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Research paper

Anticipated labour market discrimination and educational achievement[☆]

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ABSTRACT

Some theories suggest that ethnic minority students who anticipate discrimination in the labour market may invest more in easily observable human capital, such as education, to signal their productivity to employers. Empirical research has been hampered, however, by a lack of direct information on anticipated labour market treatment. We link ethnic minority student expectations of facing discrimination in the labour market to subsequent performance in high-stakes certificated national exams in England. Our findings suggest that anticipating labour market discrimination is associated with better exam performance, consistent with the view that students are seeking to counteract potential future penalties.

1. Introduction

How does the anticipation of discrimination in the labour market influence human capital investments 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 labour market returns to these unobserved investments (Coate and Loury, 1993; 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 et al., 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 omitting education).

☆ This paper builds on a chapter in Bertha's Ph.D. thesis (Rohenkohl, 2020). Anita proposed the research question. Anita, Bertha, and Nic constructed the data and guided the empirical analysis. Andy provided expertise on the UK education system. All co-authors contributed to drafting the paper and intellectual discussions. We thank two anonymous referees whose comments and suggestions have greatly improved this paper. We also thank Markus Eberhardt, Arne Risa Hole, Abhijeet Singh, Jon Temple, Emma Tominey, Gaston Yalonetzky, and participants at conferences and seminars for helpful comments and advice. The views expressed in this paper are those of the authors alone. For the purpose of open access, the authors have applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission.

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In this paper, we examine the impact of anticipating labour market discrimination on an easily-observed measure of educational achievement in a sample of ethnic minority students. To do so, we exploit a unique question in Next Steps, a large-scale survey of English adolescents, that measures 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. A secure-access version of Next Steps links to the National Pupil Database, an administrative dataset containing academic performance in high-stakes exams taken at age 15/16 at the end of compulsory schooling (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2020). These exams result in nationally accredited, externally graded and validated, academic qualifications, General Certificates of Secondary Education (GCSEs), that certify a student's performance in each exam subject, and that play an important role in accessing jobs and further education (see e.g. Jerrim, 2023; Machin et al., 2020).

We show that ethnic minority students who report anticipating labour market discrimination achieve GCSE grades in English, maths, and science that are approximately one quarter of a grade higher than ethnic minority students who do not anticipate such discrimination. They also perform better overall, being, 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. Our main findings are identified by comparing ethnic minority students of the same ethnic background living in the same region who do or do not anticipate labour market discrimination, and are conditional on an extensive set of controls, including socioeconomic and demographic characteristics, attitudes and beliefs, proxies for ability, and experience of discrimination by teachers. We obtain similar results when replacing region fixed effects with school or ethnicity-by-school fixed effects. We also find some evidence that students anticipating labour market discrimination exert more effort, in so far as they are more likely to spend every weekday evening doing homework, and that they take a higher number of GCSEs and are less likely to take a General National Vocational Qualification (a vocational alternative to GCSEs).

We use several further strategies to attempt to rule out the possibility that our results are driven by unobservables. 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 results to establish bounds on the cumulative effect of anticipated discrimination on GCSE exam performance. The bounds we estimate typically suggest a positive (cumulative) effect for anticipated discrimination.

Our paper contributes to a better understanding of the relationship between (anticipated) labour market discrimination and observable human capital, one of the broader consequences of labour market discrimination that has received less attention in the empirical literature than the direct labour market effects on, for instance, (un)employment or wages. Lang and Manove (2011) and Arcidiacono et al. (2010) raise the possibility that ethnic minorities anticipating statistical discrimination invest more in easily-observed human capital to signal or reveal their productivity to employers. In Lang and Manove (2011), direct observation of the productivity of ethnic minorities is assumed to be less reliable, so employers put more weight on observable education when assessing the productivity of ethnic minorities. As a result, while education signals productivity in the same way for everybody, 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 between groups in the reliability of the employer's direct observation of productivity, but employers instead believe ethnic minorities 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. argue that obtaining a college degree in particular directly reveals an individual's ability to the labour market (for a review of this literature, see Rohenkohl, 2020).[1] In our context, the arguments in these papers imply that ethnic minority students who anticipate discrimination have a stronger incentive to do well in their GCSE exams than those students who do not expect discrimination (and therefore see no reason to adjust their educational investments), with GCSE performance acting both as an (imperfect) signal of productivity and as a gateway to access further education, which can then provide additional signals to employers or can even fully reveal productivity. An advantage of focusing on GCSE performance rather than completed years of education is that the former provides a more comparable (across students) signal of educational achievement, whereas years of education covers a wide range of subjects studied at a variety of institutions, all potentially with very different signalling values.

The main contribution of our paper is that it adds to the empirical evidence testing these theories. Existing support for these theories relies on test scores from the Armed Forces Qualification Test (AFQT), which provides a measure of cognitive ability typically unobserved by employers.[2] Arcidiacono et al. (2010), for instance, find that returns to AFQT scores for college graduates are large upon labour market entry and do not change with experience, whereas for high school graduates AFQT returns are initially zero but rise quickly with experience. This suggests a college degree fully reveals ability, while employers only learn gradually about the ability of high school graduates, which raises the possibility of statistical discrimination in the latter labour market. Consistent with this notion, Arcidiacono et al. find a Black–White wage gap 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

[1] We thank an anonymous reviewer for pointing out that the size and possibly even sign of the predicted effects in the theoretical models in these papers may depend on the underlying assumptions made, in particular about the shape of the ability distributions. In our view, this only makes it more imperative to examine these effects empirically.

[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.

(2011) show that Black students of the same ability as White students (i.e. with the same AFQT score) acquire more years of schooling, while Nordin and Rooth (2009) present similar evidence for South- and non-European ethnic minorities in Sweden. Our approach of directly relating expectations of labour market discrimination to educational performance complements existing evidence based on AFQT scores, while also side-stepping various concerns raised with respect to these scores (see e.g. Darity and Mason, 1998; Rodgers and Spriggs, 1996). Having access to a measure of anticipated discrimination also allows us to identify which ethnic minority students the theoretical mechanisms proposed in Arcidiacono et al. (2010) and Lang and Manove (2011) should apply to, so that we can exploit within-ethnicity variation in the anticipation of discrimination for identification rather than relying on comparisons between ethnicities.

Our research also adds to a nascent, largely experimental, empirical literature suggesting that individuals engage in strategic behaviour to avoid anticipated discrimination (see e.g. Zussman, 2013; Charness et al., 2020; Kudashvili and Lergetporer, 2022; Aksoy et al., 2023). By being experimental, these papers have strong internal validity, but typically focus on less consequential outcomes. The relationship that we document between anticipated discrimination and exam scores is suggestive of such strategic behaviour in observational data, in the context of an outcome – results on high-stakes exams – of significance to future careers.

Finally, our research contributes to a literature on the drivers of educational outcomes of ethnic minorities in the UK, and the role played by anticipated discrimination in determining these outcomes. The UK has a large and diverse ethnic minority population.[3] Field experiments reveal these minorities face sustained high levels of discrimination (Heath and Di Stasio, 2019), with bespoke surveys also indicating racial harassment is pervasive in the workplace (Business in the Community, 2015). Discrimination is further mentioned as one reason why ethnic minorities are more likely to feel their career progression has failed to meet their expectations (Chartered Institute of Personnel and Development, 2017). Against this backdrop of labour market discrimination, ethnic minorities tend to place a high value on education (e.g. Fitzgerald et al., 2000; Modood, 2004; Strand and Winston, 2008), having higher post-compulsory-education participation rates conditional on socio-economic background and prior attainment (e.g. Leslie and Drinkwater, 1999; Fernández-Reino, 2016; Jackson, 2012). Some studies – without making the link to Arcidiacono et al. (2010) or Lang and Manove (2011) – suggest that ethnic minorities may view education as a way to counteract anticipated labour market discrimination (e.g. Li, 2018; Fernández-Reino, 2016; Jackson, 2012), and this sentiment is sometimes echoed in interviews with ethnic minority students (e.g. Dale et al., 2002, pp. 949–950; Scandone, 2018, p. 528).

Despite this, very little research exists to test this hypothesis in the UK, with Fernández-Reino (2016) providing a notable exception. Using the same anticipated discrimination measure as ours, they show that anticipated labour market discrimination does not affect the first transition made by ethnic minority students at the end of compulsory schooling (after taking GCSEs); i.e. whether to study academic courses, to pursue other types of qualifications (including vocational qualifications or apprenticeships, or retaking GCSEs), or to drop out of education altogether. This result is conditional on GCSE exam performance and a small set of control variables. Our paper instead shows that students anticipating labour market discrimination already have better GCSE exam performance. Our finding that strategic responses manifest early in the UK is perhaps not surprising given the importance of a good GCSE performance for accessing further education and labour market opportunities.

2. Institutional background

Before 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 and 10/11 respectively, and KS3 and KS4 in secondary school at ages 13/14 and 15/16 respectively. Since there is little or no grade repetition, pupils entering school in the same year took KS exams together. 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. Performance at KS4 is used by the Department for Education, policymakers, and academics to benchmark educational achievement and measure school quality.

KS4 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). The majority of students took a GCSE for each subject studied, while a minority took GCSE equivalents, such as the General National Vocational Qualification (GNVQ), designed to prepare students for employment. For English and maths no GCSE equivalents are available, so only a GCSE could be taken. GCSE grades ranged from A*-G, with grade A* being the highest grade awarded, grade C the lowest grade associated with a 'good pass', and grade G the lowest possible grade (with grade U being unclassified, i.e. no certificate awarded).[4] In 2006, the year that the students in our sample took their KS4 assessments, 62% of GCSE entries were awarded grade C or higher, with 6% awarded grade A* and 25% awarded grade C (Joint Council for Qualifications, 2022).

[3] https://www.ethnicity-facts-figures.service.gov.uk/uk-population-by-ethnicity/national-and-regional-populations/population-of-england-and-wales/latest shows population numbers from the 2021 Census.

[4] GNVQ grades are more limited; the four outcomes being Distinction, Merit, Pass, and Unclassified. Full Foundation GNVQs are broadly equivalent to four GCSE subjects at grades D-G and Full Intermediate GNVQs broadly equivalent to four GCSE subjects at grades A*-C. In 2006, there were around 120,000 GNVQ entries compared to 5.75 million GCSE entries in the UK, as well as half a million Short GCSEs (counting for half of a GCSE), 166,000 Applied Double GCSEs (vocational; counting for two GCSEs), 120,000 entry level certificates (equivalent to below a grade G at GCSE), and a small number of Applied Single GCSEs (Joint Council for Qualifications, 2022).

Table 1
Anticipated labour market discrimination by ethnicity.

	% No	% Yes	% Don't know	*N*
Asian or Asian British				
Indian	70.4 (45.7)	11.3 (31.7)	18.3 (38.7)	717
Pakistani	62.7 (48.4)	12.6 (33.2)	24.7 (43.1)	689
Bangladeshi	61.9 (48.6)	14.0 (34.7)	24.2 (42.9)	480
Any other Asian background	64.2 (48.2)	10.5 (30.9)	25.3 (43.7)	95
Black or Black British				
Black Caribbean	46.6 (49.9)	29.3 (45.6)	24.1 (42.8)	382
Black African	51.2 (50.1)	28.0 (45.0)	20.8 (40.6)	371
Any other Black background	52.6 (50.4)	26.3 (44.4)	21.1 (41.1)	57
Mixed				
White and Black Caribbean	61.9 (48.6)	17.6 (38.1)	20.5 (40.5)	302
White and Black African	60.3 (49.3)	XXX	XXX	73
White and Asian	71.1 (45.5)	9.4 (29.3)	19.5 (39.8)	128
Any other mixed background	78.8 (41.1)	XXX	XXX	85
Chinese or Other ethnic group				
Any other ethnicity	63.5 (48.4)	10.6 (30.9)	26.0 (44.1)	104
Total	61.7 (48.6)	16.3 (36.9)	22.0 (41.4)	3483

Note: based on the main ethnic minority groups identified in the 2001 Census. We combine Chinese and Any other due to the small number of students in each group. Redacted statistics (XXX) comply with terms and conditions of restricted-access data, so as not to identify any statistics based on fewer than 10 observations. Standard deviations in parentheses.

3. 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 interviewed in 2004, aged 13/14, and then annually until 2010, with a final interview in 2015 at age 25. In the initial waves, parents were also interviewed. 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. We use a secure-access version of these data that links to the National Pupil Database (NPD), a pupil-level census containing individual attainment data from KS2 onward (University College London, UCL Institute of Education, Centre for Longitudinal Studies, 2020).[5]

We examine the influence of anticipated discrimination on educational performance in a sample of ethnic minority students using the following linear reduced-form education production function:

$$T_{iera} = \alpha + \beta AD_{ier,a-1} + \gamma X_{ier,a-2} + \eta_e + \theta_r + u_{iera} \tag{1}$$

where the subscripts denote student i, of ethnic background e, living in region r, at age a. T_{iera} is one of five measures of KS4 performance, taken in secondary school, when students are aged 15/16; $AD_{ier,a-1}$ is a dummy for whether a student anticipates labour market discrimination; $X_{ier,a-2}$ is a vector of control variables; and u_{iera} is an error term. Though we use a single cross-section in estimation, we include an index for the student's age (a), 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 take their KS4 assessments. Eq. (1) is estimated using OLS, with standard errors that are robust to heteroskedasticity and clustering by school. In our main sample, we have 518 clusters.

In all specifications, we include fixed effects η_e for the main ethnic minority groups identified in the 2001 Census (as listed in Table 1), and region fixed effects θ_r (for the nine Government Office Regions, see Table 2). As a result, the coefficient on anticipated discrimination is identified by comparing students of the same ethnic background living in the same region who do or do not anticipate labour market discrimination. Lang and Manove (2011) find support for their theory by showing that Black people accumulate more years of education than White people with the same AFQT score. In general, however, between-group differences could also be explained by between-group unobservables – Lang and Manove examine school quality and parental background – or by alternative theories, e.g., in the UK context, immigrant optimism (see e.g. Fernández-Reino, 2016). Moreover, for a given behavioural response from the minority group, the gap in educational attainment might also depend on how many White people anticipate (positive or negative) discrimination and how they respond to it. Having a direct measure of anticipated discrimination instead allows us to identify which ethnic minority students the theoretical mechanisms proposed in Lang and Manove (2011) (and in Arcidiacono et al., 2010) should apply to, and so we can move to within-ethnicity comparisons that circumvent these issues.

We see the remaining threats to identification as coming mostly from the following (groups of) variables contained in u_{iera} that affect educational performance, and that potentially also influence anticipated discrimination: socioeconomic and demographic

[5] 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.

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***
Indian⊗	0.21	0.40	0.16	0.24	−0.08	0.000***
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
London⊗	0.41	0.49	0.42	0.40	0.02	0.184
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
Summer born⊗	0.25	0.43	0.25	0.24	0.01	0.519
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 only English at home	0.40	0.49	0.43	0.38	0.05	0.003***
Main language not English at home	0.19	0.39	0.18	0.19	−0.01	0.413
Speaks Eng. & other language(s) at home⊗	0.42	0.49	0.39	0.43	−0.04	0.015**
Mum aged under 25 at child's birth⊗	0.35	0.48	0.33	0.37	−0.03	0.040**
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
No siblings⊗	0.11	0.31	0.12	0.10	0.01	0.257
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***
Household getting by financially⊗	0.54	0.50	0.55	0.53	0.02	0.273
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

(continued on next page)

Table 2 (*continued*).

	Mean (1)	Std. dev. (2)	Yes/don't know (3)	No (4)	Diff. (5)	p-value (6)
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 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. ⊗ denotes reference categories in regressions. See Online Appendix A for details on the control variables.

characteristics, students' perceived experiences of discrimination, ability, and attitudes and beliefs. In what follows, we set out these threats in more detail, and discuss how we attempt to mitigate their impact with an extensive set of control variables. These control variables are described briefly in the text below, and in more detail in Online Appendix A, with summary statistics shown in Table 2. The causal interpretation of $\hat{\beta}$ in Eq. (1) therefore rests on a selection-on-observables assumption, which we probe in more detail in Section 4.3 below. We start by estimating a model that only contains ethnicity and region fixed effects, labelling this baseline specification without any control variables as model 0. In model 1, we add a set of arguably predetermined socioeconomic and demographic characteristics, while in models 2 and 3 we further 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.

Socioeconomic and demographic characteristics matter for exam results (e.g. Farquharson et al., 2022), and may also influence how aware students are of discrimination or to what extent they believe that they themselves might be subject to discrimination in the future.[6] The direction of bias from failing to control for these characteristics is not obvious. For instance, if students growing up in better socioeconomic circumstances (e.g. with richer, more highly educated parents who are more likely to work in professional occupations and less likely to interact with the welfare system) are less exposed to discrimination, then $\hat{\beta}$ should be downward biased. If these students are instead more aware or more exposed to discrimination, $\hat{\beta}$ should be upward biased. To capture these characteristics, in model 1 we add controls for 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, parental health, parental education, and several variables capturing parents' economic and financial circumstances. In addition, we control for the 2004 value of the Index of Multiple Deprivation (IMD), which captures the local area level of deprivation.

Other factors contained in u_{iera} might include whether students have experienced discrimination, or have experienced adverse events that they believe might be linked to discrimination, such as bullying or school exclusions. Such experiences are likely associated with worse educational outcomes (e.g. Brown and Taylor, 2008; Strand, 2011; Gorman et al., 2021), and may make students more likely to anticipate further discrimination in the future. Failure to take these into account could then lead to a downward bias in $\hat{\beta}$. In model 2 we therefore add controls for any temporary or permanent school exclusion and for whether the student has been bullied in the past year. 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 the anticipation of discrimination.

u_{iera} also likely contains student ability. A priori, it is not clear how this may affect our results, as we do not know the sign of the correlation between ability and anticipated discrimination. A concern might be that high-ability students think more about their future, or are more aware of how the world works (including the potential for discrimination), and are therefore more likely to report anticipating discrimination. If this is the case, the omission of ability would push towards a positive relationship between anticipated discrimination and GCSE performance. Our socioeconomic controls may already partially account for this, but in model

[6] 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 (i.e. via family, friends, and the broader treatment of ethnic minorities in society), as well as personal experiences in other areas of life, to form an opinion on anticipated labour market discrimination. Herda (2016), for instance, 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.

2 we also introduce more specific proxies of student ability and student attitudes and beliefs about the future: self-reported ability in English, maths, and science, whether the student has special educational needs (SEN), parental expectations about whether the student will go to university, student beliefs about their future educational choices, and whether students think about what they will be doing in future more generally.

Students may also possess other attitudes and beliefs that correlate with anticipating labour market discrimination and educational performance. For instance, students who are more pessimistic or who believe that they do not have much scope to shape their life outcomes (i.e. who have a more external locus of control; see Rotter, 1966) may also be more likely to anticipate discrimination. Having a more external locus of control is linked to weaker GCSE performance (Mendolia and Walker, 2014), which could reflect its influence on expected payoffs to human capital investments (e.g. Coleman and DeLeire, 2003; Caliendo et al., 2022) or its correlation with ability (Cebi, 2007). Hence, any bias from neglecting these considerations is likely to be downward. In model 3, we add 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 does not simply proxy for a more general outlook in life in our results.

Finally, we discuss two sources of bias that are distinct from omitted variable bias, and that are therefore less readily mitigated by the inclusion of a rich set of control variables. We argue, however, that neither of these would be able to explain the positive coefficient we find later for anticipated discrimination.

The first remaining concern relates to the possibility of reverse causality. In both Arcidiacono et al. (2010) and Lang and Manove (2011), there is a level of education where an individual's productivity is fully revealed and where, therefore, there is no longer any reason for the employer to engage in statistical discrimination. Arcidiacono et al., for instance, find that a college degree fully reveals ability to employers. At all levels of education below this, including the lowest level (high-school drop-outs), they find evidence consistent with statistical discrimination (see e.g. their figure 2). So it may be the case that students with the best GCSE performance expect to reach a level of education that fully reveals their productivity, and are therefore less likely to report anticipating discrimination in the labour market. This would create a negative correlation between GCSE performance and anticipated discrimination, causing a downward bias in $\hat{\beta}$. In Lang and Manove, there is also no statistical discrimination for those at the lowest end of the education distribution. This would complicate the signing of the bias in $\hat{\beta}$ as now some students who expect to receive very poor GCSE grades might also be less likely to anticipate discrimination. Empirically, however, Lang and Manove tend to find evidence consistent with their proposed form of statistical discrimination across most of the distribution of AFQT scores or education, except for small fractions of people at the edges of these distributions – mostly those situated at the top end – suggesting a small and likely again downward bias in $\hat{\beta}$.[7] The second remaining concern is measurement error in anticipated discrimination. Since $AD_{i,a-1}$ is a binary variable, such measurement error should lead us to underestimate its true effect.[8]

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.[9] 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 corresponding variable is included in the estimated model.[10]

For our dependent variables, we focus on GCSEs – national exams, taken by almost all students – because better GCSE grades are unambiguous observable signals of educational achievement that are crucial for further education and future careers (Machin et al., 2020; Jerrim, 2023), and students are acutely aware of this (Denscombe, 2000). GCSE results determine whether students can continue to study a subject in KS5 (A levels), as well as the quality of the KS5 institution and course they can enroll in. They also play an important role in university admissions, through GCSE entry requirements that vary across universities and subjects, and because they affect predicted A level grades that feed into admission decisions. For students leaving education at age 16 and entering the workforce, GCSEs are the only certificated educational qualifications they possess and can therefore include on their CVs. Employers view good GCSE grades (typically grade C or above) as useful indicators of some core competencies, especially numeracy and literacy, required of their employees (e.g. Confederation of British Industry, 2008; Learning and Skills Council, 2006; Confederation of British Industry/Pearson, 2012), with a majority of employers viewing maths and English GCSEs at grades A*-C to

[7] This reverse causality bias would be further dampened if students, when answering the question about anticipated labour market discrimination at age 14/15, cannot perfectly predict whether or not they will end up at a level of education where there is no statistical discrimination, or if our control variables pick up most of the predictable reasons for why students believe they will reach such a level of education.

[8] Measurement error in a binary variable leads to a bias in the opposite direction of the true effect. In practice, this bias is typically an attenuation bias; i.e. it would only bias the *sign* of the estimated coefficient if the measurement error is very severe (Aigner, 1973).

[9] 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.

[10] 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. These variables exhibit varying degrees of missingness as seen in Table 2, with household income having by far the greatest proportion of missing values (31%).

be “significant” or “critical” factors in assessing job applicants (Shury et al., 2014). In line with this, just failing to obtain a grade C in English increases the probability of not being in education, employment or training at age 18 (Machin et al., 2020).

We focus on performance in compulsory subjects: English (language), 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 policy circles.[11] 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, 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 Eq. (1) represent the average grade difference associated with anticipating labour market discrimination.[12] 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. Some authors emphasise that test scores convey only ordinal information (see e.g. Lang, 2010; Bond and Lang, 2013; Jacob and Rothstein, 2016, 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).[13] 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.[14]

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’.[15] At this age, 16% of our estimation sample respond ‘yes’ while 22% respond ‘don’t know’. Reasons for ‘don’t know’ responses are unknown; they may reflect a combination of lacking a firm opinion, uncertainty, not wanting to disclose one’s opinion, or finding the question too difficult to answer (see e.g. Piekut, 2021; Alwin and Krosnick, 1991). In our main analysis, we combine ‘yes’ and ‘don’t know’ responses to create a binary variable that distinguishes between students who 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.

Table 1 shows how our measure of anticipated labour market discrimination varies across ethnic groups. Approximately half of Black or Black British students entertain the possibility of facing labour market discrimination, falling to just under 40% for students of mixed White and Black ethnic heritage, with responses fairly evenly split between ‘yes’ and ‘don’t know’, but tilting towards ‘yes’. Among Asian or Asian British students, and White and Asian students, approximately one third entertain the possibility of labour market discrimination, with a smaller proportion of ‘yes’ compared to ‘don’t know’ responses. Overall, ‘yes’ responses are more varied across ethnic groups, ranging from 9% to 29%, while ‘don’t know’ accounts for between 18% to 25% of responses.

Fig. 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.[16] Summary statistics presented in Table 2 for the whole sample, and also separately by expectations of facing labour market discrimination, show higher average grades across these three subjects among those anticipating discrimination, as well as a higher probability of attaining the gold standard. At a 5% significance level, there is balance across 45 of 57 controls (including reference categories and dummies for missing values, but excluding ethnicity dummies). Exceptions are that those anticipating discrimination are more likely to speak only English at home and less likely to speak another language alongside English, less likely to have a mother younger than 25 at birth, less likely to have three or more siblings, more likely to have parents with a degree, less likely to be part of a household that reports managing well financially and more likely to come from a household that says it is getting into financial difficulties. 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.

[11] 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 (AA, 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.

[12] For science, but not for English or maths, the grade might be based on GCSE equivalents like GNVQs or vocational GCSEs for a small number of students. For fewer than 1% of observations, the science point score takes on ‘in-between’ values of 49 and 55, corresponding to a Merit and Distinction grade respectively for a Full Intermediate GNVQ (see Annex M in National Pupil Database, 2011). 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 Fig. 1 below.

[13] For some students these aggregate performance measures might feature the GCSE equivalents listed in footnote 4.

[14] 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.

[15] 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).

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

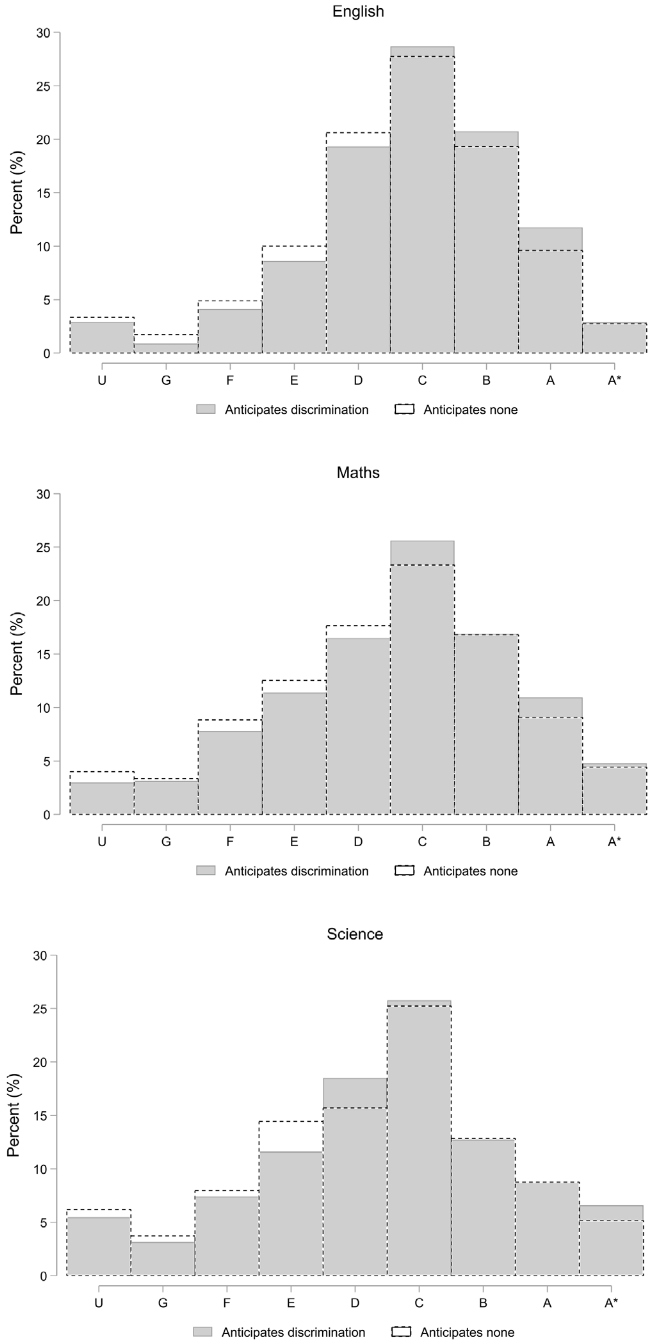

Fig. 1. Distribution of GCSE grades by anticipated discrimination.

4. Results

4.1. Main results

Table 3 reports the estimated coefficients on anticipated discrimination in Eq. (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 Online Appendix C). Panel A presents results from our baseline specification, model 0, which includes ethnicity and region fixed effects only. Students who anticipate labour market discrimination score approximately one quarter of a grade higher in each of the core GCSE subjects compared to students of the

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 (ethnicity and region fixed effects only)					
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
N	3483	3483	3483	3483	3483
Panel B: model 1 (model 0 plus socioeconomic and demographic variables)					
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
N	3483	3483	3483	3483	3483
Panel C: model 2 (model 1 plus ability and experienced discrimination variables)					
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
N	3483	3483	3483	3483	3483
Panel D: model 3 (model 2 plus locus of control)					
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
Panel E: model 3 (replacing region with school fixed effects)					
Anticipates discrimination	0.25***	0.33***	0.33***	0.24***	0.077***
	(0.052)	(0.060)	(0.063)	(0.055)	(0.017)
R^2	0.51	0.51	0.49	0.52	0.41
N	3370	3370	3370	3370	3370
Panel F: model 3 (replacing region with school×ethnicity fixed effects)					
Anticipates discrimination	0.33***	0.39***	0.41***	0.32***	0.10***
	(0.061)	(0.071)	(0.078)	(0.067)	(0.020)
R^2	0.58	0.59	0.56	0.59	0.52
N	2499	2499	2499	2499	2499

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 in Panels A-D gradually include more control variables, as described in Section 3 and, in more detail, in Online Appendix A. Tables C.1-C.4 in Online Appendix C report the estimated coefficients for all covariates for models 0 through to 3. Panels E and F drop region fixed effects for school and school×ethnicity fixed effects, respectively, estimated using `reghdfe` in Stata (Correia, 2019). In these panels, N excludes singleton observations. '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 onto 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. Standard errors robust to heteroskedasticity and clustering by school. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

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, column 5 shows 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 an 18% increase from the sample baseline of 45% among those that do not anticipate discrimination.

Panel B reports results for model 1, which adds control variables to take into account socioeconomic and demographic 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 further 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 significant for science at a 10% significance level). Adding these variables again substantially increases the R^2 while leaving the estimated coefficients on anticipated discrimination almost unchanged.

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 in life. Consistent with prior research (e.g. Mendolia and Walker, 2014), students with an external LOC have weaker GCSE performance (Table C.4). Notably, 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 lower 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 the remaining panels of Table 3, we continue with model 3 but replace region fixed effects with school fixed effects (Panel E) or with school×ethnicity fixed effects (Panel F). As schools in England typically draw students from narrowly-defined geographical catchment areas, these school fixed effects also partly capture relevant differences between neighbourhoods, for instance in local segregation. A disadvantage of identifying the effect of anticipating discrimination from students attending the same school is that for some schools in our sample we observe few ethnic minority pupils, with schools dropped when only one ethnic minority student is observed. This especially affects the results with school×ethnicity fixed effects. Despite this, results with school fixed effects are remarkably similar to those with region fixed effects, while, if anything, including school×ethnicity fixed effects increases the size of the estimated coefficients. In light of these findings, in the remaining analysis, we mostly focus on the model with ethnicity and region fixed effects and a full set of controls (model 3).

In Tables D.1–D.3 in Online Appendix D we examine coefficient heterogeneity along several dimensions – by ethnicity, gender, and school ethnic composition. We find somewhat larger coefficients for Asian or Asian British students compared to Black or Black British students,[17] and for female versus male students, and smaller coefficients for students attending majority-White schools, but we rarely reject equality of coefficients between groups.

We also look at whether anticipated discrimination affects the frequency of doing homework or the number and types of qualifications students pursue. These additional analyses come with some caveats, so we only provide a brief discussion here, leaving the results and further details for Online Appendix E.

We first examine whether students anticipating labour market discrimination exert more effort as a potential mechanism for improving their GCSE performance. In wave 2, which corresponds to the first of two years dedicated to studying KS4 subjects and a year before taking KS4 assessments, students are asked how many weekday evenings they spend doing homework during term time. We analyse both the number of evenings and a set of binary variables indicating whether homework is done on at least one, two, and so forth, evenings. Although an imperfect proxy of effort – it ignores the hours spent on homework, homework done at the weekend, and any additional study beyond school-assigned homework – it takes a snapshot of behaviour well in advance of KS4 assessments that may cumulate towards better performance. As homework policies vary across schools (just under 70% of students report being given homework most days, for instance), we present results with school fixed effects in addition to results with region fixed effects. Furthermore, as the question pertains to term-time behaviour and many students are interviewed during summer holidays, we also separately present results restricting the sample to students interviewed during term time.

Results are presented in Table E.1. Across all specifications, we find that students anticipating labour market discrimination are more likely to spend every weekday evening doing homework. Focusing on students interviewed during term time, which should reduce measurement error, we find that students anticipating discrimination are between five and seven percentage points more likely to spend every weekday evening doing homework, representing an increase of about a quarter to a third of the baseline probability for students not anticipating discrimination. For students interviewed during term time, there is also some evidence of being more likely to spend at least four evenings doing homework if students anticipate discrimination. For the number of weekday evenings spent on homework, anticipated discrimination is only significant (at a 10% significance level) when we include school fixed effects and restrict the sample to students interviewed during term time.

Finally, we explore whether anticipating discrimination changes the number or type of qualifications that students pursue at KS4. Most students take between 7–10 GCSEs (or the equivalent of this in alternative qualifications), complementing compulsory subjects with optional GCSEs or vocational qualifications (most commonly GNVQs and Applied Double GCSEs – see footnote 4) in a range of subjects. As students take bundles of subjects/qualifications, it is difficult to unambiguously identify which combinations provide better signals of productivity. Moreover, the signalling value of a given optional choice might also differ depending on other optional choices (e.g. subjects/qualifications may be chosen to display a range of skills) and on the counterfactual choice (taking an alternative, or one fewer, optional subject/qualification). As a result, we restrict ourselves to a broad comparison between the more academic GCSEs, which are, for instance, more useful for further study, and the main vocational qualifications. For students taking at least 7 GCSEs, we also create a series of binary variables to analyse optional GCSE subject choices. As schools often restrict student choices, we present results with school fixed effects in addition to those with region fixed effects.

Table E.2 in Online Appendix E shows that students anticipating labour market discrimination take 0.15 more GCSEs compared to students that do not (this counts only full GCSEs, so excluding the GCSE equivalents listed in footnote 4). They are also around 2–3 percentage points less likely to take GNVQs (relative to a baseline of 21% for students not anticipating discrimination) but not any less likely to take Applied Double GCSEs. In terms of optional GCSE subject choice (Table E.3), we do not find clear patterns: students anticipating discrimination are about 2.5 percentage points more likely to take all three separate sciences (instead of dual or single science) against a baseline of 7% for students who do not anticipate discrimination, and are around 6 percentage points more likely to take history (against a baseline of 32% for those not anticipating discrimination), but these are the only two robustly significant results among the 17 possible choices we consider.

[17] We do not pursue any further disaggregation into more narrowly defined ethnicities due to small sample sizes.

In summary, students who anticipate labour market discrimination achieve results that are approximately one quarter of a grade higher in core 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. They are also around eight percentage points more likely to attain the 'gold standard'. 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. Students anticipating discrimination are also more likely to spend every weekday evening doing homework, take more GCSEs, and are less likely to take a GNVQ.

To provide some insight into the magnitude of the effects on GCSE grades, for students taking GCSEs around the same time as our sample, Hodge et al. (2021) find that the average return to a one grade GCSE improvement is a £8,500 rise in the present value of lifetime earnings (around 1.7% of total present value earnings, at £515,000),[18] while discounted returns to a one grade improvement in English and maths are approximately £7,300 and £14,500, respectively. However, for ethnic minorities, the returns to better GCSE grades might be very different.[19] Moreover, while it may be individually rational for students to invest more in education in response to anticipating discrimination, from society's point of view, this is an inefficient overinvestment in education (for signalling reasons) compared to a world without statistical discrimination (see Lang and Manove, 2011).

4.2. Robustness: alternative data choices

We now examine the sensitivity of our main results on GCSE performance to various changes in variable definitions and the sample used in estimation. In all robustness checks that follow, we start from model 3. We first examine the implications of alternative ways to categorise responses to the anticipated discrimination question. In our main analysis, we group 'yes' and 'don't know' responses. In Panel A of Table 4, we instead 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 as 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 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 outperform 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 samples 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.[20] Estimated coefficients in these weighted regressions are comparable to their unweighted counterparts. In Panels B and C 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 Online Appendix A.4 for details). In Panel B, we present results using factor analysis to construct this underlying index, with our results invariant to this modification. In Panel C, 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 D, 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. In Panel E, 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 Eq. (1), and may even reverse its sign (see e.g. Bond and Lang, 2013; Jacob and Rothstein, 2016; Schröder and Yitzhaki, 2017, for discussions). Kaiser and Vendrik (2023) 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

[18] This would imply that our effect of a one fifth of a grade increase across the average of the best 8 GCSEs corresponds roughly to $(1/5)\times £8,500\times 8 = £13,600$, or around 2.6% of total present value earnings.

[19] The arguments in Arcidiacono et al. (2010) and Lang and Manove (2011), for instance, suggest that the return to education for ethnic minorities should be higher, as an additional benefit for them of better GCSE performance would come from a reduction in statistical discrimination. There may be other reasons, however, that lower the returns for ethnic minorities. Lang and Manove (2011), for instance, find similar earnings for Black and White workers controlling for AFQT scores, suggesting Black workers are not rewarded for their greater education (which they attribute to missing variables or remaining labour market discrimination).

[20] Solon et al. (2015) discuss the circumstances under which using weights in regression analysis could be both appropriate and preferred.

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 3 and Online 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.

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 on the probability of obtaining at least (rather than less than or equal to) each specified grade (except for U). Beyond forming the basis for the Kaiser–Vendrik test, the results in Table 6 are of independent interest, having the advantage that they 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 often required to access jobs and further education). To aid the interpretation of the size of the estimated coefficients the table includes the baseline probabilities of obtaining at least each grade for those students who do not anticipate discrimination. We see, for instance, that anticipating discrimination increases the probability of getting at least a C by 6 percentage points for English (from a baseline probability of 59% for those not anticipating discrimination), by 8 percentage points for maths (from a baseline of 54%), and by 5 percentage points for science (from a baseline of 52%).

Within each subject, the coefficients on anticipated discrimination have the same sign across all regressions, establishing that any monotonically increasing transformation of the values assigned to grades would not change the sign of $\hat{\beta}$ in our earlier results. 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.

4.3. Robustness: selection on unobservables

Lastly, we investigate in more detail the possibility that our results are driven by unobservables. While we are able to include an unusually rich set of control variables in our analysis, these are unlikely to perfectly capture all relevant unobservables. Nevertheless, as long as these controls are correlated with the relevant unobservables, we can use the change in results when these controls are added to infer the likely remaining influence of selection on unobservables. In this respect, the stability of the estimated coefficients alongside substantial increases in explanatory power when adding 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 how changes in the estimated coefficient and 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 Eq. (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}.[21] For $R_{max} = 1$

[21] 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.

Table 5
Alternative 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: 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 C: 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 D: 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 E: 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 3 and Online Appendix A for details). Panel A uses survey weights in estimation. Panel B uses factor analysis to construct the locus of control variable from which our external locus of control dummy is derived. Panel C drops any individual responding 'don't know' to any question used in the construction of the locus of control variable. Panel D drops individuals who report a different ethnicity in wave 1 and wave 2. Panel E 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).

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
Baseline	0.97	0.95	0.90	0.80	0.59	0.32	0.12	0.03
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
Baseline	0.96	0.93	0.84	0.71	0.54	0.30	0.14	0.04
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
Baseline	0.94	0.90	0.82	0.68	0.52	0.27	0.14	0.05
N	3483	3483	3483	3483	3483	3483	3483	3483

Note: 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 3 and Online Appendix A for details). The different panels focus on grades for different subjects. 'Baseline' is the sample mean of the outcome variable for students that do not anticipate discrimination. Standard errors robust to heteroskedasticity and clustering by school. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

Table 7
Oster (2019) analysis.

	Implied δ for $\beta = 0$		Bounds for β when $\delta = 1$	
	$R_{max} = 1$ (1)	$R_{max} = 1.3\widetilde{R}$ (2)	$R_{max} = 1$ (3)	$R_{max} = 1.3\widetilde{R}$ (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 3 and Online 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).

(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.[22]

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. 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 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. 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 other persistent traits, as well as 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 et al. (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 et al. (2015) show that, in simulations, the VA specification estimated by OLS performs well 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:

$$T_{iera} = \tau + \rho T_{ier,a-l} + \pi AD_{ier,a-1} + \theta X_{ier,a-2} + \varepsilon_{iera} \tag{2}$$

where $T_{ier,a-l}$ is the KS2 test result taken in the same subject at age 10/11 ($l = 5$), or the KS3 result taken in the same subject at age 13/14 ($l = 2$), and where we standardise KS2 and 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 some further caveats. We observe students' 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 and KS3 scores. As a result, the coefficient on anticipated discrimination, π, does not capture the total cumulative effect of anticipated discrimination as in our previous estimates. In Online Appendix B we show how the true cumulative effect of anticipating discrimination can reasonably be bounded by π and $\frac{\pi}{1-\rho}$, being close (or even identical) to $\frac{\pi}{1-\rho}$ 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 π and $\frac{\pi}{1-\rho}$, 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.[23]

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

[22] 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 removed. In a simulation exercise where the true effect is known and different combinations of control variables are randomly excluded, Oster

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
$\hat{\pi}/(1-\hat{\rho})$		0.17		0.18		0.13
		(0.056)		(0.061)		(0.050)
p-value $\pi/(1-\rho)=0$		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 $\pi/(1-\rho)$ (see main text for details) and its standard error, and a p-value for the null hypothesis that $\pi/(1-\rho)=0$.

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
$\hat{\pi}/(1-\hat{\rho})$		0.18		0.14		0.044
		(0.065)		(0.091)		(0.078)
p-value $\pi/(1-\rho)=0$		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 $\pi/(1-\rho)$ (see main text for details) and its standard error, and a p-value for the null hypothesis that $\pi/(1-\rho)=0$.

the sample for 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 $\frac{\hat{\pi}}{1-\hat{\rho}}$ together with its standard error, as well as a p-value for H_0: $\frac{\pi}{1-\rho}=0$. 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), $\hat{\pi}$ is approximately half the magnitude of the coefficient in the non-VA model, and is statistically significant throughout, while $\frac{\hat{\pi}}{1-\hat{\rho}}$, 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 Online Appendix B we discuss how $\hat{\pi}$ 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 $\hat{\pi}$ is smaller in this model, and only significant for English. In contrast, estimates of $\pi/(1-\rho)$, which in this model is even more likely to be close to the true cumulative effect, are similar to

(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.

[23] In our derivations in Online 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 Eq. (1) these biases should attenuate the true effect, but in the VA model these biases in the estimation of π and hence also $\frac{\pi}{1-\rho}$ are harder to sign. $\frac{\hat{\pi}}{1-\hat{\rho}}$ might further be affected by biases in estimating ρ: persistent unobservables would tend to lead to an upward bias in $\hat{\rho}$, while iid measurement error in test scores would push towards a downward bias.

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.

5. Conclusion

Labour market 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 ethnic minority students who anticipate such discrimination have stronger incentives to invest in observed education to reveal or signal their productivity to employers. While some 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 certified 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, proxies for ability, and experienced discrimination by teachers. 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. We further find some evidence that students who anticipate discrimination are more likely to do homework every weekday evening, take slightly more GCSEs in total, and are less likely to take a (vocational) GNVQ.

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. One way to interpret these findings is that not all of the burdens of labour market discrimination are expressed through worse labour market outcomes, and that some consequences may already be felt prior to entering the labour market if students find it necessary to invest more in observable human capital as a strategic response to counteract discrimination later in life.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2024.04.014.

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