Published in final edited form as:

Res Soc Stratif Mobil. 2012 September ; 30(3): 246–264. doi:10.1016/j.rssm.2012.01.004.

Parental income and the fruits of labor: Variability in homework efficacy in secondary school

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Abstract

Research in the sociology of education has shown that noncognitive traits are important predictors of educational outcomes and a mechanism of the intergenerational transmission of status. However, previous research on this topic typically posits that there is a constant effect of these traits with variable prevalences of these traits by socioeconomic status. Using time spent on homework as an example, I analyze income-based heterogeneity in homework efficacy, defined as the individual effect of study time on academic achievement, using a national U.S. probability sample of secondary students. Higher income students gain more knowledge from their homework time than their counterparts in all grades and all subjects except history, with greater group differences for math than for science and reading. These results are confirmed by models accounting for time-invariant unobserved heterogeneity in the 8th–10th, but not 10th–12th, grade windows. These results imply that increases in the amount of homework assigned may increase the socioeconomic achievement gap in math, science, and reading in secondary school.

Keywords

Homework; Efficacy; Academic achievement; Secondary school; Parental income; Education

1. Introduction

Research in the sociology of education is frequently concerned with the importance of noncognitive traits such as behavioral habits and personality on academic achievement outcomes. For example, the groundbreaking research of Bowles and Gintis (1976), Farkas and colleagues (Farkas, Grobe, Shehan, & Shuan, 1990; Farkas, 1996), Lareau (Lareau & Horvat, 1999; Lareau, 2000, 2001, 2002) and others (DeLuca & Rosenbaum, 2001; Farkas et al., 1990; Farkas, 1996; Lleras, 2008; Roscigno & Ainsworth-Darnell, 1999; Rosenbaum, 2001) suggests that those who are more attentive, spend more time on work, and avoid disruptive behaviors experience greater learning in school, greater educational attainment, and labor force success than comparably skilled persons who do so to a lesser degree. This important line of research assumes that these inequalities are created when more advantaged students disproportionately engage in the behaviors in question and thereby attain greater academic achievement than do less advantaged students. However, this research largely does not investigate the possibility that the rewards accruing to these behaviors vary by social background. To the degree that students derive differential rewards from favored behaviors

in the educational system, this line of research overlooks an important potential mechanism of educational inequality.

To address this possibility, in this research I investigate variability in the effect of time spent on homework in secondary school on academic achievement outcomes by parental income, grade, and subject. I hypothesize that more advantaged students will derive greater academic benefit from an additional hour of homework time than do less advantaged students who spend the same amount of time on their homework. Investigating this question for math, science, history, and reading, I show that, compared to less advantaged students, students with higher parental incomes derive additional knowledge from their studies in all subjects in 8th and 10th grade, and that this is true of all subjects except reading in 12th grade. However, this pattern is occasionally reversed at comparatively high amounts of time spent on homework. Because students with higher parental incomes also have higher initial test scores in 8th grade, these findings suggest that moderate increases in the homework load of secondary students will tend to increase inequality in academic achievement by parental income early in secondary school.

2. Background

2.1. Noncognitive traits and academic achievement

Sociological and other educational researchers have investigated the importance of a wide range of noncognitive traits for academic achievement and educational and occupational attainment, although many (Farkas, England, Vicknair, & Kilbourne, 1997; Farkas, 2003; Kerckhoff, Raudenbush, & Glennie, 2001; Lleras, 2008; Raudenbush & Kasim, 1998) argue that these processes have been understudied relative to cognitive skills. Among many others, parent–teacher and teacher–student relationships have been found to be important determinants of learning (e.g., Hamre & Pianta, 2001; Liew, Chen, & Hughes, 2010), as is parental social closure (e.g., Morgan & Sorensen, 1999), personality (e.g., Jackson, 2006), cultural capital and social skills (e.g., Lareau, 2003), and educational aspirations (Kao & Tienda, 1998).

However, school work habits and other goal-oriented behaviors occupy a prominent place in this literature. Bowles and Gintis (1976) emphasized the importance of perseverance, dependability, and consistency in school and labor force behavior, arguing that these traits were more important for stratification outcomes than was cognitive ability. Similarly, Farkas and colleagues (Farkas et al., 1990; Farkas, 1996) attribute similar importance to these traits in middle school net of cognitive skill influences. Similar findings are widely reported (e.g., DeLuca & Rosenbaum, 2001; Lleras, 2008; Roscigno & Ainsworth-Darnell, 1999; Rosenbaum, 2001).

Of these investigations, only DeLuca and Rosenbaum (2001) investigated variability in the effects of these traits. Their investigation found that harder-working low socioeconomic status students were less rewarded in their educational attainment outcomes than were their higher SES peers. The present investigation extends this important finding by examining socioeconomic variability in the academic achievement returns to time spent on homework in secondary school.

2.2. Time spent on homework

A key noncognitive behavior in this literature is work ethic, and time spent on homework is a potentially important means by which work ethic is expressed. Although the literature on noncognitive traits in education tends to emphasize their importance in grades, it may be that these are important for learning, as well. Time spent on homework is especially likely to do so because homework is assigned in the interests of promoting learning. As such the amount

of time spent on homework is a potentially important linkage between socioeconomic status and academic achievement.

However, there is no strong linear relationship between parental SES and time spent on homework. Instead, it may be that the important socioeconomic difference in homework is how effectively this time is spent. However, there is no consensus on whether homework promotes learning at all. Some studies document positive effects (Di Napoli, 1937; Dickinson & O'Connell, 1990; Koch, 1965; Maertens & Johnson, 1972) and others report null effects (Dettmers, Trautwein, & Luedtke, 2009; Gray & Allison, 1971; Hill, 1991; Schuman, Walsh, Olson, & Etheridge, 1985; Teahan, 1935). Despite this lack of evidentiary basis, over the last fifty years secondary students have taken on steadily increasing homework loads (U.S. Department of Education, 2007).

One reason for these inconsistent and generally weak associations between homework time and achievement may be the insufficient attention which has been paid to the heterogeneous effects of homework time on learning. These previous studies have generally attempted to estimate the association or causal effect thereof for a population as a whole. This paper contends that there is no single effect of study time on learning – rather, students vary in the benefits of their homework time. In other words, they vary in their homework efficacy.

2.3. Perspectives on learning and homework efficacy

Theories of learning in the educational literature suggest a number of mechanisms which vary by parental socioeconomic status and which may influence homework efficacy. Although this analysis will not be able to determine which of these mechanisms, if any, link parental income to socioeconomic inequalities in homework efficacy, a brief review of these theoretical traditions should highlight potential avenues for future research on this important topic.

Learning is a process which takes place through time, and the time required to master material varies between students. As discussed at length by Trautwein and Köller (2003), there are two dominant perspectives on the learning process which shed light on how variable effects of time studying might occur. The classic approach is known as the Opportunity to Learn (OTL) paradigm (Carroll, 1963, 1984; Paschal, Weinstein, & Walberg, 1984; Walberg and Paschal, 1995), in which learning occurs at the conjunction of *time spent on learning* (influenced by time constraints and perseverance) and *time needed to learn* (influenced by academic aptitude, ability to follow instructions, and the quality of instruction). This perspective suggests that time spent on homework should yield positive learning rewards, but only up to the amount of time needed to learn the material, which is shorter for students with greater cognitive abilities and better teachers. The implication is that higher achieving students and those with more effective teachers will gain greater knowledge returns to their time studying than will their counterparts up to the point at which they have mastered the material.

Both of these factors – measured cognitive ability and teacher quality – vary by parental socioeconomic status. Cognitive skill may shorten time needed to learn as higher skill students are able to more quickly master the homework material (Sorensen & Hallinan, 1977). Cognitive skill is positively associated with parental socioeconomic status (Alexander, Entwisle, & Dauber, 1993; Bloom, 1964; Duncan, Brooks-Gunn, & Klebanov, 1994; Escalona, 1982; Fryer & Levitt, 2005; Grodsky, Warren, & Felts, 2008; Hess, Holloway, Price, & Dickson, 1982; Pianta, Egeland, & Sroufe, 1990). Additionally, better teachers and teacher–student relationships may promote how much one learns from homework (Liew et al., 2010), and higher quality teacher–student relationships are

positively associated with parental SES (Birch & Ladd, 1997; Ladd, Birch, & Buhs, 1999; Pianta & Stuhlman, 2004a, 2004b).

A second perspective on self-guided learning is a combination of self-regulated learning theory (Boekaerts, 1999) and expectancy-value theory (Eccles, Adler, & Meece, 1984) explicated by Trautwein and Köller (2003). In this blending, there are three components of self-guided learning: cognitive (learning styles and strategies), metacognitive (goal specification), and motivational (motivation locus, control beliefs) components. Variability in these three components should yield variability in the rate of learning during study time – i.e., homework efficacy.

The *cognitive* component of this theory refers to learning styles and self-regulation of school effort. There are two primary styles of learning: reproductive (memorization and summarization) and constructive (meaning-seeking learning; Biggs, 1987; Entwisle, 1998; Marton & Säljö, 1984; Marton, Dall'Alba, & Beaty, 1993; Vermunt, 1992). Compared to reproductive styles, constructive learning strategies promote faster rates of learning during time spent on homework, even for assessments of factual knowledge (Beishuizen & Stoutjesdijk, 1999; Lindblom-Ylänne & Lonka, 1999; Vermunt & Vermetten, 2004). Self-regulation describes how students steer their learning activities. Examples include time management and diagnosing one's work for errors (Zimmerman, 1998). This concept is closely related to learning style – students exhibiting constructive learning strategies are more likely to demonstrate self-regulated learning (Schunk, 1990; Vermunt, 1998). Self-regulatory behaviors are associated with parental socioeconomic status in ways which advantage higher SES students. Additionally, lower SES students exhibit lower rates of self-regulated learning (Brody & Flor, 1997; Brody, Stoneman & Flor, 1996; Evans & English, 2002; Evans & Rosenbaum, 2008; Evans, Gonella, Marcynyszyn, Gentile, & Salpekar, 2005), suggesting that high SES students will have higher homework efficacy.

The *metacognitive* component of this theory refers to differences in mistake recognition, self-monitoring of one's current state of understanding, and expression of thoughts. The sparse evidence concerning socioeconomic patterns of metacognitive traits suggests that higher SES students will on average exhibit higher homework efficacy than lower SES students. An analysis of 5–6 year old children in day care showed that high SES children are better able to explain their ideas and thinking in a clinical setting (Pappas, Ginsburg, & Jiang, 2003). Middle class children typically show greater verbal skills than lower class children (Jordan, Huttenlocher, & Levine, 1992). Although I am unaware of any studies investigating socioeconomic patterns of metacognition in secondary school, these patterns are consistent with the hypothesis that higher SES students will have greater homework efficacy.

The *motivational* component refers to student differences in their locus of control and motivation to accomplish the task at hand. Locus of control (e.g., Battle & Rotter, 1963; Bialer, 1961; Findley & Cooper, 1983) describes the degree of control students believe they exert over the outcomes of a learning process. Those with external loci of control ('externals') on average show less persistence in the face of difficult tasks (Ducette & Wolk, 1972) and are on average associated with worse academic performance (Nelson & Mathia, 1995; Nowicki & Strickland, 1973). Additionally, motivation to achieve plays an important role, and more motivated students have better average academic performance (Schmitz & Skinner, 1993).

Research on the association of socioeconomic status with motivational factors suggests that students from higher SES homes could exhibit greater homework efficacy in both preschool (Day & Burns, 2011) and adulthood (Padawer, Jacobs-Lawson, Hershey, & Thomas, 2007).

However, I found no study investigating the relationship between school work motivations and parental socioeconomic status in secondary school. Additionally, internal locus of control is positively related to parental SES (Battle & Rotter, 1963; Findley & Cooper, 1983; Gore & Rotter, 1963). Finally, although evidence on this subject is limited, academic self-efficacy (a concept closely related to academic motivation and locus of control) may be positively related to parental SES, as well (Usher & Pajares, 2006; Vekiri, 2010). Additionally, qualitative work in sociology (e.g., Lareau, 2002) suggests that middle class students disproportionately display behavioral profiles consistent with high self-efficacy. Although much is unknown about the socioeconomic patterns of academic motivation in this literature, taken together this evidence suggests that higher SES students will demonstrate greater homework efficacy.

In sum, the bulk of the predictors of homework efficacy in the education literature predict that higher socioeconomic status students will demonstrate higher homework efficacy in secondary school. To the degree that parental socioeconomic status is linked to variation in homework efficacy, it is likely that socioeconomic differentials in academic ability, teacher relationships, cognitive learning styles, metacognitive characteristics, and sense of control and academic motivation to some degree mediate this relationship.

2.4. Homework and achievement: obstacles to inference

Unfortunately, assessing the independent effects of homework on learning is not a straightforward process. In addition to the challenge of identifying the individually variable effects of homework on learning, well-known spurious processes between these two characteristics could lead to misleading conclusions concerning their association. For instance, classes involving large homework loads, and students who spend a great deal of time on them, likely vary in systematic ways from classes and individuals which do not, which could result in biased estimates. Honors courses could attract more highly achieving students and involve more homework, resulting in the appearance of a homework–learning association regardless of whether there is a true such effect. Similarly, higher achieving students could be more motivated to work in school regardless of whether doing so is efficacious for them. Also, over time students may adjust the amount of time they spend studying to their achievement level depending on whether they have achieved their academic goals – students who are doing either very well or very poorly may throttle down their study efforts in order to ‘cruise’ (in the case of high achieving students) or give up (in the case of lower achieving students).

2.4.1. Association studies—The majority of observational studies (Dickinson & O’Connell, 1990; Koch, 1965; Maertens & Johnson, 1972; Rau & Durand, 2000) addressing this topic do not adequately address these difficulties. Although most document positive effects of homework effort (Cooper, 1989; Cooper, Robinson, & Patall, 2006), cross-sectional studies by definition cannot address the direction or causal status of an effect without an exogenous source of variation (as in a natural or designed experiment or instrumental variable study). Furthermore, many such studies fail to address teacher effects or other sources of unobserved heterogeneity which could bias their estimates.

2.4.2. Causal studies—Even so, a number of studies have tried to address these methodological challenges in a more interpretable manner. For instance, Cooper and colleagues (Cooper et al., 2006) find four studies (Foyle, Lyman, Tompkins, Perne, & Foyle, 1990; Foyle, 1984; McGrath, 1992; Meloy, 1987) which randomly assign a homework/no homework policy to different classrooms in different grades and subjects. All four such studies found some evidence of positive influences. Unfortunately, the necessarily small

scale of such studies and the difficulties of producing equivalent comparison groups in such settings limits their generalizability.

Other studies use observational, larger scale data to attempt to address some or all of these issues. Aksoy and Link (2000) use panel methods (fixed or random effects depending on the result of a Hausman specification test) using the NELS:88 dataset, and find positive influences of studying. Also using the NELS:88 dataset, Eren and Henderson (2008) find evidence of a positive, moderate, and declining marginal effect of study hours in 10th grade net of previous achievement, school fixed effects, and classroom achievement level. Stinebrickner and Stinebrickner (2008) use whether one's randomly assigned roommate at a small college has a video game system as an instrumental variable for study efforts, and document a positive effect of studying on GPA. Finally, Trautwein, Schnyder, Niggli, Neumann, and Ludtke (2009) find strong positive homework effort and homework time causal effects at the individual level among a moderate sample of foreign language students in Switzerland.

Collectively, therefore, these studies address some of the interpretation challenges raised by the previously reviewed research efforts. Fixed effects studies (such as Aksoy & Link, 2000 and Trautwein et al., 2009) eliminate individually-stable components of variance, including any time-invariant individual confounders of the homework–achievement relationship. Instrumental variables – even weak ones such as a roommate's gaming system – address the causal ordering question while also eliminating sources of spurious association (at the cost of efficiency). And the Eren and Ozkan (2008) study, by controlling for school fixed effects and classroom achievement level, address the multilevel nature of the homework completion process. Because all of these studies concur in their findings while differing in their methods and samples, they collectively provide some assurance that the *average* effect of homework on achievement is positive and causal.

2.4.3. Interactive studies—However, properly measuring variability in the effect of homework on achievement while accounting for these other challenges also poses inferential difficulties, and many of these more causally informative studies do not address this shortcoming. Variability in this effect may occur in one of two ways: due to variable mean effects of studying, and variable functional forms.

A few other studies attempt to investigate this subject. Possible moderators of homework efficacy include grade in school (Cooper et al., 2006), female gender (Mau & Lynn, 2000, but see Foyle, 1984), and class achievement levels (Eren & Henderson, 2008). Although not directly tested as such, the literature also suggests a number of other possible predictors of homework efficacy, among them test anxiety (Culler & Holahan, 1980), study skills (Credé & Kuncel, 2008), and parental involvement (Hoover-Dempsey et al., 2001). In the last decade, therefore, research on the homework–achievement relationship is beginning to recognize the potential for heterogeneity in its effects. To further this literature, the present research investigates socioeconomic and grade differentials in homework efficacy within a causally interpretable model.

3. Methods

3.1. Data: national educational longitudinal study of 1988

The NELS:88 public use dataset offers several advantages for studying the topic at hand. It provides a large ($N = 27,394$ cases), nationally representative data set of the cohort of U.S. adolescents in the 8th grade in 1988 with a school-based sampling design, and follows a subset ($N = 15,437$) of them longitudinally through five waves of data collection, including data from ages 14 to about 26. Importantly, the data includes repeated administrations of an

identical set of subject-specific academic achievement tests in 8th, 10th, and 12th grades. I restrict my analysis to those who participated in the first three waves of data, whose school was marked with an identifier, and who remained in school through 12th grade and completed all three achievement test administrations, leaving 16,489 cases in the analytical sample, clustered in 1,468 schools. Data were multiply imputed (Allison, 2002; Rubin, 1987) using the multivariate imputation by chained equations (MICE) method in Stata (Royston, 2004).

3.2. Measures

3.2.1. Time spent on homework—I measure study time using student categorical reports of the number of hours the respondent typically expends studying each subject outside of class in each week. The question reads, “In the following subjects, about how much time do you spend on homework each week?” Response categories for the first wave of data were “none,” “less than 1 hour,” “1 hour,” “2 hours,” “3 hours,” “4–6 hours,” “7–9 hours,” and “10 or more.” In subsequent waves the scales of the categories shifted upward, so to make measures comparable between waves each category was recoded with the number of hours if it is a specific value listed, the median if a range is listed, and the lowest value in the highest category (i.e., in the first wave, 10; in the second and third, 15). For each category the midpoint of the range is assigned as the numerical value; for the upper category, ten hours were assigned for the highest category in 8th grade and fifteen hours for the highest category in 10th and 12th grades.

3.2.2. Academic achievement—Academic achievement is measured using a subject-specific achievement test administered to students by NELS 88 in the 8th, 10th, and 12th grades, employing the item response theory (IRT) estimated number right metric. NELS 88 staff recommend this metric for longitudinal analysis (Rock & Pollock, 1991) as it is a reliable measure (thus somewhat reducing the problem of regression to the mean) and is directly comparable across administrations. Furthermore, this computer-administered test uses student performance on early questions to scale the difficulty level of subsequent questions, increasing precision of measurement.

3.2.3. Demographic characteristics—Information on respondents’ gender, race/ethnicity, and parental income are also employed in this analysis to provide information on the demographic characteristics of the sample and to test the hypothesis that homework efficacy varies by parental socioeconomic status. These are treated as time-invariant characteristics since parental income is measured only in 8th grade in NELS:88. Gender and race/ethnicity are measured by student report. Parental income is measured by parental report and grouped into fifteen categories, which in this analysis are recoded to the midpoint of the range and logged.

3.3. Models

Regression analyses proceeded in two primary steps. First, to test whether there is an average association between time spent on homework and academic achievement scores, OLS regression models were estimated predicting subject-specific academic achievement as a cubic function of time spent on homework, parental income, race, gender, and an interaction between all homework terms and parental income. The results of these models will establish whether there is an average association between homework and standardized test performance (stratified by subject and grade in school), and whether this association varies by parental income. As such these results will constitute the first test of the hypothesis that homework efficacy varies proportionally to parental income.

However, it is likely that these estimates will be biased due to unobserved heterogeneity in time-invariant factors such as academic potential. Accordingly, these results will be confirmed in a first differences regression analysis focused on change in homework time and academic achievement scores. First differences models are substantively very similar to fixed effects regression (Halaby, 2004) in that time-invariant, unobserved characteristics with constant effects are differenced out from the estimating equation. However, as with all panel methods, time-varying sources of unobserved heterogeneity and time-invariant characteristics with time-varying effects may still bias the estimates obtained.

A key refinement of the standard first differences model is required for present purposes. Although the main effects of time-invariant variables are not estimated in this model, the effects of changes in homework are interacted separately with a time-invariant characteristic – parental income in 8th grade. This adjustment produces the following model:

$$\Delta Y_{it,(t-1)} = \beta_0 + \beta_1 \Delta X_{it,(t-1)} + \beta_2 \Delta X_{it,(t-1)}^2 + \beta_3 \Delta X_{it,(t-1)}^3 + \beta_4 \Delta X_{it,(t-1)} I_0 + \beta_5 \Delta X_{it,(t-1)}^2 I_0 + \beta_6 \Delta X_{it,(t-1)}^3 I_0 + \Delta \varepsilon_{it,(t-1)} \quad (1)$$

where $\Delta Y_{it,(t-1)}$ is change in academic achievement, $\Delta X_{it,(t-1)}$ is change in study time, and I_0 is logged parental income in 8th grade.¹ The interactive effect of parental income and time spent on homework (captured in β_4 , β_5 , and β_6) is of crucial concern for the present analysis and is taken as a measure of homework efficacy when potential time-invariant sources of spuriousness are accounted for.

As described, this model will be estimated for the NELS:88 sample by examining the association of changes in study time and academic achievement for four different subjects – mathematics, science, history/social studies, and reading. In each case the study time measure used will be matched by subject to the academic achievement measure being explained. In other words, hours spent studying for math will be used to explain variation in mathematics achievement. The lone exception to this practice will be the models of reading achievement, for which hours spent studying for English class will be the predictor variable.²

3.4. Margins of responses

In addition to properly estimating the association between study time and academic achievement, a further challenge of this analysis is to synthesize the large number of regression coefficients the analysis produced into an interpretable form. This is done by converting the regression coefficients into margins of the change in achievement scores associated with different values of study time. In this analysis, this consists of calculating the mean change in achievement expected if all respondents reported a 0–10 hour amount of homework time for a subject, while using the observed values on all control variables. In other words, this exercise calculates the predicted value of the change in academic achievement score when some covariates (homework time) are manipulated while others are used as observed. This approach is known as adjusted predictions or the method of recycled predictions. The key virtue of this approach is that it reduces the several regression

¹At first it may appear to run against the spirit of the first differences model to include a non-differenced measure of parental income in the regression equation. However, because this term is only interacted with the change in homework time variables – it has no main effects terms – this term does not reintroduce unobserved heterogeneity against which the first differences model was intended to guard (Allison, 2005), and permits examination of another dimension of homework efficacy. In effect, the average regression parameters estimated for these interactive terms show how the marginal value of an additional hour of study time changes depending on one's parental income.

²This is a less satisfactory measure of the relevant homework time than for the other subjects because, although one likely learns relatively little math when completing homework assignments for other subjects, one is likely to learn something about reading comprehension when one is doing homework for nearly any subject. Unfortunately, no satisfactory alternative to this measure exists in the dataset, so the reading results must be examined with this caveat in mind.

coefficients associating changes in study time with changes in achievement in the proposed model into readily understood predicted change scores.

However, because the NELS:88 academic achievement tests vary by subject in their scale – for instance, the maximum math score is higher than the maximum science score – these marginal values are converted to an especially interpretable and comparable form with an eye on understanding changes in inequality associated with changes in study time. Each margin is displayed as the counterfactual rate of change (CRC) value

$$CRC_{j=0}=100 \left(\frac{M_j - M_0}{M_0} \right) \quad (2)$$

where j is the increase in study effort being evaluated and M_j is the margin value observed when all observations are assigned a k increase in homework time. Therefore M_j is the percentage increase in learning expected when one increases one's homework time by k compared to the amount of learning expected with no increase in homework time. So for instance, if M_3 is 10 and M_0 is 8, $R_{3-0} = 25\%$, indicating that one would learn 25% more in that time interval if one studied three hours per week than if one had not studied. The results on the left hand side of Figs. 2–4 (discussed below) are displayed in CRC form.

To assess the degree to which increases in homework hours would increase the socioeconomic achievement gap, these results are also shown in a different form, as

$$MDR_{jkl} = 100 \left\{ \frac{(M_{jkt} - M_{0kt}) - (M_{jlt} - M_{0lt})}{(\bar{y}_{k(t-1)} - \bar{y}_{l(t-1)})} \right\} \quad (3)$$

where MDR_{jkl} is the margins difference ratio (hereafter MDR), M is the margin of response, j is the value of change in homework time being evaluated, k and l denote the designated reference and comparison groups, t designates the grade at the end of the interval being examined, and y are the mean achievement scores at the beginning of that interval. This ratio is interpretable as the percentage increase or decrease in the achievement gap between groups k and l associated with a uniform j hour increase in homework time over the interval $t-1$ to t . In other words, it is the percentage growth in the achievement gap between two groups predicted by the model if all students increased their homework time by j hours. The results on the right hand side of Figs. 2–4 (discussed below) are shown in MDR form.

4. Results

4.1. Homework and achievement – variability over time

There is sufficient variability in the key variables just described to estimate these models. This is important to investigate because, if students' reported study time or academic achievement did not substantially vary over time, it would be impossible to estimate the desired effects. Comparing change in achievement scores between the 10th and 12th grades for math, science, history, and reading with cross-sectional variability in the same tests in 10th grade, as Table 1 shows, the standard deviation in the change in test scores is 69, 82, 76, and 84% the standard deviation of the cross-sectional distributions respectively. Therefore while the variability in the change scores are somewhat reduced, ample variability in test score changes still remain. Similarly for time spent on homework, the comparable figures are 80, 73, 69, and 81%. Thus there remains sufficient variability in both the first-differenced study time and academic achievement measures to efficiently estimate the proposed models in order to assess the contribution of differences in study time and homework efficacy to the achievement gap.

Another potential limitation of the analysis would be if the majority of changes in time spent on homework values were between adjacent categories across waves, potentially suggesting that apparent changes in studying time are the result of measurement error. This is not the case. For all subjects and grades, more than 40% of respondents shifted their self-reported time spent on homework between non-adjacent categories in the original survey measure (not shown).³ Depending on the grade window and subject, only 22–31% of respondents report studying amounts in the same categories between windows of observation. These results suggest that changing the amount of time spent on homework students report is the norm, not the exception.

4.2. The achievement and homework gaps by parental income

Table 2 reports mean achievement scores by subject and parental income percentile in 8th and 10th grades, where achievement scores are calculated as the mean of students within two percentage points in either direction from the indicated parental income percentile. The data show large differences in academic achievement by parental income. For instance, the mean math achievement test score in 8th grade is 26% lower for those in the 10th income percentile compared with those in the 90th percentiles. Gradations in academic achievement in both grades and all subjects are well-ordered by income, such that each percentile listed in Table 2 shows a higher mean score on the achievement test than all lower percentiles. In general, the smallest proportional achievement gaps by income are observed for history, followed by science, reading, and math. All differences in academic achievement by grade and subject listed in Table 2 are statistically significant compared to the values for the 90th percentile income group.

Fig. 1 graphically depicts similar information for time spent on homework in all four subjects by parental income for 8th, 10th, and 12th grades. The data show a curvilinear relationship between parental income and time spent on homework. The relationship is relatively flat for all subjects in 8th grade. However, a strong curvilinear relationship between self-reported time spent on homework and parental income is observed in 10th and 12th grades. Those with the lowest parental incomes report the highest typical time spent on homework values, and the relationship with high levels of income is concave up.⁴

4.3. Other descriptive statistics

Additionally, Table 3 reports the demographic composition of the imputed, unweighted NELS:88 analytical sample,⁵ as well as descriptive statistics on all time-variant control variables employed in the regression models reported. The analytical sample was 51% female and 49% male. Sixty-eight percent of the respondents were non-Hispanic white, 10% were non-Hispanic black, 12% were Hispanics of any race, 6% were Asian Americans, and 4% were Native Americans. The average logged parental income in 8th grade (in thousands of dollars) was 10.3, with a standard deviation of 0.93.

4.4. Homework efficacy inequality by parental income

The first question to answer in this analysis is whether time spent on homework is statistically significantly associated with standardized test scores. Tables 4 and 5 show the

³To make figures comparable between the 8th and 10th grade periods of observation, for the purpose of this calculation only time spent on homework was recoded so that the top value for 10th and 12th grades for all subjects was 10 or more hours a week, as it was coded in the original survey in 8th grade.

⁴This pattern may be partially skewed by a tendency among the lowest income respondents to report the maximum amount of study time at rates higher than any other group. It is unclear whether this is the result of a differential tendency toward measurement error or a real spike in studying patterns among those at the lowest parental incomes.

⁵These figures are unweighted to reflect the characteristics of the sample rather than the target population. All other analyses are weighted.

results of all regression models employed in this analysis. All models control for income, gender, and race. As can be seen in models (1), (3), and (5) in Tables 4 and 5, time spent on homework is statistically significantly associated with performance on standardized tests in all subjects and grades.

Models (2), (4), and (6) report the results of the same models, with interactions estimated between all time on homework terms and logged parental income in 8th grade. The results of this analysis are less consistent. There is a statistically significant interactive effect of time spent on homework and parental income for math in 8th and 12th grades, but not 10th grade. For science, the interactive effect is observed in the 10th grade only. In contrast, no evidence is found for an interactive effect of time spent on homework and standardized test performance in history and reading in any grade.

The functional form of these relationships is best depicted visually. The leftmost panels of Figs. 2–4 depict the results of this analysis in CRC form, separately by parental income percentile. For all subjects, grades, and parental income levels, evidence is seen in these results for a strong, curvilinear, concave down relationship between time spent on homework and academic achievement on a standardized test in the same subject. For all grades and subjects, this relationship peaks at around five hours spent studying, although depending on the grade, subject, and parental income group, the peak varies at between three and nine hours spent on homework per week.

These CRC plots also show that, at low to moderate homework totals, those with higher parental incomes benefit the most from time spent studying. In 8th grade, this generalization holds for math and science at nearly all homework tallies and through four hours spent studying per week for reading. (However, the reading interaction was not statistically significant.) In 10th grade, this pattern holds for all subjects, although the pattern is reversed above eight hours of homework per week for science. However, the degree to which income determines CRC values by income is generally smaller in 12th grade, and those patterns that are observed are sometimes not consistent with the hypothesis that parental income is positively associated with homework efficacy. Little substantively important difference in study efficacy is observed for science, history, and reading in 12th grade, and none of these differences are statistically significant. For math, there is a statistically significant interaction between time spent on homework and parental income, but the result is very little difference in homework efficacy through about four hours of studying per week, and higher levels of homework efficacy above that level.

Those grade and subject combinations which do show statistically significant interactions of time spent on homework and parental income suggest that higher homework loads will be associated with higher degrees of academic achievement inequality by income in these settings. There is a statistically significant interaction between time spent on homework and parental income for math in 8th and 12th grades. In 8th grade, this pattern results in a curvilinear relationship between time spent on studying and the predicted change in the achievement gap compared to 90th percentile parental earners, as seen in Fig. 2. No matter the homework level employed above 0, it is predicted that the size of the achievement gap will increase. A similar pattern is observed in 12th grade up through six hours spent on math homework per week, as shown in Fig. 4. Above this amount of time spent on homework, however, the pattern is reversed, and a decrease in the achievement gap is predicted.

The only other statistically significant interaction between time spent on homework and academic achievement is for science in the 10th grade. As seen in Fig. 3, those with the highest parental incomes have the highest homework efficacy up through approximately six hours of time spent on homework per week. Above that level, this pattern is reversed, as

those with the lowest parental incomes are predicted to have the highest homework efficacies. As a result, this model predicts increases in the 10th grade science achievement gap up through eight hours of homework time per week, followed by a reduction therein at higher levels of time spent on homework. Although other income interactions with time spent on homework are not statistically significant, these results invariably predict increases in the achievement gap by parental income at low to moderate levels of homework.

Finally, the cross-sectional models achieve a reasonable degree of fit with the data, as measured by the model R^2 values. Math models for all grades explain about 20% of the variance, depending on the exact specification. The fit for other subjects is somewhat lower but still reasonable, as science models explain between 15 and 19% of the variance in test scores across models, history about 14%, and reading 11–15%.

4.5. Robustness check – first differences models

As discussed above, however, the results of this model do not adequately address concerns that the results are biased due to unobserved heterogeneity in time-invariant factors such as individual ability and school characteristics. As such, the results discussed so far are supplemented with interactive first differences models in which the changes in test scores are predicted as a function of changes in time spent on homework, interactively with parental income. The results of this analysis are presented in the right hand sides of Tables 4 and 5. In both of these tables, models (7) and (8) present the results of a specification analogous to models (2), (4), and (6) – but without controls for race, gender, or the main effect of parental income. These variables are omitted from the specification because they are time-invariant. The purpose of these analyses is to confirm that the findings of the cross-sectional analyses are robust to adjustment for the effects of time-invariant sources of unobserved heterogeneity.

The results for both the 8th–10th and 10th–12th grade windows confirm that homework and parental income statistically significantly interact in predicting gains in academic achievement for all subjects except history. As with the cross-sectional analysis, the CRC plots (not shown) for the first difference models predict that, in 8th–10th grade, those with higher parental incomes will enjoy higher homework efficacy. CRC scores are uniformly positive for math and history; predicted change scores are slightly negative for the lowest income students at very high increases in studying for science and reading. Concomitantly, the MDR plots for the same time window (not shown) predict strong, roughly linear increases in the achievement gap compared to students with 90th percentile parental income for all subjects except history, for which the predicted change in the achievement gap is slightly positive and concave down with respect to increases in homework levels. In sum, with the exception of history, in the 8th–10th grade window the results of the first differences regression analysis support the conclusions of the cross-sectional analysis that students with higher parental income enjoy higher homework efficacy.

However, this pattern is contradicted by the results of the first differences models for the 10th–12th grade window, which finds that lower income students have higher homework efficacy, and that increases in homework loads will reduce, not increase, the socioeconomic achievement gap for all subjects. The MDR plots for the first difference models in the 10th–12th grade (not shown) show that the inequality-negating effect of these model results is roughly equal in magnitude to the positive MDR coefficients for the 8th–10th grade window. These effects are approximately negatively linear (except for math, where the effect is somewhat concave down) and strong (except for history). In short, although the results of the 10th–12th grade first differences models confirm the interactive importance of homework and parental income, the direction of this interaction contradicts the findings of the cross-sectional analysis.

However, although statistically significant interactive effects of time spent on homework and parental income are documented in these models, it should be noted that the fit of these models to the data is extremely poor, with no first differences regression model explaining even 1% of the variance in change in test scores. Thus, although the predicted CRC scores for the first differences models are typically larger in magnitude than for the cross-sectional model, the fit to the data is substantially poorer. Overall, the first differences models confirm the findings of the 8th–10th grade cross-sectional analysis that students with higher parental incomes have higher average homework efficacy, but cast doubt on the same finding for the 10th–12th grade window.

5. Discussion

Policymakers and educational researchers frequently recommend heavy homework loads as a mechanism of improved educational achievement in America (e.g., National Commission on Excellence in Education, 1983). However, the causal effect of study time on learning is a matter of debate. The consensus to date was that time spent on homework has a moderate, positive, causal effect on learning, a conclusion frequently stated in tandem with the caveat that “homework is a complicated thing” (Corno, 1996). Although this phrase is frequently quoted, rarely mentioned is Corno’s (1996) admonishment that “Students respond differently to the same assignments, depending on their interests, their home environments, and their study habits” (28). In other words, students vary in the amount they learn from their out-of-school studies – i.e., they have variable homework efficacy. Using NELS:88 data to model the effect of time spent on homework in secondary school, this analysis shows that homework efficacy varies substantially by parental income and grade and subject in school, and suggests that increased homework loads will, all else equal, increase educational inequality between these groups due to these homework efficacy differentials. These findings are robust over the 10th–12th grade time period; however, the conclusion for the 10th–12th grade window is uncertain and merits further study.

These findings demonstrate that self-reported time spent on homework has a curvilinear relationship with standardized test performance for all types of students in all grades and subjects. This is, to my knowledge, a novel finding, and presents an interpretive puzzle. On the one hand, it may be that, beyond a certain level of studying, spending additional time on homework is counterproductive to learning. Such an interpretation could be supported by research investigating the role of student stress (e.g., Daly, Chamberlain, & Spalding, 2011) and sleep deprivation (e.g., Taras & Potts-Datema, 2005) on test performance. From another perspective, though, it may be that students who study the most do so because they need to – i.e., because they are performing poorly in that subject in school. Comparing the first differences and cross-sectional analysis results suggest that the latter may be the stronger interpretation. If one assumes that large increases in study time are at least as stressful and contributory to sleep deprivation as a steadily high level of study activity, one would expect to find the same, strong curvilinear relationship between study time and test performance in the first differences results as in the cross-sectional results. This is not the case. Instead, the curvilinear, concave-down relationship between change in study time and change in test scores is either greatly ameliorated or not present at all in the first difference CRC plots compared to the cross-sectional plots. This result suggests that much of the curvilinear relationship is explained by the negative correlation between school performance and study time. However, the persistence of a weak concave down relationship between homework and CRC scores suggests that stress and sleep deprivation, or related processes, may yet play a role as well.

The interactive analysis results partially support the hypothesis that parental income is positively associated with homework efficacy. These differences are large in the 10th grade,

and somewhat lessened in the 8th and 12th grades with the exception of math. Furthermore, these results are confirmed in the 8th–10th grade first differences models, which control for time-invariant sources of unobserved heterogeneity. However, the results of the 10th–12th grade first differences models are not consistent with this conclusion. Although the reason for this finding cannot be known with certainty, it is likely that selection into continuing to take courses plays something of a role. Many students complete their required course taking in core subjects by their senior year in high school. If patterns of course taking are differentially related to academic abilities by income such that the relationship is stronger among higher SES students, this could account for the divergent finding in the 10th–12th grade window. Future research should investigate this possibility.

On the whole, these results are consistent with the implications of the literature on learning, which identified a number of factors (such as motivation, homework efficacy, and locus of control) which are positively related to parental SES and which promote faster rates of learning. Unfortunately, the present analysis is incapable of determining which candidate mechanisms are the source of socioeconomic differences in homework efficacy. The patterns of association between homework time and test performance, however, are suggestive. Specifically, there is no interactive association between income and time spent on homework for the history test, and the interaction is generally strongest for math, with middle magnitude interactions observed for science and reading. Students with parents in the top NELS:88 income category are more likely to have paid or peer tutor help with their homework, while lower income students are more likely to rely on siblings (not shown), which suggests that access to formal tutelage may be a key mechanism of socioeconomic inequality.

Correspondingly, it may be that socioeconomic differences in parental and/or sibling knowledge play a role. Proportionally, socioeconomic inequalities in history knowledge are smaller for history than for the other subjects, and inequalities in math homework are the largest. If patterns of knowledge in focal students are reproduced in their family members, it could be that familial knowledge plays a key mechanism in socioeconomic inequalities in homework efficacy. Furthermore, noncognitive traits such as study skills, metacognitive traits, etc. have been found to play a large role in the intergenerational transmission of status (e.g., Bowles & Gintis, 1976).

Unfortunately, the present data are unable to ascertain which likely mechanisms ultimately account for these differences. In light of prominent theories of learning (Trautwein and Köller, 2003), group differences in home and family environments, availability of family or hired tutors, time constraints, academic aptitude, ability to follow instructions, teacher quality, cognitive skills, metacognitive skills, and motivational characteristics are likely candidates. Future research should collect detailed measures of these candidate mechanisms to identify which of these are responsible for this interactive effect.

The larger goal of this research is to advance the literature on the effects of noncognitive traits in the sociology of education. Frequently this literature functions by identifying noncognitive traits which predict academic achievement net of cognitive skills and exploring how social differences in these traits create academic achievement inequality. This research suggests that family background may modify the effects of noncognitive behaviors as well as influence their prevalence in different segments of the population. In other words, students may vary in *both* their *behaviors* and the *effects thereof* on academic achievement outcomes. Future research should investigate the degree to which this is true for other noncognitive traits identified in the sociology of education literature.

This study is subject to a number of potential limitations. As Trautwein (2007) observes, time spent on homework, the amount of homework assigned, and the effort the student puts into the homework are analytically separable constructs which are conflated in the measure used here. As more suitable nationally representative datasets become available which are capable of distinguishing between these characteristics, the robustness of these findings should be assessed in light of these differences. Additionally, the response categories of study time per week are relatively coarse, lumping together students whose homework time may be up to two hours different. Furthermore, because the response categories are measured on different scales in the 8th grade than in the other waves, some apparent movement in study time scores may in fact reflect no change, which can bias the results of the analysis in unpredictable ways. Moreover, it may be that for many purposes it is not socioeconomic inequality in academic achievement which is the important question, but the overall degree of inequality in academic achievement. Future research should investigate how increases in homework loads are likely to increase this important dependent variable. Finally, and most importantly, the lack of a full set of measures of theoretically important mediators of the parental income–homework efficacy relationship means the degree to which these play a role in this process cannot be directly tested in this dataset. Future research should seek to rectify this limitation of the present analysis.

6. Conclusion

Academic achievement gaps can arise both as a result of group differences in predictors of achievement as well as differential effects. This paper assesses group differences in the homework–achievement relationship, called homework efficacy. The results indicate that there is a positive, moderate, and curvilinear average homework–achievement relationship for all subjects except reading in all grades, and that the effects of study time are larger for math than science and reading, which are larger than those for history. Results further demonstrate that average homework efficacy is higher for high SES students than for lower SES students, with a sharp cleavage in effect observed between students in the 90th percentile of the income distribution compared to all others. The finding of higher homework efficacy for high SES students is confirmed with more stringent first differences models in the 8th–10th grade, but not 10th–12th grade, window.

These results suggest that educational policies encouraging increases in homework assignments in secondary school may have the effect of raising socioeconomic inequality in academic achievement as well as on individual predicted achievement. Unless group differences in homework efficacy are eliminated or are counteracting influences present, such policies will tend to result in increasing advantages for higher income individuals in secondary school. Policymakers and educators should remain mindful of this possibility, lest ongoing achievement gaps persist or increase. Policies which promote greater time spent on homework may be best paired with policies which teach all students study skills and promote other predictors of homework efficacy.

Acknowledgments

This research was supported by grants T32 HD007168, R01 HD061622, R24 HD066613, and T32 HD007289. The author wishes to thank Ted Mouw, Guang Guo, Ken Bollen, and Ashton Verdery for comments on previous versions of this manuscript. Any errors are the author's alone.

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Fig. 1. LOWESS curves of homework hours by subject and income percentile. *Note:* Lines are LOWESS curves plotted separately by subject and grade for the relationship between parental income percentile and hours spent on homework per week.

Fig. 2.

8th grade learning and achievement gap eliminated, by income percentile, study hours, and subject. *Note:* CRC values are model-predicted change in learning associated with increase in study time compared to no change in study time, separately by subject. MDR values are the percent change in achievement gaps predicted by interactive first differences model if all students increase their study time uniformly. Students with parental incomes in the 90th percentile are the reference group.

Fig. 3.

10th grade learning and achievement gap eliminated, by income percentile, study hours, and subject. *Note:* CRC values are model-predicted change in learning associated with increase in study time compared to no change in study time, separately by subject. MDR values are the percent change in achievement gaps predicted by interactive first differences model if all students increase their study time uniformly. Students with parental incomes in the 90th percentile are the reference group.

Fig. 4.

12th grade learning and achievement gap eliminated, by income percentile, study hours, and subject. *Note:* CRC values are model-predicted change in learning associated with increase in study time compared to no change in study time, separately by subject. MDR values are the percent change in achievement gaps predicted by interactive first differences model if all students increase their study time uniformly. Students with parental incomes in the 90th percentile are the reference group.

Table 1

Cross-sectional and longitudinal test score and study effort, by grade and subject.

	Math		Science		History		Reading	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Test scores								
8th	35.28	(11.76)	18.48	(4.80)	29.28	(4.56)	26.52	(8.53)
10th	42.72	(13.69)	21.29	(5.96)	31.15	(5.13)	30.06	(9.97)
12th	47.51	(13.69)	23.17	(5.81)	34.42	(5.12)	32.75	(9.84)
Change, 8–10	7.39	(8.13)	2.79	(4.44)	1.85	(3.58)	3.50	(6.64)
Change, 10–12	4.72	(9.39)	1.85	(4.86)	3.25	(3.88)	2.64	(8.28)
Study hours								
8th	1.74	(2.38)	1.35	(2.24)	1.54	(2.35)	1.50	(2.31)
10th	2.88	(4.53)	2.80	(4.63)	2.88	(5.03)	2.83	(4.47)
12th	3.71	(5.44)	3.35	(5.47)	3.66	(5.47)	4.50	(5.39)
Change, 8–10	0.36	(3.09)	0.59	(2.89)	0.21	(3.03)	0.63	(2.97)
Change, 10–12	0.12	(3.61)	−0.08	(3.40)	0.41	(3.46)	0.88	(3.64)

Table 2

Test scores and achievement gaps by grade, subject, and parental income percentile.

Income percentile	8th grade				10th grade			
	Math	Science	History	Reading	Math	Science	History	Reading
10th	29.4 [*] (10.0)	16.7 [*] (3.1)	27.4 [*] (3.2)	23.3 [*] (5.7)	35.0 [*] (12.4)	18.2 [*] (4.7)	29.0 [*] (3.6)	25.6 [*] (7.2)
25th	32.7 [*] (6.8)	17.5 [*] (2.3)	28.5 [*] (2.1)	24.7 [*] (4.2)	39.4 [*] (8.0)	20.2 [*] (2.7)	30.2 [*] (2.4)	27.8 [*] (5.0)
50th	35.1 [*] (4.4)	18.6 [*] (1.3)	29.3 [*] (1.3)	26.7 [*] (2.2)	42.9 [*] (4.5)	21.3 [*] (1.6)	31.3 [*] (1.4)	30.4 [*] (2.4)
75th	37.6 [*] (1.9)	19.3 [*] (0.6)	30.1 [*] (0.4)	27.9 [*] (1.0)	45.3 [*] (2.1)	22.3 [*] (0.6)	32.0 [*] (0.7)	31.4 [*] (1.5)
90th (Ref.)	39.5	19.9	30.6	28.9	47.4	22.9	32.7	32.8

Note: Mean achievement test scores by group and subject are listed first; achievement gap (defined as $Y_{Ref} - Y_{Com}$ where former is reference group and latter is comparison group) in that test score shown in parentheses second.

^{*} Indicate that, compared to the 90th percentile mean, the difference in means is statistically significant at the p .05 level.

Table 3

Analytical sample demographic composition.

	Mean	SD
Gender		
Male	0.49	–
Female	0.51	–
Race		
White	0.68	–
Black	0.10	–
Hispanic	0.12	–
Asian	0.06	–
Native American	0.04	–
Logged Income	10.30	(0.93)

Note: Figures are unweighted.

Table 4

Math and science regressions by grade.

	Cross-sectional				First difference		
	8th	10th	12th		8th-10th	10th-12th	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(1)	(2)	(3)	(4)	(5)	(6)	(8)
Math							
Homework	3.017**	-8.958*	2.857**	-1.889	3.521**	-3.069	-0.160
Homework ²	-0.162	1.313	-0.324**	0.031	-0.380**	0.997	-0.227**
Homework ³	-0.014	-0.046	0.008*	0.011	0.009**	-0.047	0.012 ⁺
Income	3.319**	2.363**	4.005**	3.668**	2.905**	3.086**	-
Homework × income	-	1.168**	-	0.455	-	0.624*	0.036
Homework ² × income	-	-0.147	-	-0.033	-	-0.130 ⁺	0.023**
Homework ³ × income	-	0.003	-	0.000	-	0.005	-0.001*
Intercept	0.230	10.041**	1.648	5.130 ⁺	18.017**	16.163**	7.287**
R ²	0.209	0.212	0.200	0.202	0.197	0.201	0.004
Science							
Homework	0.776**	-0.834	0.822**	-4.095**	1.608**	0.377	-0.652
Homework ²	-0.112 ⁺	-0.175	-0.075**	0.831*	-0.205**	-0.059	-0.099
Homework ³	0.002	0.029	0.001	-0.036*	0.006**	0.005	0.008
Income	1.143**	1.040**	1.499**	1.286**	0.978**	1.055**	-
Homework × income	-	0.156	-	0.475**	-	0.115	0.079*
Homework ² × income	-	0.006	-	-0.087**	-	-0.013	0.011
Homework ³ × income	-	-0.003	-	0.004*	-	0.000	-0.001
Intercept	7.591**	8.663**	7.069**	9.258**	14.112**	13.321**	2.684**
R ²	0.151	0.152	0.192	0.194	0.182	0.185	0.005

Note: All regressions include controls for race and gender. The sample size for all models is 15,825.

⁺ $p < 0.10$.

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* $p < 0.05$.
** $p < 0.01$.

Table 5

History and Reading Regressions by Grade.

Cross-sectional					First difference					
8th	(1)	(2)	10th	(3)	(4)	12th	(5)	(6)	(7)	(8)
History										
Homework	0.498**	1.456	0.417**	– 1.140	0.771**	– 0.831	– 0.205	0.349		
Homework ²	0.002	– 0.546	– 0.027	0.022	– 0.102**	0.099	– 0.030	0.028		
Homework ³	– 0.006	0.043	– 0.001	0.004	0.003*	– 0.001	0.004	– 0.001		
Income	1.215**	1.254**	1.363**	1.279**	1.145**	1.194**	–	–		
Homework × income	–	– 0.094	–	0.151	–	0.153	0.030	– 0.024		
Homework ² × income	–	0.053	–	– 0.005	–	– 0.019	0.003	– 0.003		
Homework ³ × income	–	– 0.005	–	0.000	–	0.000	– 0.001	0.000		
Intercept	17.423**	17.033**	18.069**	18.935**	23.408**	22.905**	1.855**	3.261**		
R ²	0.145	0.145	0.142	0.143	0.140	0.145	0.003	0.003		
Reading										
Homework	1.442**	– 4.402	1.483**	– 1.201	1.459**	1.352	– 0.461	0.728		
Homework ²	– 0.152	1.264	– 0.165**	– 0.192	– 0.138**	– 0.141	– 0.202**	0.194**		
Homework ³	– 0.001	– 0.075	0.004	0.02	0.002	0.006	0.016*	– 0.013 ⁺		
Income	2.295**	2.039**	2.561**	2.290**	1.692**	1.881**	–	–		
Homework × income	–	0.565	–	0.260	–	0.006	0.058	– 0.080		
Homework ² × income	–	– 0.136	–	0.003	–	0.001	0.020**	– 0.019**		
Homework ³ × income	–	0.007	–	– 0.002	–	0.000	– 0.002*	0.001*		
Intercept	2.394*	5.040 ⁺	3.060 ⁺	5.843**	14.119**	12.205**	3.437**	2.650**		
R ²	0.151	0.152	0.150	0.151	0.111	0.112	0.003	0.004		

Note: All regressions include controls for race and gender. The sample size for all models is 15,825.

⁺ $p < 0.10$.

* $p < 0.05$.

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 $p < 0.01$
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