Understanding Differences in Children's Test Scores Across Socioeconomic Status and Race

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1 Introduction

Cognitive achievement of young children are of great interest to economists and policy makers alike. Thomas and Currie (2001) believe that test scores are of crucial importance due to their correlation with future employment prospects and wages. They find supporting evidence for the proposition that test scores at age 16 are highly responsible for determining wages at age 33 for any given individual. Hutchinson et. al (1979) find that test scores when children are 16 could be predicted strongly by test scores at age 7. Neal and Johnson (1996) and Murnane, Willet and Levy (1995) arrive at similar conclusions regarding test scores: high performance at early ages, particularly in math, lead to high incomes later on in life. In summary, test scores of young children predict test scores of those same children when they are young adults, and test scores of those young adults can have big implications on wage earnings.

The importance of school performance on future wages has led researchers to study potential factors that affect test score performance at a young age. For example, Fryer and Levitt (2004), as well as Phillips, Crouse, and Ralph (1998), have studied the gap in test scores as they relate to race. Todd and Wolpin (2006) use the HOME survey in the NLSY-CS to see how factors of the home environment play a different roles in the production of cognitive achievement. We study test scores as they relate to various socioeconomic statuses and race.

Since income is highly correlated with socioeconomic status (SES), our work is intrinsically related to income as well. The literature has not yet come to a consensus on the exact definition of SES: it can be defined as either permanent or transitory. In the former definition, permanent income measures such as parents' education are usually used as a proxy for SES. For the latter definition of transitory SES, changes in income is used instead. Fryer and Levitt (2004) use a more permanent notion of SES by creating a measure compiled from parents' education, parents' occupation, and household income. As the algorithm for computing this measure is unavailable to us, we use mother's education as the basis for SES for we believe it plays a large role in a child's life. We identify three SES groups: children of mothers who dropped out of high school, children of mothers who have graduated high school, and children of mothers who have had at least one year of college.

In order to focus on how SES affects the gap in test scores over time, we must give a brief overview of the potential reasons for the gap in test scores in general. It could be possible that children with genetically superior ability perform relatively better on ability tests than those with less ability. Psychologists before the 1970s argued that genetic differences are not primarily responsible for test score performance since age scores of children vary with their respective ages (Kleinberg 1963). Many arguments have been made that it is school quality that affects children's test scores (Loehlin, Lindzey, and Spuhler 1975). Phillips et. al (1998), focusing on black children, argues that it is in fact home environment that contributes to lower tests scores, causing those with poor home environments to start school at a disadvantage with regards to tests scores. Fryer and Levitt provide evidence against this by finding that there is no gap at entry between black and white children, implying that it is in fact something about the school environment that induces such gaps. The consensus within the economic and psychologist literature appears to be aligned more with the view of Phillips than of Fryer and Levitt.

We aim to provide evidence for or against Fryer and Levitt's findings by trying to replicate their results using a different data set. Our initial methodology will bear high resemblance to their original paper. We use pooled cross-sections to construct trends in tests scores among various age groups. But our work extends the research done by Fryer and Levitt by tracking the gap in scores at five different instances in time, as opposed to two instances.

We also extend on their research by studying transitory income shocks as they relate to test scores via first differences models. Unfortunately, first differences models remove a permanent notion of SES precisely because SES is defined as time-invariant. We instead look at how SES and race affect changes in test scores and let the effect of income shocks differ by SES and race by including interaction terms.

In summary, we use pooled cross-sections to analyze permanent income measures similar to the analysis in Fryer and Levitt and first difference models to analyze transitory income shocks as they relate to changes in test scores.

2 Data

To determine the impact of socioeconomic status on the academic achievement of children we use the National Longitudinal Survey of Youth 1979 (NLSY). This study has data from mothers who were surveyed annually from 1979 to 1994 and biannually thereafter. Data from the children of the mothers of original survey is contained in the biannual NLSY79 Children and Young Adults (NLSY-CS) survey, which followed children from 1986 to 2006. We merge the data sets to relate the mother data to the child data. It should also be noted that the NLSY oversampled minority populations, and we normalize the data to be more representative of the national population using the given sample weights in the NLSY-CS.

The NLSY survey used the Peabody Individual Achievement Test (PIAT) Mathematical and Reading percentile scores as a measure of children academic achievement. All models we implement use this score measure of child achievement.

Our definition of SES is based on mother's education. For each child, we define mother's education as the maximum of all possible reported mother's education levels in the NLSY across all years. We then define socioeconomic status in three categories: children of mothers with less than twelve years of education (high school dropouts), children of mothers with twelve years of education (high school graduates), and children of mothers with more than twelve years of education (college students). We add two indicator variables for the three groups with children of high school dropouts as the baseline group.

As the NLSY-CS is a biannual survey, we follow children at the two-year age categories: 5-6, 7-8, 9-10, 11-12, and 13-14, beginning at age five since this is the age at which children start taking the PIAT test. Our covariates include the gender of the child, binary variables for the mother's age at first birth (young if age was less than 20 years old or mature if age was more than 30), Hispanic and black. To control for the environment of the child in the home we include binary variables for number of books within the home. We designate binary variables for the number of books as follows: significant number of books if more than 10 books were present in the home and some books if between 1 and 9 books were present in the home. We also include a control for birth weight to account for the development of child if his/her weight was below or above 5.5 pounds. According to Johnson and Schoeni (2007), low birth weight reduces human capital accumulation and therefore interferes with the future success of an adult in the labor market.

To see how transitory income shocks relates to test scores, we examine changes in test scores from year to year along with changes in annual income. We observe changes in income by looking at net family income found in the NLSY mothers' data. To make interpretation of our estimates easier, we use income in thousands of dollars. We adjust for inflation by using all reported income measures in 2006 dollars.

3 Models

This section presents the models we estimate to reestimate Fryer and Levitt's analysis using the NLSY and NLSY-CS as well as our extensions.

3.1 Baseline Specifications

In addition to emulating Fryer and Levitt's analysis, we estimate our specifications for later age categories. Specifically, for data on children of age categories 5-6, 7-8, 9-10, 11-12, 13-14, we estimate

$$testscore_i = \beta_0 + \beta_1 hispanic_i + \beta_2 black_i + \beta_3 mcol_i + \beta_4 mhsgrad_i + \beta X + \epsilon \qquad (1)$$

where *testscore* denotes the PIAT math or reading score, *hispanic* and *black* are indicator variables taking the value 1 if the child is Hispanic or black, respectively, *mcol* and *mhsgrad* are indicator variables taking the value 1 if the mother of the child has taking college courses or graduated high school, respectively, and X is a vector of controls, including the age of the child, HOME scores, the number of books in the home, and indicator variables tracking the age of the mother at the birth of the child.

We estimate several versions of the model by varying which covariates we include. We also estimate specifications using a variable representing family income. Interaction terms are included to allow the effect of income, holding the other covariates constant, on test scores to vary by race and SES.

3.2 Differences Model

Coefficients estimated from this model, however, are not likely to be unbiased. This is due to several issues, of which we address three. First, we do not exploit the panel structure of our data. Though we pool our estimates for several age categories, they are estimated independently, but represent the same children. We can better approximate the true parameters by pooling children from all age categories. Second, the model also likely suffers from omitted variables bias as the covariates do not present an exhaustive set of controls. Third, some of our controls may suffer from endogeneity due to being correlated with time-invariant variables in the error term. We address these issues by estimating a first differences model. Differencing removes any time-invariant variables that are not included in the model and thus works to remove both omitted variables bias and endogeneity. Using data on children of age categories 5-6, 7-8, 9-10, 11-12, 13-14, we estimate

$$\Delta testscore_i = \gamma_0 + \gamma_1 \Delta income_i + \gamma_2 \Delta age_i + \gamma_3 \Delta HOME_i + \gamma race_i + \lambda SES_i + \delta. \quad (2)$$

Again, we estimate several specifications of this model by varying covariates. We interact differences in income with the race indicator variables and SES indicator variables. Data on children are pooled across all age categories to estimate this model.

In effect, we study the role of family income shocks in the production of cognitive achievement. We have reason to believe that these shocks and the other covariates play a cumulative role in the production of cognitive achievement (Todd and Wolpin 2006). Thus we also run a first differences model with one- and two-period lags on income, HOME scores, and age. Specifically, we estimate

$$\Delta testscore_i = \phi_0 + \phi_1 \Delta income_i + \phi_2 \Delta age_i + \phi_3 \Delta HOME_i + \phi race_i + \sigma SES_i \quad (3)$$

$$+\rho \Delta lagincome_i + \tau \Delta lagage_i + \theta \Delta lagHOME_i + \mu.$$

We find that estimating these models using balanced panels does not give us sufficient observations for significant statistical analysis. Thus we only estimate the models for an unbalanced panel of children across all age groups collected from all years.

4 Estimation

Table 1 has been created to track the changes in mhsgrad and mcol coefficients across sections for different years. The first point on the mhsgrad trend line corresponds to the 3rd model of the math baseline models for ages 5 and 6, and can be interpreted as the percentile score change for children whose mother's graduated high school when compared to mothers who did not graduate from high school, ceteris paribus. To continue with our example, the point previously mentioned tells us that children whose mothers graduate from high school, on average, had mean percentile score that was 8.56 points higher than a high school drop out. The corresponding 95% confidence interval for the corresponding point estimate is (4.73, 9.13). The corresponding 95% confidence interval for mcol for ages 5 and 6 is (12.27, 16.54). The range of each confidence interval, since zero is not included within either one, indicates that we can be fairly certain that there is a difference in test scores among children whose mothers graduated high school or had some college experience, as opposed to those children whose mothers were high school drop-outs. This result is not surprising, and in fact mirrors a result in Fryer and Levitt: that there is a significant difference in test scores among various SES groups. From the two confidence intervals, it can also be inferred that there is a clear distinction between the tests scores of children whose mothers were high school graduates and the test scores of children whose mothers had at least one year of college.

The chart also indicates that test score differences stay relatively constant about time. That is, children who mothers were high school graduates consistently score better than children whose mothers drop out of school. It appears that the initial disadvantage that children have when they enter school is not exacerbated as they grow older. A plausible and likely trend line that would lie within the confidence interval for both mhsgrad and mcol is one with zero slope. This holds for both reading and math test scores. One should not be deceived by the apparent fluctuation in reading point estimates graphed across time, for a perfectly plausible trend line could still be one of zero slope.

Looking at math scores and emulating the study by Fryer and Levitt according to race, we find varying results. Table 3 shows that blacks between the ages five and six start at a lower standing on the PIAT Math score when compared to whites. Blacks score -13.99 percentage points lower than whites at ages 5-6 with a confidence interval of (-15.56, -12.41). This gap persists over time until the age of fourteen where we see the difference in test scores fall to negative -15.97 percentage points with a confidence interval of (-17.83,-14.1049). This is different from the findings of Fryer and Levitt who were able to eliminate the gap between blacks and whites by including a number of covariates. Although we included similar covariates as done by Fryer and Levitt, we see that there is a gap present. We also see that Hispanics start out scoring -11.38 percentage points lower than whites with a confidence interval of (-9.55,-13.20). This is a smaller gap to whites than blacks have to whites. Hispanic children more or less maintain this trend at around this range as they grow older with scoring -9.02 percentage points lower when compared to whites at age fourteen with a confidence interval of (-11.23,-6.80).

The PIAT Reading baseline trend tells a different story than that of the PIAT Math. Table 4 shows that blacks score at about the same level as whites between the ages of five to six score -2.41 percentage points lower than whites with a confidence interval of (-3.85, -0.96). However, there is a significant drop in the performance for black children as they grow older with the difference in test scores being 14.63 percentage points lower than whites at age thirteen and fourteen with a confidence interval (-16.72,-12.55). This is the only portion of our baseline model that parallels the results found by Fryer and Levitt. However, Hispanics in this estimation, exhibit a trend unlike that of blacks as they perform at a lower level than that of whites, with a (-7.99,-4.37) confidence interval at the 95% level, at the initial survey at age 5 and then slightly close that gap at age fourteen to the confidence interval of (-6.23, -1.20) at the 95% level.. In addition, it is important to note that Hispanics start at a lower growth rate than whites. We believe that this could be due to the fact that a large percentage of Hispanic children grow up in a home where Spanish is the language that is primarily spoken. On the other hand, blacks grow up in homes where English is the primary language spoken at home.

Estimation of the first differences model (see tables in Appendix) indicates that current changes in income do not have a significant effect on the growth rate of test scores: only one variant of one specification shows the coefficient on the current change in income as significant at least at the 10 % level. The change in age and the change in HOME score remain significant in the math model, but lose significance in the reading model.

Only one specification, math with one-period lags, shows that the one-period lag in income has a significant effect: a $1000 increase two-years in the past causes an approximate 0.014 drop in the growth rate of test scores. This same specification is the only one to show that either one-period lags in age or HOME scores are significant. In particular, our estimation shows that a one-month increase in age increases the growth rate of test scores by about .155.

Estimates from the two-period lag models show that most regressors, across several specifications, are insignificant. We suspect that the sharp drop in observations for these two-period lag models may have decreased variance in the regressors and thus decreased statistical power.

5 Conclusion

The cross sectional findings of differences in test scores by SES groups at entry level are not surprising. Indeed, many authors who have examined test score gaps among race groups note that socioeconomic differences may be the main driving force. However, it is interesting that our cross sections indicate, for both math and reading scores, that the effect of belonging to a particular education group remains constant over time.

It should noted that in contrast to Fryer and Levitt's work, we do find a gap in scores for black and Hispanic children at entry when looking at math scores- a noticeably small one at approximately 11%. The results of the cross sectional regressions with math as a dependent variable are for the most part consistent with the literature: black children had significantly lower test scores than white and moderately lower test scores than Hispanics, and the trend continues across time - though the effect also does not increase or decrease.

The analysis of reading scores highlights a few more important findings. First of all, the gap at entry between blacks and whites is noticeably small at only about 2%. Blacks also outperform Hispanics at entry, in contrast to the findings for math. Perhaps the most interesting aspect of the trend in race coefficients is that the effect of being black quickly worsens. By ages 7 and 8 Hispanics are significantly outperforming blacks, and both blacks and Hispanics are performing worse than whites. By age 9 and 10, blacks are about scoring approximately 13 percentile points below their white counterparts.

The results from the difference model estimation were mostly inconclusive. The significant cumulative effect from HOME scores (Todd and Wolpin 2006) was not found in family income in our model. However, differences in differences in test scores among SES and race groups were found to be significant.

Possible extensions from our work include looking at the impact of socioeconomic measures across a longer horizon of time. For such an endeavor, it might be necessary to construct or obtain a longitudinal survey that looked at children's test scores through age 18, or maybe even later in life. It would have also been interesting to have data available on the cognitive abilities of parents. Perhaps a more pervasive sense of economic status might have taking into account the degree of education or income of children's grandparents or other relatives.

6 References

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Appendix

Table 1: PIAT Math and SES

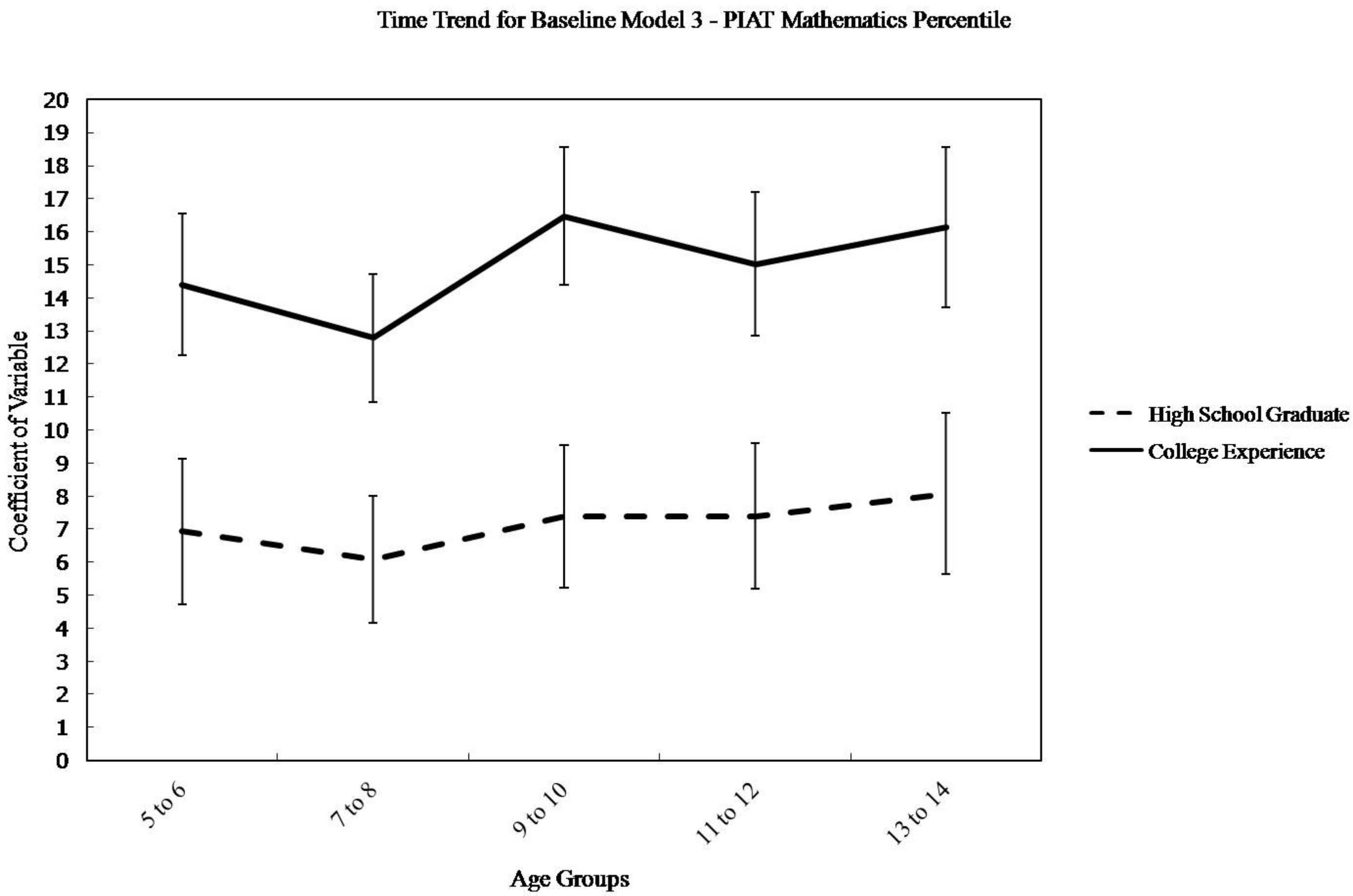


Table 2: PIAT Reading and SES

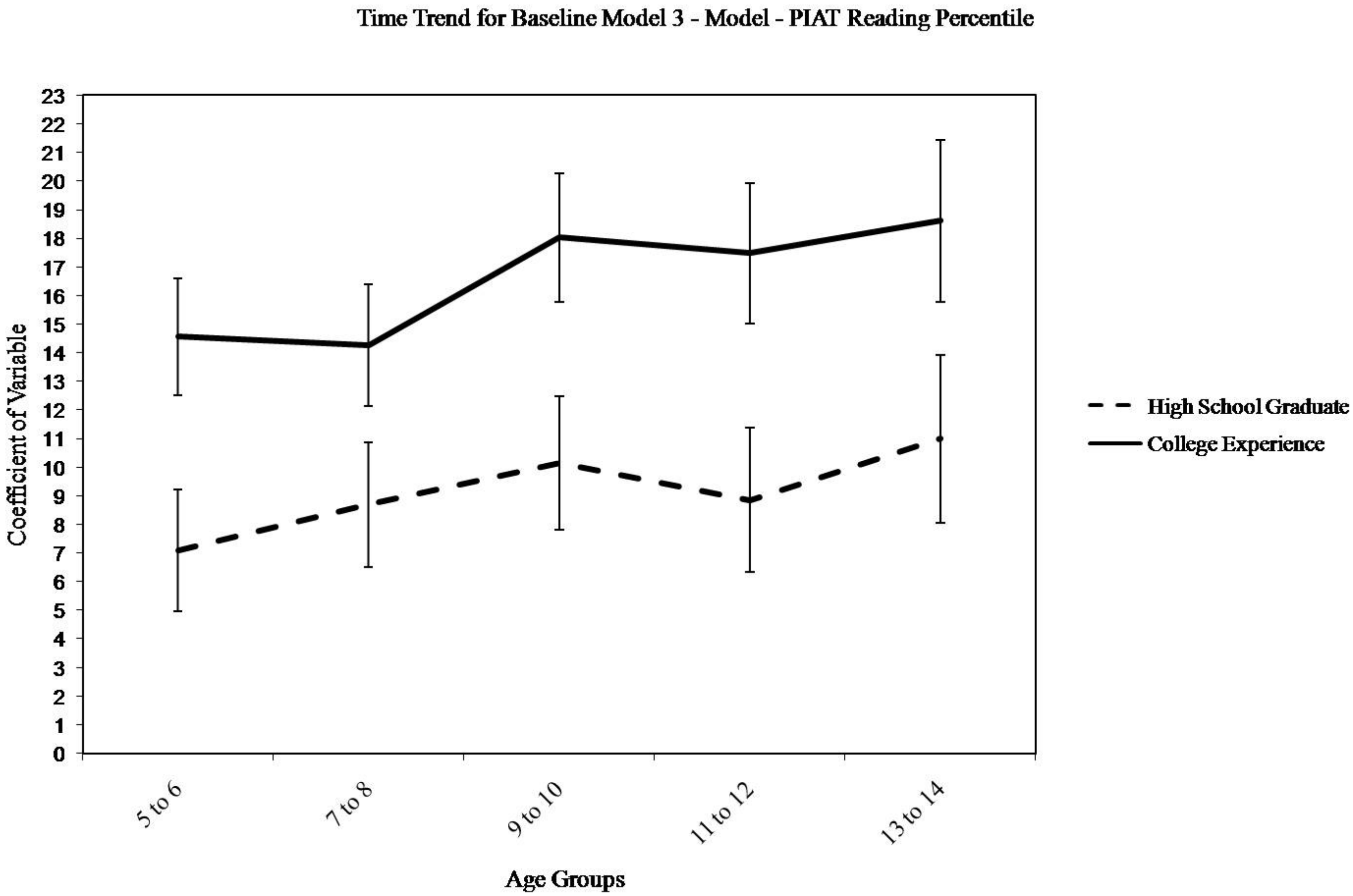


Table 3: PIAT Math and Race

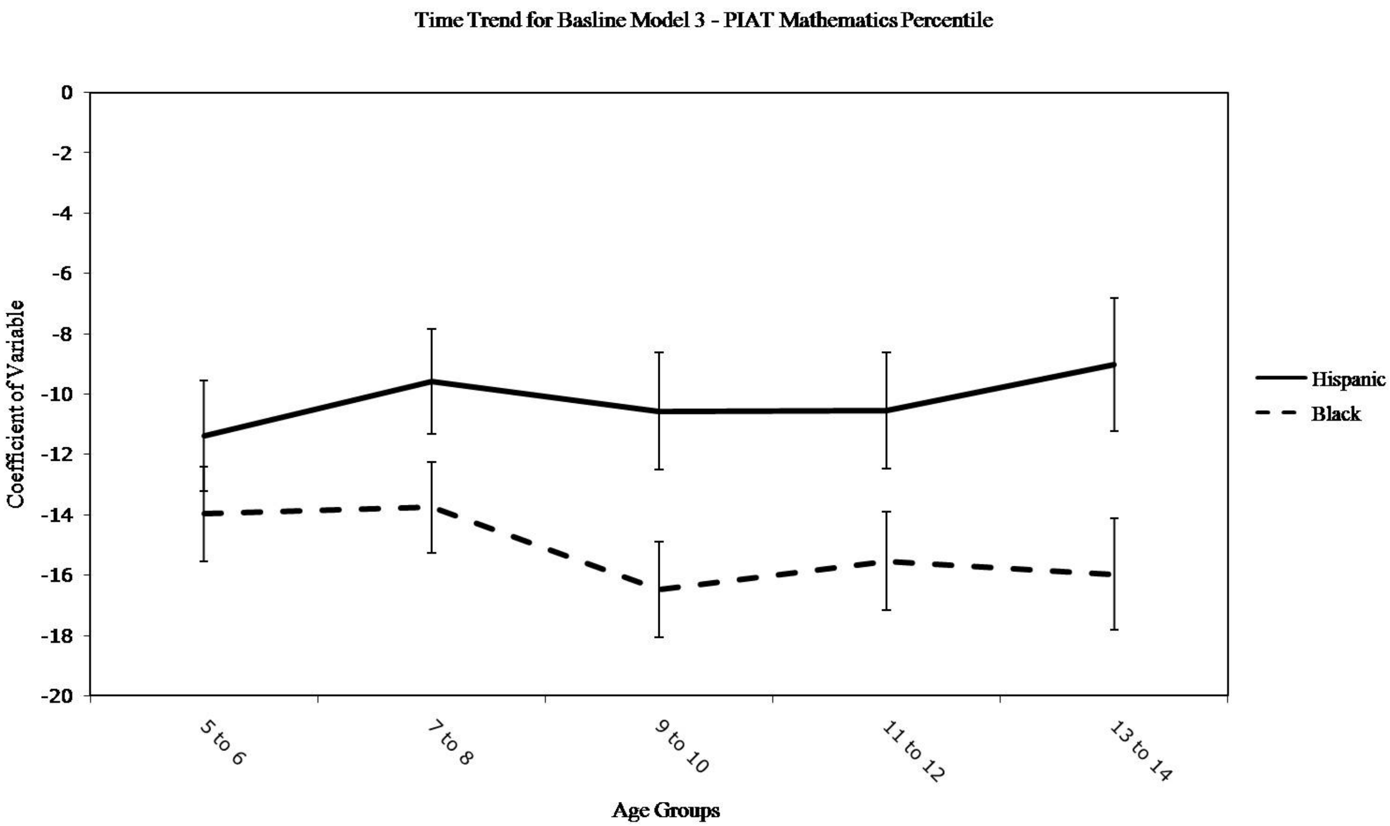
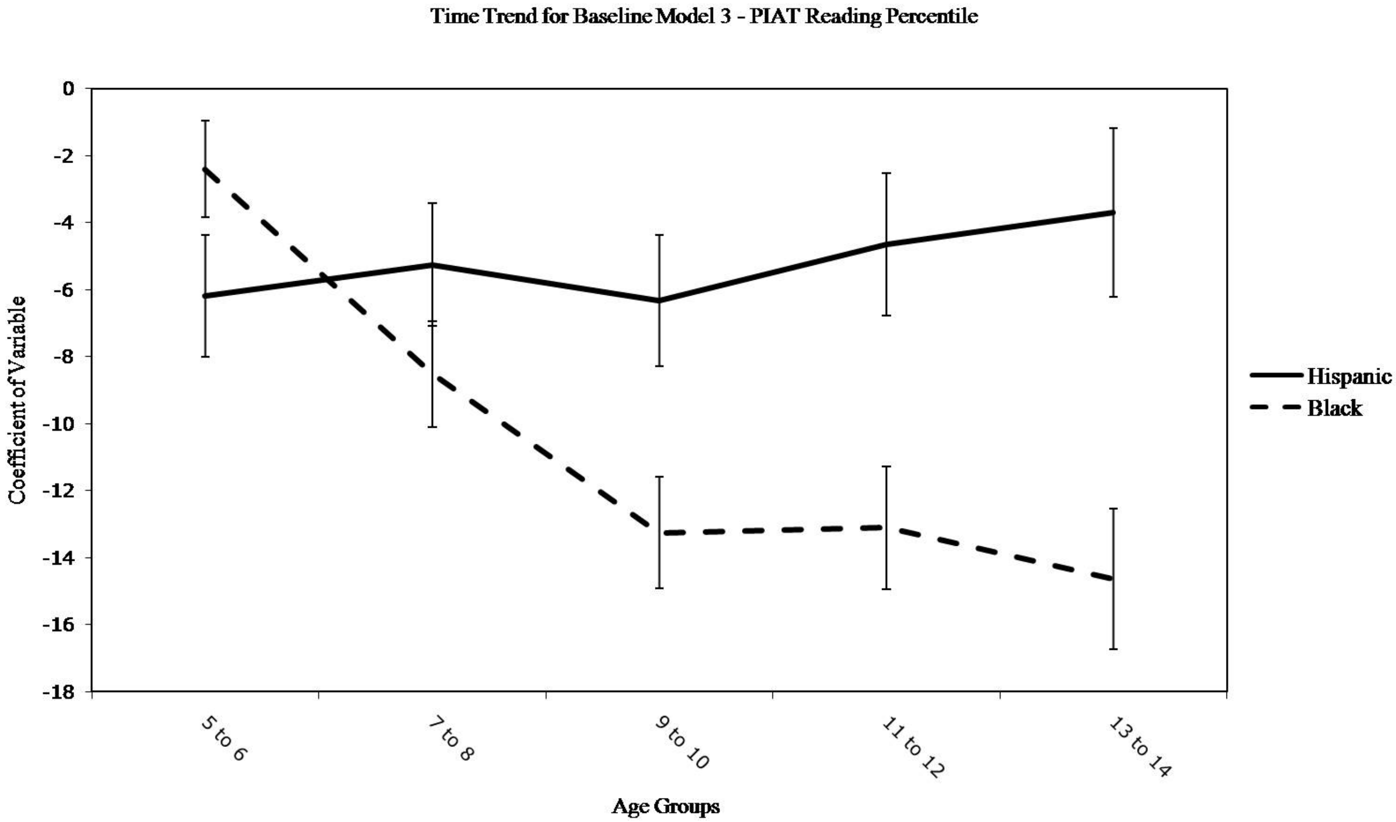


Table 4: PIAT Reading and Race



Summary Statistics for Math Baseline Models

	(1)	(2)	(3)	(4)	(5)
VARIABLES	mean (sd)	mean (sd)	mean (sd)	mean (sd)	mean (sd)
math_pct	50.04	51.97	52.66	51.24	47.53
	(27.52)	(26.18)	(28.76)	(27.85)	(27.43)
income	58.40	56.89	56.28	57.89	56.92
	(95.80)	(90.67)	(79.75)	(89.57)	(76.08)
mhsgrad	0.346	0.347	0.344	0.344	0.344
	(0.476)	(0.476)	(0.475)	(0.475)	(0.475)
mcol	0.460	0.451	0.440	0.435	0.425
	(0.498)	(0.498)	(0.496)	(0.496)	(0.494)
mcolincome	36.92	34.90	33.85	33.96	31.80
	(93.70)	(86.89)	(76.40)	(82.98)	(67.01)
mhsgradincome	16.13	16.43	16.25	17.24	17.73
	(40.95)	(43.73)	(38.52)	(43.40)	(44.62)
male	0.505	0.502	0.496	0.505	0.505
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
age	71.82	95.80	119.7	143.6	164.9
	(6.755)	(6.852)	(6.858)	(6.803)	(5.722)
correctbirthweight	0.0746	0.0769	0.0743	0.0787	0.0794
	(0.263)	(0.266)	(0.262)	(0.269)	(0.270)
youngmother	0.103	0.153	0.191	0.213	0.236
	(0.304)	(0.360)	(0.393)	(0.409)	(0.424)
maturemother	0.256	0.234	0.206	0.181	0.129
	(0.436)	(0.423)	(0.405)	(0.385)	(0.336)
somebooks	0.0829	0.154	0.0811	0.350	0.396
	(0.276)	(0.361)	(0.273)	(0.477)	(0.489)
lotsbooks	0.388	0.821	0.421	0.613	0.562
	(0.487)	(0.383)	(0.494)	(0.487)	(0.496)
hispanic	0.198	0.201	0.200	0.209	0.208
	(0.399)	(0.401)	(0.400)	(0.407)	(0.406)
black	0.282	0.288	0.307	0.321	0.332
	(0.450)	(0.453)	(0.461)	(0.467)	(0.471)
hispanicincome	10.30	10.01	10.57	10.65	11.36
	(44.64)	(39.65)	(46.54)	(44.05)	(46.12)
blackincome	10.18	10.02	10.34	12.23	11.41
	(35.75)	(34.52)	(22.63)	(44.95)	(25.99)
Observations	5801	5798	5571	5123	3740

Summary Statistics for Reading Baseline Models

	(1)	(2)	(3)	(4)	(5)
VARIABLES	mean (sd)	mean (sd)	mean (sd)	mean (sd)	mean (sd)
read_pct	60.60	59.92	57.63	54.80	54.60
	(25.61)	(26.83)	(28.84)	(29.66)	(30.17)
income	58.54	56.96	56.33	58.04	56.88
	(96.40)	(90.71)	(79.79)	(89.68)	(75.96)
mhsgrad	0.344	0.347	0.343	0.345	0.343
	(0.475)	(0.476)	(0.475)	(0.475)	(0.475)
mcol	0.462	0.452	0.439	0.435	0.425
	(0.499)	(0.498)	(0.496)	(0.496)	(0.494)
mcolincome	37.10	35.01	33.86	34.04	31.81
	(94.24)	(86.94)	(76.44)	(83.09)	(66.93)
mhsgradincome	16.06	16.43	16.24	17.32	17.68
	(41.10)	(43.74)	(38.53)	(43.48)	(44.56)
male	0.506	0.502	0.496	0.505	0.505
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
age	71.85	95.79	119.7	143.6	164.9
	(6.756)	(6.849)	(6.853)	(6.806)	(5.728)
correctbirthweight	0.0750	0.0761	0.0737	0.0783	0.0794
	(0.263)	(0.265)	(0.261)	(0.269)	(0.270)
youngmother	0.104	0.154	0.192	0.211	0.236
	(0.305)	(0.361)	(0.394)	(0.408)	(0.425)
maturemother	0.260	0.235	0.207	0.181	0.129
	(0.438)	(0.424)	(0.405)	(0.385)	(0.336)
somebooks	0.0820	0.152	0.0813	0.350	0.395
	(0.274)	(0.359)	(0.273)	(0.477)	(0.489)
lotsbooks	0.387	0.823	0.421	0.613	0.562
	(0.487)	(0.382)	(0.494)	(0.487)	(0.496)
hispanic	0.199	0.199	0.200	0.209	0.208
	(0.399)	(0.400)	(0.400)	(0.407)	(0.406)
black	0.281	0.289	0.307	0.322	0.332
	(0.449)	(0.453)	(0.461)	(0.467)	(0.471)
hispanicincome	10.40	9.980	10.57	10.64	11.37
	(44.99)	(39.67)	(46.53)	(44.10)	(46.07)
blackincome	10.13	10.05	10.32	12.26	11.48
	(35.91)	(34.55)	(22.59)	(45.02)	(26.06)
Observations	5707	5795	5574	5110	3755

Summary Statistic for Difference Models

	(1) Math	(2) Reading
VARIABLES	mean (sd)	mean (sd)
read_pct		57.45 (28.75)
income	58.34 (82.61)	58.60 (83.84)
age	129.1 (25.74)	128.9 (25.67)
home	967.3 (179.1)	970.9 (171.7)
hispanic	0.202 (0.402)	0.199 (0.400)
black	0.295 (0.456)	0.297 (0.457)
mcol	0.452 (0.498)	0.453 (0.498)
mhsgrad	0.346 (0.476)	0.349 (0.477)
hispanicincomediff	0.324 (39.67)	0.437 (38.76)
blackincomediff	0.472 (37.04)	0.455 (37.93)
mcolincomediff	0.871 (81.89)	0.911 (82.82)
mhsgradincomediff	0.633 (37.23)	0.806 (36.05)
math_pct	48.92 (29.63)	
Observations	17207	16266

Math Baseline Models for Ages 5 and 6

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
income				0.0200*	0.0195*
				(0.0119)	(0.0117)
mhsgrad	8.5675***		6.9340***	6.1845***	6.1361***
	(1.1266)		(1.1229)	(1.4171)	(1.4155)
mcol	15.8759***		14.4048***	13.7014***	13.6958***
	(1.0945)		(1.0899)	(1.2973)	(1.2945)
mcolincome				-0.0057	-0.0062
				(0.0129)	(0.0127)
mhsgradincome				0.0043	0.0045
				(0.0178)	(0.0175)
male	-2.1195***	-2.1193***	-2.1710***	-2.4822***	-2.4735***
	(0.7553)	(0.7601)	(0.7465)	(0.8008)	(0.8009)
age	0.1345	0.1799*	0.1384	0.1047	0.1051
	(0.0994)	(0.0998)	(0.0981)	(0.1047)	(0.1047)
correctbirthweight	-6.2019***	-6.0823***	-5.2369***	-4.9280***	-4.9215***
	(1.4425)	(1.4578)	(1.4323)	(1.5570)	(1.5584)
youngmother	-1.7964	-3.7268***	-0.6642	-0.0057	-0.0040
	(1.3097)	(1.2793)	(1.2781)	(1.3666)	(1.3672)
maturemother	5.5872***	6.6677***	4.9788***	4.7334***	4.7331***
	(0.8747)	(0.8711)	(0.8674)	(0.9386)	(0.9386)
somebooks	-12.3285***	-9.4950***	-7.5126***	-6.7989***	-6.7630***
	(1.9850)	(2.0105)	(1.9751)	(2.1140)	(2.1147)
lotsbooks	0.8172	0.7886	0.0166	-0.3412	-0.3666
	(1.3645)	(1.3733)	(1.3445)	(1.4401)	(1.4414)
hispanic		-13.4000***	-11.5742***	-11.3757***	-12.6370***
		(0.9317)	(0.9320)	(0.9995)	(1.1940)
black		-14.4073***	-13.9857***	-13.1951***	-13.0789***
		(0.8120)	(0.8024)	(0.8846)	(1.0876)
hispanicincome					0.0231*
					(0.0123)
blackincome					-0.0042
					(0.0161)
Constant	34.5371***	45.0721***	38.6412***	40.6439***	40.6966***
	(7.7283)	(7.7479)	(7.6311)	(8.1504)	(8.1554)
Observations	6760	6760	6760	5801	5801
R-squared	0.0877	0.0912	0.1248	0.1233	0.1237
F-statistic	57.3405	85.1514	91.3447	60.9020	55.1634

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Math Baseline Models for Ages 7 and 8

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
income				0.0042	0.0029
				(0.0133)	(0.0126)
mhsgrad	7.0871***		6.0821***	5.7173***	5.6824***
	(0.9967)		(0.9851)	(1.3237)	(1.3097)
mcol	13.5240***		12.7906***	12.2828***	12.2159***
	(0.9959)		(0.9875)	(1.2165)	(1.2083)
mcolincome				0.0100	0.0097
				(0.0141)	(0.0133)
mhsgradincome				0.0052	0.0045
				(0.0186)	(0.0180)
male	0.8782	0.7756	0.7113	0.2467	0.2711
	(0.6859)	(0.6899)	(0.6780)	(0.7345)	(0.7348)
age	0.0648	0.0859*	0.0786	0.0841	0.0826
	(0.0512)	(0.0512)	(0.0506)	(0.0549)	(0.0549)
correctbirthweight	-6.6426***	-5.9183***	-5.5858***	-5.4325***	-5.3577***
	(1.3708)	(1.3923)	(1.3649)	(1.4713)	(1.4704)
youngmother	-2.9831***	-4.3917***	-2.0023*	-2.0830*	-2.0498*
	(1.0296)	(1.0100)	(1.0302)	(1.1416)	(1.1424)
maturemother	5.5944***	6.3527***	5.0796***	4.4023***	4.4537***
	(0.8299)	(0.8254)	(0.8194)	(0.8961)	(0.8975)
sevenninesomebooks	-3.8803	-2.9569	-1.5199	0.6991	0.7574
	(2.3796)	(2.3541)	(2.2665)	(2.4655)	(2.4674)
sevenninelotsbooks	11.0956***	9.7871***	7.9779***	9.3502***	9.2302***
	(2.2329)	(2.2054)	(2.1184)	(2.2959)	(2.2986)
hispanic		-10.9105***	-9.5851***	-8.7279***	-9.3552***
		(0.8991)	(0.8920)	(0.9610)	(1.2311)
black		-13.7653***	-13.7560***	-13.2932***	-14.3706***
		(0.7819)	(0.7708)	(0.8633)	(0.9587)
hispanicincome					0.0104
					(0.0141)
blackincome					0.0266***
					(0.0098)
Constant	30.8031***	41.9109***	35.6165***	33.2965***	33.6943***
	(5.3965)	(5.3899)	(5.3098)	(5.7832)	(5.7867)
Observations	6793	6793	6793	5798	5798
R-squared	0.1186	0.1256	0.1558	0.1503	0.1509
F-statistic	90.3590	116.8322	115.0061	73.5229	67.5265

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Math Baseline Models for Ages 9 and 10

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
income				0.0375***	0.0352***
				(0.0101)	(0.0100)
mhsgrad	9.2164***		7.3941***	5.5189***	5.3347***
	(1.1190)		(1.0987)	(1.4612)	(1.4419)
mcol	18.0997***		16.4698***	16.1088***	15.7299***
	(1.0820)		(1.0654)	(1.2688)	(1.2866)
mcolincome				-0.0123	-0.0104
				(0.0112)	(0.0109)
mhsgradincome				0.0248	0.0253
				(0.0185)	(0.0177)
male	2.8379***	2.8452***	2.8200***	2.5773***	2.5777***
	(0.7653)	(0.7717)	(0.7524)	(0.8074)	(0.8074)
age	0.0616	0.0349	0.0604	0.0764	0.0774
	(0.0946)	(0.0953)	(0.0928)	(0.1006)	(0.1006)
correctbirthweight	-5.8767***	-4.3977***	-3.8469***	-4.0308**	-3.8663**
	(1.4907)	(1.4934)	(1.4478)	(1.5714)	(1.5746)
youngmother	-5.7395***	-7.7004***	-4.4697***	-3.7519***	-3.6879***
	(1.1045)	(1.0701)	(1.0926)	(1.1794)	(1.1801)
maturemother	7.4979***	8.5187***	6.7110***	5.6788***	5.6705***
	(0.9510)	(0.9529)	(0.9388)	(1.0170)	(1.0164)
sevenninesomebooks	-13.5834***	-12.5527***	-8.8811***	-7.1353***	-6.8884***
	(1.8608)	(1.9314)	(1.8874)	(1.9544)	(1.9603)
sevenninelotsbooks	3.0513**	1.8903	2.1188*	2.2251	2.2032
	(1.3056)	(1.3254)	(1.2833)	(1.3923)	(1.3933)
hispanic		-12.5602***	-10.5628***	-10.7719***	-10.7768***
		(1.0089)	(0.9936)	(1.0745)	(1.3395)
black		-17.1455***	-16.4714***	-15.1187***	-17.5586***
		(0.8255)	(0.8049)	(0.8946)	(1.2692)
hispanicincome					-0.0017
					(0.0149)
blackincome					0.0677***
					(0.0242)
Constant	36.4305***	55.6777***	41.5087***	37.7314***	37.9415***
	(11.9005)	(11.9597)	(11.6772)	(12.6437)	(12.6502)
Observations	6565	6565	6565	5571	5571
R-squared	0.1325	0.1347	0.1784	0.1831	0.1839
F-statistic	96.9680	123.4494	134.5504	93.5055	85.3235

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Math Baseline Models for Ages 11 and 12

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
income				-0.0007	-0.0019
				(0.0110)	(0.0108)
mhsgrad	9.1786***		7.4007***	5.4697***	5.3993***
	(1.1425)		(1.1271)	(1.5160)	(1.5122)
mcol	16.3427***		15.0278***	12.5094***	12.4705***
	(1.1256)		(1.1110)	(1.3796)	(1.3734)
mcolincome				0.0242*	0.0246*
				(0.0132)	(0.0129)
mhsgradincome				0.0300	0.0309*
				(0.0189)	(0.0187)
male	3.9112***	3.5864***	3.6213***	3.5099***	3.5258***
	(0.7729)	(0.7772)	(0.7611)	(0.8228)	(0.8232)
age	-0.1303**	-0.1215**	-0.1224**	-0.1387**	-0.1374**
	(0.0579)	(0.0579)	(0.0569)	(0.0617)	(0.0618)
correctbirthweight	-6.2407***	-4.9761***	-4.2779***	-4.0445**	-4.0422**
	(1.4967)	(1.5580)	(1.4979)	(1.6543)	(1.6558)
youngmother	-5.4137***	-7.1298***	-4.1230***	-4.0286***	-4.0208***
	(1.0480)	(1.0164)	(1.0379)	(1.1269)	(1.1272)
maturemother	4.8292***	6.0549***	4.5249***	4.2484***	4.2642***
	(1.0476)	(1.0435)	(1.0317)	(1.1186)	(1.1230)
elevensomebooks	3.4758*	2.7391	2.7279	2.5132	2.4954
	(1.9636)	(2.0861)	(1.9347)	(2.1352)	(2.1349)
elevenlotsbooks	15.3441***	12.6604***	10.8886***	10.1166***	10.0820***
	(1.9086)	(2.0533)	(1.9033)	(2.1134)	(2.1139)
hispanic		-12.3568***	-10.5444***	-10.3755***	-11.1107***
		(0.9884)	(0.9805)	(1.0689)	(1.3657)
black		-15.8708***	-15.5360***	-14.9848***	-15.0582***
		(0.8476)	(0.8314)	(0.9178)	(1.0932)
hispanicincome					0.0138
					(0.0159)
blackincome					0.0009
					(0.0121)
Constant	51.6259***	67.2090***	58.4217***	61.4263***	61.3596***
	(8.6105)	(8.6405)	(8.4739)	(9.1843)	(9.1870)
Observations	6059	6059	6059	5123	5123
R-squared	0.1499	0.1568	0.1933	0.1938	0.1940
F-statistic	101.3802	133.9260	138.6593	90.5291	81.3260

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Math Baseline for Ages 13 and 14

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
income				0.0336	0.0235
				(0.0228)	(0.0265)
mhsgrad	9.3009***		8.0807***	7.2069***	6.8252***
	(1.2593)		(1.2432)	(1.5835)	(1.6524)
mcol	16.8851***		16.1365***	14.4637***	13.9795***
	(1.2497)		(1.2406)	(1.7535)	(1.7897)
mcolincome				0.0076	0.0166
				(0.0258)	(0.0277)
mhsgradincome				0.0078	0.0158
				(0.0241)	(0.0268)
male	4.6851***	4.3935***	4.3705***	3.8892***	3.8914***
	(0.9200)	(0.9326)	(0.9069)	(0.9701)	(0.9704)
age	-0.3325***	-0.3196***	-0.3397***	-0.3650***	-0.3622***
	(0.0814)	(0.0820)	(0.0800)	(0.0864)	(0.0865)
correctbirthweight	-7.7078***	-6.8663***	-5.6672***	-5.4935***	-5.4437***
	(1.6878)	(1.7344)	(1.6789)	(1.8311)	(1.8365)
youngmother	-3.8194***	-5.7058***	-2.3211**	-3.0343**	-3.0200**
	(1.1668)	(1.1548)	(1.1575)	(1.2578)	(1.2583)
maturemother	3.4974**	4.7454***	2.9598**	2.4068*	2.3922*
	(1.3628)	(1.3839)	(1.3515)	(1.4505)	(1.4489)
thirteensomebooks	2.6484	2.2452	0.8706	2.4446	2.4544
	(2.5831)	(2.5766)	(2.4972)	(3.0551)	(3.0612)
thirteenlotsbooks	13.5633***	12.4792***	9.0876***	9.8109***	9.7712***
	(2.5924)	(2.6060)	(2.5398)	(3.1037)	(3.1110)
hispanic		-10.7479***	-9.0159***	-8.5891***	-9.5437***
		(1.1422)	(1.1302)	(1.1980)	(1.5599)
black		-16.0761***	-15.9669***	-14.6488***	-15.8920***
		(0.9710)	(0.9500)	(1.0556)	(1.5488)
hispanicincome					0.0160
					(0.0183)
blackincome					0.0317
					(0.0306)
Constant	85.8609***	99.4540***	94.5537***	96.1702***	96.2697***
	(13.6347)	(13.7652)	(13.4255)	(14.5689)	(14.5773)
Observations	4392	4392	4392	3740	3740
R-squared	0.1514	0.1546	0.1972	0.2109	0.2112
F-statistic	71.6018	93.3146	96.8456	69.2107	62.6858

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Reading Baseline Models for Ages 5 and 6

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
income				0.0292***	0.0286***
				(0.0074)	(0.0073)
mhsgrad	7.7034***		7.0895***	6.5089***	6.4510***
	(1.0768)		(1.0831)	(1.3713)	(1.3690)
mcol	15.1563***		14.5552***	13.9893***	13.9689***
	(1.0318)		(1.0382)	(1.2063)	(1.2071)
mcolincome				-0.0168**	-0.0172**
				(0.0083)	(0.0082)
mhsgradincome				-0.0095	-0.0091
				(0.0151)	(0.0149)
male	-4.9682***	-4.9194***	-4.9680***	-5.2195***	-5.2110***
	(0.6794)	(0.6917)	(0.6786)	(0.7317)	(0.7318)
age	-0.3106***	-0.2760***	-0.3107***	-0.3094***	-0.3092***
	(0.0944)	(0.0965)	(0.0943)	(0.1018)	(0.1018)
correctbirthweight	-4.6381***	-5.3244***	-4.4923***	-4.3880***	-4.3710***
	(1.3567)	(1.3895)	(1.3587)	(1.4744)	(1.4749)
youngmother	2.5707**	-0.4149	2.7394**	4.0228***	4.0283***
	(1.1862)	(1.1727)	(1.1801)	(1.2777)	(1.2778)
maturemother	6.9409***	8.4834***	6.7900***	6.5128***	6.5166***
	(0.7739)	(0.7792)	(0.7758)	(0.8455)	(0.8456)
somebooks	-6.1152***	-7.1091***	-4.9849**	-4.8663**	-4.8132**
	(1.9246)	(1.9849)	(1.9507)	(2.0859)	(2.0873)
lotsbooks	6.2846***	6.7921***	6.0821***	6.1150***	6.0893***
	(1.1498)	(1.1817)	(1.1473)	(1.2291)	(1.2297)
hispanic		-7.9782***	-6.1836***	-5.0886***	-6.1495***
		(0.9321)	(0.9236)	(0.9925)	(1.1733)
black		-2.8047***	-2.4091***	-1.4503*	-1.5612
		(0.7499)	(0.7370)	(0.8138)	(1.0154)
hispanicincome					0.0192**
					(0.0097)
blackincome					0.0017
					(0.0155)
Constant	73.5214***	81.9847***	74.9025***	74.0576***	74.1403***
	(7.2531)	(7.4067)	(7.2470)	(7.8124)	(7.8169)
Observations	6648	6648	6648	5707	5707
R-squared	0.1388	0.1029	0.1433	0.1422	0.1425
F-statistic	89.6494	62.7239	79.4980	53.3739	47.8059

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Reading Baseline Models for Ages 7 and 8

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
income				0.0383***	0.0374***
				(0.0095)	(0.0092)
mhsgrad	9.2656***		8.6807***	8.4190***	8.3451***
	(1.1095)		(1.1111)	(1.4405)	(1.4372)
mcol	14.6681***		14.2588***	15.0771***	15.0523***
	(1.0786)		(1.0824)	(1.2926)	(1.2928)
mcolincome				-0.0262**	-0.0268***
				(0.0102)	(0.0099)
mhsgradincome				-0.0011	-0.0006
				(0.0162)	(0.0160)
male	-5.5732***	-5.6235***	-5.6681***	-5.8307***	-5.8096***
	(0.6958)	(0.7047)	(0.6928)	(0.7463)	(0.7464)
age	0.0861*	0.1064**	0.0951*	0.1221**	0.1200**
	(0.0512)	(0.0515)	(0.0510)	(0.0551)	(0.0551)
correctbirthweight	-6.3904***	-6.0924***	-5.7299***	-5.2599***	-5.1908***
	(1.4219)	(1.4739)	(1.4323)	(1.5088)	(1.5107)
youngmother	0.4410	-1.7234	1.0203	1.3526	1.3913
	(1.0908)	(1.0691)	(1.0923)	(1.1938)	(1.1943)
maturemother	5.2039***	6.1079***	4.8951***	4.1082***	4.1545***
	(0.8002)	(0.8073)	(0.7987)	(0.8698)	(0.8703)
sevenninesomebooks	-5.5339**	-5.5268*	-4.0538	-3.0901	-3.0007
	(2.7607)	(2.8235)	(2.6783)	(2.9942)	(2.9963)
sevenninelotsbooks	9.2832***	9.5892***	7.4467***	6.5788**	6.5068**
	(2.6045)	(2.6584)	(2.5234)	(2.8197)	(2.8230)
hispanic		-6.8686***	-5.2591***	-4.9881***	-4.9305***
		(0.9459)	(0.9371)	(1.0156)	(1.4178)
black		-8.6284***	-8.5196***	-8.1189***	-9.2322***
		(0.8223)	(0.8024)	(0.8944)	(1.0501)
hispanicincome					-0.0024
					(0.0184)
blackincome					0.0283**
					(0.0125)
Constant	38.7732***	48.9108***	41.5435***	38.0072***	38.3686***
	(5.5776)	(5.6185)	(5.5518)	(6.0231)	(6.0331)
Observations	6784	6784	6784	5795	5795
R-squared	0.1193	0.1006	0.1326	0.1291	0.1298
F-statistic	86.8513	84.8889	91.4932	59.7539	53.4202

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Reading Baseline Models for Ages 9 and 10

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
income				0.0469***	0.0431***
				(0.0144)	(0.0132)
mhsgrad	11.4159***		10.1499***	9.4619***	9.2411***
	(1.1889)		(1.1867)	(1.5571)	(1.5265)
mcol	19.1088***		18.0097***	18.8613***	18.4345***
	(1.1452)		(1.1463)	(1.3385)	(1.3492)
mcolincome				-0.0236	-0.0208
				(0.0151)	(0.0138)
mhsgradincome				0.0092	0.0103
				(0.0217)	(0.0201)
male	-4.7037***	-4.7117***	-4.7162***	-4.9639***	-4.9563***
	(0.7645)	(0.7776)	(0.7574)	(0.8059)	(0.8059)
age	0.1206	0.1043	0.1247	0.0783	0.0791
	(0.0970)	(0.1001)	(0.0965)	(0.1030)	(0.1030)
correctbirthweight	-5.7024***	-4.8093***	-4.0536***	-5.2133***	-5.0405***
	(1.5337)	(1.5685)	(1.5154)	(1.6490)	(1.6517)
youngmother	-0.8977	-3.4406***	0.1842	0.9163	0.9823
	(1.1351)	(1.1296)	(1.1333)	(1.2034)	(1.2046)
maturemother	4.4536***	5.6320***	3.8478***	3.0931***	3.0949***
	(0.9296)	(0.9407)	(0.9242)	(0.9942)	(0.9934)
sevenninesomebooks	-13.3889***	-13.6687***	-9.7019***	-8.2996***	-8.0459***
	(1.9635)	(2.0763)	(2.0302)	(2.1505)	(2.1588)
sevenninelotsbooks	3.8901***	3.1026**	3.2401**	2.5340*	2.5019*
	(1.3149)	(1.3566)	(1.3074)	(1.4042)	(1.4048)
hispanic		-8.6248***	-6.3205***	-6.3749***	-6.9649***
		(1.0132)	(1.0002)	(1.0754)	(1.3132)
black		-14.0671***	-13.2537***	-11.4030***	-13.9065***
		(0.8795)	(0.8525)	(0.9396)	(1.3661)
hispanicincome					0.0086
					(0.0128)
blackincome					0.0685***
					(0.0261)
Constant	35.2329***	53.6861***	38.3345***	41.5361***	41.8616***
	(12.1633)	(12.5307)	(12.1040)	(12.9297)	(12.9385)
Observations	6565	6565	6565	5574	5574
R-squared	0.1153	0.0958	0.1438	0.1526	0.1535
F-statistic	80.3190	82.7165	103.6955	74.4822	68.2757

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Reading Baseline Models for Ages 11 and 12

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
income				0.0013	0.0011
				(0.0178)	(0.0180)
mhsgrad	9.9750***		8.8495***	5.7564***	5.7338***
	(1.2848)		(1.2858)	(1.6765)	(1.6845)
mcol	18.2282***		17.4741***	14.9660***	14.9480***
	(1.2439)		(1.2488)	(1.5413)	(1.5451)
mcolincome				0.0226	0.0231
				(0.0183)	(0.0183)
mhsgradincome				0.0395*	0.0402*
				(0.0220)	(0.0221)
male	-2.8416***	-3.0709***	-3.0544***	-3.0729***	-3.0712***
	(0.8175)	(0.8296)	(0.8087)	(0.8694)	(0.8700)
age	0.0251	0.0304	0.0285	0.0243	0.0244
	(0.0614)	(0.0620)	(0.0607)	(0.0657)	(0.0658)
correctbirthweight	-5.7570***	-4.8181***	-4.0010***	-3.6434**	-3.6595**
	(1.5563)	(1.6285)	(1.5507)	(1.6977)	(1.6987)
youngmother	-2.2405*	-4.6563***	-1.1693	-0.9882	-0.9929
	(1.1484)	(1.1404)	(1.1498)	(1.2444)	(1.2451)
maturemother	3.8727***	5.4113***	3.6279***	2.8403***	2.8311**
	(1.0361)	(1.0512)	(1.0296)	(1.0986)	(1.0999)
elevensomebooks	-3.2595	-3.7613	-3.8939	-4.3925	-4.3866
	(2.6175)	(2.5771)	(2.5379)	(2.7569)	(2.7572)
elevenlotsbooks	9.4023***	8.0569***	5.9454**	4.8519*	4.8579*
	(2.5643)	(2.5388)	(2.5095)	(2.7339)	(2.7354)
hispanic		-6.7878***	-4.6481***	-4.7755***	-5.0421***
		(1.0955)	(1.0873)	(1.1834)	(1.4281)
black		-13.5370***	-13.1070***	-12.9279***	-12.7094***
		(0.9536)	(0.9312)	(1.0214)	(1.1704)
hispanicincome					0.0053
					(0.0132)
blackincome					-0.0053
					(0.0116)
Constant	39.5141***	54.9447***	44.8466***	46.9189***	46.8999***
	(9.2062)	(9.2853)	(9.1019)	(9.8553)	(9.8571)
Observations	6046	6046	6046	5110	5110
R-squared	0.1342	0.1156	0.1596	0.1624	0.1625
F-statistic	81.0480	91.6439	107.6485	73.5786	65.0414

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Reading Baseline Models for Ages 13 and 14

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
income				0.0608***	0.0584**
				(0.0227)	(0.0257)
mhsgrad	11.7701***		10.9885***	11.3968***	11.1364***
	(1.4978)		(1.4923)	(2.0188)	(2.0225)
mcol	18.9683***		18.6060***	19.0233***	18.6751***
	(1.4453)		(1.4462)	(1.8455)	(1.9135)
mcolincome				-0.0278	-0.0270
				(0.0242)	(0.0261)
mhsgradincome				-0.0170	-0.0160
				(0.0287)	(0.0289)
male	-1.6370*	-1.8402*	-1.9062**	-2.1514**	-2.1499**
	(0.9711)	(0.9877)	(0.9593)	(1.0237)	(1.0239)
age	0.0155	0.0303	0.0063	-0.0012	0.0037
	(0.0876)	(0.0889)	(0.0868)	(0.0934)	(0.0935)
correctbirthweight	-4.2986**	-3.8653**	-2.3713	-1.1704	-0.9906
	(1.9147)	(1.9384)	(1.8764)	(2.0038)	(2.0065)
youngmother	-2.7831**	-5.3909***	-1.3859	-0.8955	-0.8876
	(1.3629)	(1.3522)	(1.3727)	(1.4861)	(1.4872)
maturemother	4.1499***	5.5610***	3.7178***	2.7585*	2.7468*
	(1.3451)	(1.3639)	(1.3291)	(1.4131)	(1.4113)
thirteensomebooks	3.3413	3.7837	2.0580	3.3757	3.2594
	(2.6408)	(2.6907)	(2.6087)	(3.0285)	(3.0346)
thirteenlotsbooks	14.9420***	15.4020***	11.4401***	11.6227***	11.3893***
	(2.6206)	(2.6912)	(2.6212)	(3.0386)	(3.0456)
hispanic		-5.8554***	-3.7131***	-3.3181**	-3.2132*
		(1.2861)	(1.2844)	(1.3716)	(1.9166)
black		-14.8832***	-14.6335***	-13.7722***	-16.4982***
		(1.1001)	(1.0652)	(1.1824)	(1.5426)
hispanicincome					-0.0042
					(0.0220)
blackincome					0.0741***
					(0.0224)
Constant	34.3611**	47.7365***	41.6302***	39.3128**	39.0738**
	(14.6569)	(14.9548)	(14.5417)	(15.7292)	(15.7365)
Observations	4406	4406	4406	3755	3755
R-squared	0.1378	0.1228	0.1698	0.1786	0.1799
F-statistic	61.9019	69.8360	84.0746	59.0463	56.0368

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Math Unbalanced Difference Models with No Lag

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
incomediff	0.0007	0.0006	0.0006	-0.0168	0.0003
	(0.0028)	(0.0028)	(0.0028)	(0.0090)	(0.0031)
agediff	-0.1613***	-0.1604***	-0.1582***	-0.1603***	-0.1613***
	(0.0479)	(0.0479)	(0.0481)	(0.0479)	(0.0479)
homediff	0.0105***	0.0105***	0.0105***	0.0105***	0.0105***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
hispanic	0.0219		0.1360		0.0137
	(0.6146)		(0.6275)		(0.6151)
black	-1.5622**		-1.4970**		-1.5659**
	(0.5137)		(0.5200)		(0.5138)
mcol		0.6568	0.5207	0.6218	
		(0.6893)	(0.7012)	(0.6892)	
mhsgrad		0.6595	0.5216	0.6035	
		(0.7118)	(0.7241)	(0.7116)	
mcolincomediff				0.0169	
				(0.0095)	
mhsgradincomediff				0.0292**	
				(0.0112)	
hispanicincomediff					0.0048
					(0.0061)
blackincomediff					0.0020
					(0.0051)
Constant	4.6508***	3.8488**	4.1106**	3.8832**	4.6517***
	(1.2195)	(1.3596)	(1.3688)	(1.3593)	(1.2196)
Observations	16739	16719	16719	16719	16739
R-squared	0.0059	0.0056	0.0059	0.0062	0.0059
F-statistic	13.7300	11.7983	10.0081	9.4485	10.0144

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Math Unbalanced Difference Models with 1 Period Lag

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
incomediff	-0.0029	-0.0029	-0.0030	-0.0255	-0.0027
	(0.0038)	(0.0038)	(0.0038)	(0.0138)	(0.0042)
agediff	-0.2450**	-0.2455**	-0.2432**	-0.2430**	-0.2450**
	(0.0810)	(0.0808)	(0.0811)	(0.0808)	(0.0810)
homediff	0.0090***	0.0090***	0.0090***	0.0090***	0.0090***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
hispanic	-0.5288		-0.3759		-0.5356
	(0.7896)		(0.8070)		(0.7918)
black	-0.9141		-0.8176		-0.9102
	(0.6665)		(0.6759)		(0.6667)
incomedifflag1	-0.0138**	-0.0138**	-0.0138**	-0.0135**	-0.0138**
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
agedifflag1	0.1546*	0.1538*	0.1562*	0.1541*	0.1548*
	(0.0681)	(0.0681)	(0.0682)	(0.0680)	(0.0681)
homedifflag1	-0.0005	-0.0006	-0.0005	-0.0006	-0.0005
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
mcol		1.0711	0.9536	1.0094	
		(0.9055)	(0.9225)	(0.9054)	
mhsgrad		0.6602	0.5440	0.5614	
		(0.9374)	(0.9544)	(0.9373)	
mcolincomediff				0.0232	
				(0.0145)	
mhsgradincomediff				0.0396*	
				(0.0163)	
hispanicincomediff					0.0013
					(0.0072)
blackincomediff					-0.0032
					(0.0072)
Constant	2.1181	1.2196	1.3341	1.2080	2.1133
	(2.5982)	(2.7744)	(2.7726)	(2.7719)	(2.5986)
Observations	9397	9386	9386	9386	9397
R-squared	0.0087	0.0088	0.0089	0.0098	0.0088
F-statistic	5.7198	5.6401	4.7132	5.4798	4.6882

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Math Unbalanced Difference Models with 1 and 2 Period Lags

VARIABLES	(1) mathpct	(2) mathpct	(3) mathpct	(4) mathpct	(5) mathpct
incomediff	0.0003	0.0004	0.0003	-0.0327*	0.0008
	(0.0066)	(0.0066)	(0.0066)	(0.0163)	(0.0070)
agediff	-0.2341	-0.2308	-0.2346	-0.2272	-0.2355
	(0.1699)	(0.1693)	(0.1701)	(0.1699)	(0.1701)
homediff	0.0090*	0.0090*	0.0091*	0.0093*	0.0090*
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
hispanic	1.1069		1.3879		1.1291
	(1.1119)		(1.1365)		(1.1120)
black	-0.3053		-0.0911		-0.3052
	(0.9534)		(0.9666)		(0.9532)
incomedifflag1	-0.0081	-0.0082	-0.0082	-0.0078	-0.0082
	(0.0098)	(0.0098)	(0.0098)	(0.0094)	(0.0099)
agedifflag1	-0.0068	-0.0003	-0.0034	-0.0033	-0.0065
	(0.1207)	(0.1203)	(0.1205)	(0.1199)	(0.1208)
homedifflag1	0.0035	0.0035	0.0035	0.0035	0.0035
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
incomedifflag2	0.0047	0.0047	0.0047	0.0043	0.0047
	(0.0069)	(0.0069)	(0.0069)	(0.0069)	(0.0070)
agedifflag2	-0.1562	-0.1572	-0.1571	-0.1494	-0.1569
	(0.1175)	(0.1172)	(0.1174)	(0.1171)	(0.1175)
homedifflag2	0.0027	0.0026	0.0026	0.0028	0.0027
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
mcol		1.0920	1.1989	0.9924	
		(1.2919)	(1.3134)	(1.2839)	
mhsgrad		2.3765	2.4775	2.2597	
		(1.3323)	(1.3561)	(1.3244)	
mcolincomediff				0.0366*	
				(0.0173)	
mhsgradincomediff				0.0474*	
				(0.0189)	
hispanicincomediff					-0.0108
					(0.0094)
blackincomediff					-0.0017
					(0.0103)
Constant	7.4817	5.8622	5.8643	5.7510	7.5234
	(6.2439)	(6.3970)	(6.4010)	(6.4015)	(6.2499)
Observations	4480	4475	4475	4475	4480
R-squared	0.0057	0.0066	0.0068	0.0094	0.0057
F-statistic	1.2364	1.5092	1.3459	1.8994	1.0770

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Reading Unbalanced Difference Models with No Lag

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
incomediff	-0.0003	-0.0003	-0.0004	0.0107	-0.0005
	(0.0018)	(0.0018)	(0.0018)	(0.0103)	(0.0020)
agediff	-0.0857*	-0.0857*	-0.0801*	-0.0855*	-0.0858*
	(0.0368)	(0.0369)	(0.0368)	(0.0369)	(0.0368)
homediff	0.0011	0.0011	0.0012	0.0011	0.0011
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
hispanic	0.2618		0.4624		0.2624
	(0.4587)		(0.4651)		(0.4588)
black	-3.9674***		-3.7790***		-3.9721***
	(0.3863)		(0.3893)		(0.3862)
mcol		2.0457***	1.7002***	2.0716***	
		(0.5077)	(0.5146)	(0.5063)	
mhsgrad		1.6512**	1.2879*	1.6781**	
		(0.5341)	(0.5398)	(0.5331)	
mcolincomediff				-0.0118	
				(0.0105)	
mhsgradincomediff				-0.0131	
				(0.0116)	
hispanicincomediff					-0.0004
					(0.0046)
blackincomediff					0.0028
					(0.0036)
Constant	2.3906*	0.2344	0.8920	0.2063	2.3939*
	(0.9323)	(1.0310)	(1.0330)	(1.0298)	(0.9325)
Observations	15269	15249	15249	15249	15269
R-squared	0.0060	0.0021	0.0069	0.0025	0.0060
F-statistic	25.8410	4.6798	19.6642	3.6591	18.6385

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Reading Unbalanced Difference Models with 1 Period Lag

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
incomediff	0.0003	0.0003	0.0003	-0.0043	0.0009
	(0.0022)	(0.0022)	(0.0022)	(0.0043)	(0.0024)
agediff	-0.0464	-0.0484	-0.0443	-0.0482	-0.0466
	(0.0546)	(0.0546)	(0.0546)	(0.0546)	(0.0546)
homediff	0.0012	0.0011	0.0012	0.0011	0.0012
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
hispanic	0.1015		0.2523		0.0931
	(0.5404)		(0.5495)		(0.5399)
black	-2.3759***		-2.2588***		-2.3673***
	(0.4601)		(0.4647)		(0.4599)
incomedifflag1	-0.0013	-0.0014	-0.0013	-0.0012	-0.0013
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
agedifflag1	0.0041	0.0030	0.0085	0.0025	0.0045
	(0.0429)	(0.0428)	(0.0429)	(0.0428)	(0.0429)
homedifflag1	0.0027	0.0026	0.0027	0.0026	0.0028
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
mcol		1.5175*	1.3014*	1.4998*	
		(0.6061)	(0.6165)	(0.6062)	
mhsgrad		0.7007	0.4746	0.6955	
		(0.6413)	(0.6488)	(0.6410)	
mcolincomediff				0.0057	
				(0.0047)	
mhsgradincomediff				0.0015	
				(0.0066)	
hispanicincomediff					0.0017
					(0.0053)
blackincomediff					-0.0069*
					(0.0032)
Constant	0.7599	-0.4913	-0.2619	-0.4723	0.7509
	(1.7448)	(1.8116)	(1.8080)	(1.8123)	(1.7451)
Observations	8671	8660	8660	8660	8671
R-squared	0.0030	0.0018	0.0038	0.0019	0.0031
F-statistic	4.2420	1.3382	3.9155	1.2237	3.8249

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Reading Unbalanced Difference Models with 1 and 2 Period Lags

VARIABLES	(1) readpct	(2) readpct	(3) readpct	(4) readpct	(5) readpct
incomediff	0.0017	0.0018	0.0017	-0.0054	0.0024
	(0.0040)	(0.0040)	(0.0040)	(0.0052)	(0.0041)
agediff	-0.1597	-0.1613	-0.1622	-0.1631	-0.1615
	(0.1020)	(0.1022)	(0.1022)	(0.1021)	(0.1022)
homediff	-0.0014	-0.0016	-0.0013	-0.0016	-0.0014
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
hispanic	0.5141		0.5087		0.5283
	(0.8078)		(0.8142)		(0.8066)
black	-1.6456*		-1.6064*		-1.6512*
	(0.6678)		(0.6725)		(0.6685)
incomedifflag1	0.0038	0.0038	0.0037	0.0040	0.0036
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0048)
agedifflag1	-0.0288	-0.0328	-0.0276	-0.0344	-0.0285
	(0.0868)	(0.0868)	(0.0869)	(0.0867)	(0.0867)
homedifflag1	0.0025	0.0024	0.0026	0.0025	0.0025
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
incomedifflag2	0.0047	0.0046	0.0046	0.0040	0.0046
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
agedifflag2	-0.0764	-0.0762	-0.0725	-0.0701	-0.0773
	(0.0812)	(0.0808)	(0.0811)	(0.0806)	(0.0813)
homedifflag2	-0.0030	-0.0030	-0.0029	-0.0029	-0.0031
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
mcol		0.7138	0.6043	0.6872	
		(0.8717)	(0.8834)	(0.8715)	
mhsgrad		0.1376	0.0104	0.1456	
		(0.9255)	(0.9334)	(0.9253)	
mcolincomediff				0.0116	
				(0.0060)	
mhsgradincomediff				-0.0049	
				(0.0076)	
hispanicincomediff					-0.0077
					(0.0093)
blackincomediff					-0.0054
					(0.0051)
Constant	5.9872	5.5255	5.5911	5.4695	6.0437
	(4.1922)	(4.2360)	(4.2339)	(4.2272)	(4.1986)
Observations	4154	4149	4149	4149	4154
R-squared	0.0050	0.0043	0.0053	0.0058	0.0051
F-statistic	1.7965	1.1576	1.5734	1.5315	1.6197

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05