statistically significant and both should be included in the model.

Our tests show that these variables should still be controlled for in the final regression model, MVR III. Though they do not all show statistical significance in this model, some of the variables come close. All of the independent variables also yield the expected positive correlation with the dependent variable, though some are not as significant as hypothesized. The regression shows that higher average incomes, higher percentages of white populations, higher percentages of married households, and higher percentages of college-educated members in the population have a positive relationship with the average CRCT score of the respective county.

Table 5: 2014 Regression Results

Independent Variables	SVR (1)	MVR I (2)	MVR II (3)	MVR III (4)
avgincome	.00037*** (5.20)	.00026*** (3.24)	.0001692 (1.47)	.000012 (.10)
race_white		2.23 (.27)	19.37*** (2.87)	6.70 (.86)
house_married		32.35* (1.87)		43.05** (2.63)
edu_collegeplus			36.47* (1.84)	48.82** (2.61)
β_0	813.78	803.68	794.14	784.43
Observations	36	34	34	34
R-squared	.44	.59	.59	.67

** significant at 10%, ** significant at 5%, *** significant at 1%*

Table 6: 2007 Regression Results

Independent Variables	SVR (1)	MVR I (2)	MVR II (3)	MVR III (4)
avgincome	.00037*** (5.79)	.00028*** (4.38)	.00026*** (2.96)	.00013 (1.25)
race_white		11.05* (1.58)	19.48*** (3.63)	10.99 (1.63)
house_married		15.89 (1.25)		26.35* (1.93)
edu_collegeplus			12.02 (.94)	23.59* (1.73)
β_0	677.11	667.28	664.92	659.39
Observations	32	30	30	30
R-squared	.53	.71	.71	.74

** significant at 10%, ** significant at 5%, *** significant at 1%*

6. Conclusion

Our results show positive relationships between all variables and the average score, an outcome that largely coincides with our hypotheses and also corroborates the conclusions reached by the studies summarized in our literature review research.

The coefficient for average household income was relatively constant between 2007 and 2014 in the simple regression and the first multiple regression model. The results from the simple variable regression in both years are significant, even at 10%, 5%, and 1%. In both analyses, a $10,000 increase in average income translate into a 3.7-point increase in the average test score of the county.

The coefficient for race was substantially higher in 2007 than in the 2014 MVR I and MVR III regressions, a general indication that race, as a variable, may have had a greater impact on test scores in 2007. Our results parallel the U.S. Department of Education's black-white achievement gap findings that same year, with the NAEP reporting that, among eighth graders tested in public schools across Georgia, there was a 5.4% math gap and a 5.0% reading gap between black and white student populations. Somewhat ironically, the report, based on interpolations of NAEP assessment datasets collated by NCES for various years between 1992 and 2007, went on to highlight Georgia as one of only twelve states with a *smaller* math gap than the "nation's gap" of 31 points. Nonetheless, NCES acknowledges the persistence of the racial gap despite two decades of widespread effort to address it.

In the final multiple regression model, the relationship between the average household income of the county and average test score is not statistically significant at all. This result is consistent with Dahl and Lochner's findings. Employing instrumental variable estimates and simple dynamic models, their study of income increases over time suggests that current, or contemporaneous, income has a significant effect on achievement, while past income yields a smaller effect, with larger impact on children from more disadvantaged backgrounds.

We conclude that average income can have some impact on standardized test scores, yet it may not be the main influencing factor. This could be due, at least in part, to the variables examined. Our dataset consisted of county aggregate data, as opposed to individual performance data and demographics. Therefore, using individual scores may generate more statistically significant relationships.

7. References

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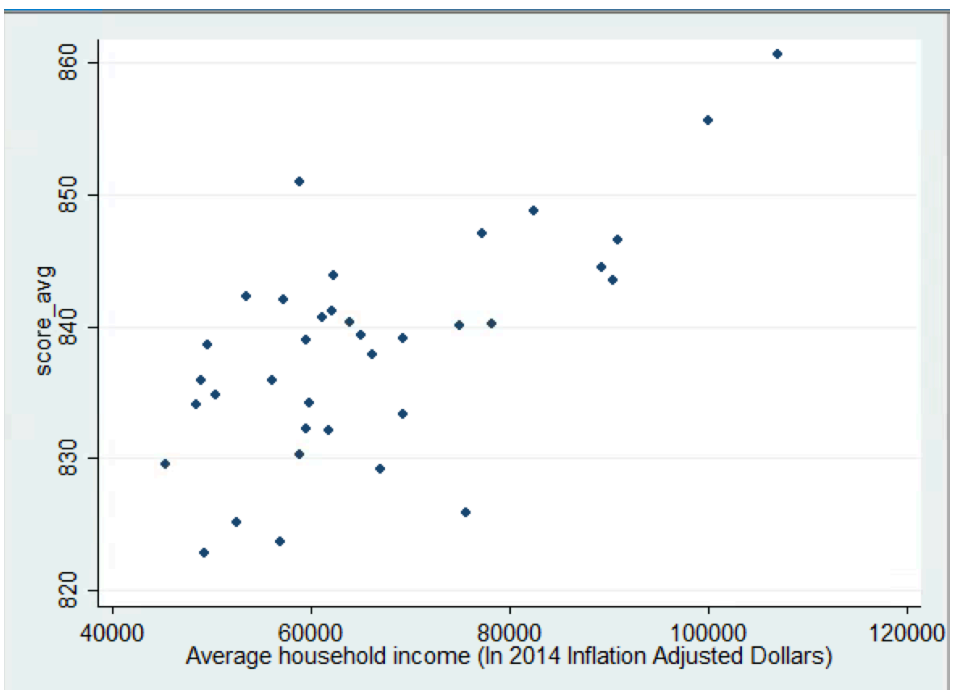
8. Appendix

1. Figure 1: Average Score, Average Income Scatter Plot



2. 2014 SVR

```
. regress score_avg avgincome
```

Source	SS	df	MS
Model	1115.59268	1	1115.59268
Residual	1401.69731	34	41.2263914
Total	2517.28999	35	71.9225711

Number of obs	=	36
F(1, 34)	=	27.06
Prob > F	=	0.0000
R-squared	=	0.4432
Adj R-squared	=	0.4268
Root MSE	=	6.4208

score_avg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgincome	.0003722	.0000715	5.20	0.000	.0002268	.0005176
_cons	813.7801	4.849016	167.82	0.000	803.9258	823.6345

3. 2014 MVR I

```
. regress score_avg avgincome race_white house_married
```

Source	SS	df	MS
Model	1472.4569	3	490.818968
Residual	1013.57009	30	33.7856698
Total	2486.027	33	75.3341514

Number of obs	=	34
F(3, 30)	=	14.53
Prob > F	=	0.0000
R-squared	=	0.5923
Adj R-squared	=	0.5515
Root MSE	=	5.8125

score_avg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgincome	.0002617	.0000808	3.24	0.003	.0000968	.0004267
race_white	2.233193	8.327178	0.27	0.790	-14.77317	19.23956
house_married	32.3499	17.28611	1.87	0.071	-2.953047	67.65284
_cons	803.6816	5.370708	149.64	0.000	792.7131	814.65

4. 2014 MVR II

```
. regress score_avg avgincome race_white edu_collegeplus
```

Source	SS	df	MS
Model	1469.01422	3	489.671406
Residual	1017.01278	30	33.900426
Total	2486.027	33	75.3341514

Number of obs	=	34
F(3, 30)	=	14.44
Prob > F	=	0.0000
R-squared	=	0.5909
Adj R-squared	=	0.5500
Root MSE	=	5.8224

score_avg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgincome	.0001692	.000115	1.47	0.152	-.0000657	.000404
race_white	19.36668	6.737985	2.87	0.007	5.605876	33.12748
edu_collegeplus	36.46835	19.81017	1.84	0.076	-3.989425	76.92612
_cons	794.1449	8.819227	90.05	0.000	776.1337	812.1562

5. 2014 MVR III

```
. regress score_avg avgincome race_white house_married edu_collegeplus
```

Source	SS	df	MS			
				Number of obs	=	34
				F(4, 29)	=	14.71
Model	1665.38551	4	416.346378	Prob > F	=	0.0000
Residual	820.641485	29	28.2979822	R-squared	=	0.6699
				Adj R-squared	=	0.6244
Total	2486.027	33	75.3341514	Root MSE	=	5.3196

score_avg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgincome	.0000124	.0001207	0.10	0.919	-.0002345	.0002594
race_white	6.702585	7.810816	0.86	0.398	-9.272329	22.6775
house_married	43.0499	16.34221	2.63	0.013	9.62632	76.47348
edu_collegeplus	48.81869	18.69673	2.61	0.014	10.57959	87.05779
_cons	784.4284	8.861714	88.52	0.000	766.3041	802.5526

6. 2007 SVR

```
. regress score_avg avgincome
```

Source	SS	df	MS			
				Number of obs	=	32
				F(1, 30)	=	33.49
Model	846.049629	1	846.049629	Prob > F	=	0.0000
Residual	757.777253	30	25.2592418	R-squared	=	0.5275
				Adj R-squared	=	0.5118
Total	1603.82688	31	51.736351	Root MSE	=	5.0259

score_avg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgincome	.0003654	.0000631	5.79	0.000	.0002365	.0004944
_cons	677.1053	4.237942	159.77	0.000	668.4503	685.7603

7. 2007 MVR I

```
. regress score_avg avgincome race_white house_married
```

Source	SS	df	MS			
				Number of obs	=	30
				F(3, 26)	=	21.50
Model	1141.1588	3	380.386268	Prob > F	=	0.0000
Residual	460.033263	26	17.6935871	R-squared	=	0.7127
				Adj R-squared	=	0.6795
Total	1601.19207	29	55.2135195	Root MSE	=	4.2064

score_avg	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
avgincome	.000283	.0000646	4.38	0.000	.0001501	.0004159
race_white	11.0493	6.994702	1.58	0.126	-3.328516	25.42711
house_married	15.88885	12.73987	1.25	0.223	-10.29832	42.07602
_cons	667.2818	4.290208	155.54	0.000	658.4631	676.1004

8. 2007 MVR II

```
. regress score_avg avgincome race_white edu_collegeplus

      Source |       SS           df       MS      Number of obs   =        30
-------------+----------------------------------   F(3, 26)        =     20.75
       Model |  1129.52779         3  376.509264   Prob > F        =    0.0000
    Residual |  471.664275        26  18.1409337   R-squared       =    0.7054
-------------+----------------------------------   Adj R-squared   =    0.6714
       Total |  1601.19207        29  55.2135195   Root MSE        =    4.2592

------------------------------------------------------------------------------
   score_avg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   avgincome |   .0002604   .0000879     2.96   0.006      .0000796    .0004412
  race_white |   19.48353   5.360649     3.63   0.001      8.464559     30.5025
edu_collegeplus | 12.01901  12.84194     0.94   0.358     -14.37798    38.41601
       _cons |   664.9162    5.71759   116.29   0.000      653.1635    676.6688
------------------------------------------------------------------------------
```

9. 2007 MVR III

```
. regress score_avg avgincome race_white house_married edu_collegeplus

      Source |       SS           df       MS      Number of obs   =        30
-------------+----------------------------------   F(4, 25)        =     18.12
       Model |  1190.48147         4  297.620367   Prob > F        =    0.0000
    Residual |  410.710599        25   16.428424   R-squared       =    0.7435
-------------+----------------------------------   Adj R-squared   =    0.7025
       Total |  1601.19207        29  55.2135195   Root MSE        =    4.0532

------------------------------------------------------------------------------
   score_avg |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   avgincome |    .000133   .0001067     1.25   0.224     -.0000867    .0003527
  race_white |   10.99851   6.740053     1.63   0.115     -2.882892    24.87991
house_married |   26.3519   13.68075     1.93   0.066     -1.824134    54.52792
edu_collegeplus | 23.59822  13.61927     1.73   0.095     -4.451198    51.64763
       _cons |   659.3893   6.151235   107.20   0.000      646.7206     672.058
------------------------------------------------------------------------------
```

10. F Test: Joint Hypothesis Test on Income & Education

2014

Corr(avgincom, edu_collegeplus) = .72

H_0: βavgincome = 0, βedu_collegeplus = 0

H_1: H_0 is not true

unrestricted model: *score_avg* = 784.43 + .000012*avgincome* + 6.70*race_white* + 43.05*house_married* + 48.82*edu_collegeplus*

n = 34, SSR = 820.6, R2 = .6699

restricted model: *score_avg* = 810.08 - 1.75*race_white* + 60.2*house_married* + *u*

n = 34, SSR = 1368.5, R2 = .4495

F = (SSRrestricted - SSRunrestricted)/q / SSRunrestricted/(n - k - 1)

F = (1368.5 - 820.6)/2 / 1368.5/31

F = 273.95/44.1451613

F = 6.206

CV = 2.49 @ 10%

CV = 3.32 @ 5%

6.206 > 2.49 & 6.206 > 3.32

therefore, reject H_0 in favor of H_1

-->They are jointly statistically significant

11. F Test: Joint Hypothesis Test on Race (White) & Household Type (Married-Couple)

2014

Corr(race_white, house_married) = .74

H_0: βrace_white = 0, βhouse_married = 0

H_1: H_0 is not true

unrestricted model: *score_avg* = 784.43 + .000012*avgincome* + 6.70*race_white* + 43.05*house_married* + 48.82*edu_collegeplus*

n = 34, SSR = 820.6, R2 = .6699

restricted model: *score_avg* = 814.28 + .00038*avgincome* - 1.71*edu_collegeplus*

n = 36, SSR = 1401.3, R2 = .4433

F = (SSRrestricted - SSRunrestricted)/q / SSRunrestricted/(n - k - 1)

F = (1401.3 - 820.6)/2 / 1401.3/31

F = 290.35/45.203

F = 6.423

CV = 2.49 @ 10%

CV = 3.32 @ 5%

6.423 > 2.49 & 6.423 > 3.32

therefore, reject H_0 in favor of H_1

-->They are jointly statistically significant