EARLY TEST SCORES, SCHOOL QUALITY AND SES: LONGRUN EFFECTS ON WAGE AND EMPLOYMENT OUTCOMES

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ABSTRACT

This study uses data from the British National Child Development Survey (NCDS) to examine interactions between socio-economic status (SES), children's test scores, and future wages and employment. We find that children of lower SES have both lower age 16 test scores and higher returns to these test scores in terms of age 33 wages and employment probabilities than high-SES children.

We then examine determinants of age 16 scores. Conditional on having had the same age 7 mathematics scores, high-SES children go on to achieve higher age 16 mathematics scores than children of low or middle-SES. They are also much more likely to pass O-levels in English and Mathematics. These differences are either eliminated or greatly reduced when observable measures of school quality are added to the model, suggesting that high-SES children get better age 16 test scores at least in part because they attended better schools.

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On the other hand, conditional on age 7 scores, low-SES children achieve higher age 16 reading scores than high-SES children and the estimated relationship between the two is not affected by the addition of school quality variables. This observation provides evidence consistent with the conjecture that success in reading may be less dependent on school quality than success in mathematics.

I. INTRODUCTION

Much of the current debate over education policy centers on raising test scores. We care about test scores because of the many studies that have demonstrated links between children's scores on achievement tests, future wages, and employment probabilities. Scores are viewed as a key intermediate measure that can tell us both how schools are doing and how the children who attend them are likely to do in future life. Judged by this test score metric, children of lower socio-economic status (SES) do more poorly than children of higher SES on average. Key questions raised by this observation are how much the gap in test scores matters for future outcomes, and whether the gap in test scores can be reduced via improvements in school quality?

This study uses data from the British National Child Development Survey (NCDS) to address these questions. We first verify that age 16 test scores are important determinants of wages and employment at age 33 for all individuals. We find however, that a given age 16 test score has a smaller effect on the wages and employment probabilities of a high-SES individual than on the labor market outcomes of a low-SES person. This finding serves as an important motivation for our focus on test scores, though it suggests that it might be possible to eliminate SES-related gaps in earnings without fully equalizing test scores.

We then examine the determinants of age 16 test scores in models which include interactions between age 7 test scores and SES. Age 7 and age 16 correspond roughly to the ages of school entry and exit for a large fraction of the children in our sample. We find that among children with similar age 7 scores, high-SES children go on to achieve higher age 16 mathematics scores. They are also much more likely to pass O-level exams in the academic subjects of English and Mathematics. These O-levels are critical hurdles, in that students who do not pass them cannot continue with an academic education, though they may receive further vocational training.[1]

This high-SES advantage is greatly reduced when measures of school quality are added to the model, regardless of whether family circumstances are controlled for. Thus, superior school quality for high-SES children is responsible for a significant part of the SES gap in mathematics test scores and schooling attainment that opens up among children with similar age 7 scores between age 7 and age 16.

Our findings for reading scores do not fit this pattern, however. We find that among children with similar age 7 scores, it is the high achieving low-SES children who tend to achieve the highest age 16 reading scores. And in this case, the relationship between SES and age 7 scores is not affected by the addition of school quality variables. This observation suggests that for the average child in our sample, success in reading is less dependent on school quality than success in mathematics. It is consistent with increasing evidence that reading difficulties tend to start prior to school entry, and that the best readers are those who obtain a good deal of practice outside the classroom.

The rest of the paper is laid out as follows. Section II provides a summary of some of the existing evidence regarding the relationship between test scores, SES, and future outcomes. Section III discusses our conceptual and empirical framework. Section IV introduces the NCDS data, while results appear in Section V. Conclusions follow in Section VI.

II: THE RELATIONSHIP BETWEEN TEST SCORES, SES, SCHOOL QUALITY AND OUTCOMES

Several studies have shown that the test scores of older children are associated with future wages. For example, Neal 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.[2] 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) show that in the Wisconsin Longitudinal Study, IQ scores measured at age 17 are significant predictors of wages at ages 35 and 53.[3]

British cohort studies such as the NCDS have allowed researchers to investigate the links between the test scores of younger children and future outcomes. For example, Hutchison, Prosser and Wedge (1979) examine the link between test scores at age 7 and 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; and 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 significant effects of age 7 test scores on the chosen outcomes.

The relationship between SES and outcomes is also well-documented. In U.S. studies, SES is generally proxied using parent's education, occupation or income, mother's marital status, and/or race. We know, for example, that relative to children of better educated parents, children of high school dropouts are less likely to finish high school themselves, and more likely to be unemployed or in low-wage jobs.

In the U.K., SES is often measured using the father's occupation. As in the U.S., children of lower SES are likely to have lower test scores as well as lower-paying jobs and are less likely to be employed than children from higher-SES families. This paper takes the analysis a step further by examining the way that returns to test scores vary with SES.

The literature on the relationship between school quality and future outcomes is too vast to be properly summarized here. Dolton and Vignoles (1996) and Dearden, Ferri and Meghir (1997) are particularly relevant because they provide direct examinations of the effects of school quality on future wages and employment using NCDS data. However, neither study focuses on the extent to which SES-linked differentials in outcomes may be due to differences in school quality. One attraction of the NCDS for this type of research is that it is one of very few surveys that collects information about *both* a broad range of school quality and family background variables.

Recent work on the relationship between school and family inputs, on one hand, and mathematics and reading scores, on the other hand, is of particular interest. In the U.S., mathematics scores have improved somewhat over the past 10 years, presumably partly in response to many efforts to improve the teaching of mathematics. However, reading scores have stagnated despite aggressive attempts to improve the way that reading is taught. In commenting on these trends Lawrence Feinbert, the assistant director of the National Assessment of Educational Progress, said that "Reading is a skill that is important to develop in people's everyday lives . . . It's harder to show gains in reading when children and their parents are reading less on their own at home" (Groves, 2000).

Similarly, the National Research Council (Snow, Burns & Griffin, 1998) reports that reading difficulties generally start prior to school entry and that one of the most important determinants of reading success is a language-rich environment in the home. It is possible that low-SES children who score well on age 7 tests have parents who have provided them with such a background, and that this is why they are able to perform well on age 16 reading tests regardless of the subsequent quality of their schools.

III. CONCEPTUAL AND EMPIRICAL FRAMEWORK

We know from previous research (c.f. Neal & Johnson) that people with higher test scores have higher future wages, and thus we write y = g(S16), where S16 is the age 16 test score and specifically assume that:

$$g'(S16)/g(S16) = b_i - k_1 S16, \; k_1 >= 0, \tag{1}$$

where b_i is an individual specific measure of the marginal return to higher test scores in terms of either wages or future test scores. Here, k_1, the rate at which the return falls with increasing scores is assumed to be fixed across individuals, for simplicity.

We also assumed that scores depend on effort, as well as an individual's ability, background, and opportunities. The marginal cost of increasing test scores increases with the score:

$$f'(S16) = r_i + k_2 S16, \; k_2 >= 0, \tag{2}$$

but also varies across individuals. Here r_i represents an individual specific marginal cost of acquiring a high test score. Marginal costs can vary because individuals have different tastes for education, because they face differential costs of borrowing to finance their educations, or because they have different levels of ability. We again assume, for simplicity, that the rate at which the marginal cost increases with the score, k_2, is constant across individuals.

If individuals with similar age 16 test scores earn different future wages, this could be a reflection of their opportunities. For example, individuals with superior social networks may be better positioned to gain access to higher paying jobs, and individuals who attend better schools may be more able to translate a given level of measured ability at age 7 into a higher test score at age 16. Alternatively, a high bi might reflect superior non-cognitive skills (e.g. social skills, motivation) that help someone translate a given cognitive test score into a better future outcome.

Following Becker (1967), we assume that individuals trade off the cost of educational effort against the future gains from such effort in order to maximize a utility function of the form:

$$U(y,S16) = \text{benefit} - \text{cost} = \log y - f(S16). \tag{3}$$

This model has the same functional form as Card (1995). Thus, we can simply rely on his analysis to work out an expression for the relationship between test scores and income.[4]

Integration of (1) leads to the following equation for the relationship between log earnings and test scores:

$$\log y_i = a + b_i S16_i - 0.5 k_1 S16_i^2. \tag{4}$$

Card shows that in a model of this form, the population regression coefficient of log y_i on $S16_i$, ρ, is a weighted average of *b* and *r*, where an underscore represents the population averages of these two variables:

$$\rho = (1-c)b + cr. \tag{5}$$

If we divide the population into high, medium, and low-SES groups, then the way that rho varies with SES will depend on the relationship between b and r. For example, if moving up the SES scale increases b (returns) and reduces r (costs), then rho could well be equal for all three groups. On the other hand, if moving up the SES scale reduces r faster than it increases b, then rho will be smaller in high-SES groups than in low-SES groups, and vice-versa. Hence, the model shows that relationship between SES, test scores, and outcomes must be determined empirically.

In what follows, we will apply this model to data measured at two points in time. First, we examine the relationship between age 16 test scores, SES, and age 33 outcomes. Specifically, we will examine the extent to which returns to age 16 tests scores are higher or lower for low-SES individuals in terms of better age 33 wage and employment outcomes. Age 16 represents the point at which the young people in our sample were making critical decisions about future schooling and training, and the age at which the majority of them (two thirds) left school without passing O-levels.

The model we estimate is of the form:

$$\begin{gathered} \log y33_i = a + \rho_0 S16_i + \rho_1 S16_i{*}LSES + \rho_2 S16_i{*}HSES + \\ b_0 SES + b_1 X + e, \end{gathered} \tag{6}$$

where y33 indicates wages at age 33, LSES is an indicator for low SES and HSES is an indicator for high SES, SES is a vector of indicators of the father's occupational category, X is a vector of background variables which are measured as of age 7 or before, and e is a normally distributed, uncorrelated error. We also estimate models in which log y33 is replaced with an indicator for whether or not the person was employed.

This functional form allows rho to vary with SES. Note that a high b_i leads to both higher wages and higher estimated returns to test scores other things being equal. Hence, if we find that low-SES individuals have lower mean age 16 scores but higher estimated returns to those scores, then the model outlined above suggests that r may be falling faster than b is rising with SES. In other words, low-SES individuals may face relatively high r, as they would if they found themselves less able to finance continued educational investments after age 16.

We then examine the way in which the production of age 16 test scores varies with SES among children with similar measured test scores at age 7. These models take the form:

$$S16_i = a + \rho_0 S7_i + \rho_1 S7_i{*}LSES + \rho_2 S7_i{*}HSES + b_0 SES + b_1 X + e, \qquad (7)$$

where S7 indicates test scores at age 7. Including test scores at age 7 controls for measured "ability" at a point close to school entry. Suppose that children of high-SES achieve higher age 16 scores than low-SES children with the same age 7 scores. If r falls or remains constant as SES rises, then this result would suggest that low-SES children have lower b_i's.

As discussed above, one thing a low value of b_i might represent is poor school quality. Hence, we also estimate variants of model (7) which include school quality variables measured at ages 7, 11, and 16. Because it is often difficult to separate the effects of school quality from those of family background, we estimate these models with and without family background characteristics measured at age 11 and 16. These models allow us to assess the extent to which SES-related differences in rho may be attributed to inferior school quality among low-SES children.

IV. THE NCDS DATA

(a) Overview

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.[5] 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 in 1958. 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 and Advanced ("A") level examinations.

Overall response rates have remained high, considering the length of the panel.[6] 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 follow-ups. Previous analyses of these data suggest that attriters are slightly more likely than non-attriters to be from disadvantaged backgrounds, although observable differences between the two groups are quite small (Fogelman, 1976, 1983; Robertson & Symons, 1996; Connolly, Micklewright & 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 at various points in time with those from more limited subsamples of individuals with complete data over time.

(b) Measures of Achievement Tests and SES

The achievement 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 ages 7 and 16 are listed in Chart 1.

Chart 1. Tests of Attainment Administered to NCDS Children

At Age 7

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

At Age 16

- 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.[7] Persons without a father present at the time of their birth are assigned to the low-SES group. Table 1

Table 1. Means by SES.

	All	High SES	Medium SES	Low SES
Outcomes				
Reading @ 7	−0.08	0.34	−0.14	−0.39
	(1.00)	(0.82)	(1.10)	(1.22)
Mathematics @ 7	0.01	0.36	−0.06	−0.20
	(1.12)	(1.07)	(1.10)	(1.12)
Reading @ 16	0.05	0.51	−0.06	−0.28
	(0.96)	(0.73)	(0.94)	(1.04)
Mathematics @ 16	0.02	0.54	−0.12	−0.28
	(1.00)	(1.00)	(0.93)	(0.91)
Mathematics O-level	0.18	0.35	0.13	0.10
English O-level	0.28	0.50	0.21	0.17
Hourly Net Pay @ 33	4.63	5.30	4.49	4.15
	(2.10)	(2.35)	(1.98)	(1.82)
Employment @ 33	0.79	0.83	0.80	0.75
Family Background				
No. of children < 21 in HH @ 7	3.09	2.74	3.11	3.44
	(1.61)	(1.28)	(1.62)	(1.84)
First born	0.38	0.41	0.39	0.34
Mother's age (@ 7)	27.5	28.2	27.1	27.5
	(5.68)	(5.10)	(5.72)	(6.05)
Father Professional	0.05	0.18	–	–
Father Supervisor	0.13	0.49	–	–
Father Skilled Non-Manual	0.09	0.33	–	–
Father Skilled Manual	0.42	–	0.96	–
Father Semi-Skilled Non-Manual	0.02	–	0.04	–
Father Semi-Skilled Manual	0.15	–	–	0.50
Father did not stay in school past min. age	0.85	0.52	0.90	0.95
Mother did not stay in school past min. age	0.75	0.52	0.83	0.86
In Care by 16	0.02	0.01	0.02	0.04
Persons per room @ 16	1.40	1.16	1.44	1.58
	(0.67)	(0.43)	(0.68)	(0.77)

Table 1. Continued.

	All	High SES	Medium SES	Low SES
Financial problems @ 11	0.09	0.04	0.08	0.14
Financial problems @ 16	0.07	0.02	0.06	0.12
No father @ 11	0.04	0.02	0.02	0.09
No father @ 16	0.07	0.05	0.06	0.12
Father main source income @ 11	0.94	0.98	0.96	0.88
Father main source income @ 16	0.88	0.93	0.91	0.79
School Quality Measures @ 7				
Early phonics	0.34	0.40	0.32	0.32
Medium phonics	0.51	0.49	0.53	0.51
Early mathematics	0.17	0.23	0.16	0.14
Medium mathematics	0.68	0.65	0.69	0.68
No. of class fathers	8.14	13.0	6.65	5.75
high SES	(8.47)	(9.95)	(7.01)	(6.91)
No. of class fathers	17.7	15.2	19.1	18.2
medium SES	(8.98)	(9.01)	(8.71)	(8.83)
No. of class fathers	6.86	4.16	7.52	8.45
low SES	(7.46)	(5.40)	(7.54)	(8.29)
No. of pupils in school	269	260	277	265
	(151)	(146)	(154)	(150)
School Quality Measures @ 11				
Class teacher is male	0.47	0.46	0.48	0.47
Pupil/teacher ratio	23.9	22.9	24.4	24.0
	(9.32)	(9.68)	(9.08)	(9.29)
% Students suitable	0.26	0.33	0.24	0.23
for GCE	(0.16)	(0.20)	(0.13)	(0.13)
School Quality Measures @ 16				
Comprehensive school	0.63	0.57	0.64	0.65
Grammar school	0.12	0.23	0.09	0.07
Secondary Modern school	0.23	0.18	0.24	0.25

Table 1. Continued.

	All	High SES	Medium SES	Low SES
% Boys staying past min. school leaving	0.57	0.68	0.55	0.51
% Girls staying	0.57	0.68	0.54	0.50
% Teachers leaving last year	0.14	0.13	0.14	0.14
All girl school	0.09	0.14	0.08	0.08
Hours english per week	3.61	3.49	3.65	3.68
	(1.01)	(.94)	(1.00)	(1.08)
Hours mathematics per week	3.45	3.44	3.48	3.43
	(0.93)	(0.84)	(0.96)	(0.98)
Pupil/teacher ratio	16.9	16.5	17.1	17.0
	(2.28)	(2.32)	(2.19)	(2.31)
No. of Obs.	14670	4018	6360	4292

Note: Standard deviations in parentheses.

shows the fraction of each of our 3 “classes” whose fathers fall into each of the more detailed categories.

Means of the standardized test scores at age 7 and 16 are shown by SES in the first 4 rows of Table 1. In this table, all scores have been converted to Z-scores for ease of interpretation – hence a score of 1 would indicate that a group scored one standard deviation above the mean while a score of -1 would indicate that they fell one standard deviation below the mean for all children. There is a striking gradient in test scores by SES, with the difference between the high-SES and low-SES group at age 7 exceeding half of a standard deviation. Moreover, this difference widens between ages 7 and 16. These patterns are not affected by restricting the sample to those who had valid scores at both interview dates.

Ceiling effects are a significant concern in the case of the age 7 reading test – approximately 20% 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 place more weight on results obtained using age 7 math scores than on those obtained using age 7 reading scores in what follows, though the use of either score leads to similar conclusions.

Finally, it is interesting to note that the distribution of standardized scores across SES groups is virtually identical for the age 16 math and reading scores.

This suggests that the estimated differences in the determinants of these scores discussed below are not driven by differences in the distribution of math and reading scores across groups.

(c) Educational and Labor Market Outcomes

As discussed above, we first look at the effects of age 16 test scores on wages and employment at age 33.[8] Table 1 shows that there is an SES gradient in hourly wages, and in (full-time or part-time) employment probabilities.[9] We then examine the relationships between age 7 test scores, SES, and age 16 test scores in an effort to shed light on the determinants of SES-related differences in age 16 scores.

In order to corroborate our results for age 16 test scores, we also examine the effects of age 7 scores on the O-level tests, which are usually written at age 16. The results of these exams are extremely important because they determine whether or not a student can continue with an academic education. We focus on whether the student passed O-levels in the academic subjects of english and mathematics.[10]

Table 1 shows that fewer than a third of the children in this cohort passed O-levels in these subjects. O-levels are not compulsory and many of those who did not pass may have chosen not to attempt the exams because they had no plans to continue with their educations.

(d) Measures of Family Background

The NCDS provides a rich portrait of family life at each wave of the survey. Table 1 shows the variation by SES for a subset of the family background variables included in our models.[11] Those variables shown had statistically significant effects in at least some of our regression models. In addition to these variables, we also controlled for whether there was a father present at age 7, whether the child was a twin, birth weight, number of mother's siblings, mother's father's social class, whether the child was an immigrant, the child's ethnicity (African, Indian, Other Asian, or other non-northern European), and for the number of times the child had changed schools by age 16.

At age 7, the high-SES children lived in smaller families and hence were more likely to be first born. Their mothers were slightly older, and much more likely to have continued their educations beyond the minimum school leaving age than other mothers. The fathers were also much more educated, with 48% of the high-SES fathers having continued their educations beyond minimum school leaving age, compared to only 5% of the low-SES fathers.

At age 11, the low-SES children were more than 4 times more likely to be without a father living in the household than either middle or high-SES children. They were correspondingly less likely to live in a household in which the father's income was the main source of revenue, and more than three times more likely to live in a household that reported "financial difficulties".

These patterns also held at age 16. In addition, Table 1 shows that by age 16, children of low SES were four times more likely to have ever been "in care" (i.e. wards of the state) than children of high SES. They also report more crowding as measured by "persons per room" at home.

These measures present a picture of low-SES children who suffer from cumulative disadvantages between age 7 and age 16. In what follows, we will ask to what extent these disadvantages can account for the lower age 16 test scores of these children.

(e) Measures of School Quality

The NCDS also provides exceptionally detailed measures of school quality at each wave, though unfortunately the reported measures vary somewhat from wave to wave. These data were collected from school administrators rather than from parents. Table 1 shows the variation in a subset of these measures by SES.[12] The age 7 survey asks about the age at which teaching of phonics and mathematics began. We classify children who began to study phonics before 5 years, 5 months as "early phonics" children, while those who began between 5 years, 5 months and 6 years, 6 months are classified as "medium phonics" children, and the remainder are classified as "late phonics". The timing of mathematics instruction is coded similarly. Table 1 shows that high-SES children are more likely than others to have begun phonics and mathematics instruction "early".

Administrators were also asked the number of children in the class with fathers in each social category. Among high-SES children, 36% of the other children are from high-SES backgrounds, whereas for low-SES children this proportion is only 19%. By adding up the number of fathers in each social category, one can also obtain a measure of class size. These figures suggest that there is little variation in class size at age 7 (which hovers around 32 or 33 children). However, the average school size is slightly smaller among the high-SES children.

In the age 11 survey, there appears to be little difference by SES in the proportion of teachers who are male or in the pupil/teacher ratio. However, the percentage of children judged "suitable" for writing the General Competency Exam was higher in schools attended by high-SES children.

At age 16, we know whether the child attended a comprehensive, secondary modern, or grammar school.[13] High-SES children were much more likely to have attended grammar schools than other children. They also attended schools in which the fraction of boys and girls expected to stay on past the minimum school leaving age was higher, and high-SES girls were more likely to attend all girl schools. Hours devoted to studying english and mathematics were quite similar across the three groups, as were pupil/teacher ratios, and teacher turnover.

Finally, we know the child's local educational authority (LEA) at both 11 and at age 16.[14] The LEA plays a role similar to an American school board in the setting of local educational policy. We include a set of dummy variables for the LEA at age 16 in order to capture unobserved aspects of school quality, as well as regional effects. However, the results reported below are robust to the exclusion of these dummy variables, or to the use of LEA at age 11 rather than 16.

The comparisons in Table 1 suggest that the most consistent differences in measured school quality across SES groups were in terms of peer groups and/or expectations about the academic success of students. High-SES students were more likely than others to be in schools in which they were expected to achieve academically.

V. ESTIMATION RESULTS

(a) Effects of Age 16 Scores on Wages and Employment at 33

Table 2 shows estimates of the effects of age 16 mathematics scores on age 33 wages and employment probabilities. The estimates show that although average age 16 test scores are lower for low-SES individuals, the return to test scores is significantly higher than it is for high-SES individuals. A one standard deviation increase in age 16 math scores would translate into a 14% higher wage rate at age 33 for a low or medium-SES person, compared to a return of only 11% for a high-SES person. Similarly, the same increase in age 16 test scores would increase employment probabilities by 7% among low-SES individuals compared to only 3% among high and medium-SES individuals.[15]

As discussed above, these models control for the main effect of SES, as well as for all of the measured age 7 family background variables. The estimated coefficients on family background serve as a means of gauging the importance of age 16 test scores. For example, they suggest that a half standard deviation difference in age 16 test scores has roughly the same effect as having a mother who stayed in school beyond minimum school leaving age.

Table 2. Effects of Age 16 Mathematics on Wages and Employment at 33.

	Log Wages	Employment
Mathematics @ 16	0.141	0.030
	(0.008)	(0.007)
Math * low SES	−0.005	0.041
	(0.014)	(0.012)
Math * high SES	−0.037	−0.001
	(0.013)	(0.011)
Father Professional	0.097	0.035
	(0.031)	(0.028)
Father Supervisory	0.089	0.046
	(0.024)	(0.021)
Father Skilled	0.085	0.024
Non-Manual	(0.025)	0.022)
Father Skilled	0.060	0.039
Manual	(0.020)	(0.017)
Father Semi-Skilled	0.076	−0.019
Non-Manual	(0.042)	(0.038)
Father Semi-Skilled	−0.013	−0.002
Manual	(0.022)	(0.019)
Father left school	−0.065	0.007
before min. age	(0.015)	(0.013)
Mother left school	−0.068	0.008
before min. age	(0.013)	(0.012)
Mother's age	0.157	0.046
@ 7 (* 100)	(0.099)	(0.086)
Male	0.275	0.215
	(0.010)	(0.009)
No. of children < 21	−0.015	−0.007
in HH @ 7	(0.004)	(0.003)
First born	0.004	0.002
	(0.012)	(0.011)
Intercept	1.18	0.716
	(.058)	(0.050)
R-squared	0.281	0.098
No. of Obs.	5536	7578

Notes: Standard errors in parentheses. Models also included other family background variables as of age 7 as discussed in text.

The first panel of Table 3 compares the estimated effects of age 16 mathematics scores to those of age 16 reading scores. These models are of the same form as those shown in Table 2. For convenience, the estimated coefficients on age 16 mathematics test scores are repeated in the first two columns of the first panel of Table 3.

Table 3. Effects of Mathematics and Reading Scores at Age 16 on Wages and Employment at Age 33.

	Log Wages	Employment	Log Wages	Employment
Panel 1: Estimates Including Family Background Variables @ Age 7				
Mathematics @ 16	0.141	0.030	–	–
	(0.008)	(0.007)		
Math * low SES	−0.005	0.041	–	–
	(0.014)	(0.012)		
Math * high SES	−0.037	−0.001	–	–
	(0.013)	(0.011)		
Reading @ 16	–	–	0.133	0.030
			(0.009)	(0.008)
Reading * low SES	–	–	−0.012	0.040
			(0.013)	(0.011)
Reading * high SES	–	–	0.029	0.010
			(0.017)	(0.014)
R-squared	0.281	0.098	0.279	0.099
No. of Obs.	5536	7578	5536	7578
Panel 2: Estimates Including All Available Family Background and School Quality Measures				
Mathematics @ 16	0.132	0.030	–	–
	(0.09)	(0.008)		
Math * low SES	−0.009	0.037	–	–
	(0.014)	(0.012)		
Math * high SES	−0.044	−0.001	–	–
	(0.013)	(0.011)		
Reading @ 16	–	–	0.116	0.030
			(0.009)	(0.008)
Reading * low SES	–	–	−0.012	0.036
			(0.013)	(0.012)
Reading * high SES	–	–	0.014	0.010
			(0.017)	(0.014)
R-squared	0.324	0.116	0.318	0.117
No. of Obs.	5536	7578	5536	7578

Notes: Standard errors in parentheses. The models in Panel 1 are of the same form and include the same variables as those in Table 2. The models in Panel 2 also include measures of family background at age 11 and at age 16, as well as all of the school quality variables (measured at ages 7, 11, and 16) that are discussed in the text.

When we use age 16 reading scores instead of mathematics scores, the estimated effects on employment probabilities are very similar to those obtained using age 16 mathematics scores, implying once again that low-SES individuals have higher returns to a given increase in age 16 test scores even though they have lower average scores. However, interactions of age 16 reading scores with SES are not statistically significant in the model of age 33 wages.

The second panel of Table 3 shows estimates from models similar to those contained in the first panel except that the models also include measures of family background as measured at ages 11 and 16 as well as all of the school quality discussed above. These estimates are remarkably similar to those in the first panel, which indicates that age 16 test scores are not acting as a proxy for these observed background and school quality variables in the models of wages and employment.

(b) Determinants of Age 16 Scores

The models of Tables 2 and 3 suggest that low-SES individuals have higher returns to a given increase in age 16 test scores than high-SES individuals, even though they have lower average scores. This observation raises the question of what determines age 16 test scores?

These questions are addressed in the first panel of Table 4, which examines he relationship between age 7 test scores and age 16 test scores (or passage of O-levels) for children of different SES levels. We show linear probability models for O-levels, for ease of interpretation. Logit models produced similar estimates.

The first column of Table 4 shows that conditional on having the same age 7 mathematics score, high-SES children get significantly higher mathematics scores at age 16. They are also much more likely than low-SES children to get O-level accreditation in mathematics and in english, as shown in columns 3 and 4. However, column 2 shows that this relationship does not hold for reading scores. Conditional on the same age 7 mathematics score, low-SES children actually achieve higher reading scores at age 16 than high-SES children.

The next 4 columns of panel 1 of Table 4 show estimates of the relationship between age 7 reading scores, age 16 test scores, and O-levels. Recall that the age 7 reading scores suffer from significant "ceiling effect" problems; yet these estimates tell a story that is qualitatively similar to that obtained using mathematics test scores. Specifically, among children with similar age 7 scores, those from high-SES backgrounds achieve higher age 16 mathematics scores and are more likely to obtain O-level accreditation in the academic subjects of mathematics and english.

Table 4. Effects of Mathematics and Reading Scores at Age 7 On Test Scores and O-levels at Age 16.

	Math @ 16	Reading @ 16	Math O-level	English O-level	Math @ 16	Reading @ 16	Math O-level	English O-level
Mathematics @ 7	0.340	0.336	0.078	0.099	–	–	–	–
				(0.011)	(0.011)	(0.004)	(0.005)	
Math * low SES	−0.007	0.064	-0.011	−0.009	–	–	–	–
	(0.017)	(0.017)	(0.007	(0.008)				
Math * high SES	0.041	−0.101	0.057	0.035	–	–	–	–
	(0.018)	(0.017)	(0.007)	(0.008)				
Reading @ 7	–	–	–	–	0.364	0.448	0.069	0.104
					(0.011)	(0.010)	(0.004)	(0.005)
Reading * low SES	–	–	–	–	−0.032	0.026	−0.019	−0.021
					(0.017)	(0.015)	(0.006)	(0.007)
Reading * high SES	–	–	–	–	0.142	−0.002	0.086	0.084
					(0.022)	(0.020)	(0.009)	(0.010)
Background @ 7 or earlier								
Father Professional	0.583	0.506	0.189	0.213	0.520	0.378	0.184	0.188
	(0.048)	(0.046)	(0.019)	(0.022)	(0.048)	(0.043)	(0.019)	(0.022)
Father Supervisory	0.364	0.396	0.088	0.124	0.294	0.274	0.080	0.101
	(0.037)	(0.035)	(0.014)	(0.016)	(0.037)	(0.033)	(0.014)	(0.016)
Father Skilled	0.328	0.445	0.053	0.117	0.225	0.298	0.035	0.082
Non Manual	(0.038)	(0.037)	(0.015)	(0.018)	(0.038)	(0.035)	(0.015)	(0.017)
Father Skilled	0.159	0.222	0.014	0.025	0.118	0.149	0.011	0.017
Manual	(0.029)	(0.028)	(0.011)	(0.013)	(0.027)	(0.030)	(0.013)	(0.011)
Father Semi-Skilled	0.121	0.215	0.062	0.060	0.119	0.186	0.064	0.058
Non Manual	(0.067)	(0.065)	(0.026)	(0.030)	(0.067)	(0.061)	(0.026)	(0.030)
Father Semi-Skilled	0.090	0.143	−0.003	0.006	0.059	0.093	−0.007	−0.002
Manual	(0.033)	(0.032)	(0.013)	(0.014)	(0.033)	(0.030)	(0.013)	(0.014)
Father left school	−0.247	−0.199	−0.102	−0.133	−0.225	−0.160	−0.099	−0.123
before min. age	(0.024)	(0.023)	(0.009)	(0.011)	(0.022)	(0.024)	(0.011)	(0.010)

	Math @ 16	Reading @ 16	Math O-level	English O-level	Math @ 16	Reading @ 16	Math O-level	English O-level
Mother left school	−0.258	−0.199	−0.092	−0.121	−0.267	−0.188	−0.100	−0.125
before min. age	(0.021)	(0.020)	(0.008)	(0.009)	(0.020)	(0.019)	(0.008)	(0.009)
Mother's age @ 7	0.012	0.017	0.004	0.005	0.012	0.017	0.005	0.004
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Male	0.148	−0.019	0.040	−0.084	0.289	0.138	0.072	−0.041
	(0.016)	(0.015)	(0.006)	(0.007)	(0.016)	(0.014)	(0.006)	(0.007)
No. of children in HH	−0.065	−0.113	−0.015	−0.027	−0.038	−0.076	−0.011	−0.019
< 21 @ 7	(0.006)	(0.006)	(0.002)	(0.003)	(0.006)	(0.005)	(0.002)	(0.003)
First born	0.145	0.165	0.042	0.051	0.109	0.130	0.033	0.039
	(0.020)	(0.019)	(0.008)	(0.009)	(0.020)	(0.018)	(0.008)	(0.009)
R-squared	0.368	0.366	0.227	0.257	0.370	0.450	0.207	0.259
No. of Obs.	10350	10350	12276	12270	10350	10350	12276	12270

Notes: Standard errors in parentheses. These models also include all of the available measures of family background measured at age 7.

Turning to models of age 16 reading scores, the estimates shown in column 6 of Table 4 are similar to, though weaker than, those shown in column 2. Once again, they suggest that in contrast to the estimates from models of other outcomes, low-SES children obtain reading scores that are the same or higher than high-SES children with similar age 7 reading scores.

The models in Table 7 all include measures of family background up to age 7, as well as the child's gender and an indicator for first born. The coefficients on these variables generally have the signs that one would expect. For example, higher SES, as measured by father's occupation, is associated both with higher test scores and higher probabilities of passing O-levels. Both having a mother and having a father who left school before minimum school leaving age, have strong negative effects on these outcomes. First born children tend to have higher test scores and greater probability of passing O-levels, while children in larger families have poorer outcomes.

The effects of gender are striking. Conditional on age 7 math scores, boys obtain much higher age 16 math scores than girls. The estimated difference becomes even greater if we control for age 7 reading scores instead of age 7 math, which suggests that these age 7 tests really do measure different types of achievement. Conditional on age 7 math scores, there is no difference between boys and girls in age 16 reading scores. However, if we condition on age 7 reading scores instead, boys once again have higher age 16 scores. This result suggests that although boys start out with lower reading scores at age 7, they catch up by age 16. Similar patterns are evident in terms of gender differences in O-levels performance.

The estimates in Table 4 are based on a somewhat different sample than those that were shown in Tables 2 and 3. Specifically, people for whom outcomes at age 33 are missing are not excluded. Appendix Table shows estimates based on a sample in which those missing employment information at age 33 have been excluded. These estimates are qualitatively similar to those shown in Table 4.

(c) Effects of Family Background and School Quality

Table 5 shows estimates from models similar to those of the first 4 columns of the first panel of Table 4, except that measures of family background at ages 11 and 16 have been added as well as measures of school quality at 7, 11, and 16. In order to limit the length of the table, only variables that had statistically significant effects in at least some models are shown.

Table 5 indicates that when these measures are added to the model, interactions between SES and mathematics scores at age 7 become statistically insignificant in the model of age 16 math scores. Moreover, the importance of these interactions in the models of O-levels is greatly reduced. Thus, it appears that a significant portion of the high-SES advantage in terms of higher age 16 outcomes can be explained in terms of what happened to the children between the ages of 7 and 16, both in their homes and in their schools. In contrast, the coefficients on interactions between SES and age 7 test scores in the model of age 16 reading scores are remarkably unaffected by the addition of these variables.

The estimated coefficients on the family background and school quality measures are of some independent interest, although given the possible endogeneity of school quality, we are wary of attaching causal interpretations to them. Once again, measures of family background at age 7 are all highly significant. We also find that reports of financial difficulties at ages 11 and 16, and having an absent father at age 16 have consistently negative effects on our measures of age 16 outcomes. However, having an absent father at age 11 is not associated with significant reductions in age 16 outcomes (nor was having an absent father at age 7, which is not shown in the table).

An earlier introduction to phonics is associated with higher reading scores, and a higher probability of passing the english O-level. However, the early introduction of mathematics appears to have little effect on age 16 math scores or O-levels. Schools with fathers from higher-SES backgrounds are also associated with better age 16 outcomes, as are larger schools.[16]

At age 11, the most important measure by far is the percent of children judged "suitable" for taking General Competency Exams. Similarly, at age 16, the fraction of children expected to stay past minimum school leaving age is important, as are attending grammar schools, and attending all girl schools (for girls). These results are all consistent with Lazear (1999) who develops a model of educational production that stresses the paramount importance of good peers.

We find negative effects of hours of english instruction (on both reading and mathematics scores), and positive effects of hours of math instruction. It is possible that schools with more math hours have curriculums that are generally more rigorous. Finally, we find negative effects of higher pupil/teacher ratios at age 16 on mathematics scores and on the probability of passing the mathematics O-level, as well as negative effects of teacher turnover on both reading and mathematics scores.

Table 6 sheds light on the extent to which the superior age 16 outcomes achieved by high-SES children can be attributed to school quality alone. The table shows estimates of models similar to those of Table 5, except that measures of family background at ages 11 and 16 have been excluded. This exclusion has very little effect on the estimated test score coefficients or on the interactions between test scores and SES.

Table 5. Effects of Mathematics @ 7 on Age 16 Outcomes Controlling for Family Background and School Quality.

	Math @ 16	Reading @ 16	Math O-levels	English O-levels
Mathematics @ 7	0.276	0.292	0.058	0.073
	(0.010)	(0.010)	(0.004)	(0.005)
Math * low SES	−0.007	0.051	−0.011	−0.011
	(0.016)	(0.016)	(0.006)	(0.007)
Math * high SES	0.017	−0.115	0.042	0.018
	(0.016)	(0.017)	(0.007)	(0.007)
Background @ 7 or earlier				
Father Professional	0.320	0.314	0.105	0.113
	(0.048)	(0.048)	(0.019)	(0.021)
Father Supervisory	0.172	0.265	0.031	0.060
	(0.038)	(0.038)	(0.015)	(0.016)
Father Skilled	0.154	0.309	0.007	0.066
Non Manual	(0.039)	(0.039)	(0.015)	(0.017)
Father Skilled	0.060	0.153	−0.005	0.010
Manual	(0.031)	(0.031)	(0.012)	(0.014)
Father Semi-Skilled	0.000	0.134	0.034	0.033
Non Manual	(0.064)	(0.064)	(0.025)	(0.028)
Father Semi-Skilled	0.024	0.107	−0.017	−0.002
Manual	(0.034)	(0.035)	(0.013)	(0.015)
Father left school	−0.173	−0.135	−0.065	−0.085
before min. age	(0.022)	(0.022)	(0.009)	(0.010)
Mother left school	−0.167	−0.137	−0.060	−0.082
before min. age	(0.020)	(0.020)	(0.008)	(0.009)
Mother's age @ 7	0.009	0.014	0.003	0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.165	0.002	0.037	−0.070
	(0.017)	(0.017)	(0.006)	(0.007)
No. children in HH	−0.039	−0.079	−0.010	−0.018
< 21 @ 7	(0.006)	(0.006)	(0.002)	(0.003)
First born	0.120	0.156	0.033	0.044
	(0.018)	(0.018)	(0.007)	(0.008)
Background @ 11				
Financial problems	−0.092	−0.093	−0.025	−0.025
	(0.029)	(0.029)	(0.011)	(0.012)
No father	−0.035	0.089	−0.025	−0.009
	(0.047)	(0.048)	(0.018)	(0.020)
Father main source	0.064	0.186	−0.015	0.015
income	(0.039)	(0.039)	(0.015)	(0.017)
Background @ 16				
In care by 16	−0.130	−0.115	−0.017	−0.020
	(0.050)	(0.051)	(0.020)	(0.023)
Persons per room	−0.020	−0.072	0.001	−0.004
	(0.014)	(0.015)	(0.006)	(0.007)
Financial problems	-0.097	−0.109	−0.017	−0.036
	(0.031)	(0.031)	(0.012)	(0.014)
No father	−0.112	0.001	−0.045	−0.044
	(0.049)	(0.050)	(0.019)	(0.022)
Father main source	−0.013	0.056	−0.022	−0.025
income	(0.041)	(0.041)	(0.016)	(0.018)

Table 5. Continued.

	Math @ 16	Reading @ 16	Math O-levels	English O-levels
School Quality @ 7				
Early phonics	0.019	0.103	0.016	0.037
	(0.028)	(0.028)	(0.011)	(0.012)
Medium phonics	0.011	0.088	0.007	0.026
	(0.025)	(0.025)	(0.010)	(0.011)
Early math	0.049	0.054	−0.001	0.025
	(0.031)	(0.032)	(0.012)	(0.014)
Medium math	0.020	0.074	−0.009	−0.010
	(0.024)	(0.025)	(0.010)	(0.011)
No. class fathers of high SES	0.338	0.437	0.200	0.191
	(0.136)	(0.137)	(0.053)	(0.059)
No. class fathers of medium SES	0.080	0.167	0.030	0.047
	(0.119)	(0.120)	(0.046)	(0.051)
No. class fathers of low SES	−0.279	−0.173	0.066	−0.033
	(0.142)	(0.143)	(0.055)	(0.061)
No. pupils in school (divided by 100)	0.012	0.020	0.003	0.006
	(0.006)	(0.006)	(0.003)	(0.003)
School Quality @ 11				
Class teacher male	0.010	0.038	0.003	0.006
	(0.016)	(0.016)	(0.006)	(0.007)
% students suitable for GCE	0.322	0.301	0.103	0.139
	(0.057)	(0.058)	(0.023)	(0.026)
Pupil/teacher ratio (divided by 100)	−0.095	0.166	0.031	−0.012
	(0.091)	(0.092)	(0.037)	(0.041)
School Quality @ 16				
Comprehensive school	−0.061	0.167	−0.095	−0.116
	(0.053)	(0.053)	(0.023)	(0.025)
Grammar school	0.621	0.501	0.219	0.264
	(0.056)	(0.057)	(0.024)	(0.027)
Secondary modern school	−0.113	0.169	−0.151	−0.211
	(0.053)	(0.054)	(0.023)	(0.025)
% Boys staying past min. leaving age	0.279	0.162	0.086	0.046
	(0.46)	(0.046)	(0.020)	(0.023)
% Girls staying	0.076	0.117	−0.044	0.045
	(0.045)	(0.045)	(0.020)	(0.22)
All girl school	0.213	0.266	0.034	0.033
	(0.046)	(0.046)	(0.020)	(0.024)
Hrs. english per week	−0.064	−0.052	−0.007	0.000
	(0.009)	(0.009)	(0.004)	(0.005)
Hrs. math per week	0.099	0.069	0.000	−0.012
	(0.010)	(0.010)	(0.004)	(0.005)
Pupil/teacher ratio (divided by 100)	−1.60	−0.518	−0.006	−0.312
	(0.401)	(0.403)	(0.002)	(0.205)
% Teachers leaving last year	−0.219	−0.213	0.050	0.016
	(0.102)	(0.103)	(0.045)	(0.050)
Intercept	−1.05	−1.79	0.494	0.467
	(0.190)	(0.191)	(0.115)	(0.128)
R-squared	0.477	0.431	0.336	0.394
No. of Obs.	10350	10350	12276	12270

Notes: Standard errors in parentheses. Models also included LEA dummies and other variables as described in text.

Table 6. Effects of Mathematics @ 7 on Age 16 Outcomes Controlling for School Quality and Family Background at Age 7 Only.

	Math @ 16	Reading @ 16	Math O-levels	English O-levels
Mathematics @ 7	0.279	0.294	0.059	0.073
	(0.010)	(0.010)	(0.004)	(0.005)
Math * low SES	0.001	0.059	−0.010	−0.008
	(0.016)	(0.016)	(0.006)	(0.007)
Math * high SES	0.015	−0.116	0.041	0.017
	(0.017)	(0.017)	(0.007)	(0.007)
R-squared	0.469	0.423	0.335	0.391
No. of Obs.	10350	10350	12276	12270

Notes: Standard errors in parentheses. These models are similar to those shown in Table 5, except that measures of family background at ages 11 and 16 have been excluded.

Hence, it appears that much of the SES-related gap in mathematics test scores and schooling achievement that opens up between age 7 and age 16 can be explained by the fact that these children attend superior schools.

(d) Differences Between Men and Women

Author – Only 1 table supplied for Appendix ? OK

It may seem odd to discuss determinants of wages and employment in models which pool men and women. After all, there are well-known gender differences in the levels of these outcomes. Moreover, as noted above, there are large gender differences in test scores, and in the evolution of test scores over time.However, despite these differences, the pattern of interactions between SES and test scores are remarkably similar for men and women. In view of this similarity, we have focused on the pooled estimates above. The estimated coefficients on the SES-test score interactions from models corresponding to those in Tables 2, 4, and 6 are shown separately for males and females in Appendix Table.

(e) The Relationship Between Age 7 Scores and Age 33 Outcomes

Interactions between SES and age 7 test scores are generally insignificant in models of age 33 outcomes. This is not surprising given the pattern of results discussed above. Low-SES children had lower returns to age 7 test scores in terms of age 16 mathematics test scores and passage of O-levels than high-SES children. However, they have higher returns to age 16 test scores in terms of age 33 outcomes. Together, these effects tend to cancel out.

VI. CONCLUSIONS

We find that children of lower SES have both lower age 16 test scores and higher returns to these test scores in terms of wages and employment probabilities than high-SES children. We also find that conditional on having the same age 7 mathematics scores, high-SES children go on to achieve higher age 16 mathematics scores than children of low or middle-SES. They are also much more likely to pass O-levels in English and Mathematics. These differences are either eliminated or greatly reduced when observable measures of school quality are added to the model, suggesting that much of the gap in test scores and schooling attainment that opens up during the school years between high-SES and low-SES children with the same initial scores reflects the better quality schools attended by high-SES children.

On the other hand, conditional on age 7 scores, low-SES children achieve higher age 16 reading scores than high-SES children and the estimated relationship between the two is not affected by the addition of school quality variables. This observation lends support to the conjecture that, for the average child, reading scores are less sensitive to what goes on in schools than mathematics scores. Together these findings suggest that test scores reflect opportunities as well as ability, and that many of the low-SES children in this cohort could have benefitted from increased opportunity in the form of access to higher quality schools.

NOTES

1. We treat the test score at age 7 as a predetermined measure of something that is potentially important in later life. These scores reflect both ability and the cumulative effects of early experience. As one might expect, factors such as parent's education, birthweight, being first born, and number of children in the household are all important determinants of age 7 scores, in addition to our measures of SES.

2. 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.

3. 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).

4. Card's model deals with the relationship between schooling and wages rather than test scores and wages, but is otherwise identical. He assumes that b and r are symmetrically distributed. If they are not, then the formula for rho (below) contains a term in the third central moment of the non-symmetrically distributed variable.

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

6. For example, 82% of the original sample were contacted at age 16, and 72% were contacted at age 33.

7. 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.

8. In an earlier version of this paper, we also examined wages and employment at age 23. Interpretation of these results was complicated by a number of factors. First, this cohort turned 23 in 1981, in the midst of a severe recession which compressed the distribution of earnings among young workers (Meghir & Whitehouse, 1996). Second, individuals pursuing a college education may not be in the labor force at age 23.

9. Respondents were asked their usual weekly hours, their net pay, their gross pay, and their pay interval (e.g. weekly, biweekly, monthly, etc.). We first calculated the number of hours in the pay interval by examining the usual weekly hours, and then calculated 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. 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 5, this affected people with hourly net wages less than 1 and greater than 20. Those excluded accounted for less than 2% of the sample observations.

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

11. These means are computed over the non-missing observations for the variables in question. In order to preserve degrees of freedom in the regression models, we created flags for missing data. Thus, for example, a person with missing information about financial difficulties at age 16 would be assigned a value of zero for that variable, and a value of 1 for the flag for missing data on this variable.

12. Other measures which were included in the regression models but which are not shown here included whether the school was run by the local educational authority (at age 7, 11, and 16); the fraction of children who teachers discussed with parents at age 7; the number of teachers with less than 2 years of experience at age 11; and the school size at age 11 and age 16.

13. Traditionally, grammar schools have been academically oriented, while secondary modern schools were geared towards technical training. Comprehensive schools were

originally conceived of as schools that would replace the other two categories of schools, and which would combine both academic and technical training.

14. The measure for age 16 actually comes from not from the age 16 survey but from the collection of transcript information in 1978.

15. These estimates are reminiscent of Ashenfelter and Rouse (1997), who find using U.S. data that the returns to education in terms of wages are higher for low-SES individuals. Similarly, 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.

16. A possible explanation for the school size effect is that larger schools are more likely to be found in urban areas. However, we have also controlled for the local educational authority dummies in these regressions, and these should absorb much of the effect of location on outcomes.

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REFERENCES

Ashenfelter, O., & Rouse, C. (July 1996). Income, Schooling, and Ability: Evidence from a New Sample of Twins, Industrial Relations Section Working Paper No. 365, Princeton University.

Becker, G. (1967). *Human Capital and the Personal Distribution of Income*, Ann Arbor: University of Michigan Press.

Bishop, J. (March 1989). Is the Test Score Decline Responsible for the Productivity Growth Decline? *American Economic Review*, *79*(1), 178–197.

Blackburn, M., & Neumark, D. (July 1993). Omitted-Ability Bias and the Increase in Returns to Schooling. *Journal of Labor Economics*, *11*(3), 521–544.

Bound, J., Griliches, Z., & Hall, B. (February 1986). Wages, Schooling and IQ of Brothers and Sisters: Do the Family Factors Differ? *International Economic Review*, *27*(1), 77–105.

Cameron, S., & Heckman, J. (January 1993). The Nonequivalence of High School Equivalents. *Journal of Labor Economics*, *11*(1), Part 1, 1–47.

Card, D. (1995). Earnings, Schooling, and Ability Revisited. *Research in Labor Economics*.

Cawley, J., Heckman, J., & Vytlacil, E. (May 1997). *The Optimal Policy to Reward the Value Added by Educators*. University of Chicago Dept. of Economics, xerox.

Cohn, E., & Kiker, B. (November 1986). Socioeconomic Background, Schooling, Experience and Monetary Rewards in the United States. *Economica*, *53*(212), 497–503.
Connolly, S., Micklewright, J., & Nickell, S. (1992). The Occupational Success of Young Men who Left School at Sixteen. *Oxford Economic Papers*, *44*, 460–479.
Dearden, L., Ferri, J., & Meghir, C. (October 1997). The Effect of School Quality on Educational Attainment and Wages. London: Institute for Fiscal Studies, Working Paper No. W98/3.
Dolton, P., & Vignoles, A. (October 1996). *The Impact of School Quality on Labor Market Success in the United Kingdom*. Dept. of Economics, University of Newcastle upon Tyne.
Fogelman, K. (1983). *Growing Up in Great Britain: Papers from the National Child Development Study*. London: MacMillan.
Fogelman, K. (1976). *Britain's Sixteen-Year-Olds*. London: National Children's Bureau.
Fogelman, K., & Wedge, P. (1981). The National Child Development Study. In: S. A. Mednick & A. E. Baert (Eds), *Prospective Longitudinal Research*. Oxford: Oxford University Press.
Groves, M. (2000). Student Scores Stalled in '90s in 2 Key Areas. *Los Angeles Times*, (Friday August 25), A–1.
Harmon, C., & Walker, I. (February 1998). Selective Schooling and the Returns to the Quantity and Quality of Education, Dublin: Dept. of Economics University College Dublin.
Hutchison, D., Prosser, H., & Wedge, P. (1979). The Prediction of Educational Failure. *Educational Studies*, *5*(1).
Kiker, B., & Condon, C. (Winter 1981). The Influence of Socioeconomic Background on the Earnings of Young Men. *The Journal of Human Resources*, *16*(1), 99–104.
Lazear, E. (September 1999). Educational Production. NBER Working Paper No. 7349.
Meghir, C., & Whitehouse, E. (Jan. 1996). The Evolution of Wages in the United Kingdom: Evidence from Micro Data. *Journal of Labor Economics*, *14*(1).
Murnane, R., Willett, J. B., & Levy, F. (1995). The Growing Importance of Cognitive Skills in Wage Determination. *The Review of Economics and Statistics*, 251–266.
National Children's Bureau (1991). National Child Development Study Summary prepared: December, 1991, xerox, Essex Survey Research Center Data Archive.
Neal, D., & Johnson, W. (October 1996). The Role of Premarket Factors in Black/White Wage Differences. *Journal of Political Economy*, *104*(5), 869–895.
Pringle, M. K., Butler, N., & Davies, R. (1966). 11,000 Seven Year Olds, London: Longman.
Robertson, D., & Symons, J. (November 1996). Do Peer Groups Matter? Peer Group Versus Schooling Effects on Academic Attainment? London: Centre for Economic Performance London School of Economics. Working Paper No. 311.
Snow, C., Burns, S., & Griffin, P. (Eds) (1998). *Preventing Reading Difficulties in Young Children*. Washington, D.C.: National Academy Press.
Southgate, V. (1962). *Southgate Group Reading Tests: Manual of Instructions*. London: University of London Press.
Zax, J., & Rees, D. (March 1998). Environment, Ability, Effort and Earnings, Denver: Center for Research on Economic and Social Policy. Working Paper 9801.

APPENDIX

RESULTS FOR MALES AND FEMALES

Panel 1: Effects of Age 16 Mathematics on Wages and Employment at 33 – Compare to Table 2.

	Log Wages	Employment	Log Wages	Employment
Males				
Mathematics @ 16	0.141	0.038	–	–
	(0.011)	(0.007)		
Math * low SES	–0.017	0.036	–	–
	(0.018)	(0.012)		
Math * high SES	–0.049	–0.015	–	–
	(0.017)	(0.011)		
Reading @ 16	–	–	0.121	0.035
			(0.011)	(0.007)
Reading * low SES	–	–	–0.012	0.039
			(0.017)	(0.011)
Reading * high SES	–	–	0.036	–0.019
			(0.022)	(0.013)
R-squared	0.193	0.053	0.181	0.050
No. of Obs.	2767	3686	2767	3686
Females				
Mathematics @ 16	0.143	0.020	–	–
	(0.013)	(0.013)		
Math * low SES	0.008	0.049	–	–
	(0.021)	(0.021)		
Math * high SES	–0.027	0.016	–	–
	(0.019)	(0.019)		
Reading @ 16	–	–	0.147	0.025
			(0.014)	(0.014)
Reading * low SES	–	–	–0.011	0.051
			(0.021)	(0.020)
Reading * high SES	–	–	0.017	0.042
			(0.025)	(0.025)
R-squared	0.184	0.018	0.179	0.021
No. of Obs.	2769	3892	2769	3892

Panel 2: Effects of Mathematics and Reading Scores at Age 7 on Test Scores and O-levels at Age 16 – Compare to Table 4, Panel 1.

	Math @ 16	Reading @ 16	Math O-levels	English O-levels
Males				
Mathematics @ 7	0.349	0.351	0.087	0.091
	(0.016)	(0.015)	(0.006)	(0.007)
Math * low SES	0.022	0.064	–0.006	–0.010
	(0.025)	(0.024)	(0.010)	(0.010)
Math * high SES	0.044	–0.090	0.048	0.036
	(0.026)	(0.025)	(0.010)	(0.011)
R-squared	0.367	0.349	0.238	0.245
No. of Obs.	5266	5266	6235	6234
Females				
Mathematics @ 7	0.332	0.318	0.070	0.107
	(0.015)	(0.014)	(0.006)	(0.007)
Math * low SES	–0.033	0.066	–0.017	–0.008
	(0.024)	(0.023)	(0.009)	(0.011)
Math * high SES	0.037	–0.107	0.066	0.036
	(0.024)	(0.023)	(0.009)	(0.012)
R-squared	0.363	0.393	0.215	0.261
No. of Obs.	5084	5084	6041	6036

Panel 3: Effects of Mathematics @ 7 on Age 16 Outcomes Controlling for School Quality and Family Background up to Age 7 – Compare to Table 6.

	Math @ 16	Reading @ 16	Math O-levels	English O-levels
Males				
Mathematics @ 7	0.281	0.307	0.064	0.065
	(0.015)	(0.015)	(0.006)	(0.006)
Math * low SES	0.014	0.045	–0.007	–0.014
	(0.023)	(0.024)	(0.009)	(0.009)
Math * high SES	0.016	–0.102	0.031	0.018
	(0.024)	(0.025)	(0.010)	(0.010)
R-squared	0.483	0.423	0.364	0.383
No. of Obs.	5266	5266	6235	6234
Females				
Mathematics @ 7	0.268	0.268	0.053	0.078
	(0.014)	(0.014)	(0.006)	(0.007)
Math * low SES	–0.025	0.059	–0.016	–0.005
	(0.022)	(0.022)	(0.009)	(0.010)
Math * high SES	0.015	–0.124	0.052	0.019
	(0.023)	(0.022)	(0.009)	(0.011)
R-squared	0.484	0.470	0.322	0.415
No. of Obs.	5084	5084	6041	6036

Notes: See notes to comparison tables.