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Abstract

Some theories suggest that students who anticipate discrimination in the labour market may invest more in easily observable human capital like education, to signal their productivity to employers and reduce the scope for statistical discrimination. Empirical research on this issue has been hampered, however, by a lack of direct information on anticipated labour market treatment. We use data from a unique longitudinal survey of young people in England to link student expectations of facing discrimination in the labour market to subsequent performance in high-stakes exams. Our findings suggest that the anticipation of labour market discrimination is associated with better exam performance, consistent with the view that students are seeking to counteract potential future penalties.

JEL codes: I24, I26, J24, J71.

Keywords: Anticipated discrimination; human capital investment; ethnic minorities; high-stakes exams.

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1 Introduction

How does the anticipation of discrimination in the labour market influence human capital investment decisions of ethnic minorities? The answer to this question matters for the long-term economic and social outcomes of ethnic minorities, and is far from settled in the literature. Early theoretical models predict that ethnic minorities invest less in hard-to-observe human capital, such as developing good working habits, because they receive lower returns to unobserved investments in the labour market (Coate and Loury, 1993*b*; Lundberg and Startz, 1983). Later contributions predict that ethnic minorities invest more in easily-observed human capital, such as education, to signal or even fully reveal their ability to employers and counteract the potential for statistical discrimination (Arcidiacono, Bayer and Hizmo, 2010; Lang and Manove, 2011). These issues are also debated as part of the literature that tries to identify labour market discrimination from estimated wage gaps between ethnic groups: as Lang and Manove (2011) point out, if anticipated discrimination increases educational investments, a strong case can be made for including education in these regressions to avoid underestimating the extent of discrimination (counter to, for instance, Neal and Johnson, 1996, who argue in favour of dropping education).

This paper contributes to the literature by documenting the relationship between anticipated labour market discrimination and educational attainment in a sample of English students. As most surveys lack information on anticipated discrimination, much of the evidence of how anticipated labour market discrimination could influence investment in education is indirect (we discuss this evidence in section 2 below). We exploit a unique question in a large-scale survey of English adolescents that gauges expectations of facing discrimination in the labour market. Importantly, all students report these expectations at the same stage in their schooling career, and prior to completing compulsory education and then entering the labour market or continuing in post-compulsory education. We combine these expectations of facing discrimination with administrative data on academic performance in high-stakes certificated national exams (GCSEs) at the end of compulsory schooling (at age 15/16). Our main findings are that ethnic minority students who report anticipating labour market discrimination achieve grades in English, maths, and science that are approximately one quarter of a grade higher than other ethnic minority students who do not anticipate such discrimination. These students also have better overall performance. They are, for instance, around eight percentage points more likely to reach the much coveted 'gold standard' of at least five GCSEs with grades A*-C in subjects including English and maths.

These findings shed more light on the broader consequences of labour market discrimination, which have received less attention in the empirical literature than the direct labour market effects on, for instance, (un)employment or wages. In particular, with the caveat that our analysis is based on observational data, and that we do not have access to a natural experiment that provides exogenous manipulation of anticipated discrimination, our findings are consistent with anticipated labour market discrimination providing greater incentives to invest in education (Arcidiacono et al., 2010; Lang and Manove, 2011).[1] This suggests that ethnic minority students opt for strategies to counteract anticipated labour market discrimination, which also resonates with experimental evidence showing that ethnic minority students and adults engage in strategic behaviour to avoid discrimination (in these experiments, by concealing or misrepresenting their identity; see e.g. Kudashvili and Lergetporer, 2022; Zussman, 2013). This also matters for how we should interpret wage comparisons between ethnic groups. Specifically, our findings suggest that any wage comparisons that fail to take into account education may underestimate the degree of discrimination in the labour market (Lang and Manove, 2011). Finally, documenting the relationship between anticipated discrimination and educational attainment also contributes to a better understanding of the educational achievement of ethnic minority students.

We use a number of different strategies to attempt to rule out the possibility that our results are driven by unobservables. We are able to control for a rich set of variables in our analysis, including expectations, attitudes, and proxies for ability not routinely available in survey data. Compared to our baseline specification, the model with a full set of controls is able to explain substantially more of the variation in educational attainment, while the estimated coefficient on anticipated discrimination remains largely unchanged. We use the methods proposed in Oster (2019) to show that unobservables would have to be much more important than the variables we have controlled for to explain away the estimated positive effect of anticipated discrimination. As an alternative approach, we also estimate a value-added (VA) specification where a lagged test score serves as a proxy for unobserved ability and lagged inputs in the education production function (Todd and Wolpin, 2003). We discuss how to use these VA

[1] Since the anticipation of discrimination is measured at age 14/15 and students sit exams at age 15/16, it is not possible to use exposure to an exogenous event (e.g. a high profile instance of discrimination) that could induce variation in awareness of labour market discrimination depending on the timing of interviews at age 14/15 because all students would have been exposed to the event by the time they sit their exams.

results to establish bounds on the cumulative effect of anticipated discrimination on exam performance at age 15/16. The bounds we estimate typically suggest a positive (cumulative) effect for anticipated discrimination.

To deal with the concern that grades convey only ordinal information (see e.g. Bond and Lang, 2013), we use the method proposed in Kaiser and Vendrik (2022) to test if the sign of the estimated effect of anticipated discrimination on GCSE grades could be reversed by alternative order-preserving labelling schemes for GCSE grades. Results for this test reject this possibility. Carrying out this test also reveals that the effect of anticipating labour market discrimination appears to be largest around achieving at least a grade C in these high-stakes exams taken at age 15/16. Obtaining a C grade is a crucial threshold for accessing further education as well as employment opportunities (Jerrim, forthcoming; Machin, McNally and Ruiz-Valenzuela, 2020), and therefore likely to have a high signalling value at this stage in life.

To our knowledge, just one other paper attempts to link the anticipation of labour market discrimination to educational investments. Using the same data as ours, Fernández-Reino (2016) finds little evidence that anticipated labour market discrimination influences post-compulsory (i.e. post-16) choices, but this result is conditional on exam performance at age 15/16. However, as our findings suggest, students anticipating discrimination in the labour market have better exam performance at age 15/16, consistent with the notion that individuals seek to counteract labour market discrimination and that these strategic responses manifest early on. This is perhaps not surprising given the importance of these high-stakes exams for future educational and labour market prospects (Jerrim, forthcoming; Machin et al., 2020).

2 Related literature

Our paper relates to a theoretical literature on human capital investment in the presence of labour market discrimination, and an empirical literature stemming from these contributions. Early models of statistical discrimination, where employers infer individual worker productivity on the basis of a noisy signal (i.e. worker productivity plus a random error) as well as group membership, provide the foundations for this theoretical literature. In the class of models proposed by Phelps (1972) and Aigner and Cain (1977), the wage offered to a worker is a weighted average of their productivity signal and the average productivity of the group they belong to, with the weights reflecting the reliability of the productivity signal. The lower the information content of the productivity signal, the more employers disregard it in favour of group average productivity, so if productivity signals are noisier for ethnic minority workers, as is typically assumed, wages offered to these workers anchor more towards group average productivity. In the class of models proposed by Arrow (1973) and Coate and Loury (1993*b*) differential beliefs held by employers about the average productivity of different groups, as opposed to signal quality, lead to worse labour market outcomes for ethnic minorities.

To consider the implications of statistical discrimination in the labour market for the acquisition of human capital, productivity is modelled as a function of unobserved ability and a costly human capital investment. In Arrow (1973), Coate and Loury (1993*b*), and Lundberg and Startz (1983) this human capital investment is also unobserved and is variously described as "not the usual types of education or experience, which are observable, but more subtle types of personal deprivation and deferment to gratification which lead to the habits of action and thought that favor good performance" (Arrow, 1973, p. 27), or "as acquiring knowledge (working hard at high school) or as acquiring life skills (developing good manners and work habits)" (Coate and Loury, 1993*b*, p. 1224). Lundberg and Startz (1983) show that ethnic minority workers face weaker incentives to acquire human capital precisely because employers attach less importance to their less informative productivity signals, reducing the expected payoff to unobserved human capital investments. Even if productivity signals are equally informative for ethnic minority workers, if employers hold more negative beliefs regarding their group productivity and require a higher signal of individual productivity before assigning these workers to better jobs, a self-fulling prophecy can emerge: a lower expected payoff weakens incentives for ethnic minorities to invest in unobserved human capital, confirming employers' initial beliefs (e.g. Arrow, 1973; Coate and Loury, 1993*b*). Coate and Loury (1993*a*) reach a similar conclusion when there is perfect information about productivity but employers are prejudiced towards ethnic minority workers.

In Lang and Manove (2011), by contrast, human capital investments are observed, as they relate to investments in education, and are therefore useful to signal productivity. Since employers' direct observation of the productivity of ethnic minorities is less reliable, employers put more weight on education when assessing this group's productivity. As a result, while education signals productivity in the same way for both groups, this signal is more valuable for ethnic minorities, who therefore have a stronger incentive to invest in education for a given ability. In Arcidiacono et al. (2010), there is no difference in signal quality, but employers instead anticipate ethnic minorities to have lower ability on average. This again creates a greater incentive for ethnic minorities to invest in education in order to reduce the scope for statistical discrimination. Arcidiacono et al. (2010) argue that obtaining a college education in particular directly reveals an individual's ability to the labour market, thereby removing any weight employers attach to group average ability in their assessment of an individual's ability.

The indirect evidence consistent with these theories often relies on researchers having access to Armed Forces Qualification Test (AFQT) scores that provide a measure of cognitive ability typically unobserved by employers.[2] Arcidiacono et al. (2010), for instance, show that, for high-school graduates, the return to AFQT scores is initially negligible but increases with labour market experience while, for college graduates, the return is immediate, changing little thereafter. This is consistent with imperfect information in the labour market for high-school, but not college, graduates and raises the possibility of statistical discrimination in the former labour market. In line with this reasoning, an ethnic wage gap is observed upon labour market entry for high-school, but not college, graduates. Taken together, their findings suggest that ethnic minorities face stronger incentives to acquire a college education. Lang and Manove (2011) show that ethnic minority students of the same ability as White students (i.e. having the same AFQT score) acquire more years of schooling, while Nordin and Rooth (2009) present similar evidence for non-European ethnic minorities in Sweden. Our approach of directly relating expectations of labour market discrimination to educational performance provides complementary evidence to existing strategies based on AFQT scores while also side-stepping various concerns raised with respect to these scores. For example, as noted in Darity and Mason (1998) and Rodgers and Spriggs (1996), there is no consensus in the literature as to what AFQT scores represent, how to approach the fact that students take AFQT tests at different ages/years of schooling, and whether the AFQT test is racially biased.

The impact of anticipated discrimination on human capital investment is also relevant for a large empirical literature on ethnic wage gaps, with the extent to which discrimination explains these gaps labelled as "one of the most divisive issues in social sciences" (Fryer, Pager and Spenkuch, 2013, p. 633). This literature aims to control for various productivity-relevant characteristics in wage regressions, attributing remaining differences by ethnicity to labour market discrimination, with education (i.e. years of schooling – the most widely available measure of educational attainment) a standard regressor in early contributions (see,

[2]The AFQT is used to assess candidates for the US Armed Forces, comprising a battery of tests for language comprehension, arithmetic reasoning, and mathematical knowledge.

for example, Altonji and Blank, 1999; O'Neill, 1990). In highly influential research, however, Neal and Johnson (1996) champion using AFQT scores alone to measure cognitive skills, on the basis that years of schooling is a poor measure of skills – especially if ethnic minorities attend lower quality schools – and that post-compulsory schooling is endogenous to labour market discrimination. In contrast, Lang and Manove (2011) advocate including education alongside AFQT scores. They point out that, if ethnic minorities obtain *more* schooling in response to anticipated labour market discrimination, excluding years of schooling would understate discrimination (for a given AFQT score, ethnic minorities would obtain more education, which should be rewarded by higher wages).

Estimated ethnic wage gaps are small when controlling for AFQT scores alone but typically increase when years of schooling is included alongside AFQT scores (e.g. Carneiro, Heckman and Masterov, 2005; Lang and Manove, 2011; Nordin and Rooth, 2009). This result is another piece of indirect evidence that is consistent with ethnic minorities investing more in education to counteract statistical discrimination.[3] In our empirical analysis we directly link anticipated labour market discrimination to educational attainment, with our finding of a positive connection providing further evidence in support of the inclusion of educational attainment in wage regressions and of a greater role for labour market discrimination in generating wage gaps.

Finally, our research also contributes to an empirical literature on the drivers of educational outcomes of ethnic minorities. The UK has a large and diverse ethnic minority population, with the Asian and Black ethnic groups comprising the largest ethnic minority groups.[4] Points of focus in this literature include the initial gap in academic performance between ethnic minorities and their White peers and how this gap closes during secondary school (see e.g. Dustmann, Machin and Schönberg, 2010; Strand, 2014; Wilson, Burgess and Briggs, 2011), as well as the higher propensity of ethnic minority students to pursue post-compulsory education for a given exam performance at age 15/16 (see e.g. Fernández-Reino, 2016; Jackson, 2012; Leslie and Drinkwater, 1999). While we do not seek to explain these stylised facts, our paper adds to this literature by investigating the role of one particular aspect of the experience of ethnic minority students, namely their possible anticipation of labour market discrimination, in explaining their educational outcomes.

[3] An alternative explanation is measurement error in schooling, and particularly that schooling exaggerates the skills accumulated by ethnic minorities if they attend lower quality schools. Lang and Manove (2011) attempt to rule out this explanation by showing that ethnic wage gaps change very little when several measures of school quality (school inputs and measures of student composition and behavior) are controlled for.

[4] https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/national-and-regional-populations/population-of-england-and-wales/latest.

3 Background

Prior to the 2008 Education and Skills Act – the relevant time frame for our empirical analysis – schooling in England was compulsory between ages 5-16, with achievement targets set by the UK government. Students were tested in four Key Stages (KS), with KS1 and KS2 assessed in primary school at ages 6/7 (school year 2) and 10/11 (school year 6) respectively, and KS3 and KS4 in secondary school at ages 13/14 (school year 9) and 15/16 (school year 11) respectively. Assessments were, for the most part, anonymously graded by external examiners, reducing the scope for racial biases in marking when students are known to teachers (Burgess and Greaves, 2013). KS1-KS3 focused on English, maths, and science alone while KS4 examined a broad range of largely optional subjects, though English, maths, and science remained compulsory for all students. At KS4, the majority of students took a General Certificate in Secondary Education (GCSE) for each subject studied while a small minority of students took GCSE equivalents, such as the General National Vocational Qualification (GNVQ), designed to prepare students for employment. In 2006, the year students in our sample took their KS4 assessments, there were around 120,000 Intermediate GNVQ entries compared to 5.75 million GCSE entries in the UK (Joint Council for Qualifications, 2022). Since there is little or no grade repetition, pupils entering school in the same year took KS exams together.

Performance at KS4 is used by the Department for Education, policymakers, and academics to benchmark educational achievement and measure school quality. In 2006, GCSE grades ranged from A*-G, with grade A* being the highest grade awarded, grade C the lowest grade associated with a pass, and grade G the minimum standard (with grade U being unclassified, i.e. no certificate awarded). 62% of the 5.75 million GCSE entries were awarded grade C or higher, with 6% awarded grade A* and 25% awarded grade C. GNVQ grades are more limited; the four outcomes being Distinction, Merit, Pass, and Unclassified. Full Foundation GNVQs are deemed broadly equivalent to four GCSE subjects at grades D-G and Full Intermediate GNVQs broadly equivalent to four GCSE subjects at grades A*-C.

4 Data and empirical model

We use data from Next Steps (formerly known as the Longitudinal Study of Young People in England (LSYPE)), a large national survey of over 15,000 children born between 1st September 1989 and 31st August 1990. Adolescents were initially interviewed in 2004, aged 13/14 (school year 9), and then annually until 2010, with a final interview in 2015 at age 25. Next Steps follows a two-stage sampling design, sampling first at the school level and then sampling students within the selected schools. Schools in deprived areas or with ethnically diverse student bodies are over-sampled, thus allowing meaningful analysis of ethnic minority populations.[5] The survey collects detailed information on socioeconomic and family circumstances, attitudes, and beliefs, with parents also interviewed in the initial waves. A secure-access version of the dataset links to the National Pupil Database (NPD), a pupil-level census containing individual attainment data from KS2 onward.[6]

We examine the influence of anticipated discrimination on the educational performance of ethnic minorities using the following linear reduced-form education production function:

$$T_{ia} = \alpha + \beta AD_{i,a-1} + \gamma X_{i,a-2} + u_{ia} \tag{1}$$

where T_{ia} is one of five measures of GCSE (or equivalents) performance, $AD_{i,a-1}$ is a dummy for whether a student anticipates labour market discrimination, $X_{i,a-2}$ is a vector of control variables, and u_{ia} is an error term. i indexes students, and a denotes the student's age, to help clarify when different variables are measured: most control variables are measured in wave 1, anticipated discrimination is measured a year later in wave 2, and educational performance another year later when students sit their KS4 assessments. The explanatory variables are described briefly in the text below, and in more detail in Appendix A. All estimation is carried out on a cross-sectional sample of ethnic minority students, and uses OLS, with standard errors that are robust to heteroskedasticity and clustering by school.

Our measures of educational performance are KS4 assessments (GCSEs or GCSE equivalents), taken in secondary school in school year 11, when students are aged 15/16. We focus on performance in compulsory subjects: English, maths, and science. Since students can take between one and three GCSEs in science, performance in this subject is less comparable across students, but it remains of interest given the emphasis on STEM subjects in education and

[5]The school and pupil selection probabilities ensure that all pupils within an ethnic group and deprivation stratum had an equal probability of being selected (Department for Education, 2011, p. 7).

[6]Data obtained from University College London, UCL Institute of Education, Centre for Longitudinal Studies. (2020). Next Steps: Linked Education Administrative Datasets (National Pupil Database), England, 2005-2009: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 7104 http://doi.org/10.5255/UKDA-SN-7104-6. The use of these data does not imply the endorsement of the data owner or the UK Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

policy circles.[7] For each subject, GCSE grades are awarded point scores with grade A* awarded 58 points and each subsequent grade attracting 6 fewer points, dropping to 16 points for grade G, and U attracting 0 points. Instead of using the GCSE point scores to assign numeric values to grades, we assign the values 1-9 to grades U-A* (i.e. U=1, G=2, F=3,. . . , A=8, A*=9) so that estimates of β in equation (1) represent the average grade difference associated with anticipating labour market discrimination.[8] Our main analysis therefore treats the difference between achieving a grade F vs. G as representing the same increase in subject knowledge as achieving a grade A vs. B. A number of authors emphasise that test scores convey only ordinal information (see e.g. Bond and Lang, 2013; Jacob and Rothstein, 2016; Lang, 2010, for discussions), so we return to this assumption in our robustness analysis below.

We also consider average performance across the best 8 (also known as 'capped') GCSEs, and the 'gold standard' (i.e. the achievement of five or more GCSE grades A*-C in subjects including English and maths), with the latter formally introduced to benchmark school performance in league tables in 2006 (Strand, 2015).[9] This allows an assessment of whether KS4 performance differs across the board or if any differences in performance in core subjects are offset by differences in performance in optional subjects. To measure average performance, we take the total point score across the best 8 subjects, divide by 8 to obtain an average point score ranging between 0-58, and map these onto a 1-9 scale to be comparable to the grades we use for English, maths, and science.[10]

To measure anticipated discrimination in the labour market, we exploit a unique survey question asked of adolescents aged 14/15 in Next Steps wave 2: 'Do you think that your skin colour, ethnic origin or religion will make it more difficult for you to get a job after you leave education?', with answers 'yes', 'no', or 'don't know'. At this age, 16% of our estimation sample respond 'yes' while 22% respond 'don't know'. Reasons for 'don't know'

[7]Students can take single, dual, or separate sciences, which count for one, two, or three GCSEs respectively. Students are awarded one GCSE grade in science for the single award, a (symmetric) double grade (e.g. AA or BB) in science for the dual award, or separate GCSE grades for physics, chemistry, and biology taken as separate subjects. For students taking separate sciences, the science grade reported in our data is the best of the three separate grades.

[8]For a small number of observations (<1%), the science point score can take on 'in between' values of 49 and 55, corresponding to a Merit and Distinction grade respectively for a Full Intermediate GNVQ. These point scores are coded as 7.5 and 8.5 respectively for our empirical analysis, and, for ease of presentation, as 7 and 8 when producing the histograms in Figure 1 below.

[9]For some students these aggregate performance measures might again feature GCSE equivalents. Henceforth, we refer to GCSEs and GSCE equivalents collectively as GCSEs.

[10]Point scores in the [0,16] interval are projected onto the interval [1,2] (by dividing by 16 and adding 1). Point scores in (16,58] are projected onto (2,9] (by subtracting 4 and dividing by 6). Less than 0.5% of students have a capped point score exceeding $58 \times 8 = 464$. We set these to 464 at the start of the calculation.

responses are unknown; they may reflect a combination of uncertainty, discomfort of responding 'yes', or not understanding the question (Alwin and Krosnick, 1991; Piekut, 2021). In our main analysis, we combine 'yes' and 'don't know' responses to create a binary variable that distinguishes between students that have at least entertained the possibility of facing future labour market discrimination and students not expecting problems, though we consider alternative classifications in robustness analysis.

We would argue that responses to this question are informative about how students feel about the chances of encountering future discrimination in the labour market. For example, using the same question, Hole and Ratcliffe (2020) show that Muslim teenage girls are more likely to anticipate labour market discrimination relative to others after the July 2005 London bombings, mirroring qualitative interviews of British Muslims revealing the perception that extremist Islamic terrorist attacks increase the harassment and labour market discrimination of Muslim women in particular (Change Institute, 2009). Herda (2016) examines anticipated discrimination in various contexts (though not explicitly the labour market) and finds that individuals who have either experienced discrimination themselves, or whose parents have experienced discrimination, are more likely to anticipate discrimination in future. Thus whether a person anticipates discrimination likely reflects a combination of factors, including personal and vicarious (i.e. via family, friends, and the broader treatment of ethnic minorities in society) experiences of discrimination, as well as various idiosyncratic factors such as media consumed and personality traits. In the context of anticipating labour market discrimination, at age 14/15 most students do not have any personal experience of the labour market, and may draw on what they see and hear from others as well as personal experiences in other areas of life. These expectations may be formed independently as students weigh the evidence for themselves, or may be influenced by significant others (for example parents cultivating an awareness of labour market discrimination). In this paper, our interest lies in documenting differences in educational performance that emerge as a consequence of holding these expectations, rather than investigating who or what is responsible for generating and influencing these expectations.

Table 1 shows how our measure of anticipating labour market discrimination varies across ethnic groups. Approximately half of the Black ethnic group anticipates labour market discrimination, which falls to just under 40% among White and Black Caribbean students and White and Black African students. Approximately one third of the Asian ethnic group anticipates discrimination, with students of Indian ethnicity about eight percentage points

Table 1: Anticipated labour market discrimination by ethnicity

	%No	%Yes/don't know
Asian or Asian British		
Indian	70.4	29.6
Pakistani	62.7	37.3
Bangladeshi	61.9	38.1
Any other Asian background	64.2	35.8
Black or Black British		
Caribbean	46.6	53.4
African	51.2	48.8
Any other Black background	52.6	47.4
Mixed		
White and Black Caribbean	61.9	38.1
White and Black African	60.3	39.7
White and Asian	71.1	28.9
Any other Mixed background	78.8	21.2
Chinese or Other ethnic group		
Chinese and Any other	63.5	36.5
Total	61.7	38.3
N	2148	1335

less likely to anticipate discrimination than students of Pakistani or Bangladeshi ethnicity. Bespoke surveys aimed at better understanding the workplace environment suggest that racial harassment is pervasive (BITC, 2015) and discrimination provides one reason for why ethnic minorities are more likely to feel their career progression has failed to meet their expectations, with some indication these concerns are greater among the Black ethnic group (CIPD, 2017). Evidence from field experiments in hiring reveals similarly high levels of discrimination for the Black and Asian ethnic groups, declining only recently for the Indian ethnic group (Heath and Di Stasio, 2019).

Given differences by ethnicity in both educational performance and the propensity to anticipate discrimination, in our set of control variables $X_{i,a-2}$ in equation (1) we always include dummies for the main ethnic minority groups identified in the 2001 Census (as listed in Table 1 above). We also control for region dummies in all specifications so that the baseline effect is identified by comparing students of the same ethnic background living in the same region who do or do not anticipate labour market discrimination. We label the baseline specification with only these ethnicity and regional controls as model 0. In the remaining specifications, we gradually add more control variables (full details of these control variables are available in Appendix A). In model 1, we include a set of arguably predetermined socioeconomic and demographic characteristics, while in model 2 and model 3 we include several proxies of ability, as well as personal characteristics and beliefs whose exclusion may lead to omitted variable bias, albeit at greater risk of these control variables responding to anticipated discrimination. As we will show, despite adding a large number of control variables that collectively explain a good deal of the variation in educational outcomes, the coefficient on anticipated discrimination varies little between the different specifications.

Compared to our baseline model 0, model 1 adds a range demographic and socioeconomic characteristics that may be correlated with educational achievement as well as anticipated discrimination. Specifically, we control for student gender, season of birth, whether a student was born in the UK, and language spoken at home. We also control for the age of the mother at the time of the student's birth, family composition, as well as parental health, education, and their economic and financial circumstances. For the latter, we include variables for parental employment, (professional) occupation, household income of at least £20,800 (i.e. in the top third of the ethnic minority household income distribution in our sample), whether the household receives financial support through the welfare system, subjective financial circumstances, and living in social housing. In addition, we control for the 2004 value of the Index of Multiple Deprivation (IMD), which captures the local area level of deprivation.

Our final two specifications leverage rich data on ability proxies, personal attitudes and beliefs, expectations of both students and their parents, and adverse events potentially linked to experiences of discrimination to further mitigate the scope for omitted variable bias. A key concern in the education literature is bias associated with unobserved student ability. A priori, it is not clear how this bias might affect our results, as we do not know the sign of the correlation between ability and anticipated discrimination. Students might also possess other personality traits and beliefs that correlate with anticipating labour market discrimination and educational performance, such as being pessimistic, or being forward-thinking.

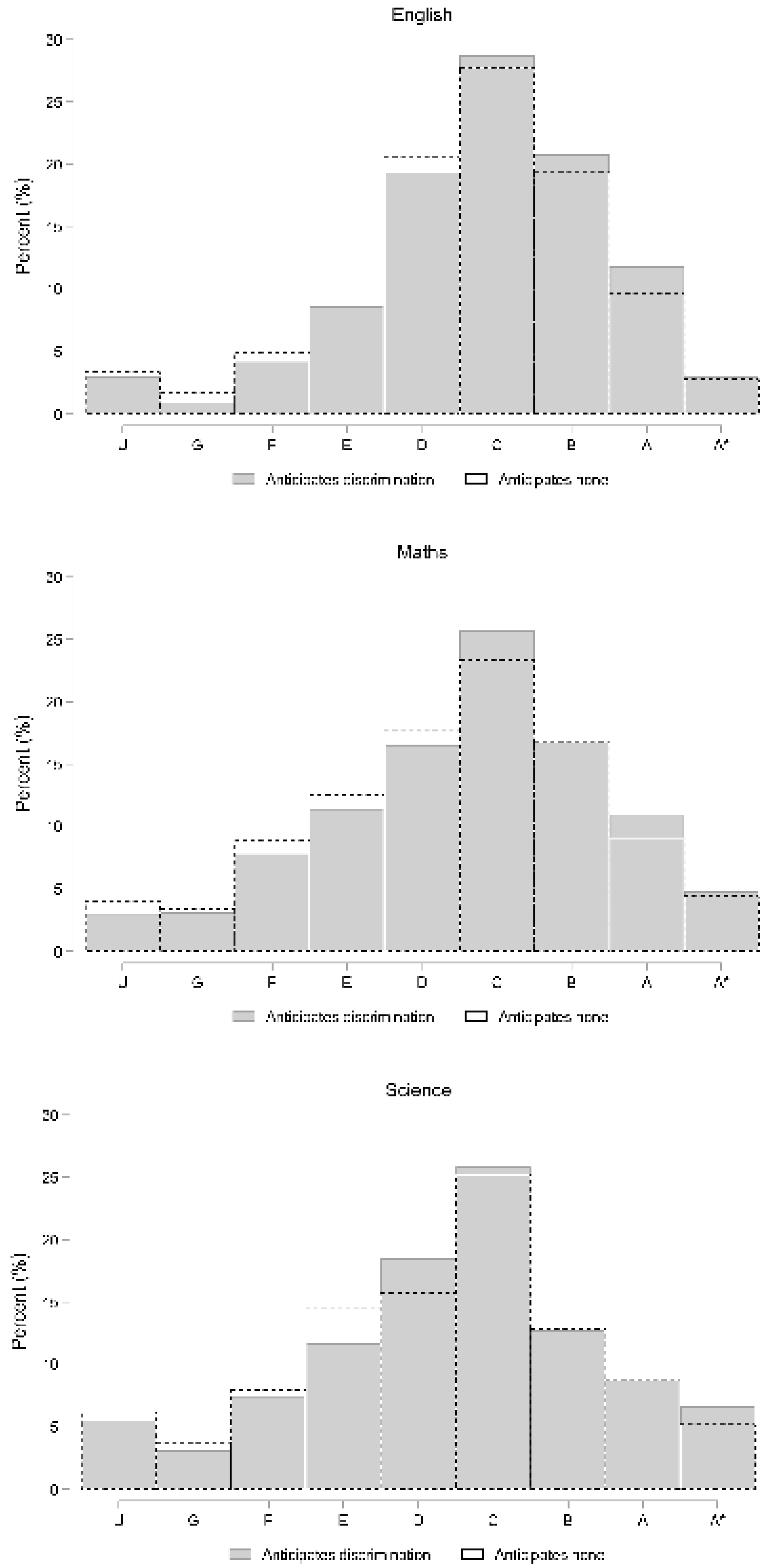
In model 2, we include self-reported ability in English, maths, and science, whether the student has special educational needs (SEN), student (and parental) hopes for continuing in post-compulsory education, and whether the student thinks about the future, all of which are associated with educational performance (Strand, 2011). We also control for circumstances associated with educational performance that may be directly or indirectly linked to the anticipation of discrimination. We control for any temporary or permanent school exclusion and for whether the student has been bullied in the past year, both of which are associated with weaker educational performance (Brown and Taylor, 2008; Gorman, Harmon, Mendolia, Staneva and Walker, 2021; Strand, 2011). If students believe their ethnicity plays a role in being excluded from school or in being bullied, this may increase the likelihood of anticipating labour market discrimination. In a similar vein, we control for whether the student thinks they have experienced discrimination by teachers at their school. These controls aim to disentangle the effect of contemporaneous experiences of discrimination from anticipated future experiences, as the former may influence both educational performance and beliefs about future discrimination in the labour market.

In our final specification, model 3, we further control for 'locus of control' – the extent to which individuals believe their actions influence life outcomes (Rotter, 1966). Locus of control may play a role in shaping human capital investment if it influences expected payoffs (see e.g. Caliendo, Cobb-Clark, Obst, Seitz and Uhlendorff, 2022; Coleman and DeLeire, 2003) or if it correlates with unobserved ability (Cebi, 2007). Using the Next Steps data, Mendolia and Walker (2014) show that locus of control is associated with educational attainment in the UK. We construct a measure of external locus of control (corresponding to the belief that personal efforts have little influence on life outcomes) to ensure that anticipated discrimination in our results does not simply proxy for a more general outlook in life. As with the control variables in model 2, there remains a concern that locus of control may be a function of anticipated labour market discrimination.

Most control variables are taken from wave 1 to limit how much they could be influenced by anticipated discrimination, measured in wave 2; though such influences are impossible to rule out completely, as expectations of facing discrimination likely form prior to wave 2. There are a few exceptions: self-reported ethnicity, region, discrimination by teachers, and locus of control are taken from wave 2, with the latter two variables only available in wave 2. There are some changes in self-reported ethnicity between wave 1 and wave 2, and we seek to use self-designated ethnicity and region at the time individuals answer the question on anticipated discrimination.[11] To avoid losing too many observations, for a number of dummy variables we turn missing values to zero, each time creating an extra dummy variable that identifies these observations. These indicators for missing values are always included as controls whenever the

[11] Approximately 18% of the students in our sample report a different ethnicity in wave 1 and wave 2. We show below that our results are robust to excluding these observations. A further small minority ($< 0.5\%$) do not report an ethnicity in wave 1. 40% of the changes in ethnicity are either within the Asian ethnic group as a whole or within the Black ethnic group as a whole. Another 22% are movements between Asian and Mixed Asian ethnicities or between Black and Mixed Black ethnicities. A further 7% of changes are students who identify as White in wave 1 while reporting having a Mixed ethnic background in wave 2. The three most common transitions, each accounting for about 5% of the total number of changes in ethnicity between wave 1 and wave 2, are: Indian to Pakistani; Caribbean to White and Black Caribbean; and Any other Black background to Caribbean.

Figure 1: Distribution of GCSE grades by anticipated discrimination



corresponding variable is included in the estimated model. The dummy variables for which we do this are: whether a student is born outside of the UK, mother's age at birth, household income, exclusion from school, whether the student reports discrimination by teachers, and external locus of control.

Table 2: Summary statistics

	Mean (1)	Std. dev. (2)	Yes/don't know (3)	No (4)	Diff. (5)	p-value (6)
English (U=1,. . . , A*=9)	5.75	1.68	5.86	5.68	0.18	0.003***
Maths (U=1,. . . , A*=9)	5.52	1.89	5.63	5.46	0.17	0.010***
Science (U=1,. . . , A*=9)	5.37	2.01	5.46	5.32	0.15	0.040**
Average (best 8)	5.82	1.81	5.89	5.78	0.11	0.106
Gold standard (5+ A*-C grades)	0.47	0.50	0.50	0.45	0.05	0.004***
Pakistani	0.20	0.40	0.19	0.20	−0.01	0.522
Bangladeshi	0.14	0.34	0.14	0.14	0.00	0.923
Any other Asian background	0.03	0.16	0.03	0.03	0.00	0.618
Caribbean	0.11	0.31	0.15	0.08	0.07	0.000***
African	0.11	0.31	0.14	0.09	0.05	0.000***
Any other Black background	0.02	0.13	0.02	0.01	0.01	0.178
White and Black Caribbean	0.09	0.28	0.09	0.09	0.00	0.928
White and Black African	0.02	0.14	0.02	0.02	0.00	0.805
White and Asian	0.04	0.19	0.03	0.04	−0.01	0.026**
Any other Mixed background	0.02	0.15	0.01	0.03	−0.02	0.000***
Chinese and Any other	0.03	0.17	0.03	0.03	0.00	0.718
North East	0.02	0.14	0.02	0.02	0.00	0.758
North West	0.11	0.31	0.10	0.11	−0.01	0.625
Yorkshire and the Humber	0.10	0.31	0.11	0.10	0.01	0.453
East Midlands	0.06	0.25	0.05	0.07	−0.02	0.061*
West Midlands	0.15	0.36	0.15	0.15	0.00	0.764
East of England	0.06	0.24	0.07	0.06	0.01	0.143
South East	0.07	0.25	0.06	0.07	−0.01	0.193
South West	0.02	0.14	0.02	0.02	0.00	0.587
Female	0.51	0.50	0.50	0.52	−0.02	0.173
Autumn born	0.24	0.43	0.23	0.25	−0.02	0.224
Winter born	0.26	0.44	0.26	0.25	0.01	0.412
Spring born	0.25	0.44	0.25	0.26	0.00	0.768
Born abroad	0.18	0.38	0.19	0.18	0.01	0.548
Born abroad missing	0.03	0.17	0.03	0.02	0.01	0.102
Speaks English only	0.40	0.49	0.43	0.38	0.05	0.003***
Main language not English	0.19	0.39	0.18	0.19	−0.01	0.413
Mum aged 25-29 at child's birth	0.31	0.46	0.32	0.31	0.01	0.695
Mum aged 30+ at child's birth	0.30	0.46	0.31	0.29	0.02	0.191
Mum age at child's birth missing	0.05	0.21	0.05	0.05	0.01	0.392
Two-parent family	0.72	0.45	0.71	0.74	−0.03	0.100*
Parent(s) not in good health	0.28	0.45	0.27	0.28	−0.01	0.451
One sibling	0.27	0.44	0.29	0.26	0.02	0.129
Two siblings	0.28	0.45	0.27	0.28	0.00	0.779
Three or more siblings	0.34	0.47	0.32	0.36	−0.03	0.044**
Parent(s) with degree	0.14	0.35	0.16	0.13	0.03	0.015**
Parent(s) with no qualifications	0.37	0.48	0.36	0.39	−0.03	0.118
Parent(s) employed	0.69	0.46	0.68	0.69	−0.01	0.611
Parent(s) professional occupation	0.24	0.43	0.24	0.25	−0.01	0.501
Household income at least £20,800	0.24	0.43	0.24	0.24	0.01	0.599
Household income missing	0.31	0.46	0.31	0.31	0.01	0.724
Income support received	0.30	0.46	0.31	0.29	0.01	0.362
Working Tax Credit received	0.51	0.50	0.51	0.51	0.00	0.825
Household managing well financially	0.34	0.47	0.31	0.36	−0.05	0.001***

Table 2 continued from previous page

	Mean (1)	Std. dev. (2)	Yes/don't know (3)	No (4)	Diff. (5)	p-value (6)
Household getting into financial difficulties	0.12	0.33	0.15	0.11	0.03	0.004***
Social housing	0.31	0.46	0.33	0.30	0.03	0.093*
Index of Multiple Deprivation (IMD)	33.77	17.60	34.38	33.40	0.98	0.127
Maths: self-assessed as good	0.89	0.32	0.89	0.88	0.01	0.415
English: self-assessed as good	0.88	0.32	0.88	0.88	0.00	0.981
Science: self-assessed as good	0.84	0.37	0.84	0.84	0.01	0.650
Special educational needs	0.10	0.30	0.10	0.10	0.00	0.932
High parental aspirations for university	0.84	0.36	0.85	0.84	0.01	0.252
Thinks about future	0.69	0.46	0.70	0.68	0.02	0.197
Plans for non-compulsory education	0.92	0.27	0.92	0.92	0.00	0.664
Likely to apply to university	0.84	0.36	0.86	0.84	0.02	0.112
School exclusion	0.08	0.27	0.10	0.07	0.03	0.001***
School exclusion missing	0.22	0.41	0.20	0.23	−0.03	0.060*
Bullied in past year	0.37	0.48	0.41	0.35	0.06	0.001***
Discrimination by teachers	0.36	0.48	0.54	0.25	0.28	0.000***
Discrimination by teachers missing	0.02	0.13	0.03	0.01	0.02	0.000***
External locus of control	0.28	0.45	0.32	0.25	0.07	0.000***
External locus of control missing	0.03	0.16	0.03	0.02	0.01	0.063*
N	3483		1335	2148		

Note: columns 1 and 2 show the mean and standard deviation for the full sample. Columns 3 and 4 show the means for those that do and do not anticipate discrimination, respectively, while column 5 reports the difference in means between these two groups (calculated before rounding the means to two decimal places, so the rounded difference in this column does not always match the difference between the rounded means reported in columns 3 and 4). Column 6 shows the p-value of a test of equality of means, with standard errors robust to heteroskedasticity and clustering by school. $***$, $**$, and $*$ denote significant differences at the 1%, 5%, and 10% significance level, respectively. See Appendix A for details on the control variables listed in this table.

Figure 1 shows the distribution of English, maths, and science GCSE grades by our measure of anticipated discrimination, with these distributions shifted to the right for those anticipating discrimination.[12] Summary statistics presented in Table 2 for the whole sample, and also separately by expectations of facing labour market discrimination, provide further evidence of better performance among those anticipating discrimination, with higher average grades across each of these subjects, as well as a higher probability of attaining the gold standard. Interestingly, there is balance across most of the controls. Exceptions are that those anticipating discrimination are less likely to live in the East Midlands, more likely to speak only English at home, less likely to live in a two-parent family, less likely to have three or more siblings, more likely to have parents with a degree, and more likely to live in social housing. They also are more likely to come from households that say they are getting into financial difficulties and less likely to come from households that are managing well financially. Other differences are that anticipating discrimination is associated with a higher likelihood of personal experiences or perceptions of adverse treatment by others – school exclusion, bullying, and discrimination by teachers – and with a higher chance of having an external locus of control.

[12]We use the Stata graphics scheme `plotplainblind` provided by Bischof (2017) for these graphs.

5 Results

5.1 Main results

Table 3 reports the estimated coefficients on anticipated discrimination in equation (1) for models 0 through to 3 for different KS4 outcomes (full results for all covariates are reported in Tables C.1-C.4 in Appendix C). Panel A presents results from our baseline specification, model 0, which includes ethnicity and region dummies only. Students who anticipate labour market discrimination score approximately one quarter to one third of a grade higher in each of the core GCSE subjects compared to students of the same ethnicity living in the same region who do not anticipate discrimination (columns 1-3). Their overall performance is also one fifth of a grade higher across the average of their best 8 GCSE subjects (column 4). Importantly, as far as prospects for further study and jobs are concerned, they are eight percentage points more likely to achieve the highly prized 'gold standard' (i.e. at least five A*-C grades in subjects including English and maths), representing a 17% increase from the sample average of 47% (column 5).

Panel B reports results for model 1, which adds control variables to take into account demographic and socioeconomic differences between students. The coefficients on these additional variables conform to expectations; for instance having older, better educated, and wealthier parents are associated with better exam performance (Table C.2). Adding these controls increases the R^2 substantially but has only a modest impact on the coefficients for anticipating labour market discrimination, which are attenuated by around 10 percent.

Model 2 in Panel C adds controls for student ability, beliefs, expectations, and personal experiences potentially linked to discrimination, with the results suggesting that having a future orientation, higher self-reported ability, and expectations of attending post-compulsory education are associated with better GCSE performance, while being excluded from school or bullied are associated with worse performance (Table C.3). Although personal experience of discrimination by teachers is strongly correlated with anticipating labour market discrimination in Table 2, it appears to have little association with subsequent educational attainment (the coefficient is always negative, but only once significant at a 10% significance level). Adding these variables again substantially increases the R^2 while leaving the estimated coefficients on anticipated discrimination almost unchanged.

Finally, Panel D presents results from model 3, which adds external locus of control (LOC) to isolate the effect of anticipating discrimination from that of a more general outlook

Table 3: Anticipated discrimination and KS4 results

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Panel A: model 0					
Anticipates discrimination	0.26***	0.31***	0.27***	0.20***	0.080***
	(0.059)	(0.063)	(0.069)	(0.064)	(0.017)
R^2	0.06	0.11	0.08	0.07	0.07
Panel B: model 1					
Anticipates discrimination	0.24***	0.27***	0.24***	0.18***	0.072***
	(0.054)	(0.059)	(0.065)	(0.059)	(0.016)
R^2	0.22	0.24	0.20	0.21	0.18
Panel C: model 2					
Anticipates discrimination	0.23***	0.26***	0.25***	0.17***	0.074***
	(0.049)	(0.057)	(0.062)	(0.053)	(0.016)
R^2	0.39	0.39	0.36	0.40	0.29
Panel D: model 3					
Anticipates discrimination	0.26***	0.29***	0.28***	0.21***	0.080***
	(0.048)	(0.057)	(0.061)	(0.053)	(0.016)
R^2	0.40	0.40	0.37	0.41	0.30
N	3483	3483	3483	3483	3483

Note: each coefficient comes from a separate regression of the KS4 outcome listed in the column heading on the anticipated discrimination dummy. Models 0 to 3 gradually include more control variables, as described in Section 4 and, in more detail, in Appendix A. Tables C.1-C.4 in Appendix C report the estimated coefficients for all covariates for models 0 through to 3. 'English', 'Maths', and 'Science' are the GCSE grade for each of these subjects, with U=1, G=2,. . . , A=8, and A*=9. 'Average' is an average score from the best 8 GCSE subjects, mapped unto the same 1-9 scale for comparability. 'Gold standard' is a binary indicator for achieving five or more GCSE grades A*-C including English and maths. See text for further details. Standard errors robust to heteroskedasticity and clustering by school. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% significance level, respectively.

in life. Consistent with prior research (e.g. Mendolia and Walker, 2014), students with an external LOC tend to have weaker GCSE performance (Table C.4). Notably, however, including LOC increases the coefficient on anticipating labour market discrimination for all five GCSE outcomes, bringing them back to the levels found in model 0 where we only control for ethnicity and region. Summary statistics in Table 2 indicate that students anticipating labour market discrimination have a more external LOC and, as discussed above, having an external LOC may matter for human capital by lowering expected investment returns or as a reflection of low student ability. Controlling for the negative effect of having an external LOC on GCSE exam performance therefore increases the coefficient on anticipated labour market discrimination.

In summary, students who anticipate labour market discrimination achieve a grade that is approximately an extra one quarter to one third higher in core GCSE subjects (English, maths, and science), and approximately one fifth of a grade higher across the average of their best 8

GCSE subjects, compared to students who do not anticipate discrimination but are otherwise similar across a wide range of observables. These coefficients are comparable in absolute magnitude to the coefficients for having an older (aged 25 and above) versus a younger (aged 24 and under) mother, being part of a two-parent family, or living in social housing, and slightly larger in absolute magnitude than the coefficient for being bullied (see Table C.4), indicating a non-trivial association between anticipated discrimination and educational performance. The stability of the coefficients on anticipated discrimination when we add a large number of control variables that substantially increase the R^2 suggests that we are not just picking up the effects of unobservables associated with anticipating discrimination, an issue we return to in more detail below. Interpreted in this way, our results are consistent with individuals who anticipate discrimination investing more heavily in human capital acquisition while in compulsory schooling, in line with the arguments in Arcidiacono et al. (2010) and Lang and Manove (2011) that they are doing so to counteract future labour market discrimination.[13]

5.2 Robustness: specification and measurement

We now examine the sensitivity of our main results to various changes in variable definitions and in the estimated specification. In all robustness checks that follow, we start from model 3 (i.e. the model that contains all control variables, including external locus of control). We first examine the implications of alternative ways to categorise responses to the anticipated discrimination question. In our main analysis, we group together 'yes' and 'don't know' responses, contrasting the GCSE performance of students entertaining the possibility of facing labour market discrimination with students clearly stating they do not anticipate discrimination. In Panel A of Table 4, we create separate dummy variables for 'yes' and 'don't know' responses. Coefficients for these dummy variables are always similar to each other (and also similar to results where these responses are combined in Panel D of Table 3), and the null hypothesis of equality of coefficients is never rejected. In Panel B, we drop 'don't know' responses altogether, simply contrasting the GCSE performance of students responding 'yes' and 'no'. Once again, estimated coefficients on 'yes' responses are similar in magnitude to our main results. Finally, in Panel C, we combine 'don't know' responses with 'no' responses to compare the GCSE

[13] Estimation of separate models in Table C.5 in Appendix C shows that the coefficients on anticipated discrimination are somewhat larger and estimated more precisely for students whose ethnic background is Asian compared to the smaller sample of students from a Black ethnic background, but we typically cannot reject equality of coefficients, except when the dependent variable is the 'gold standard' dummy.

Table 4: Different treatments of 'don't know' responses

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Panel A: separate 'yes' and 'don't know' indicators					
Anticipates discr. – yes	0.29***	0.28***	0.28***	0.25***	0.095***
	(0.064)	(0.077)	(0.085)	(0.069)	(0.021)
Anticipates discr. – don't know	0.24***	0.30***	0.28***	0.18***	0.070***
	(0.057)	(0.064)	(0.070)	(0.061)	(0.019)
R^2	0.41	0.40	0.37	0.41	0.30
p-value for 'yes' = 'don't know'	0.45	0.77	0.95	0.32	0.29
N	3483	3483	3483	3483	3483
Panel B: 'yes' vs. 'no' (i.e. dropping 'don't know' responses)					
Anticipates discr. – yes	0.27***	0.27***	0.26***	0.23***	0.089***
	(0.066)	(0.080)	(0.088)	(0.073)	(0.022)
R^2	0.42	0.41	0.37	0.42	0.31
N	2716	2716	2716	2716	2716
Panel C: 'yes' vs. 'no/don't know' (i.e. grouping 'don't know' with 'no' responses)					
Anticipates discr. – yes	0.21***	0.18**	0.18**	0.19***	0.072***
	(0.061)	(0.072)	(0.081)	(0.065)	(0.020)
R^2	0.40	0.39	0.37	0.41	0.30
N	3483	3483	3483	3483	3483

Note: see note to Table 3. Each coefficient comes from a separate regression of the KS4 outcome listed in the column heading on anticipated discrimination with a full set of controls (model 3; see Section 4 and Appendix A for details). Panel A includes separate dummies for 'yes' and 'don't know' responses, and also reports a p-value for the null hypothesis that the coefficients on both dummies are equal. Panel B drops 'don't know' responses, comparing only 'yes' to 'no' responses. Panel C groups 'don't know' with 'no' responses.

performance of students clearly stating that they expect to face labour market discrimination against the performance of those unsure in this regard as well as students not anticipating labour market discrimination. While coefficients on anticipated discrimination are now smaller in magnitude, they remain positive and significantly different from zero. Thus our central conclusion, that students anticipating labour market discrimination tend to out-perform their peers who do not, is not sensitive to our treatment of 'don't know' responses.

We next examine the sensitivity of our findings to alternative specifications and data choices. Panel A of Table 5 presents results using survey weights to take into account the Next Steps sampling design (first sampling schools and then pupils within schools), non-response, and population weights.[14] Estimated coefficients in these weighted regressions are comparable to their unweighted counterparts. In Panel B, we report results replacing region fixed effects by school fixed effects, so that the coefficient on anticipated discrimination is now identified from

[14]Solon, Haider and Wooldridge (2015) discuss the circumstances under which using weights in regression analysis could be both appropriate and preferred.

Table 5: Alternative specifications and data choices

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Panel A: using survey weights					
Anticipates discrimination	0.29***	0.27***	0.30***	0.22***	0.067***
	(0.066)	(0.072)	(0.078)	(0.069)	(0.019)
R^2	0.45	0.45	0.42	0.47	0.35
N	3483	3483	3483	3483	3483
Panel B: using school rather than region fixed effects					
Anticipates discrimination	0.25***	0.33***	0.33***	0.24***	0.077***
	(0.056)	(0.065)	(0.069)	(0.059)	(0.018)
R^2	0.53	0.53	0.51	0.54	0.43
N	3483	3483	3483	3483	3483
Panel C: external locus of control constructed using factor analysis					
Anticipates discrimination	0.26***	0.29***	0.28***	0.21***	0.080***
	(0.048)	(0.057)	(0.061)	(0.053)	(0.016)
R^2	0.41	0.40	0.37	0.42	0.30
N	3483	3483	3483	3483	3483
Panel D: dropping 'don't know' responses to any locus of control question					
Anticipates discrimination	0.29***	0.32***	0.30***	0.26***	0.087***
	(0.058)	(0.070)	(0.078)	(0.064)	(0.020)
R^2	0.40	0.39	0.37	0.41	0.30
N	2358	2358	2358	2358	2358
Panel E: dropping students who report a different ethnicity in wave 1					
Anticipates discrimination	0.25***	0.32***	0.29***	0.22***	0.083***
	(0.053)	(0.062)	(0.070)	(0.059)	(0.017)
R^2	0.41	0.41	0.37	0.41	0.30
N	2856	2856	2856	2856	2856
Panel F: dropping observations with missing values					
Anticipates discrimination	0.27***	0.27***	0.33***	0.21***	0.068***
	(0.067)	(0.078)	(0.086)	(0.070)	(0.022)
R^2	0.41	0.41	0.39	0.44	0.32
N	1780	1780	1780	1780	1780

Note: see note to Table 3. Each coefficient comes from a separate regression of the KS4 outcome listed in the column heading on the anticipated discrimination dummy with a full set of controls (model 3; see Section 4 and Appendix A for details). Panel A uses survey weights in estimation. Panel B includes school instead of region fixed effects. Panel C uses factor analysis to construct the locus of control variable from which our external locus of control dummy is derived. Panel D drops any individual responding 'don't know' to any question used in the construction of the locus of control variable. Panel E drops individuals who report a different ethnicity in wave 1 and wave 2. Panel F drops observations with missing values for: whether a student is born outside of the UK; mother's age at birth; household income; exclusion from school; whether the student reports discrimination by teachers; and external locus of control (and thus also excludes the corresponding dummies that indicate these missing values).

comparisons of students within the same school rather than just the same broad region (as well as having the same ethnicity and being comparable across a wide range of controls). A disadvantage of this approach is that in some schools there are few pupils of some ethnicities.

Nevertheless, results are similar to the within-region effects reported previously. In Panels C and D, we consider alternative approaches to constructing the LOC index that underlies our binary indicator for an external LOC. In our main analysis, we construct this index by summing responses to various LOC questions with 'don't know' responses coded as the middle response category (see Appendix A for details). In Panel C, we present results using factor analysis to construct this underlying index, with our results invariant to this modification. In Panel D, we drop students responding 'don't know' to any of the LOC questions, using our preferred summation method to create the LOC index. Despite reducing the sample by approximately one third, coefficients remain remarkably stable. In Panel E, we drop students who report a different ethnicity in wave 1 and wave 2. The coefficients of interest are again similar despite the loss of 18% of our sample. Finally, in our main analysis for several variables we recode missing values to zero and include dummy variables identifying these observations.[15] In Panel F, we instead drop all missing observations for these variables (and exclude the corresponding missing value dummies), which almost halves the sample. While this leads to a small increase in standard errors, both the magnitude and statistical significance of the coefficients on anticipated discrimination are unaffected.

We now turn our attention to assumptions made regarding the dependent variables. GCSE grades convey only ordinal information, and alternative grade-order-preserving labelling schemes to the one we have used (i.e. U=1, G=2, F=3,. . . , A=8, A*=9) may lead to different estimates of β in equation (1), and may even reverse its sign (see e.g. Bond and Lang, 2013; Jacob and Rothstein, 2016; Schröder and Yitzhaki, 2017, for discussions).[16] Kaiser and Vendrik (2022) explain how sign reversals are due to heterogeneity in the effect of group membership across the outcome distribution, which they recommend testing for directly. In our context, this test boils down to running separate regressions of dummies that indicate achieving grade U, grade G or less,. . . , up to grade A or less, and verifying that the coefficients on anticipated discrimination in these regressions always have the same sign. We implement this suggestion in Table 6, where, for presentation purposes, we estimate the effect of anticipating discrimination

[15] These variables are: whether a student is born outside of the UK, mother's age at birth, household income, exclusion from school, whether the student reports discrimination by teachers, and external locus of control. These variables exhibit varying degrees of missingness as shown in Table 2, with household income having by far the greatest proportion of missing values (31%).

[16] The pitfalls of treating ordinal data as interval data are not easily resolved by estimating ordered response models. While the coefficients from these models are invariant to different labelling schemes, they cannot be used to rank the underlying learning of groups without also assuming equal variance in learning across groups. As emphasised in Bond and Lang (2019), once this assumption is relaxed, it is possible for alternative transformations to the scale of the latent variable to reverse group rankings.

Table 6: Probability of achieving at least the specified GCSE grade threshold across subjects

	⩾G (1)	⩾F (2)	⩾E (3)	⩾D (4)	⩾C (5)	⩾B (6)	⩾A (7)	A* (8)
Panel A: English								
Anticipates discrimination	0.0052	0.015**	0.025**	0.043***	0.061***	0.061***	0.041***	0.0079
	(0.0060)	(0.0075)	(0.0099)	(0.012)	(0.015)	(0.015)	(0.011)	(0.0059)
R^2	0.10	0.13	0.20	0.26	0.31	0.24	0.16	0.07
Panel B: maths								
Anticipates discrimination	0.012**	0.014*	0.033***	0.051***	0.077***	0.051***	0.040***	0.015**
	(0.0059)	(0.0085)	(0.012)	(0.014)	(0.016)	(0.016)	(0.013)	(0.0074)
R^2	0.08	0.14	0.21	0.28	0.30	0.24	0.19	0.09
Panel C: science								
Anticipates discrimination	0.015*	0.017*	0.024**	0.068***	0.052***	0.044***	0.036***	0.024***
	(0.0078)	(0.0093)	(0.012)	(0.013)	(0.016)	(0.016)	(0.012)	(0.0087)
R^2	0.12	0.17	0.25	0.28	0.25	0.21	0.16	0.09
N	3483	3483	3483	3483	3483	3483	3483	3483

Note: see note to Table 3. Each coefficient comes from a separate regression of a dummy for achieving at least the grade indicated in the column heading on the anticipated discrimination dummy with a full set of controls (model 3; see Section 4 and Appendix A for details). The different panels focus on grades for different subjects.

on the probability of obtaining at least (rather than less than or equal to) each specified grade (except for U). The results in Table 6 rely only on the ordinal information in the test scores while still producing coefficients whose magnitudes are easy to interpret and directly relevant (for example, a GCSE C grade is the lowest grade associated with a pass and is often required to access jobs and further education), and flexibly allow the effect of anticipating discrimination (and the control variables) to differ across the grade distribution.

The largest coefficients for anticipated discrimination are found at or just around the grade C threshold (grades D through to B).[17] These results are consistent with incentives to invest in human capital to offset possible future labour market discrimination being particularly pronounced for students who expect their results to be close to the all-important grade C threshold. The coefficients on anticipated discrimination all have the same sign in these regressions, establishing that any monotonically increasing transformation of the values assigned to grades would not change the sign of $\widehat{\beta}$ in our earlier results (see Kaiser and Vendrik, 2022, for further details). In other words, the positive association we found earlier between anticipated discrimination and GCSE grades is robust to any alternative order-preserving labelling scheme for GCSE grades. However, this does not necessarily mean that the association between anticipated discrimination and true underlying learning is also positive. For this to be the case, Kaiser and Vendrik (2022) argue that a sufficient assumption is that anticipated discrimination does not lower average learning within each grade category. This assumption seems likely to hold – it would be unusual for anticipated discrimination to be associated with better GCSE grades while at the same time lowering learning within each grade – but it is not something we can test.

5.3 Robustness: selection on unobservables

Lastly, we investigate in more detail the possibility that our results are driven by unobservables. While we do not have a clear source of exogenous variation in anticipated discrimination, we are able to control for an unusually rich set of control variables, and the stability of estimated coefficients alongside substantial increases in explanatory power when adding these control variables reduces concerns that our results are mostly driven by omitted variable bias. In Table 7 we use the methods proposed in Oster (2019) to examine this more formally. Oster shows

[17] For English and maths the largest coefficient is for the C grade (for English this is joint with the B grade). For science the largest coefficient is for achieving at least a D grade, followed by the coefficient for achieving at least a C.

Table 7: Oster (2019) analysis

	Implied δ for $\beta = 0$		Bounds for β when $\delta = 1$	
	$R_{max} = 1$	$R_{max} = 1.3\widetilde{R}$	$R_{max} = 1$	$R_{max} = 1.3\widetilde{R}$
	(1)	(2)	(3)	(4)
English	5.4	25.8	[0.26,0.27]	[0.26,0.26]
Maths	2.8	13.7	[0.29,0.25]	[0.29,0.29]
Science	5.9	32.3	[0.28,0.31]	[0.28,0.29]
Average (best 8)	5.8	27.1	[0.21,0.21]	[0.21,0.21]
Gold standard	2.7	20.1	[0.08,0.08]	[0.08,0.08]

Note: Oster (2019) analysis based on a comparison of model 3 with model 0 for each KS4 outcome (see Section 4 and Appendix A for descriptions and Table 3 for the results of these models). Columns 1 and 2 report the values of δ, the degree of selection on unobservables relative to observables, needed to produce a zero effect of anticipated discrimination ($\beta = 0$). Columns 3 and 4 show the bounds for β under the assumption that $\delta = 1$. R_{max} is the hypothetical maximum R^2 if all relevant (observed and unobserved) explanatory variables were included in the model. It is either assumed to be 1 or $1.3\widetilde{R}$, where $\widetilde{R}$ is the R^2 from a regression including all observable controls (in our case, model 3).

how changes in the estimated coefficient and in the R^2 when control variables are added, in combination with an assumption about R_{max} – the hypothetical maximum R^2 if all relevant (observed and unobserved) explanatory variables were included in the model – can be used to examine to what extent results are driven by selection on unobservables. The first two columns in Table 7 show the values of δ, the degree of selection on unobservables relative to observables, needed to produce a zero effect of anticipated discrimination (i.e. $\beta = 0$ in equation (1)) for each of the five GCSE outcomes, based on a comparison of model 3 to model 0, and for two different choices of R_{max}.[18] For $R_{max} = 1$ (column 1) selection on unobservables would need to be around three to six times more important than selection on the extensive set of observables we have controlled for to produce zero effects of anticipated discrimination. $R_{max} = 1$ is a conservative choice, as for instance measurement error would push R_{max} below one, limiting the degree of remaining variation in the dependent variable left to be explained by relevant unobservables. Oster recommends setting $R_{max} = \min\left(1.3\widetilde{R}, 1\right)$ where $\widetilde{R}$ is the R^2 from the regression including all observable controls (in our case, model 3). Using this alternative value for R_{max}, column 2 shows that selection on unobservables would now have to be about 14 to over 30 times more important than selection on observables to produce zero effects of anticipated discrimination. The δs in Table 7 all clearly exceed one, which Oster argues is a reasonable upper bound on the importance of unobservables relative to observables.[19]

[18] δ is a measure of the strength of the relationship between the 'treatment' (anticipated discrimination) and unobservables relative to the strength of the relationship between the treatment and the included controls.

[19] One reason for this is that researchers would always try to include the most important controls. A second reason is that we should think of the unobservables as being residualised with respect to the observables, so we should think of the remaining unobservables as what remains after the variation related to the observables has been

The final two columns in Table 7 show estimated bounds for β for two different values of R_{max}. One side of the bound is the estimated β from model 3 as presented in panel D of Table 3. This part of the bound corresponds to assuming no omitted variable bias ($\delta = 0$). The other side of the bound is the bias-adjusted effect assuming a value of $\delta = 1$, such that unobservables are as important as our controls. For both $R_{max} = 1$ and $R_{max} = 1.3\widetilde{R}$, these bounds are tight and never stray too far from the OLS estimates of model 3.[20] Taken together, the results of the Oster (2019) analysis suggest that the estimates in Table 3 are not very sensitive to potential omitted variable bias.

As an alternative approach to addressing potential endogeneity concerns, especially those raised by unobserved ability and the unobserved history of inputs to human capital formation, we now also follow a well-established practice in the literature on educational achievement by estimating a value-added (VA) model. The assumptions needed for a lagged test score to serve as a sufficient statistic for unobserved ability and the unobserved history of inputs are very stringent (Todd and Wolpin, 2003). Nonetheless, Koedel, Mihaly and Rockoff (2015) and Singh (2015, 2020) argue that these models perform well in practice, citing various research that finds VA estimates similar to those based on (quasi-)experimental research designs. Similarly, Guarino, Reckase and Wooldridge (2015) show that, in simulations, the VA specification estimated by OLS performs well at recovering true (teachers') effects, relative to other estimation methods, across a range of data-generating processes. We estimate a VA model for English, maths, and science grades as follows:

$$T_{ia} = \tau + \rho T_{i,a-l} + \delta AD_{i,a-1} + \theta X_{i,a-2} + \varepsilon_{ia} \tag{2}$$

where $T_{i,a-l}$ is the KS2 test result taken in the same subject at age 10/11 (school year 6, $l = 5$), or the KS3 result taken in the same subject at age 13/14 (school year 9, $l = 2$), and where we standardise KS2/KS3 test scores and GCSE grades to have a zero mean and a standard deviation of one to aid comparability.

In our context, the VA model comes with a number of further caveats. We observe students'

removed. In a simulation exercise where the true effect is known and different combinations of control variables are randomly excluded, Oster (2019) finds implied values of δ that are in the $[0, 1]$ range in 86% of cases. In examples where we have some idea of the true treatment effects, Oster finds that the average value of δ required for the bias-adjusted treatment effects to match these true effects is 0.47.

[20] This exercise is quite demanding: Oster (2019) analyses a sample of 27 papers from top economic journals and finds that, for choices of $\delta = 1$ and $R_{max} = 1$, very few of her bias-adjusted estimates have the same sign as the simple estimate with controls, or lie within 2.8 standard errors either side of this estimate.

anticipated discrimination only when they are 14/15 years old, but expectations of facing discrimination in the labour market may form earlier and may already affect KS2/KS3 scores. As a result, the coefficient on anticipated discrimination, δ, does not capture the total cumulative effect of anticipated discrimination as in our previous estimates. In Appendix B we show how the true cumulative effect of anticipating discrimination can reasonably be bounded by δ and $\frac{\delta}{1-\rho}$, being close (or even identical) to $\frac{\delta}{1-\rho}$ in arguably the most plausible specifications – especially so for the VA model with the KS3 score. Since various sources of bias may hinder our ability to estimate δ and $\frac{\delta}{1-\rho}$ (see Appendix B for details), we view this exercise as approximate at best, and primarily as a check to see whether the introduction of lagged test scores makes the positive cumulative effect of anticipated discrimination disappear, which, as we now show, is mostly not the case.[21]

Table 8: Value added specification with KS2 scores

Dependent variable:	English		Maths		Science	
	(1)	(2)	(3)	(4)	(5)	(6)
Anticipates discr.	0.15***	0.075***	0.15***	0.071***	0.14***	0.068**
	(0.031)	(0.025)	(0.032)	(0.024)	(0.033)	(0.027)
KS2 English		0.56***				
		(0.015)				
KS2 maths				0.61***		
				(0.015)		
KS2 science						0.47***
						(0.018)
R^2	0.40	0.59	0.39	0.64	0.36	0.52
$\widehat{\delta}/\left(1-\widehat{\rho}\right)$		0.17		0.18		0.13
$\widehat{\delta}/\left(1-\widehat{\rho}\right)$ SE		0.056		0.061		0.050
$\delta/\left(1-\rho\right)=0$ p-value		0.00		0.00		0.01
N	3195	3195	3198	3198	3192	3192

Note: see note to Table 3. KS4 grades and KS2 scores are standardised to have mean zero and a standard deviation of one. Columns 1, 3, and 5 show results without controlling for the KS2 score, but restricting the sample to those observations for which the KS2 score is available. The bottom of the table shows estimates of $\delta/\left(1-\rho\right)$ (see main text for details) and its standard error, and a p-value for the null hypothesis that $\delta/\left(1-\rho\right)=0$.

Tables 8 and 9 present the VA specification using KS2 and KS3 results for the lagged test score, respectively. For each subject, we first report the estimated coefficient on anticipated discrimination from a model without the KS2/KS3 variable but restricted to the sample for

[21] In our derivations in Appendix B, we treat $AD_{i,a-1}$ as a (possibly imperfect) proxy for anticipated discrimination felt by students at earlier ages, and the resulting measurement errors can introduce biases. In the non-VA model of equation (1) these biases should attenuate the true effect, but in the VA model these biases in the estimation of δ and hence also $\frac{\delta}{1-\rho}$ are harder to sign. $\frac{\widehat{\delta}}{1-\widehat{\rho}}$ might further be affected by biases in estimating ρ: persistent unobservables would tend to lead to an upward bias in $\widehat{\rho}$, while iid measurement error in test scores would push towards a downward bias.

which we have students' KS2/KS3 results, while the second column presents the model including the KS2 or KS3 score. At the bottom of the tables, we also report $\frac{\widehat{\delta}}{1-\widehat{\rho}}$ together with its standard error, as well as a p-value for H_0: $\frac{\delta}{1-\rho} = 0$. In both tables, results from the non-VA models reported in columns 1, 3 and 5, suggest that, for each of the three subjects, the performance of students anticipating labour market discrimination is approximately 0.15 standard deviations higher than it is for students not anticipating discrimination. In the VA model with KS2 scores (Table 8), $\widehat{\delta}$ is approximately half the magnitude of the coefficient in the non-VA model, and is statistically significant throughout, while $\frac{\widehat{\delta}}{1-\widehat{\rho}}$, which should be close to the true cumulative effect under a wider range of scenarios, is similar in magnitude to the coefficient in the non-VA model (and again statistically significant throughout). In Appendix B we discuss how $\widehat{\delta}$ is particularly likely to underestimate the true cumulative effect in the VA model with the KS3 scores (Table 9). This is primarily because anticipations of discrimination almost certainly already matter before KS3 assessments take place at ages 13/14, only two years before KS4 assessments and only one year before we measure anticipated discrimination in our data. Hence, it is no surprise that $\widehat{\delta}$ is smaller in this model, and only significant for English. In contrast, estimates of $\delta/(1-\rho)$, which in this model is even more likely to be close to the true cumulative effect, are similar to the coefficient in the corresponding non-VA model in two out of three subjects (though, in the case of maths, just insignificant at conventional levels, with a p-value of 0.11). Overall, then, the positive association between anticipating discrimination and KS4 performance remains largely intact when controlling for lagged KS2 and KS3 performance.

Table 9: Value added specification with KS3 scores

Dependent variable:	English		Maths		Science	
	(1)	(2)	(3)	(4)	(5)	(6)
Anticipates discr.	0.16***	0.062***	0.16***	0.029	0.14***	0.012
	(0.029)	(0.022)	(0.030)	(0.018)	(0.031)	(0.021)
KS3 English		0.66***				
		(0.015)				
KS3 maths				0.80***		
				(0.013)		
KS3 science						0.73***
						(0.017)
R^2	0.39	0.64	0.39	0.77	0.36	0.67
$\widehat{\delta}/\left(1-\widehat{\rho}\right)$		0.18		0.14		0.044
$\widehat{\delta}/\left(1-\widehat{\rho}\right)$ SE		0.065		0.091		0.078
$\delta/\left(1-\rho\right)=0$ p-value		0.01		0.11		0.57
N	3360	3360	3414	3414	3394	3394

Note: see note to Table 3. KS4 grades and KS3 scores are standardised to have mean zero and a standard deviation of one. Columns 1, 3, and 5 show results without controlling for the KS3 score, but restricting the sample to those observations for which the KS3 score is available. The bottom of the table shows estimates of $\delta/\left(1-\rho\right)$ (see main text for details) and its standard error, and a p-value for the null hypothesis that $\delta/\left(1-\rho\right)=0$.

6 Conclusion

Discrimination may directly affect the employment and wages of ethnic minorities, but it may also already affect their lives even before they enter the labour market. In particular, several papers raise the possibility that ethnic minorities' investment in human capital is influenced by the anticipation of discrimination in the labour market. Most relevant for our work, Arcidiacono et al. (2010) and Lang and Manove (2011) describe how, when faced with the prospect of statistical discrimination, ethnic minorities have stronger incentives to invest in observed education in order to reveal or signal their productivity to employers. While several papers have produced indirect evidence consistent with these theories, a lack of information on whether adolescents expect to face labour market discrimination has made direct tests almost non-existent.

Our main contribution in this paper is that we link data on expectations of facing labour market discrimination to subsequent performance in high-stakes national exams taken at ages 15/16 (i.e. GCSEs) for a sample of ethnic minority students in England. We find that ethnic minority students anticipating discrimination obtain GCSE grades that are approximately one quarter of a grade higher in English, maths, and science, and have better overall performance. This positive association is robust to an unusually rich set of control variables including various beliefs and expectations, personal experiences potentially linked to discrimination, and proxies for ability. Using the methods proposed in Oster (2019), we show that unobservables would have to be much more important than the observables we have controlled for to make the positive effect of anticipating discrimination disappear. As an alternative approach to dealing with unobservables, we also demonstrate that this positive association mostly remains after controlling for performance in academic assessments at earlier ages. Finally, in trying to address concerns that GCSE grades convey only ordinal information, we are able to establish that this positive association is largest around achieving at least a grade C, an important threshold to access further study and job opportunities (Jerrim, forthcoming; Machin et al., 2020).

Overall, our results are consistent with the arguments in Arcidiacono et al. (2010) and Lang and Manove (2011), in that we find that ethnic minority students anticipating labour market discrimination invest more in education, as measured via their performance in high-stakes national exams. These results also suggest that wage comparisons between different ethnic groups that do not control for educational outcomes may underestimate the extent of wage discrimination. One way to interpret these findings is that not all of the burdens of labour market discrimination are expressed through lower wages, and that some consequences may already be felt prior to entering the labour market if students find it necessary to invest more in human capital as a strategic response to counteract discrimination later in life.

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Appendix A Description of explanatory variables

This appendix describes the explanatory variables used in the different models in more detail. All variables are taken from wave 1, unless otherwise noted.

A.1 Model 0

- **Anticipated discrimination in the labour market (wave 2)**: in our main analysis we use a dummy that is equal to one when students answer 'yes' or 'don't know' to the question 'Do you think that your skin colour, ethnic origin or religion will make it more difficult for you to get a job after you leave education?' 'No' is coded as zero.

- **Ethnicity (wave 2)**: dummies for the main ethnic minority groups identified in the 2001 Census. These are Pakistani, Bangladeshi, Any other Asian background, Caribbean, African, Any other Black background, White and Black Caribbean, White and Black African, White and Asian, Any other Mixed background, and Chinese and Any other, with Indian as the reference category. We combine Chinese and Any other due to the small number of students in each group. See https://www.ethnicity-facts-figures.service.gov.uk/style-guide/ethnic-groups#2001-census for details.

- **Region (wave 2)**: dummies for North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, South East, and South West. The reference region is London.

A.2 Model 1

Model 1 further adds the following explanatory variables:

- **Gender**: a dummy for whether the student is female.

- **Season of birth**: dummies for having been born in Autumn (September-November), Winter (December-February), and Spring (March-May). Reference category is having been born in Summer.

- **Born abroad**: a dummy for whether the student was born outside of the United Kingdom.

- **Language spoken at home**: dummies for speaking English only at home, and for speaking another language than English as first or main language. The omitted category comprises bilingual students and students whose first or main language is English but who also speak another language at home.

- **Mother's age at birth**: dummies for mother's age at the time of the student's birth being in the 25-29 range, and for being 30 or older. Younger than 25 is the reference category.
- **Two-parent family**: a dummy that is equal to one if the student lives with two parents.
- **Parental health**: a dummy for at least one parent reporting their general health in the last 12 months as having been 'not very good' or 'not good at all.'
- **Number of siblings in household**: dummies for having one sibling, two siblings, and three or more siblings. No siblings is the omitted category.
- **Parental education**: dummies for whether the highest parental qualification is a degree (or equivalent), and for no qualifications. All in-between qualifications form the reference category.
- **Parental employment**: a dummy for whether at least one parent is working.
- **Parental occupation**: a dummy for whether at least one parent classifies their occupation as being a manager, senior official, or professional.
- **Household income**: a dummy for gross household income equal to or exceeding £20,800 (i.e. in the top third of the ethnic minority income distribution in our sample).
- **Income support**: a dummy for the household receiving job seeker allowance and/or income support.
- **In-work support**: a dummy for the household receiving working tax credit and/or child tax credit.
- **Social housing**: a dummy for whether the family lives in social housing (i.e. is renting from a council or new town, or from a housing association).
- **Subjective financial situation**: The main parent is asked 'Thinking about how your household is managing on your total household income at the moment, would you say that it was...' with two dummies created for responses 'Getting into difficulties' and 'Managing quite well, able to save or spend on leisure.' The reference category is 'Just getting by, unable to save if wanted to.'

- **Local area deprivation**: 2004 value of the Index of Multiple Deprivation (IMD). The IMD is a measure of multiple deprivation at small area level (LSOAs: lower super output areas, of which there were around 32,000 for England) and is a weighted average of seven domains of deprivation: income deprivation; employment deprivation; health deprivation and disability; education, skills and training deprivation; barriers to housing and services; living environment deprivation; and crime. Each of these domains may have more than one component. This variable is taken from wave 2, but corresponds to 2004.

A.3 Model 2

Model 2 further adds the following explanatory variables:

- **Self-reported ability**: for each of English, maths, and science, we construct a dummy that equals one if the student reports being 'very good' or 'fairly good' in the subject.
- **Special educational needs**: a dummy for whether the student has ever been identified as having special educational needs.
- **Parental expectations about higher education**: a dummy for whether the main parent thinks it is 'very likely' or 'fairly likely' that the student will go to university.
- **Student expectations about higher education**: a dummy for whether the student intends to stay on in full-time education after year 11, and a dummy for whether the student is 'very likely' or 'fairly likely' to apply to university.
- **Thinks about future**: a dummy equal to one if a student responds 'strongly disagree' or 'disagree a little' with the statement 'I really don't think much about what I might be doing in a few years time.'
- **School exclusion**: a dummy that equals one if a student has ever been temporarily suspended or excluded from school, or has ever been expelled or permanently excluded from school.
- **Bullied**: a dummy equal to one if the student reports having been bullied in any way in the last 12 months.
- **Discrimination by teachers (wave 2)**: a dummy equal to one if the student answers 'yes' or 'don't know' to the question 'Do you think you have ever been been treated unfairly

by teachers at your school because of your skin colour or ethnic origin?'

A.4 Model 3

Model 3 adds external locus of control (LOC) (measured at wave 2). Following Caliendo, Cobb-Clark and Uhlendorff (2015), we first construct a single index to measure the extent of external locus of control by summing responses to a series of questions. We then create a dummy variable for external locus of control that is equal to one if the student falls into the top 75th percentile of the distribution on this index.

Students are asked how much they agree or disagree with the following statements: 'If someone is not a success in life, it is usually their own fault'; 'Even if I do well at school, I'll have a hard time getting the right kind of job'; 'Working hard a school now will help me get on later in life'; 'People like me don't have much of a chance in life'; 'I can pretty much decide what will happen in my life'; 'How well you get on in this world is mostly a matter of luck'; and 'If you work hard at something you'll usually succeed.' Possible responses are 'strongly agree'; 'agree'; 'don't know'; 'disagree'; and 'strongly disagree.' We assign these answers values from 1 to 5 in such a way that for each question a higher value reflects a more external locus of control, with 'don't know' responses always assigned a value of 3 (the middle category).

Appendix B Recovering the cumulative effect of anticipating discrimination

Before discussing how to recover the cumulative effect of anticipating discrimination in a value added (VA) model, it is worth recounting how the specification without a lagged test score estimates this cumulative effect. For notational convenience, we focus on a model that only contains expectations of facing labour market discrimination, leaving a brief mention of the role of covariates for later. Suppose the true model is:

$$T_{ia} = \alpha + \beta_1 AD_{i,a-1} + \beta_2 AD_{i,a-2} + \ldots + \beta_{a-1} AD_{i1} + e_{ia} \tag{B.1}$$

where T_{ia} is student i's achievement in KS4 assessments (at age a), $AD_{i,a-l}$ (for $l = 1, \ldots, a-1$) are dummy variables capturing whether the student anticipates discrimination l years before their KS4 assessment, and e_{ia} is an error term. Recall that $AD_{i,a-1}$ is the variable we observe; we do not have data on whether students anticipate discrimination at younger ages.

If anticipated discrimination is perfectly persistent over time (i.e. $AD_{i,a-1} = AD_{i,a-2} = \ldots = AD_{i1}$) then:

$$\begin{aligned} T_{ia} &= \alpha + (\beta_1 + \beta_2 + \ldots + \beta_{a-1})\, AD_{i,a-1} + e_{ia} \\ &= \alpha + \beta AD_{i,a-1} + e_{ia} \end{aligned} \tag{B.2}$$

with the coefficient, β, on our measure of anticipated discrimination, $AD_{i,a-1}$, capturing the cumulative effect of anticipating discrimination up until the age at which students sit their KS4 assessments.[22]

In practice, expectations are unlikely to be perfectly persistent, and we can think of $AD_{i,a-1}$ as an imperfect proxy for anticipating discrimination at younger ages:

$$AD_{i,a-l} = AD_{i,a-1} + v_{i,a-l} \quad \text{for} \quad l = 2, \ldots, a-1 \tag{B.3}$$

where $-v_{i,a-l}$ measures the change in anticipated discrimination between $a-l$ and $a-1$, with

[22] In reality, expectations of discrimination only form some time after age one, in which case the coefficient on $AD_{i,a-1}$ captures the cumulative effect on KS4 assessments from the point at which these expectations first form and start to matter for KS4 assessments.

$v_{i,a-l}$ taking on possible values 1, 0, and -1. Substituting (B.3) into equation (B.1) yields:

$$\begin{aligned} T_{ia} &= \alpha + \beta_1 AD_{i,a-1} + \beta_2 \left(AD_{i,a-1} + v_{i,a-2} \right) + \ldots + \beta_{a-1} \left(AD_{i,a-1} + v_{i1} \right) + e_{ia} \\ &= \alpha + \beta AD_{i,a-1} + \left(e_{ia} + \beta_2 v_{i,a-2} + \ldots + \beta_{a-1} v_{i1} \right) \end{aligned}$$

This model estimates the same cumulative effect as when anticipated discrimination is perfectly persistent, the only difference being that the composite error term now contains the measurement errors $v_{i,a-l}$ for $l = 2, \ldots, a-1$. From (B.3) it is easy to see that, when $AD_{i,a-1} = 1$, the only possible values for $v_{i,a-l}$ are -1 and 0. Likewise, when $AD_{i,a-1} = 0$, $v_{i,a-l}$ is either 0 or 1. Hence, $\text{Cov}\left(AD_{i,a-1}, v_{i,a-l} \right) \leqslant 0$, with this covariance equal to zero only in the case where anticipating discrimination is perfectly persistent and $v_{i,a-l}$ is zero for all students. As a result, the lack of perfect persistence in anticipated discrimination will tend to bias estimates of the cumulative effect in the opposite direction of the true effects of anticipating discrimination:

$$\text{plim}\widehat{\beta} = \beta + \sum_{l=2}^{a-1} \beta_l \frac{\text{Cov}\left(AD_{i,a-1}, v_{i,a-l} \right)}{\text{Var}\left(AD_{i,a-1} \right)}$$

Thus, if the effects of anticipating discrimination are positive, we will underestimate the true cumulative effect of anticipating discrimination on KS4 assessments.[23] The signs of these biases are unchanged if we add covariates that are uncorrelated with the measurement errors (see e.g. equation 8 in Aigner, 1973).

Now consider the VA model where, for notational convenience, we focus on a model including performance in KS2 assessments, which take place five years prior to KS4 assessments. From (B.1), and assuming that the effects of anticipating labour market discrimination do not vary by age, the KS2 assessment score, $T_{i,a-5}$, can be written as:

$$T_{i,a-5} = \kappa + \beta_1 AD_{i,a-6} + \beta_2 AD_{i,a-7} + \ldots + \beta_{a-6} AD_{i1} + e_{i,a-5}$$

[23] If measurement error is very prevalent, the estimate could have the wrong sign, i.e. $\text{plim}\widehat{\beta}$ could have the opposite sign as β. This will only occur, however, when $\left|\text{Cov}\left(AD_{i,a-1}, v_{i,a-l} \right)\right| > \text{Var}\left(AD_{i,a-1} \right)$ for enough of the $v_{i,a-l}$. Following Aigner (1973), it can be shown that this will only be satisfied when the misclassification probabilities sum to more than one: $\Pr\left(AD_{i,a-l} = 0 | AD_{i,a-1} = 1 \right) + \Pr\left(AD_{i,a-l} = 1 | AD_{i,a-1} = 0 \right) > 1$. This would require that measurement error is so severe that $AD_{i,a-1}$ misclassifies more observations in $AD_{i,a-l}$ than that it classifies correctly, so that $\text{Cov}\left(AD_{i,a-1}, AD_{i,a-l} \right) < 0$.

Subtracting $\rho T_{i,a-5}$ from T_{ia} and rearranging terms produces the following VA model:

$$\begin{aligned} T_{ia} &= \tau + \rho T_{i,a-5} + \beta_1 AD_{i,a-1} + \ldots + \beta_5 AD_{i,a-5} + (\beta_6 - \rho\beta_1) AD_{i,a-6} + (\beta_7 - \rho\beta_2) AD_{i,a-7} \\ &\quad + \ldots + (\beta_{a-1} - \rho\beta_{a-6}) AD_{i1} + e_{ia} - \rho e_{i,a-5} \end{aligned}$$

When anticipated discrimination is perfectly persistent, the model becomes:

$$\begin{aligned} T_{ia} &= \tau + \rho T_{i,a-5} + (\beta_1 + \ldots + \beta_5 + \beta_6 - \rho\beta_1 + \beta_7 - \rho\beta_2 + \ldots + \beta_{a-1} - \rho\beta_{a-6}) AD_{i,a-1} + e_{ia} - \rho e_{i,a-5} \\ &= \tau + \rho T_{i,a-5} + [(1-\rho)(\beta_1 + \ldots + \beta_{a-6}) + \beta_{a-5} + \ldots + \beta_{a-1}] AD_{i,a-1} + e_{ia} - \rho e_{i,a-5} \\ &= \tau + \rho T_{i,a-5} + \delta AD_{i,a-1} + e_{ia} - \rho e_{i,a-5} \end{aligned} \tag{B.4}$$

Hence, compared to β in equation (B.2), the coefficient δ on $AD_{i,a-1}$ in equation (B.4) picks up the effects of anticipating discrimination in the distant past on KS4 assessments ($\beta_{a-5} + \ldots + \beta_{a-1}$) but only a fraction $0 < 1-\rho < 1$ of the effects of anticipating discrimination more recently ($\beta_1 + \ldots + \beta_{a-6}$). The coefficient δ therefore underestimates the true cumulative effect. On the other hand, $\frac{\delta}{1-\rho} = \beta_1 + \ldots + \beta_{a-6} + \frac{\beta_{a-5}+\ldots+\beta_{a-1}}{1-\rho}$ picks up the effects of anticipating discrimination more recently but inflates its effects in the distant past, thus overestimating the true cumulative effect. The balance of the effects of more recent versus more distant lags of anticipating discrimination therefore determines whether δ or $\frac{\delta}{1-\rho}$ is closest to the true cumulative effect. If, as seems likely, more recent effects of anticipating labour market discrimination on KS4 assessments dominate those further back in time, the balance tips towards $\frac{\delta}{1-\rho}$.

Whether δ or $\frac{\delta}{1-\rho}$ is closest to the true cumulative effect also depends on the number of lags of anticipated discrimination that matter for determining KS4 and KS2 scores. If the same number of lags of anticipated discrimination matter for both KS4 and KS2 performance, $\frac{\delta}{1-\rho}$ recovers the true cumulative effect exactly. For example, if only the three most recent lags matter, $\delta = (1-\rho)(\beta_1 + \beta_2 + \beta_3)$, and so $\frac{\delta}{1-\rho} = \beta$. On the other hand, if expectations of discrimination only form at the time of or after KS2 assessments take place, δ captures the true cumulative effect. More generally, if fewer lags of anticipated discrimination matter for $T_{i,a-5}$ than for T_{ia}, as in the set-up for equation (B.4), δ underestimates the true cumulative effect and $\frac{\delta}{1-\rho}$ overestimates it, with the disparity in the number of lags as well as the balance in the effects of more versus less recent lags determining whether δ or $\frac{\delta}{1-\rho}$ is most appropriate.

The earlier anticipated discrimination forms and starts to matter for educational outcomes, the more likely that KS2 assessments will be affected by a similar number of lags of anticipated discrimination as KS4 assessments, and hence the closer $\frac{\delta}{1-\rho}$ should be to the true cumulative effect.

This also implies that in the VA model that controls for KS3 test scores ($T_{i,a-2}$) the true cumulative effect is especially likely to be close to $\frac{\delta}{1-\rho}$. Since KS3 assessments are taken at ages 13/14 in the year just prior to when we are able to measure anticipated discrimination, we can be reasonably confident that expectations of discrimination have formed and matter prior to this point, and since KS3 assessments take place so close to KS4 assessments (only two years before), KS3 and KS4 assessments are then likely affected by a similar number of lags of anticipated discrimination. If, for instance, we replicate the set-up for equation (B.4) where all lags of anticipated discrimination matter, then we get that in the VA model with the KS3 score $\delta = [(1-\rho)(\beta_1 + \ldots + \beta_{a-3}) + \beta_{a-2} + \beta_{a-1}]$, so that now $\frac{\delta}{1-\rho}$ should be very close to the true cumulative effect, as only the effects of two lagged values of anticipated discrimination very distant from KS4 assessments, β_{a-2} and β_{a-1}, are inflated.

In summary, the faster the effects of anticipated discrimination decline with temporal distance to KS4 assessments and/or the earlier anticipations of discrimination are formed and start to matter for educational attainment, the closer $\frac{\delta}{1-\rho}$ is to the true cumulative effect. While children become aware of racial biases very early in life and exhibit a fairly sophisticated understanding of racial discrimination by age 10 (Brown and Bigler, 2005; Waxman, 2021), we are not aware of any literature considering expectations of facing labour market discrimination, and it remains an open question as to when these expectations form and start to matter. However, especially for KS3 assessments we can be reasonably confident that expectations of discrimination have formed and matter prior to this point, so that the true cumulative effect is likely closely approximated by $\frac{\delta}{1-\rho}$.

When we allow for imperfect persistence of reported anticipated discrimination, the only difference is that the composite error term in (B.4) is now

$$e_{ia} - \rho e_{i,a-5} + \beta_2 v_{i,a-2} + \ldots + \beta_5 v_{i,a-5} + (\beta_6 - \rho\beta_1) v_{i,a-6} + \ldots + (\beta_{a-1} - \rho\beta_{a-6}) v_{i1}$$

where, as before, $\mathrm{Cov}(AD_{i,a-1}, v_{i,a-l}) \leqslant 0$, so that the bias induced by $v_{i,a-2}$ through to $v_{i,a-5}$ is opposite in sign to the effects of anticipated discrimination (β_2 through β_5), as in the non-VA model. The sign of the bias induced by $v_{i,a-6}$ through to v_{i1} is more ambiguous, and depends on how fast the effects of anticipated discrimination dissipate with the distance between when the student anticipates discrimination and when their educational achievement is measured (which determines whether the $\beta_l - \rho\beta_{l-5}$ for $l = 6, \ldots, a-1$ are positive or negative).

A final complexity is that biases in the estimation of ρ might bias the estimation of $\frac{\delta}{1-\rho}$. Time-invariant or persistent unobservables would tend to lead to an upward bias in the estimation of ρ, while iid measurement error in test scores would push towards a downward bias.

Appendix C Additional tables

Table C.1: Full results: model 0

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Anticipates discrimination	0.26***	0.31***	0.27***	0.20***	0.080***
	(0.059)	(0.063)	(0.069)	(0.064)	(0.017)
Pakistani	−0.68***	−1.03***	−0.88***	−0.86***	−0.23***
	(0.083)	(0.11)	(0.11)	(0.097)	(0.030)
Bangladeshi	−0.68***	−0.99***	−0.92***	−0.70***	−0.21***
	(0.11)	(0.12)	(0.16)	(0.13)	(0.031)
Any other Asian background	0.019	0.23	0.33**	0.13	0.059
	(0.13)	(0.17)	(0.16)	(0.15)	(0.047)
Caribbean	−0.84***	−1.56***	−1.38***	−1.15***	−0.33***
	(0.11)	(0.12)	(0.13)	(0.12)	(0.033)
African	−0.61***	−1.02***	−0.85***	−0.71***	−0.21***
	(0.12)	(0.14)	(0.14)	(0.12)	(0.038)
Any other Black background	−0.72***	−1.23***	−0.99***	−0.89***	−0.17**
	(0.27)	(0.31)	(0.30)	(0.29)	(0.072)
White and Black Caribbean	−0.72***	−1.22***	−1.09***	−1.03***	−0.24***
	(0.12)	(0.14)	(0.14)	(0.13)	(0.035)
White and Black African	−0.76***	−1.15***	−0.95***	−0.90***	−0.20***
	(0.27)	(0.27)	(0.29)	(0.27)	(0.061)
White and Asian	0.16	−0.21	−0.027	−0.086	0.020
	(0.16)	(0.18)	(0.19)	(0.18)	(0.050)
Any other Mixed background	0.015	−0.23	−0.13	−0.16	0.034
	(0.21)	(0.25)	(0.25)	(0.22)	(0.057)
Chinese and Any other	−0.0057	−0.057	−0.014	−0.053	−0.043
	(0.19)	(0.21)	(0.24)	(0.20)	(0.056)
North East	−0.44**	−0.41*	−0.38*	−0.10	−0.028
	(0.21)	(0.23)	(0.23)	(0.16)	(0.056)
North West	−0.53***	−0.61***	−0.55***	−0.45***	−0.15***
	(0.13)	(0.15)	(0.17)	(0.17)	(0.035)
Yorkshire and the Humber	−0.49***	−0.70***	−0.66***	−0.50***	−0.11***
	(0.14)	(0.17)	(0.17)	(0.16)	(0.040)
East Midlands	−0.52***	−0.60***	−0.18	−0.40**	−0.12**
	(0.14)	(0.23)	(0.20)	(0.19)	(0.054)
West Midlands	−0.56***	−0.69***	−0.48***	−0.41***	−0.13***
	(0.12)	(0.12)	(0.14)	(0.11)	(0.030)
East of England	−0.12	−0.16	−0.15	−0.20	−0.10**
	(0.13)	(0.15)	(0.17)	(0.14)	(0.041)
South East	−0.12	−0.11	−0.15	−0.10	−0.010
	(0.19)	(0.21)	(0.21)	(0.20)	(0.049)
South West	−0.31	−0.71*	−0.41	−0.43	−0.13*
	(0.27)	(0.39)	(0.36)	(0.27)	(0.067)
R^2	0.06	0.11	0.08	0.07	0.07
N	3483	3483	3483	3483	3483

Note: see note to Table 3. See Appendix A for details on the covariates. Standard errors robust to heteroskedasticity and clustering by school. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% significance level, respectively.

Table C.2: Full results: model 1

Dependent variable:	English	Maths	Science	Average (best 8)	Gold standard
	(1)	(2)	(3)	(4)	(5)
Anticipates discrimination	0.24***	0.27***	0.24***	0.18***	0.072***
	(0.054)	(0.059)	(0.065)	(0.059)	(0.016)
Pakistani	−0.16**	−0.47***	−0.34***	−0.35***	−0.10***
	(0.075)	(0.099)	(0.10)	(0.091)	(0.029)
Bangladeshi	0.17*	−0.018	0.020	0.16	0.0084
	(0.10)	(0.12)	(0.15)	(0.12)	(0.032)
Any other Asian background	0.30**	0.54***	0.61***	0.41**	0.13***
	(0.14)	(0.17)	(0.18)	(0.16)	(0.049)
Caribbean	−0.74***	−1.24***	−1.08***	−0.85***	−0.30***
	(0.12)	(0.13)	(0.14)	(0.13)	(0.037)
African	−0.20*	−0.51***	−0.42***	−0.27**	−0.11***
	(0.12)	(0.14)	(0.14)	(0.12)	(0.039)
Any other Black background	−0.32	−0.67**	−0.51*	−0.38	−0.075
	(0.26)	(0.29)	(0.29)	(0.27)	(0.068)
White and Black Caribbean	−0.63***	−0.90***	−0.80***	−0.72***	−0.21***
	(0.12)	(0.14)	(0.15)	(0.13)	(0.039)
White and Black African	−0.63***	−0.91***	−0.76***	−0.63***	−0.16***
	(0.24)	(0.25)	(0.26)	(0.24)	(0.054)
White and Asian	−0.013	−0.28*	−0.11	−0.15	−0.018
	(0.14)	(0.16)	(0.17)	(0.16)	(0.047)
Any other Mixed background	−0.12	−0.24	−0.19	−0.18	0.010
	(0.20)	(0.23)	(0.24)	(0.21)	(0.055)
Chinese and Any other	0.13	0.098	0.12	0.12	−0.020
	(0.16)	(0.19)	(0.21)	(0.18)	(0.050)
North East	−0.43***	−0.40**	−0.37**	−0.12	−0.0084
	(0.15)	(0.16)	(0.16)	(0.11)	(0.047)
North West	−0.33***	−0.40***	−0.38**	−0.28*	−0.097***
	(0.11)	(0.13)	(0.15)	(0.15)	(0.030)
Yorkshire and the Humber	−0.39***	−0.60***	−0.60***	−0.44***	−0.077**
	(0.11)	(0.13)	(0.15)	(0.13)	(0.034)
East Midlands	−0.44***	−0.62***	−0.20	−0.37**	−0.11***
	(0.11)	(0.16)	(0.16)	(0.15)	(0.041)
West Midlands	−0.42***	−0.56***	−0.39***	−0.32***	−0.088***
	(0.095)	(0.10)	(0.12)	(0.10)	(0.027)
East of England	−0.20*	−0.30**	−0.27*	−0.31**	−0.11***
	(0.12)	(0.13)	(0.16)	(0.13)	(0.037)
South East	−0.34**	−0.43***	−0.45***	−0.36**	−0.065*
	(0.14)	(0.16)	(0.16)	(0.16)	(0.038)
South West	−0.20	−0.71**	−0.41	−0.35*	−0.11*
	(0.20)	(0.29)	(0.27)	(0.20)	(0.058)
Female	0.66***	0.18***	0.31***	0.60***	0.10***
	(0.062)	(0.068)	(0.078)	(0.065)	(0.018)
Autumn born	0.14*	0.16*	0.18**	0.096	0.090***
	(0.073)	(0.083)	(0.088)	(0.080)	(0.023)
Winter born	0.085	0.18**	0.10	0.093	0.093***
	(0.070)	(0.082)	(0.083)	(0.075)	(0.023)
Spring born	0.025	0.065	0.12	0.053	0.049**
	(0.072)	(0.076)	(0.084)	(0.075)	(0.023)
Born abroad	−0.12	−0.084	−0.0053	−0.0079	−0.035
	(0.081)	(0.086)	(0.096)	(0.083)	(0.024)
Born abroad missing	−0.013	0.0030	−0.032	−0.017	−0.037
	(0.13)	(0.17)	(0.15)	(0.14)	(0.046)

Table C.2 continued from previous page

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Speaks English only	0.090	−0.022	−0.021	−0.058	0.0099
	(0.072)	(0.085)	(0.091)	(0.081)	(0.024)
Main language not English	−0.25***	−0.20**	−0.29***	−0.26***	−0.050**
	(0.072)	(0.086)	(0.097)	(0.085)	(0.023)
Mum aged 25-29 at child's birth	0.26***	0.28***	0.23***	0.20***	0.088***
	(0.059)	(0.070)	(0.073)	(0.064)	(0.019)
Mum aged 30+ at child's birth	0.23***	0.32***	0.23***	0.23***	0.083***
	(0.065)	(0.080)	(0.085)	(0.077)	(0.020)
Mum age at child's birth unknown	−0.11	−0.20	−0.21	−0.19	−0.071*
	(0.15)	(0.15)	(0.17)	(0.16)	(0.039)
Two-parent family	0.18**	0.25***	0.28***	0.28***	0.024
	(0.079)	(0.089)	(0.093)	(0.087)	(0.024)
Parent(s) not in good health	−0.10	−0.11	−0.16**	−0.13*	−0.023
	(0.062)	(0.072)	(0.079)	(0.068)	(0.018)
One sibling	0.027	0.12	0.23**	0.14	0.051*
	(0.091)	(0.097)	(0.10)	(0.098)	(0.027)
Two siblings	−0.043	0.093	0.081	0.070	0.027
	(0.099)	(0.10)	(0.11)	(0.10)	(0.029)
Three or more siblings	−0.32***	−0.23**	−0.21*	−0.24**	−0.041
	(0.10)	(0.11)	(0.11)	(0.11)	(0.029)
Parent(s) with degree	0.34***	0.40***	0.56***	0.51***	0.11***
	(0.083)	(0.091)	(0.096)	(0.084)	(0.024)
Parent(s) with no qualifications	−0.36***	−0.36***	−0.33***	−0.32***	−0.093***
	(0.070)	(0.078)	(0.083)	(0.079)	(0.020)
Parent(s) employed	0.0038	0.048	−0.011	0.040	0.018
	(0.097)	(0.11)	(0.13)	(0.12)	(0.029)
Parent(s) professional occupation	0.15**	0.26***	0.25***	0.19***	0.052**
	(0.066)	(0.079)	(0.082)	(0.072)	(0.022)
Household income at least £20,800	0.23***	0.20**	0.14	0.16*	0.073***
	(0.074)	(0.084)	(0.093)	(0.081)	(0.023)
Household income unknown	−0.10	−0.12	−0.24***	−0.15**	−0.014
	(0.070)	(0.075)	(0.087)	(0.075)	(0.020)
Income support received	−0.12	−0.21**	−0.11	−0.12	−0.019
	(0.091)	(0.11)	(0.11)	(0.11)	(0.028)
Working Tax Credit received	−0.039	−0.028	−0.021	−0.011	−0.014
	(0.059)	(0.067)	(0.071)	(0.067)	(0.018)
Household managing well financially	0.15***	0.12*	0.094	0.097	0.012
	(0.055)	(0.062)	(0.078)	(0.066)	(0.019)
Household getting into financial diff.	−0.14	−0.13	−0.21*	−0.16*	−0.051*
	(0.084)	(0.099)	(0.11)	(0.099)	(0.026)
Social housing	−0.17**	−0.20**	−0.29***	−0.28***	−0.030
	(0.070)	(0.083)	(0.092)	(0.077)	(0.021)
Index of Multiple Deprivation (IMD)	−0.0084***	−0.011***	−0.0084***	−0.0075***	−0.0021***
	(0.0019)	(0.0022)	(0.0026)	(0.0021)	(0.00059)
R^2	0.22	0.24	0.20	0.21	0.18
N	3483	3483	3483	3483	3483

Note: see note to Table 3. See Appendix A for details on the covariates. Standard errors robust to heteroskedasticity and clustering by school. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% significance level, respectively.

Table C.3: Full results: model 2

Dependent variable:	English	Maths	Science	Average (best 8)	Gold standard
	(1)	(2)	(3)	(4)	(5)
Anticipates discrimination	0.23***	0.26***	0.25***	0.17***	0.074***
	(0.049)	(0.057)	(0.062)	(0.053)	(0.016)
Pakistani	−0.15**	−0.44***	−0.33***	−0.34***	−0.097***
	(0.068)	(0.091)	(0.092)	(0.081)	(0.027)
Bangladeshi	0.17*	−0.0026	0.026	0.17	0.012
	(0.093)	(0.11)	(0.13)	(0.12)	(0.031)
Any other Asian background	0.18	0.39***	0.46***	0.27**	0.097**
	(0.13)	(0.15)	(0.16)	(0.13)	(0.043)
Caribbean	−0.52***	−0.99***	−0.79***	−0.57***	−0.24***
	(0.11)	(0.13)	(0.13)	(0.11)	(0.036)
African	−0.29***	−0.59***	−0.50***	−0.36***	−0.13***
	(0.11)	(0.12)	(0.12)	(0.11)	(0.036)
Any other Black background	−0.25	−0.63**	−0.42*	−0.28	−0.063
	(0.21)	(0.26)	(0.25)	(0.23)	(0.062)
White and Black Caribbean	−0.17	−0.42***	−0.23*	−0.18	−0.097***
	(0.11)	(0.13)	(0.14)	(0.12)	(0.037)
White and Black African	−0.38*	−0.59***	−0.44**	−0.31	−0.090*
	(0.20)	(0.20)	(0.21)	(0.20)	(0.049)
White and Asian	0.014	−0.25*	−0.071	−0.11	−0.012
	(0.13)	(0.15)	(0.15)	(0.14)	(0.041)
Any other Mixed background	0.0015	−0.12	−0.053	−0.049	0.036
	(0.16)	(0.19)	(0.19)	(0.16)	(0.047)
Chinese and Any other	0.23	0.20	0.25	0.24	0.0032
	(0.15)	(0.17)	(0.19)	(0.15)	(0.047)
North East	−0.34*	−0.28	−0.25	−0.0078	0.017
	(0.19)	(0.21)	(0.20)	(0.15)	(0.047)
North West	−0.16	−0.18*	−0.15	−0.072	−0.048*
	(0.098)	(0.10)	(0.11)	(0.15)	(0.028)
Yorkshire and the Humber	−0.20**	−0.40***	−0.37***	−0.22**	−0.034
	(0.097)	(0.13)	(0.13)	(0.11)	(0.034)
East Midlands	−0.27***	−0.44***	−0.000013	−0.17	−0.072*
	(0.095)	(0.14)	(0.14)	(0.13)	(0.038)
West Midlands	−0.27***	−0.40***	−0.19*	−0.13	−0.051**
	(0.086)	(0.097)	(0.11)	(0.091)	(0.026)
East of England	−0.062	−0.13	−0.095	−0.14	−0.075**
	(0.10)	(0.12)	(0.15)	(0.12)	(0.035)
South East	−0.13	−0.20	−0.18	−0.11	−0.015
	(0.13)	(0.15)	(0.14)	(0.14)	(0.035)
South West	−0.020	−0.48*	−0.19	−0.13	−0.059
	(0.18)	(0.25)	(0.24)	(0.18)	(0.048)
Female	0.51***	0.097	0.19***	0.46***	0.078***
	(0.055)	(0.063)	(0.070)	(0.058)	(0.017)
Autumn born	0.036	0.046	0.055	−0.021	0.064***
	(0.067)	(0.079)	(0.081)	(0.070)	(0.022)
Winter born	−0.023	0.060	−0.029	−0.032	0.065***
	(0.064)	(0.077)	(0.076)	(0.067)	(0.022)
Spring born	−0.060	−0.019	0.028	−0.041	0.029
	(0.068)	(0.073)	(0.078)	(0.068)	(0.023)
Born abroad	−0.17**	−0.14*	−0.077	−0.071	−0.047**
	(0.073)	(0.079)	(0.090)	(0.074)	(0.023)
Born abroad missing	−0.020	−0.024	−0.044	−0.032	−0.043
	(0.12)	(0.16)	(0.15)	(0.13)	(0.043)

Table C.3 continued from previous page

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Speaks English only	0.20***	0.091	0.10	0.062	0.035
	(0.063)	(0.073)	(0.079)	(0.068)	(0.022)
Main language not English	−0.17***	−0.13	−0.21**	−0.17**	−0.033
	(0.064)	(0.080)	(0.090)	(0.076)	(0.022)
Mum aged 25-29 at child's birth	0.27***	0.31***	0.25***	0.22***	0.093***
	(0.055)	(0.065)	(0.069)	(0.060)	(0.019)
Mum aged 30+ at child's birth	0.20***	0.29***	0.18**	0.19***	0.074***
	(0.059)	(0.072)	(0.077)	(0.068)	(0.019)
Mum age at child's birth unknown	−0.0093	−0.078	−0.076	−0.065	−0.045
	(0.13)	(0.14)	(0.16)	(0.14)	(0.036)
Two-parent family	0.15**	0.20**	0.24***	0.23***	0.014
	(0.071)	(0.080)	(0.083)	(0.075)	(0.023)
Parent(s) not in good health	−0.041	−0.042	−0.095	−0.060	−0.0076
	(0.056)	(0.065)	(0.073)	(0.061)	(0.017)
One sibling	0.054	0.13	0.24**	0.16*	0.055**
	(0.082)	(0.088)	(0.096)	(0.088)	(0.026)
Two siblings	0.016	0.15*	0.14	0.13	0.039
	(0.089)	(0.091)	(0.10)	(0.093)	(0.027)
Three or more siblings	−0.20**	−0.10	−0.076	−0.11	−0.013
	(0.092)	(0.097)	(0.10)	(0.094)	(0.028)
Parent(s) with degree	0.30***	0.35***	0.49***	0.45***	0.095***
	(0.073)	(0.082)	(0.085)	(0.072)	(0.022)
Parent(s) with no qualifications	−0.26***	−0.25***	−0.21***	−0.20***	−0.067***
	(0.063)	(0.067)	(0.075)	(0.069)	(0.019)
Parent(s) employed	−0.13	−0.073	−0.14	−0.095	−0.010
	(0.080)	(0.092)	(0.11)	(0.095)	(0.026)
Parent(s) professional occupation	0.059	0.17**	0.13*	0.081	0.032
	(0.059)	(0.072)	(0.074)	(0.063)	(0.021)
Household income at least £20,800	0.20***	0.16**	0.099	0.12*	0.063***
	(0.066)	(0.074)	(0.082)	(0.070)	(0.021)
Household income unknown	−0.056	−0.070	−0.19**	−0.093	−0.0012
	(0.059)	(0.066)	(0.074)	(0.067)	(0.019)
Income support received	−0.13*	−0.20**	−0.11	−0.12	−0.019
	(0.078)	(0.095)	(0.098)	(0.095)	(0.025)
Working Tax Credit received	0.0040	0.013	0.029	0.037	−0.0045
	(0.054)	(0.061)	(0.066)	(0.058)	(0.017)
Household managing well financially	0.11**	0.092	0.059	0.056	0.0044
	(0.051)	(0.056)	(0.073)	(0.059)	(0.018)
Household getting into financial diff.	−0.12	−0.087	−0.19*	−0.14	−0.045*
	(0.074)	(0.086)	(0.096)	(0.088)	(0.024)
Social housing	−0.15**	−0.14*	−0.25***	−0.24***	−0.019
	(0.063)	(0.075)	(0.084)	(0.069)	(0.020)
Index of Multiple Deprivation (IMD)	−0.0071***	−0.0099***	−0.0073***	−0.0062***	−0.0019***
	(0.0017)	(0.0020)	(0.0023)	(0.0019)	(0.00056)
Maths: self-assessed as good	0.22***	0.85***	0.52***	0.44***	0.17***
	(0.081)	(0.082)	(0.088)	(0.080)	(0.023)
English: self-assessed as good	0.43***	−0.0050	0.24***	0.31***	0.059***
	(0.071)	(0.084)	(0.088)	(0.077)	(0.022)
Science: self-assessed as good	0.42***	0.47***	0.85***	0.59***	0.099***
	(0.065)	(0.073)	(0.077)	(0.067)	(0.020)
Special educational needs	−0.94***	−0.85***	−0.83***	−0.94***	−0.19***
	(0.088)	(0.097)	(0.098)	(0.092)	(0.023)
High parental aspirations for university	0.61***	0.70***	0.76***	0.74***	0.15***
	(0.077)	(0.081)	(0.095)	(0.088)	(0.021)

Table C.3 continued from previous page

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Thinks about future	0.36***	0.27***	0.30***	0.33***	0.065***
	(0.056)	(0.060)	(0.065)	(0.057)	(0.016)
Plans for non-compulsory education	0.49***	0.54***	0.60***	0.60***	0.12***
	(0.11)	(0.12)	(0.12)	(0.11)	(0.025)
Likely to apply to university	0.40***	0.43***	0.51***	0.46***	0.097***
	(0.082)	(0.086)	(0.091)	(0.085)	(0.021)
School exclusion	−0.68***	−0.59***	−0.80***	−0.84***	−0.14***
	(0.10)	(0.10)	(0.11)	(0.10)	(0.025)
School exclusion unknown	−0.24***	−0.25***	−0.25***	−0.28***	−0.064***
	(0.068)	(0.077)	(0.088)	(0.081)	(0.021)
Bullied in past year	−0.17***	−0.18***	−0.19***	−0.22***	−0.030*
	(0.049)	(0.053)	(0.058)	(0.051)	(0.015)
Discrimination by teachers	−0.017	−0.060	−0.12*	−0.040	−0.020
	(0.050)	(0.057)	(0.065)	(0.054)	(0.016)
Discrimination by teachers unknown	0.15	−0.12	−0.089	−0.062	−0.052
	(0.16)	(0.21)	(0.20)	(0.19)	(0.062)
R^2	0.39	0.39	0.36	0.40	0.29
N	3483	3483	3483	3483	3483

Note: see note to Table 3. See Appendix A for details on the covariates. Standard errors robust to heteroskedasticity and clustering by school. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% significance level, respectively.

Table C.4: Full results: model 3

Dependent variable:	English	Maths	Science	Average (best 8)	Gold standard
	(1)	(2)	(3)	(4)	(5)
Anticipates discrimination	0.26***	0.29***	0.28***	0.21***	0.080***
	(0.048)	(0.057)	(0.061)	(0.053)	(0.016)
Pakistani	−0.13**	−0.42***	−0.31***	−0.32***	−0.093***
	(0.068)	(0.092)	(0.093)	(0.082)	(0.027)
Bangladeshi	0.19**	0.017	0.047	0.19	0.016
	(0.090)	(0.10)	(0.13)	(0.12)	(0.031)
Any other Asian background	0.22*	0.42***	0.49***	0.30**	0.10**
	(0.12)	(0.14)	(0.15)	(0.12)	(0.043)
Caribbean	−0.53***	−1.00***	−0.80***	−0.58***	−0.24***
	(0.11)	(0.13)	(0.14)	(0.11)	(0.036)
African	−0.31***	−0.61***	−0.52***	−0.38***	−0.13***
	(0.10)	(0.12)	(0.13)	(0.11)	(0.036)
Any other Black background	−0.22	−0.61**	−0.40	−0.26	−0.058
	(0.21)	(0.26)	(0.24)	(0.22)	(0.061)
White and Black Caribbean	−0.15	−0.40***	−0.21	−0.16	−0.093**
	(0.11)	(0.13)	(0.13)	(0.12)	(0.036)
White and Black African	−0.38*	−0.58***	−0.44**	−0.31	−0.089*
	(0.20)	(0.20)	(0.21)	(0.20)	(0.050)
White and Asian	0.053	−0.21	−0.035	−0.071	−0.0041
	(0.13)	(0.15)	(0.15)	(0.14)	(0.041)
Any other Mixed background	−0.026	−0.15	−0.076	−0.075	0.031
	(0.17)	(0.19)	(0.19)	(0.16)	(0.048)
Chinese and Any other	0.23	0.20	0.26	0.25	0.0049
	(0.15)	(0.17)	(0.19)	(0.15)	(0.047)
North East	−0.36**	−0.30	−0.28	−0.032	0.012
	(0.18)	(0.20)	(0.19)	(0.15)	(0.047)
North West	−0.17*	−0.19*	−0.17	−0.085	−0.051*
	(0.097)	(0.10)	(0.11)	(0.15)	(0.027)
Yorkshire and the Humber	−0.23**	−0.42***	−0.39***	−0.25**	−0.040
	(0.097)	(0.13)	(0.13)	(0.11)	(0.034)
East Midlands	−0.28***	−0.44***	−0.0057	−0.18	−0.074*
	(0.095)	(0.14)	(0.14)	(0.13)	(0.038)
West Midlands	−0.29***	−0.41***	−0.21*	−0.15*	−0.055**
	(0.085)	(0.096)	(0.11)	(0.091)	(0.026)
East of England	−0.083	−0.15	−0.11	−0.16	−0.079**
	(0.099)	(0.12)	(0.15)	(0.12)	(0.035)
South East	−0.13	−0.20	−0.18	−0.11	−0.015
	(0.12)	(0.14)	(0.14)	(0.13)	(0.035)
South West	0.000053	−0.46*	−0.17	−0.11	−0.055
	(0.16)	(0.24)	(0.23)	(0.18)	(0.049)
Female	0.53***	0.11*	0.20***	0.47***	0.082***
	(0.055)	(0.063)	(0.070)	(0.058)	(0.017)
Autumn born	0.030	0.040	0.049	−0.027	0.063***
	(0.067)	(0.078)	(0.080)	(0.069)	(0.022)
Winter born	−0.015	0.067	−0.022	−0.025	0.067***
	(0.063)	(0.077)	(0.075)	(0.066)	(0.022)
Spring born	−0.070	−0.028	0.020	−0.050	0.027
	(0.067)	(0.073)	(0.077)	(0.067)	(0.022)
Born abroad	−0.15**	−0.12	−0.060	−0.054	−0.044*
	(0.071)	(0.079)	(0.089)	(0.073)	(0.023)
Born abroad missing	0.0088	−0.00019	−0.017	−0.0060	−0.038
	(0.12)	(0.15)	(0.15)	(0.13)	(0.043)

Table C.4 continued from previous page

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Speaks English only	0.19***	0.083	0.093	0.054	0.033
	(0.063)	(0.073)	(0.080)	(0.068)	(0.022)
Main language not English	−0.18***	−0.14*	−0.22**	−0.19**	−0.036
	(0.063)	(0.079)	(0.089)	(0.076)	(0.022)
Mum aged 25-29 at child's birth	0.26***	0.30***	0.25***	0.21***	0.092***
	(0.054)	(0.065)	(0.068)	(0.059)	(0.019)
Mum aged 30+ at child's birth	0.19***	0.28***	0.18**	0.18***	0.073***
	(0.059)	(0.071)	(0.077)	(0.069)	(0.019)
Mum age at child's birth unknown	−0.0076	−0.076	−0.075	−0.063	−0.045
	(0.12)	(0.14)	(0.16)	(0.13)	(0.036)
Two-parent family	0.15**	0.20**	0.24***	0.23***	0.014
	(0.070)	(0.079)	(0.082)	(0.074)	(0.023)
Parent(s) not in good health	−0.044	−0.046	−0.097	−0.064	−0.0081
	(0.055)	(0.064)	(0.072)	(0.060)	(0.017)
One sibling	0.051	0.13	0.24**	0.16*	0.054**
	(0.082)	(0.088)	(0.096)	(0.088)	(0.026)
Two siblings	−0.0084	0.13	0.12	0.11	0.034
	(0.087)	(0.090)	(0.10)	(0.093)	(0.027)
Three or more siblings	−0.22**	−0.11	−0.090	−0.12	−0.016
	(0.090)	(0.097)	(0.10)	(0.093)	(0.028)
Parent(s) with degree	0.31***	0.36***	0.50***	0.46***	0.097***
	(0.073)	(0.082)	(0.086)	(0.073)	(0.022)
Parent(s) with no qualifications	−0.24***	−0.23***	−0.20***	−0.18***	−0.063***
	(0.063)	(0.067)	(0.075)	(0.069)	(0.019)
Parent(s) employed	−0.12	−0.065	−0.13	−0.087	−0.0083
	(0.079)	(0.092)	(0.11)	(0.094)	(0.026)
Parent(s) professional occupation	0.045	0.16**	0.12	0.068	0.029
	(0.058)	(0.071)	(0.073)	(0.062)	(0.021)
Household income at least £20,800	0.19***	0.15**	0.092	0.11	0.061***
	(0.065)	(0.073)	(0.083)	(0.070)	(0.021)
Household income unknown	−0.045	−0.060	−0.18**	−0.083	0.00093
	(0.058)	(0.065)	(0.074)	(0.066)	(0.019)
Income support received	−0.13*	−0.21**	−0.11	−0.12	−0.020
	(0.076)	(0.093)	(0.095)	(0.093)	(0.025)
Working Tax Credit received	0.0083	0.016	0.033	0.041	−0.0037
	(0.053)	(0.060)	(0.065)	(0.058)	(0.017)
Household managing well financially	0.11**	0.090	0.057	0.054	0.0039
	(0.051)	(0.056)	(0.072)	(0.059)	(0.018)
Household getting into financial diff.	−0.12*	−0.091	−0.19**	−0.14*	−0.046*
	(0.072)	(0.085)	(0.095)	(0.087)	(0.024)
Social housing	−0.15**	−0.15*	−0.25***	−0.24***	−0.020
	(0.062)	(0.075)	(0.083)	(0.069)	(0.020)
Index of Multiple Deprivation (IMD)	−0.0066***	−0.0094***	−0.0068***	−0.0057***	−0.0018***
	(0.0017)	(0.0020)	(0.0023)	(0.0019)	(0.00056)
Maths: self-assessed as good	0.20**	0.83***	0.50***	0.42***	0.17***
	(0.079)	(0.081)	(0.085)	(0.079)	(0.022)
English: self-assessed as good	0.40***	−0.032	0.21**	0.29***	0.053**
	(0.071)	(0.084)	(0.088)	(0.077)	(0.022)
Science: self-assessed as good	0.40***	0.44***	0.83***	0.57***	0.094***
	(0.064)	(0.072)	(0.077)	(0.067)	(0.019)
Special educational needs	−0.90***	−0.81***	−0.79***	−0.90***	−0.18***
	(0.086)	(0.095)	(0.097)	(0.090)	(0.023)
High parental aspirations for university	0.56***	0.66***	0.72***	0.69***	0.14***
	(0.076)	(0.082)	(0.096)	(0.087)	(0.021)

Table C.4 continued from previous page

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Thinks about future	0.32***	0.23***	0.27***	0.29***	0.058***
	(0.056)	(0.060)	(0.065)	(0.056)	(0.016)
Plans for non-compulsory education	0.47***	0.53***	0.58***	0.58***	0.12***
	(0.11)	(0.12)	(0.12)	(0.11)	(0.026)
Likely to apply to university	0.37***	0.41***	0.49***	0.44***	0.092***
	(0.081)	(0.087)	(0.090)	(0.085)	(0.021)
School exclusion	−0.67***	−0.58***	−0.80***	−0.83***	−0.14***
	(0.099)	(0.10)	(0.11)	(0.10)	(0.025)
School exclusion unknown	−0.22***	−0.24***	−0.23**	−0.26***	−0.060***
	(0.066)	(0.077)	(0.088)	(0.081)	(0.022)
Bullied in past year	−0.14***	−0.16***	−0.17***	−0.19***	−0.025
	(0.049)	(0.054)	(0.058)	(0.051)	(0.015)
Discrimination by teachers	0.0069	−0.039	−0.093	−0.017	−0.016
	(0.049)	(0.057)	(0.065)	(0.054)	(0.016)
Discrimination by teachers unknown	0.18	−0.095	−0.074	−0.039	−0.048
	(0.16)	(0.21)	(0.19)	(0.18)	(0.061)
External locus of control	−0.49***	−0.42***	−0.45***	−0.46***	−0.095***
	(0.054)	(0.062)	(0.067)	(0.062)	(0.016)
External locus of control unknown	−0.24*	−0.26*	−0.14	−0.26*	−0.033
	(0.13)	(0.15)	(0.16)	(0.14)	(0.043)
R^2	0.40	0.40	0.37	0.41	0.30
N	3483	3483	3483	3483	3483

Note: see note to Table 3. See Appendix A for details on the covariates. Standard errors robust to heteroskedasticity and clustering by school. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% significance level, respectively.

Table C.5: Heterogeneity by ethnicity

Dependent variable:	English (1)	Maths (2)	Science (3)	Average (best 8) (4)	Gold standard (5)
Panel A: Indian, Pakistani, Bangladeshi, and Any other Asian background					
Anticipates discrimination	0.29***	0.37***	0.38***	0.28***	0.13***
	(0.060)	(0.073)	(0.081)	(0.066)	(0.021)
R^2	0.42	0.42	0.38	0.42	0.33
N	1981	1981	1981	1981	1981
Panel B: Caribbean, African, and Any other Black background					
Anticipates discrimination	0.27**	0.20*	0.24*	0.19*	0.0012
	(0.11)	(0.12)	(0.13)	(0.12)	(0.035)
R^2	0.40	0.34	0.34	0.38	0.27
N	810	810	810	810	810

Note: see note to Table 3. Each coefficient comes from a separate regression of the KS4 outcome listed in the column heading on anticipated discrimination with a full set of controls (model 3; see Section 4 and Appendix A for details). Regressions are run separately for students from an Asian ethnic background (panel A) and students from a Black ethnic background (panel B).