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ABSTRACT

This paper examines the long-term effects of early test scores using data from the British National Child Development Survey. We show that test scores measured as early as age 7 have significant effects on future educational and labor market outcomes. For example, men and women in the lowest quartile of the reading test score distribution have wages 20% lower at age 33 than those who scored in the highest quartile. We test several hypotheses about the interactions between socioeconomic status and high or low test scores at age 7. In terms of test scores, educational attainments, and employment at age 33, low-SES children reap both larger gains from having high age 7 test scores and smaller losses from having low age 7 test scores. The opposite is true among high-SES children who suffer larger losses from low scores and smaller gains from high scores. However we find little evidence of comparable interactive effects for wages.

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Introduction

Scores on standardized tests are often used to judge the achievements of both individual children and their schools. Children with low test scores are often tracked into remedial education--a process that may make it difficult to be reintegrated back into the mainstream. Black (1997) shows that parents are willing to pay a premium to buy a house in a neighborhood with a school that scores well. And there have been many calls to link teacher salaries to test scores. However, it has also been argued that less emphasis should be placed on test scores is misplaced because while early test scores predict future test scores, they may be poor predictors of more important future outcomes such as wages (c.f. Card and Krueger 1992, 1996).

Several studies have shown that the test scores of older children are associated with future wages. For example, Neale and Johnson (1996) use the National Longitudinal Survey of Youth to examine the relationship between scores on a test administered when youths were between the ages of 14 and 21, and future wages.[1] They find that in regressions that also controlled for age, race, and ethnicity, test scores were highly significant predictors of wages at ages 26 to 29. Similarly, Murnane, Willett, and Levy (1995) have shown that there is a relationship between the mathematics test scores of students measured in the senior year of high school, and the wages of 24 year old men and women. Zax and Rees (1998)

[1] The youths wrote the Armed Forces Qualifications Test, which is part of a larger battery of tests used by the military to help place new recruits.

show that in the Wisconsin Longitudinal Study, IQ scores measured at age 17 are significant predictors of wages at ages 35 and 53.[2]

However, there has been little evidence about the long-term consequences of poor test scores at early ages. If these scores are largely uncorrelated with future outcomes, then we may question the wisdom of using standardized tests to identify "at-risk" children and track them. Further, if test scores among young children are not related to future outcomes, then it is difficult to justify using these scores to judge the effectiveness of early intervention programs such as Head Start, which are designed to improve long-term outcomes. If, on the other hand, it is possible to use early scores to predict outcomes decades later, then perhaps greater efforts to identify and assist very young children at risk are warranted.

This study makes use of a unique data set which includes information about the entire cohort of children born in Great Britain during one week in March, 1958. Information has been collected about these children from before birth until the present. The children were given mathematics and reading tests at age 7, 11, and 16. Transcript records were merged in when the children were age 20, enabling us to examine educational achievement. Finally, we observe self-reported employment and wages at age 23, and at age 33.

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[2] These are only a few of the many papers that have examined the link between the test scores of teens or adults and earnings. See also Bishop (1989); Blackburn and Neumark (1993); Bound, Griliches and Hall (1986); Cameron and Heckman (1993); Cohn and Kiker (1986); and Kiker and Condon (1981).

We focus on two questions. First, are test scores at age 7 predictive of future test scores, educational attainment, employment, and wages? We find that early test scores are significant determinants of future labor market outcomes as well as of future test scores. However, it is easier to predict future test scores and educational attainments than wages or employment. The effects of test scores are hard to detect in samples of young male workers, and become more apparent over time.[3] Among women, test scores are stronger predictors of wages at age 33 than at age 23, but have less impact on employment at 33 than at 23. These results hold even in samples who were employed in both waves, or who had wages in both waves, which suggests that they are not due to selection effects.

The second question we address is whether the relationship between test scores and future outcomes varies with socioeconomic status (SES). Interactions between test scores and SES can help us to distinguish between several hypotheses about the way that higher test scores benefit children. For example, the relationship between SES and test scores may reflect an underlying human capital production function which is concave. Alternatively, there may be

[3] Card and Krueger find that measures of school quality are significant predictors of men's future wages. Other authors (Grogger (1996), Betts (1995, 1996), Hanushek, Rivkin, and Taylor (1996), Heckman, Layne-Farrar and Todd (1996)) have had difficulty replicating this result. A possible reason is that the replication studies typically focus on samples of young workers, whereas Card and Krueger's workers are older. The effects of school quality on wages may simply become more apparent over time, as our estimates suggest. For a direct examination of the effects of school quality measures in the NCDS see Dolton and Vignoles (1996) and Dearden, Ferri and Meghir (1997).

compensating investments for high SES children who perform poorly, or complementary investments for high SES children who do well. Finally, biases in the tests may make them less predictive for low-SES children. We find limited evidence in favor of complementary investments for children who have high math scores. A simple model of test bias is also consistent with some (but not all) of our findings.

The remainder of the paper is organized as follows: We begin with a discussion of factors that mediate the relationship between test scores at age 7 and future outcomes. This section addresses the questions of why we might expect test scores at early ages to be predictive of future outcomes, and of why we might expect the strength of this relationship to depend on socioeconomic status. Section 2 discusses the data. Results appear in Section 3. A discussion and conclusions follow in Section 4.

1. The Relationship Between Test Scores at Age 7 and Future Outcomes

a) When Will Early Test Scores be Predictive of Future Outcomes?

In order for test scores measured at age 7 to affect future outcomes, at least three conditions must hold: First, the test must actually measure some skill that has already been established by age 7. This could be cognitive ability, test-taking ability, or the ability to concentrate on the task (test) at hand. This condition would be violated if test scores for young children were dominated by measurement error, for example.

Second, it must be the case that children who are already behind at age 7 are less likely than other children to subsequently reach the same ultimate level of achievement in the test area. It is not obvious that this will be the case if, for example, young children naturally develop cognitive skills at different paces. Scores at age 7 in math and reading may largely be determined by whether children were taught these skills before school entry. Children who are initially behind may catch up once they have been exposed to the material.

Finally, in order for test scores to be predictive of employment or wages, achievement in the test area must be correlated with something that is valued in the labor market. It is possible, for instance, that early test scores might predict future test scores, but not wages or employment.

Several previous studies have used the NCDS to examine the relationship between age 7 test scores and particular outcomes. For example, Hutchison, Prosser and Wedge (1979) found that test scores at age 7 were strong predictors of test scores at age 16. Connolly, Micklewright and Nickell (1992) examine the relationship between test scores at age 7 and earnings at age 23 in a sample of young men who left school at age 16. More recently, Robertson and Symons (1996) and Harmon and Walker (1998) have examined the effects of age 7 test scores on earnings at age 33.

All of these studies find that age 7 test scores matter for future outcomes. This paper builds on this previous research by examining a wider range of outcomes in a similar framework. This will enable us to compare the size and significance of effects across outcomes. We also focus on the comparison between males and females throughout, something which has not been done by most previous authors.

b) Why Might the Relationship Between Test Scores and Outcomes Depend on Socioeconomic Status?

A second contribution of our paper is that we allow the effects of test scores to vary with socio-economic status. There are a number of hypotheses that predict that interactions between SES and test scores should matter.

The first explanation turns on the joint hypotheses that the relationship between test scores and outcomes reflects an underlying production function with diminishing returns to skill, *and* that low SES individuals are on average concentrated towards the bottom of the skill distribution. In this case, we expect to observe a stronger relationship between skills and wages among low-SES individuals simply because they are more likely to be measured at the point where the marginal payoff to an increase in skills is highest (Card, 1994).

There is some previous evidence that lends itself to this interpretation. Ashenfelter and Rouse (1997) for example, find that the returns to education in terms of wages are higher for low-SES individuals. Cawley, Heckman, and Vytlacil (1997) find using the U.S. National Longitudinal Survey of Youth that the relationship between test scores measured between the ages of 14 and 21 and wages is concave--the slope is steepest for those in the bottom quartile of the score distribution.

The health literature suggests a second explanation for interactions between SES and test scores. This literature shows for example, that low levels of prenatal lead poisoning have smaller effects on the future cognitive development of high-SES children (c.f. Needleman and Bellinger, 1994) and that high-SES children also show fewer lasting effects of perinatal trauma than low-SES children (c.f. Werner, Bierman, and French, 1971). These superior outcomes among high-SES children are thought to be the result of greater parental access to resources that can be used to compensate for initial injuries--for example, children who are well-nourished are less likely to absorb lead in their environment.

By analogy, high-SES children who test poorly at age 7 may be more likely than low-SES children to receive compensating investments in their human capital (e.g. additional tutoring) that enable them to eventually overcome initial deficits. Like the previous one, this argument suggests that poor test scores may be more predictive of future attainments for low-SES children than for high-SES children.

A third hypothesis is that high-SES children with high test scores are more likely to receive additional human capital investments which are complementary to test scores in the "production" of future outcomes. In contrast, low-SES individuals who test well at age 7 may find that their opportunities are limited. For example, Ashenfelter and Rouse (1997) argue that low-

SES children get less schooling than others because they lack opportunity rather than because they lack ability. In a system in which low-SES individuals customarily did not go on to higher education, the relationship between early test scores and educational attainment (and employment in jobs requiring those attainments) would be attenuated among these individuals.

A fourth possibility is that standardized tests are systematically biased against low-SES children. There are many forms that such measurement error could take. In order to be concrete, consider two simple forms of test bias. First, suppose that low-SES children of the same underlying ability receive lower scores on tests than high-SES children and that future wages are determined by underlying ability rather than by test scores. Then, if we compare two individuals with the same future wage, the low-SES individual will have had a lower age 7 test score. If low-SES individuals are also clustered in the lower half of the test score distribution to begin with, then test bias will lead to a flatter relationship between test scores and outcomes among low-SES individuals. Alternatively, if there is more random measurement error in the scores of low-SES children, then scores will be less predictive of outcomes among these children.

To summarize, we have put forth two hypotheses that predict a stronger relationship between test scores and outcomes among low-SES individuals. The first is the joint hypothesis of decreasing returns to skill, and low mean scores for low-SES children. The second is that high-SES parents provide compensating investments for low-scoring children which low-SES parents are unable to provide.

Alternatively, if high-SES parents are better able to provide complementary investments in the human capital of high-scoring children, then we would expect there to be a positive interaction between high scores and high SES. Finally, if tests are biased in the way we have described, then we would expect low scores to matter less to low-SES students, while high scores would matter less to high-SES students.

It is possible that all of these hypotheses are true to some extent, and it is not our intent to provide a sharp test of each one. Evidence regarding the interaction of test scores with SES will be used to shed light on the likely empirical importance of these four hypotheses, and to suggest directions for future research on the effects of test scores.

2. The Data

The National Child Development Study (NCDS) is a continuing longitudinal study of all of the approximately 17,000 children born in Great Britain between March 3 and March 9, 1958.[4] The initial group has been augmented by including immigrants born in the relevant week who arrived in Britain prior to 1974.

The study began with the Perinatal Mortality Survey which was aimed at uncovering the determinants of stillbirth and infant

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[4] Further information about this study is available in National Children's Bureau (1991).

death. The subjects have been followed up five times, when they were aged 7, 11, 16, 23, and 33. The first three followups obtained information from children, parents, schools, and local medical authorities, while the fourth and fifth followups surveyed only the subjects. In addition, schools were contacted in 1978 and asked for information about performance on public examinations including scores on Ordinary ("O") level tests and Advanced ("A") level tests.

Attrition is often a problem in longitudinal surveys, and the NCDS is no exception. Chart 1 shows the "target" sample and the realized sample from each wave. The target samples for followups 1, 2, and 3 included the original sample, plus immigrants, less known deaths and emigrants.

Chart 1:
Target and Actual Number of Respondents in Each Wave of the NCDS

Wave:	0	1	2	3	Exam	4	5
Target	17,733	16,883	16,835	16,915	16,906	16,457	15,928
Actual	17,414	15,468	15,503	14,761	14,370	12,537	11,442
Response Rate	98%	91%	91%	87%	85%	76%	72%

Overall response rates have remained high, considering the length of the panel. However, individuals disappear and reappear in this data, a fact which is not surprising given that with sufficient resources it is possible to trace members of the cohort whether or not they have appeared in earlier followups. In fact, restricting the sample to those who appear in every wave would result in a drastic reduction in sample size. Instead, we will use the available sample for each outcome measure, as well as limiting the sample to individuals who have appeared in particular waves in some of our analyses.

Previous analyses of these data suggest that attriters are more likely than non-attriters to be from disadvantaged backgrounds, although observable differences between the two groups are quite small (Fogelman, 1976, 1983; Robertson and Symons, 1996; Connolly, Micklewright and Nickell, 1992). Connolly *et al.* (1992) conduct one of the more exhaustive examinations of the attrition question, and find that controlling for sample selection in various ways makes little difference to their results. In what follows we deal with the attrition issue by controlling for observable background characteristics, and by comparing results obtained using the full available sample with those from more limited subsamples.

The tests we focus on are standardized tests of reading and mathematics which were administered to subject children in their schools, by their teachers. The tests administered at each age are listed in Chart 2.

Chart 2: Tests of Attainment Administered to NCDS Children

<u>At Age 7</u>

* Southgate Reading Test (Southgate, 1962) - A test of word recognition and comprehension designed to identify "backward" readers.
* Problem Arithmetic Test (Pringle *et al.*, 1966)

<u>At Age 16</u>

* Reading Comprehension Test - constructed by the National Foundation for Educational Research (NFER) specifically for use in the NCDS.
* Mathematics Test - devised by University of Manchester for a NFER study of comprehensive schools.

Our measure of socioeconomic status is the father's social class. The NCDS used the 1958 maternal responses to open-ended questions about paternal occupation to assign fathers to one of seven social classes using a system devised by the British Registrar General. These classes are: Professional, supervisory, skilled non-manual, skilled manual, semi-skilled non-manual, semi-skilled manual, and unskilled. In what follows, we will call those with fathers in professional, supervisory, or skilled non-manual jobs high SES, and those with fathers in semi-skilled manual and unskilled jobs low SES.[5] Persons without a father present at the time of their birth are assigned to the low-SES group.

Means of the standardized test scores at age 7 are shown by SES and gender in Panel 1 of Table 1. In this table, all scores have been converted to Z-scores for ease of interpretation--hence a score of 1 indicates that a child is one standard deviation above the mean while a score of -1 indicates that they fall one standard deviation below the mean for all children.

These means show that there is a striking gradient in test scores by SES, with the difference between the high-SES and low-SES group on reading scores being approximately three quarters of a standard deviation. The gradient in math scores is not as steep, with a difference of about half a standard deviation between scores

[5] This definition follows Robertson and Symons (1996). The data about paternal occupation is actually more detailed than what is available about father's education. We know whether father's stayed on past minimum school leaving age, whether they left school at 17 or 18, or whether they stayed on past 18.

of the highest and lowest groups. A second observation is that girls tend to have higher scores in reading, while boys tend to have better mathematics scores. These differences hold across the SES distribution.

Ceiling effects are a significant concern in the case of the age 7 reading test--approximately 20 percent of the children attained perfect scores which is not surprising since the test was designed to identify "backward" readers rather than to discriminate among other children. The distribution of scores on the age 7 mathematics test, and on the tests administered to older children, is much more bell-shaped. Given this problem, we focus on whether or not children are in the top or bottom quartile of the distribution of test scores at age 7 in all of our regression models.[6]

We will examine three broad groups of outcomes. First, we will look at the effects of age 7 test scores on age 16 test scores.[7] Second, we will examine the effects of early scores on educational attainment as measured by achievement on the O-level tests. Third, we look at labor market outcomes at age 23 and age 33.

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[6] On the reading test 25 percent of the children score above 96.7 percent and 25 percent score below 73 percent. On the math test, 25 percent score above 60 percent while 25% score below 40 percent. We also estimated models using the continuous score measures. These regressions had R-squareds only slightly higher than those reported below.

[7] In earlier work, we also examined the effects of age 7 scores on scores at age 11. However, the effects at age 11 and age 16 proved to be quite similar.

The second panel of Table 1 shows means of test scores for 7, 11 and 16 year olds, all calculated using the sample of children with valid age 16 scores. A comparison of panels 1 and 2 indicates that children who dropped out of the sample between ages 7 and 16 had slightly lower scores on average than those who stayed. The SES gradient in reading seems remarkably constant across these three age groups. However, in math scores the SES differences become more pronounced over time. Finally, the table shows that the gender gap in reading scores closes between age 7 and 16 for all three SES groups.

O-level examinations are normally written at age 16 or 17, and the results determine whether or not one continues with an academic education. Students typically take O-levels in at least 5 subjects, usually including english and mathematics. We focus on whether the respondent passed any O-levels, and on whether they passed O-levels in english and mathematics.[8] The data also has information about whether respondents wrote A-level examinations, which function like university entrance exams. We focus on O-levels rather than A-levels because all of our sample children were

[8] The NCDS reports the number of O-levels written at the student's usual school as well as the number written "any time, any where". We use the latter variable and thus include all repeat attempts at passing the examinations. Also, students could write either CSE's (regular O-levels) or SCE's (a less demanding test). Students who achieved a high enough score on the SCE were given the O-level certification. We treat these people as if they had passed the O-level examination in that subject. There are several different boards that administer O-levels (and A-levels). We do not attempt to distinguish among them. In any particular year, for each subject (and each board), all examinees write exactly the same test (at the same time) and are graded by the same rules throughout the United Kingdom.

in principle eligible to take O-levels, whereas only a selected (and rather small) group go on to take A-levels.

Panel 3 of Table 1 shows that girls are somewhat more likely than boys to have passed any O-levels, and that this relationship holds across the SES distribution. In particular, they are more likely to have passed english, though they are less likely to have passed mathematics. Note that only about half of all children passed any O-levels. O-levels are not compulsory and many of those who did not pass an O-level may have chosen not to write them because they had no plans to continue with their educations.

The fourth panel of Table 1 shows the fraction who were employed either full-time or part-time at age 23 and age 33. At 23 there is a large SES gradient in employment rates among women, but little evidence of any gradient among men. By age 33, the gap between high-SES and low-SES women has narrowed, while a gap has started to open up for men. This pattern suggests that regardless of SES, many women leave the labor market in their early 30s, presumably to care for children.

A possible source of bias is that those of low SES are slightly more likely to attrit by age 33 than those of high SES and are also less likely to be employed. The last two rows of panel 4 restrict the sample to those who have employment information available at both 23 and 33. The means are strikingly similar to those computed using the full sample of available observations at each age. Hence, there is little evidence that attrition between age 23 and 33 is systematically related to SES or employment probabilities among either men or women.

Finally, the last panel of Table 1 reports mean wages, both for all available observations, and for the subsample who report wages in both interviews. Respondents are asked their usual weekly hours, their net pay, their gross pay, and their pay interval (e.g. weekly, biweekly, monthly, etc.). We first calculate the number of hours in the pay interval by examining the usual weekly hours, and then calculate hourly pay rates by taking the pay reported and dividing by the number of hours in the pay interval. We focus on net pay in what follows as similar results were obtained using gross pay. We deleted hours and wage information for those with weekly hours greater than 96, and did not use wage information for those reporting fewer than 10 hours per week.[9]

Table 1 shows that low-SES people earned virtually the same wages as high-SES people at age 23, even though on average they had characteristics that one would expect to be less generously remunerated. One reason may be that this cohort turned 23 in 1981, in the midst of a severe recession which compressed the distribution of earnings among these young workers (Meghir and Whitehouse, 1996). However, the wage gap between high and low-SES individuals widens dramatically between ages 23 and 33, suggesting

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[9] We have also done some light data cleaning. Specifically, if the reported hourly pay seemed very high or low, we assumed that the pay amount did not match the pay interval and tried changing the pay interval. In the end, we set the most extreme outliers to missing. In wave 4, this included people with hourly net wages less than .6 or over 4, and in wave 5, this included people with hourly net wages less than 1 and greater than 20. In both waves 4 and 5 we excluded less than 2% of the sample observations.

that the high-SES individuals have steeper wage profiles.

The interpretation of these numbers is complicated by several possible selection effects. Among both sexes, those who are of lower SES are slightly more likely to attrit by age 33, as discussed above. A more serious concern is that those who are pursuing a college education are less likely to have wage data at age 23. Among women, those who had children young tend to be of lower SES and are also less likely to be in the labor market at age 23. Those who had children later tend to be of higher SES and are also more likely to have exited the labor market at age 33.

In order to shed some light on the possible magnitudes of these selection effects, in the last two rows of Table 1 we focus only on the subsample who report wages at both ages 23 and ages 33. Wages at 33 are slightly higher for this subgroup than for the full sample with age 33 wages. Thus, those who were out of the wage sample at 23 but who had come into the labor market by age 33 were earning lower wages at 33 than those who had more labor market experience. This effect is most pronounced among those of low SES. which is consistent with a Mincer (1973) story in which those of high SES enter the labor market later and at somewhat lower wages (given their productive characteristics) but subsequently enjoy faster wage growth than low SES individuals.

Finally, Table 1 shows that there is a significant gender gap in earnings at age 23, which widens considerably by age 33. This pattern is observed for each SES group, and remains true if we restrict the sample to those with wage observations at both points in time.

3. Estimation Results

a) Baseline Estimates of the Effects of Early Test Scores

Table 2 gives baseline estimates of the effects of age 7 test scores on future outcomes. We examine the effects of being in the top and bottom quartiles of the age 7 math and reading distributions. These regression models do not include any other covariates and form a baseline which will be compared to later multivariate regression models.

Some of the estimated effects of test scores are large: For example, among males, moving from the bottom quartile to the top quartile of reading scores at age 7 is associated with more than a standard deviation increase in reading and mathematics scores at 16, and with a 50% increase in the probability of passing any O-levels. The magnitudes of the estimated effects for test scores and O-levels are similar for women.

Turning to labor market outcomes, we find that among men, there are negligible effects of early scores on wages and employment at age 23. However, significant effects are found by age 33--men in the bottom quartile of the reading or math score distributions at age 7 have wages at age 33 that are 20% lower than the wages of men who scored in the top quartile. Among women, those who scored in the top quartile of the reading distribution at age 7 have wages 26% higher than those of women who scored in the bottom quartile, while women with lower quartile age 7 math scores earn 12% less than those who had math scores in the top quartile.

A striking difference between men and women is that test scores at age 7 are predictive of female labor market outcomes at age 23, while they have little predictive power for males at this age. In contrast, it is more difficult to use test scores to predict female employment probabilities at age 33 than at age 23. This result suggests that among women, the probability of exiting the labor force during ones early 30s is not strongly related to test scores. A second gender difference is that reading scores are more important predictors of female employment and wages than math scores, while both reading and math scores are significant predictors of male wages and employment at age 33.

While these results indicate that early test scores are predictive of future labor market outcomes, the R-squareds shown in Table 2 suggests that test scores are better predictors of future test scores and schooling attainments than of future employment or wages. For example, the age 7 scores explain a third of the variation in age 16 test scores for both men and women, but only 9 (8) percent of the variation in male (female) ln(wages) at age 33.

b) Multivariate Models

Tables 3a and 3b show that test scores at age 7 remain predictive of future outcomes for both men and women, even when a rich set of control variables are included. What is even more striking is that a comparison with Table 2 shows that the estimated effects of age 7 test scores are reduced by only about 25% when other background variables are included in the regressions. Thus, the test scores have an effect over and above what is captured by the rich set of observable background measures available in the NCDS.

These background measures include indicators for father's socio-economic status, father's and mother's education, and mother's socio-economic status measured using *her* father's occupation. In addition, the models include a variety of other background measures observable at age 7: The number of children in the household which measures the level of competition for resources and parent's preferences regarding quantity vs. quality tradeoffs; whether the child is the firstborn in which case previous research on the effects of birth order suggests that we might expect better outcomes; the mother's age at the birth, which we would also expect to have a positive effect on scores; the child's birthweight, which is one indicator of his or her health "endowment" and so should also have a positive effect on outcomes; whether the child was a twin, which affects competition for resources, as well as the health endowment; whether the child was an immigrant and indicators for regions of origin; and the number of mother's siblings which is likely to be related to her social class.

These models also include dummy variables for the child's local educational authority (LEA). Local educational authorities receive money from the central government for spending on primary and secondary education and have broad jurisdiction over education in their areas. For example, they determined whether and at what pace grammar schools and secondary modern schools would be merged to form "comprehensive" schools (Harmon and Walker, 1998). In terms of observable quality measures, grammar schools dominate comprehensive schools, which in turn dominate the secondary moderns. Thus, when an LEA went comprehensive, one would have expected the quality of the publicly provided schooling available to the highest ability students to fall, while the quality available to the lowest ability students increased. Given the important role of LEAs, it is remarkable that the inclusion of these dummy variables had very little effect on the estimated effects of test scores.

For the sake of brevity, only coefficients on those control variables that were most consistently statistically significant are shown in Table 3a and 3b. It is of interest to compare the effects of test scores to those of these other covariates. For example, we can see that moving from the lowest to the highest quartile of age 7 reading scores is estimated to increase age 16 test scores by approximately one standard deviation. In contrast, moving from the lowest paternal SES category to the highest is associated with an increase of about a third of a standard deviation in age 16 reading scores.

As in Table 2, math scores have larger effects than reading scores on wages at age 23 among men. The effects of both types of scores becomes stronger over time, and reading scores are as important as math scores by age 33.[10] Among women, reading scores are always important determinants of wages, and the relationship becomes somewhat stronger over time. In contrast, the role of reading scores in employment becomes less important over time.

All these results continue to hold when we restrict the sample either to those who have employment information at both points in time, or to those who have wage information in both waves though these models are not shown. The point estimates on the test score coefficients in these models were remarkably similar to those shown in Tables 3a and 3b. Thus, they are not driven by selection effects between the two waves of the survey.

c) The Relationship Between Test Scores, SES, and Outcomes

We have shown that there is a strong relationship between early test scores and future outcomes. We also saw in Table 1 that people from high SES backgrounds tend to have higher scores at age 7, and better future outcomes. In this section, we examine the way that the relationship between outcomes and background is mediated by early test scores.

Table 4 shows estimates from models that include interactions between SES and dummy variables equal to one if the person was in the *top quartile* of the reading or math score distributions at age 7. Table 5 presents estimates with interactions between SES and the indicator for respondents who scored in the *bottom quartile* of

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[10] Murnane *et al.* (1995) also find that math scores measured at 13 or 14 are more important predictors of wages measured when people are in their early 20s.

the test distributions at age 7. This presentation simplifies the interpretation slightly--in each table, the interaction is to be interpreted as the effect of, for example, scoring low and being of low SES relative to children who did not score low. If we include the full set of interactions in a single model, the excluded children are those who scored within the inter-quartile range on the relevant test which complicates the interpretation since we then have to examine the difference-in-difference between the high and low scorers.[11] All of the other background variables discussed above are also included in each specification as are the LEA fixed effects.

Table 4 addresses the hypothesis that able high-SES children receive complementary investments in their human capital, while able low-SES children lack opportunity. In this case, the interaction of "high SES" and the high test score dummy should be positive, while the interaction of the "low SES" and the high test score dummy should be negative.

In fact, we generally find that the opposite is true, at least in terms of test scores and schooling attainments. Table 4 shows that among males, low-SES individuals receive a greater than average return to high scores in terms of age 16 reading scores. Conversely, high-SES males with high scores receive a lower return in terms of age 16 test scores and the probability of writing any

[11] We also found that it was more difficult to identify all these effects in a single model in the sense that while the qualitative results were very similar, fewer coefficients were individually statistically significant.

O-levels. High-SES boys with high math scores do however, have a 33% higher probability of passign the O-level in math than high scorers of average SES.

The story is somewhat different for women. Here we see that high-SES individuals receive lower returns to age 7 test scores in terms of future reading scores and the probability of writing any O-levels. However, high scoring girls of high-SES are almost twice as likely to write math O-levels as high scoring girls of average SES.

Evidence of any interactive effect between SES and test scores is much weaker when it comes to labor market outcomes. Table 4 suggests that among males, low-SES individuals receive a greater than average return to high scores in terms of age 33 employment probabilities, while high scoring girls of high-SES are less likely to be employed at age 33 than other high scorers. However, we see no effects on employment at age 23, or on wages at either age.

In Table 5 we examine estimates from models that included interactions between SES and dummy variables for having low scores at age 7. Here we seek to test the hypothesis that less able children from low-SES backgrounds are less likely than less able children from high-SES backgrounds to receive compensating investments in their human capital. In this case, we would expect the interactions between low scores and low SES to be negative (indicating that these children suffer most from low scores), while the interaction between low scores and high SES should be positive.

Table 5 offers little support for this hypothesis. For example, high-SES children with low scores appear to be even less likely than other children with low scores to pass O-levels in math or english. The sole exceptions are that low-SES males with low reading scores have lower employment probabilities at age 23 than other low-scoring males, while high-SES girls with low age 7 math scores have higher reading scores at age 16 than other low scorers. There is also a marginally significant coefficient on the interaction between high-SES and low math scores in the model of female employment at age 33. Again, we find little evidence of any interaction between SES and test scores when it comes to wages.

4. Discussion and Conclusions

This paper offers compelling evidence that test scores measured as early as age 7 have significant effects on future test scores, educational attainments, and labor market outcomes, even after a wide array of observable characteristics have been controlled for. In many cases, the effects are similar or larger than those of other observed characteristics of the children. As Card and Krueger have suggested, it is easier to predict future test scores given past test scores, than to predict schooling attainments or labor market outcomes.

A striking result is that among men, early test scores are better predictors of both wages and employment at age 33 than at age 23. This is true even if we restrict the sample to those who reported either employment or wages in both waves of the survey. These results are consistent with a model in which deficits accumulate. For instance those with low test scores may be more likely to end up in "dead-end" jobs with flatter wage growth. They are also consistent with Farber and Gibbon's (1996) model which suggests that the estimated effects of characteristics that are not easily observed at the time a worker first enters the labor market (such as age 7 test scores) should grow stronger over time as the worker's "quality" is revealed.

Among women, test scores also become more important determinants of wages over time, but it is generally more difficult to predict employment at age 33 than at age 23. All these relationships hold when we restrict the sample to those who were working in both waves of the survey, or to those who had wages in both waves.

We also tested several hypotheses about the interactions between socioeconomic status and high or low test scores at age 7. We found significant interactions in models of future test scores and schooling attainments, some evidence of interactions in models of age 33 employment, and no evidence of any interactive effect on wages.

Our estimates are consistent with the existence of complementary investments for high-SES children with high age 7 math scores. Compared to other high scorers, these children were 36 percent (for boys) to 73 percent (for girls) more likely to go on to pass O-levels in math. However, the other estimated effects were not consistent with the hypothesis that high-SES children are more likely to receive either complementary investments (in the case of high scorers) or compensating investments (in the case of low scorers).

Measured in terms of future test scores and schooling attainments, low-SES children reap both larger gains from having high age 7 test scores, and smaller losses from having low age 7 test scores when compared to other children. The opposite is true among high-SES children. This pattern of results is not consistent with random measurement error that is concentrated in the bottom of the SES distribution. Errors of this kind would lead to less negative effects of low scores, and less positive effects of high scores among low-SES children.

If we expect low-SES children to have low mean scores on average, then this pattern of results is also inconsistent with "regression to the mean". To see this, consider the fact that a high-scoring, low-SES child would be expected to regress towards a low mean, while a low-scoring, high-SES child would be expected to regress towards a high mean. Thus, the regression to the means story would have a low-scoring, high-SES child suffering few negative consequences, while a high-scoring low-SES child would be expected to reap few benefits. The pattern we observe is just the opposite.

One hypothesis that can make sense of the pattern of interactive effects that we find in models of age 16 test scores, schooling attainments, and age 33 employment is that of systematic test bias against low-SES students. If tests are biased, then the fact that a low-SES individual scores poorly offers little information. But a low-SES student who does well is clearly exceptional. Conversely, a high-SES person who scores well on the test is doing as expected, while a high-SES person who scores poorly may have significant problems. If tests are to be used to track children and to rate schools and programs, then the possibility that there are significant test biases must be kept in mind. More research on the form of these biases would be useful.

The simple story of test bias we present suggests that we should find interactions between SES and test scores in models of wages, as well as in models of other outcomes. There are several possible explanations of the fact that we found no evidence of interactions in the wage models.

First, as discussed above, the wage distribution for this cohort may have been compressed by negative macroeconomic conditions at age 23. The next time we observe them is at age 33, which is approximately Mincer's (1974) "overtaking" age, the point at which earnings for people on very different lifetime earnings trajectories converge.[12] It has been shown empirically that inequality in male earnings in the U.S. is indeed lowest at around this age (c.f. Lillard, 1977). Thus the consequences of limited educational opportunities for low-SES individuals may only emerge as the NCDS cohort ages. For example, Zax and Rees find that the effects of IQ (measured at age 17) are larger at age 53 than at age 35.

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[12] The overtaking age might however be earlier in Britain, since most people leave school earlier than in the United States.

Second, each test measures particular aspects of ability. If there are different dimensions of skill which are not perfectly correlated, and workers sort themselves into the jobs that they are most suited for, then we should expect to see smaller effects of test scores on wages than on other outcomes. Individuals who perform poorly on standardized tests may have other skills that are rewarded in the labor market. Someone who has limited skills in math and reading may still be a gifted mechanic, or a brilliant artist and will be remunerated accordingly.

A final caveat is that while the effects of early test scores are statistically significant and large enough to be economically meaningful, most of the variation in employment and wages remains unexplained by the variables included in our models. Thus, while early test scores may be a useful diagnostic tool, it must be kept in mind that many children with low scores at age 7 will go on to do surprisingly well.

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Table 1: Means by Gender and SES

SES:	Female High	Female Medium	Female Low	Male High	Male Medium	Male Low
1. Scores at Age 7 - Full Sample						
Reading	.46	.01	-.22	.23	-.26	-.55
	(.02)	(.02)	(.03)	(.02)	(.02)	(.03)
Math	.30	-.12	-.24	.42	-.00	-.16
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Sample Size	1908	2973	2000	1934	3096	2111
2. Scores Using Age 16 Sample						
Reading at 7	.50	.03	-.17	.25	-.22	-.47
	(.02)	(.02)	(.03)	(.02)	(.02)	(.03)
Reading at 11	.57	-.10	-.24	.56	-.06	-.24
	(.03)	(.02)	(.03)	(.03)	(.02)	(.03)
Reading at 16	.51	-.08	-.30	.51	-.04	-.26
	(.02)	(.02)	(.03)	(.02)	(.02)	(.03)
Math at 7	.33	-.10	-.22	.42	.00	-.10
	(.03)	(.02)	(.03)	(.03)	(.02)	(.03)
Math at 11	.57	-.13	-.27	.58	-.05	-.23
	(.03)	(.02)	(.03)	(.03)	(.02)	(.03)
Math at 16	.43	.23	-.36	.65	-.02	-.21
	(.03)	(.02)	(.03)	(.03)	(.02)	(.02)
Sample Size	1468	2203	1413	1482	2318	1466
3. O-levels						
Any	.79	.50	.40	.73	.44	.34
English	.55	.25	.19	.45	.18	.14
Math	.31	.10	.08	.39	.15	.11
Sample size	1693	2599	1744	1691	2710	1841
4. Fraction Employed						
at 23	.74	.64	.56	.85	.84	.81
Sample Size	1571	2404	1531	1527	2362	1523
at 33	.71	.70	.63	.95	.91	.87
Sample Size	1465	2224	1400	1423	2122	1322
(Sample with Employment Information Available at Both 23 and 33)						
at 23	.75	.66	.58	.86	.87	.85
at 33	.71	.71	.64	.95	.92	.88
Sample Size	1301	1958	1193	1228	1818	1083
5. Average Hourly Net Pay (Wages)						
at 23	1.69	1.57	1.54	1.90	1.92	1.88
	(.02)	(.01)	(.02)	(.02)	(.01)	(.02)
Sample Size	1063	1415	793	1070	1769	1135
at 33	4.54	3.82	3.55	6.06	5.16	4.75
	(.06)	(.04)	(.05)	(.07)	(.05)	(.06)
Sample Size	1049	1576	977	1051	1581	973
(Sample with Wages Available at Both 23 and 33)						
at 23	1.70	1.59	1.54	1.91	1.92	1.88
	(.02)	(.01)	(.03)	(.02)	(.01)	(.03)
at 33	4.65	4.04	3.80	6.14	5.28	4.92
	(.08)	(.06)	(.07)	(.09)	(.06)	(.07)
Sample Size	669	936	479	689	1104	973

Note: Standard errors in parentheses.

Table 2: Effects of Early Test Scores on Future Outcomes

Outcomes:	**Reading @ 16**	**Math @16**	**Any O-levels**	**English O-level**	**Math O-level**	**Employed @ 23**	**Employed @33**	**Log Wage @23**	**Log Wage @33**
Males									
Reading Low	-.83	-.65	-.29	-.17	-.13	-.02	-.05	-.01	-.13
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Reading High	.36	.55	.19	.25	.21	-.01	-.00	.01	.07
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Math Low	-.32	-.30	-.10	-.17	-.07	-.01	-.01	-.05	-.10
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Math High	.23	.40	.12	.12	.14	-.01	.04	.02	.09
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Intercept	.28	.19	.55	.24	.19	.85	.92	.61	1.61
	(.02)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
R-squared	.33	.33	.21	.18	.17	.001	.01	.01	.09
# Obs.	5266	5266	6233	6233	6233	5417	4867	3974	3605
Females									
Reading Low	-.78	-.46	-.32	-.18	-.07	-.16	-.05	-.08	-.11
	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Reading High	.39	.49	.20	.23	.15	.01	.02	.04	.15
	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Math Low	-.33	-.30	-.12	-.09	-.06	-.05	-.04	-.05	-.06
	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Math High	.20	.42	.11	.15	.13	.02	.02	.04	.06
	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Intercept	.16	-.12	.59	.29	.12	.69	.69	.44	1.27
	(.02)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
R-squared	.34	.29	.22	.18	.13	.03	.01	.062	.075
# Obs.	5083	5083	6035	6035	6035	5505	5089	5270	3602

Notes: Standard errors in parentheses.

Table 3a: Effects of Early Test Scores and Background on Future Outcomes--Males

Outcomes:	Reading @ 16	Math @16	Any O-levels	English O-level	Math O-level	Employed @ 23	Employed @33	Log Wage @23	Log Wage @33
Reading Low	-.69	-.49	-.21	-.14	-.07	-.01	-.03	-.00	-.08
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Reading High	.28	.43	.14	.21	.15	-.00	-.01	.01	.05
	(.03)	(.03)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Math Low	-.31	-.29	-.09	-.04	-.06	-.01	-.01	-.06	-.09
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Math High	.19	.35	.11	.09	.13	-.01	.03	.03	.08
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Father's SES									
Professional	.37	.58	.22	.18	.15	-.01	.03	-.02	.11
	(.07)	(.07)	(.04)	(.03)	(.03)	(.03)	(.03)	(.03)	(.04)
Managerial	.27	.33	.16	.09	.08	.08	.05	-.01	.11
	(.05)	(.06)	(.03)	(.02)	(.02)	(.03)	(.02)	(.02)	(.03)
Skilled NM	.27	.29	.14	.07	.03	.08	.04	.01	.15
	(.06)	(.06)	(.03)	(.02)	(.02)	(.03)	(.02)	(.02)	(.03)
Skilled M	.14	.15	.07	-.00	.03	.08	.03	.01	.09
	(.05)	(.05)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.03)
Semi-Skilled	.21	.17	.05	.07	.09	-.02	.03	.01	.13
Non-manual	(.09)	(.09)	(.05)	(.04)	(.04)	(.04)	(.04)	(.04)	(.05)
Semi-Skilled	.08	.11	.03	-.00	-.01	-.08	.01	-.01	.03
Manual	(.05)	(.05)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.03)
Father's Education (Age When Left School)									
16	.16	.22	.10	.08	.07	.01	.01	.04	.06
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
17-18	.14	.17	.13	.12	.12	.00	-.00	-.04	.10
	(.05)	(.05)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.03)
18+	.09	.24	.11	.14	.15	-.07	.02	-.02	.10
	(.06)	(.06)	(.03)	(.03)	(.03)	(-.03)	(.02)	(.03)	(.04)
Other Background Variables Measured at Age 7									
# children	-.09	-.05	-.03	-.01	-.01	-.01	-.02	-.01	-.02
<21 in HH	(.01)	(.01)	(.004)	(.003)	(.003)	(.004)	(.003)	(.003)	(.01)
Firstborn	.16	.16	.06	.06	.05	-.00	.01	-.00	.02
	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)

Table 3a, continued.

Outcomes:	**Reading @ 16**	**Math @16**	**Any O-levels**	**English O-level**	**Math O-level**	**Employed @ 23**	**Employed @33**	**Wage @23**	**Wage @33**
Mother's age	.14	.10	.05	.04	.04	.003	.01	.001	.007
(*10)	(.02)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Mom <=16 when	-.17	-.24	-.11	-.10	-.08	.02	.00	-.03	-.07
left schl.	(.03)	(.03)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.02)
Birthweight	.03	.03	.01	.01	.01	.004	-.00	.005	.01
(*10)	(.01)	(.01)	(.003)	(.003)	(.002)	(.003)	(.002)	(.003)	(.004)
Constant	-.43	-.49	.45	.17	.26	.74	.91	.58	1.42
	(.13)	(.13)	(.18)	(.15)	(.15)	(.06)	(.05)	(.05)	(.07)
R-squared	.43	.43	.31	.32	.29	.04	.05	.07	.20
# Obs.	5266	5266	6233	6233	6233	5417	4867	3974	3605

Notes: Standard errors in parentheses. These OLS regressions also included indicators for twins, for no father present, whether the child was an immigrant and whether they came from Africa, India, or Asia, a set of indicators for the mother's social class, and the number of mother's siblings. In cases where explanatory variables were missing, dummy variables were created and included (e.g. "Don't know birth order"). Coefficients and standard errors on mother's age and birthweight multiplied by 10.

Table 3b: Effects of Early Test Scores and Background on Future Outcomes--Females

Outcomes:	Reading @ 16	Math @16	Any O-levels	English O-level	Math O-level	Employed @ 23	Employed @33	Log Wage @23	Log Wage @33
Reading Low	-.63	-.33	-.24	-.15	-.05	-.11	-.04	-.07	-.07
	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.01)
Reading High	.28	.37	.14	.18	.12	-.02	.02	.03	.11
	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Math Low	-.30	-.26	-.11	-.07	-.04	-.04	-.03	-.05	-.04
	(.02)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Math High	.16	.37	.10	.11	.11	.01	.01	.04	.05
	(.02)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Father's SES									
Professional	.38	.33	.22	.18	.16	.09	.07	.02	.13
	(.06)	(.07)	(.03)	(.03)	(.03)	(.04)	(.04)	(.03)	(.04)
Managerial	.35	.21	.20	.12	.06	.10	.07	.01	.10
	(.05)	(.05)	(.03)	(.03)	(.02)	(.03)	(.03)	(.02)	(.03)
Skilled NM	.39	.18	.17	.11	.04	.10	.03	.02	.08
	(.05)	(.06)	(.03)	(.03)	(.02)	(.03)	(.03)	(.02)	(.03)
Skilled M	.24	.03	.10	.02	-.02	.07	.08	.002	.06
	(.04)	(.04)	(.02)	(.02)	(.02)	(.03)	(.03)	(.02)	(.03)
Semi-Skilled	.26	-.01	.10	.02	-.02	.07	.00	-.02	-.03
Non-manual	(.09)	(.10)	(.05)	(.04)	(.04)	(.06)	(.06)	(.04)	(.06)
Semi-Skilled	.15	-.06	.06	-.00	-.02	.02	-.01	.02	.03
Manual	(.05)	(.05)	(.03)	(.02)	(.02)	(.03)	(.03)	(,02)	(.03)
Father's Education (Age When Left School)									
16	.11	.21	.06	.10	.06	.03	-.03	.04	.06
	(.04)	(.04)	(.02)	(.02)	(.02)	(.03)	(.03)	(.02)	(.03)
17-18	.19	.22	.09	.12	.08	.03	-.03	.03	.12
	(.04)	(.04)	(.02)	(.02)	(.02)	(.03)	(.03)	(.02)	(.03)
18+	.22	.37	.09	.15	.12	.02	.02	.04	.10
	(.05)	(.06)	(.03)	(.03)	(.02)	(.03)	(.04)	(.02)	(.04)
Other Background Variables Measured at Age 7									
# children	-.09	-.05	-.04	-.02	-.01	-.02	-.004	-.04	-.02
<21 in HH	(.01)	(.01)	(.04)	(.004)	(.003)	(.004)	(.01)	(.004)	(.01)
Firstborn	.11	.09	.05	.03	.02	-.01	.02	-.00	.02
	(.02)	(.03)	(.01)	(.01)	(.01)	(.01)	(.02)	(.01)	(.02)

Table 3b, continued.

Outcomes:	**Reading @ 16**	**Math @16**	**Any O-levels**	**English O-level**	**Math O-level**	**Employed @ 23**	**Employed @33**	**Wage @23**	**Wage @33**
Mother's age	.02	.01	.01	.01	.04	.05	-.01	.00	.04
	(.002)	(.002)	(.001)	(.001)	(.01)	(.01)	(.01)	(.01)	(.01)
Mom <=16 when	-.19	-.25	-.11	-.12	-.09	-.02	-.00	-.03	-.10
left schl.	(.03)	(.03)	(.01)	(.01)	(.01)	(.02)	(.02)	(.01)	(.02)
Birthweight	.003	.002	.01	.005	.01	.01	-.01	.002	.01
	(.001)	(.001)	(.003)	(.003)	(.002)	(.004)	(.004)	(.003)	(.004)
Constant	-.61	-.70	.50	.42	.28	.50	.60	.46	1.08
	(.11)	(.12)	(.18)	(.16)	(.14)	(.07)	(.08)	(.05)	(.08)
R-squared	.46	.40	.32	.34	.24	.08	.04	.15	.18
# Obs.	5083	5083	6035	6035	6035	5505	5089	5270	3602

Notes: See Table 3a.

Table 4: Interactions Between High Age 7 Scores and SES

Outcomes:	Reading @ 16	Math @16	Any O-levels	English O-level	Math O-level	Employed @ 23	Employed @33	Wage @23	Wage @33
Males									
High Reading	.55	.64	.23	.29	.21	-.00	-.02	.02	.11
	(.05)	(.05)	(.03)	(.02)	(.02)	(.02)	(.02)	(.02)	(.03)
x low SES	.16	.09	.05	-.03	-.02	.01	.07	.02	-.07
	(.09)	(.09)	(.04)	(.03)	(.03)	(.03)	(.03)	(.03)	(.05)
x high SES	-.25	-.19	-.09	-.07	-.04	.00	.01	-.02	-.06
	(.07)	(.07)	(.04)	(.03)	(.03)	(.03)	(.03)	(.03)	(.04)
High Math	.51	.56	.21	.14	.14	-.01	.05	.05	.11
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)	(.01)	(.01)	(.02)
x low SES	.04	.01	.01	-.03	.00	.04	-.00	-.00	.03
	(.06)	(.06)	(.03)	(.03)	(.02)	(.03)	(.02)	(.02)	(.03)
x high SES	-.18	.02	-.07	.03	.05	-.01	-.03	-.00	.01
	(.06)	(.06)	(.03)	(.02)	(.02)	(.03)	(.02)	(.02)	(.03)
Constant	-2.31	-1.60	-.02	-.08	.01	.74	.71	.52	1.21
	(.33)	(.33)	(.24)	(.20)	(.19)	(.15)	(.12)	(.13)	(.18)
R-squared	.33	.38	.27	.30	.28	.06	.05	.06	.18
# Obs.	5266	5266	6233	6233	6233	5417	4867	3974	3605
Females									
High Reading	.49	.46	.22	.20	.10	.01	.01	.05	.12
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)	(.03)	(.02)	(.03)
x low SES	.07	.04	.06	.07	.02	.05	.01	-.03	.01
	(.07)	(.07)	(.04)	(.03)	(.03)	(.04)	(.04)	(.03)	(.04)
x high SES	-.18	-.03	-.09	.01	.07	-.04	.06	.03	.00
	(.06)	(.06)	(.03)	(.03)	(.02)	(.04)	(.04)	(.02)	(.04)
High Math	.41	.54	.22	.16	.11	.07	.07	.06	.11
	(.04)	(.04)	(.02)	(.02)	(.01)	(.02)	(.02)	(.02)	(.02)
x low SES	.06	-.04	-.04	-.03	-.03	-.02	-.02	.05	-.03
	(.06)	(.06)	(.03)	(.03)	(.02)	(.04)	(.04)	(.03)	(.04)
x high SES	-.16	-.01	-.10	.02	.08	-.04	-.08	-.02	-.07
	(.06)	(.06)	(.03)	(.03)	(.02)	(.03)	(.03)	(.02)	(.04)
Constant	-1.92	-1.78	.03	.16	-.13	.09	.55	.46	.78
	(.30)	(.31)	(.23)	(.21)	(.17)	(.18)	(.18)	(.13)	(.19)
R-squared	.38	.37	.28	.32	.25	.07	.04	.14	.18
# Obs.	5083	5083	6035	6035	6035	5505	5089	5270	3602

Notes: These models included all variables listed in Tables 3a and 3b. See Table 3a notes.

Table 5: Interactions Between Low Age 7 Scores and SES

Outcomes:	Reading @ 16	Math @16	Any O-levels	English O-level	Math O-level	Employed @ 23	Employed @33	Wage @23	Wage @33
Males									
Low Reading	-.77	-.64	-.28	-.19	-.16	.01	.01	-.02	-.11
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)	(.02)	(.01)	(.02)
x low SES	-.06	.04	.02	.01	.04	-.06	-.03	-.01	.04
	(.06)	(.06)	(.03)	(.02)	(.02)	(.03)	(.03)	(.02)	(.03)
x high SES	.04	-.11	.04	-.08	-.07	-.01	.00	.03	.00
	(.07)	(.07)	(.03)	(.03)	(.03)	(.04)	(.04)	(.03)	(.04)
Low Math	-.39	-.40	-.13	-.06	-.07	.00	.02	-.06	-.12
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
x low SES	-.04	.01	.01	.02	.00	-.04	-.03	.00	-.04
	(.06)	(.07)	(.03)	(.03)	(.03)	(.03)	(.04)	(.03)	(.04)
x high SES	.10	-.16	-.02	-.13	-.12	-.01	-.03	-.03	.05
	(.07)	(.07)	(.04)	(.03)	(.03)	(.03)	(.04)	(.03)	(.04)
Constant	-1.43	-.89	.25	.11	.18	.79	.89	.58	1.38
	(.31)	(.33)	(.24)	(.20)	(.20)	(.15)	(.18)	(.13)	(.18)
R-squared	.42	.39	.28	.29	.26	.04	.04	.06	.19
# Obs.	5266	5266	6233	6233	6233	5417	4867	3974	3605
Females									
Low Reading	-.70	-.46	-.31	-.21	-.08	-.09	-.09	-.07	-.12
	(.04)	(.04)	(.02)	(.02)	(.02)	(.02)	(.03)	(.02)	(.02)
x low SES	-.03	.08	.08	.05	.02	-.04	-.04	-.02	.05
	(.06)	(.06)	(.03)	(.03)	(.02)	(.04)	(.05)	(.03)	(.04)
x high SES	.05	-.20	-.00	-.09	-.13	.01	-.00	-.03	-.02
	(.07)	(.08)	(.04)	(.04)	(.03)	(.05)	(.06)	(.03)	(.05)
Low Math	-.38	-.42	-.16	-.10	-.07	-.05	-.04	-.07	-.08
	(.03)	(.04)	(.02)	(.02)	(.01)	(.02)	(.03)	(.02)	(.02)
x low SES	-.10	.03	.01	-.01	.02	-.01	.00	.02	.00
	(.05)	(.06)	(.03)	(.03)	(.02)	(.03)	(.05)	(.03)	(.04)
x high SES	.12	-.11	.02	-.10	-.11	.02	.09	.02	.05
	(.06)	(.07)	(.03)	(.03)	(.03)	(.04)	(.05)	(.03)	(.04)
Constant	-1.26	-1.41	.23	.27	-.12	.19	.22	.49	.82
	(.28)	(.31)	(.23)	(.21)	(.18)	(.18)	(.23)	(.13)	(.19)
R-squared	.45	.35	.30	.31	.22	.08	.09	.15	.17
# Obs.	5083	5083	6035	6035	6035	5505	5089	5270	3602

Notes: These models included all variables listed in Tables 3a and 3b. See Table 3a notes.