Perceived Discrimination across Institutional Fields: Racial Minorities in the United Kingdom

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Submitted February 2014; revised November 2014; accepted November 2014

Abstract

Existing research has developed a wide range of evidence about predictors of perceived discrimination among minorities, but often generates conflicting evidence across studies. I claim this may be due to the measurement strategy. Existing research often uses cross-sectional surveys that ask minorities about their experiences with discrimination, but these questions cannot determine whether subjects with higher levels of perceived discrimination are more likely to experience discrimination or are just more likely to interpret events through the lens of discrimination. In this article, I propose a new strategy designed to measure when minorities use discrimination as a heuristic for understanding society. I use an original online survey of non-Whites in the United Kingdom and provide vignettes that describe racial inequality in education, employment, politics, the arts, and business. I then ask respondents how they would explain each form of inequality. This ensures that all minority respondents are reacting to the same stimulus. In addition to the new measurement strategy, I make a theoretical contribution to the standard analysis of variation across minority individuals by emphasizing variation in perceived discrimination across institutional fields. This approach has implications for debates about racial minorities in the United Kingdom and perceived discrimination in general.

Perceived discrimination among minorities is a key indicator of social cohesion. If minorities believe they are fundamentally disadvantaged in the broader society, they are more likely to engage in disruptive protest and violent revolt (Lijphart, 2012). In addition, perceptions of discrimination may lead minorities to develop impermeable social and cultural barriers with the majority population (Safi, 2010; Wimmer, 2013: pp. 174–203).

Despite widespread agreement that perceived discrimination is an important measure of social cohesion, there is no consensus about which minorities are more likely to have high levels of perceived discrimination. In fact, different studies often reach contradictory conclusions. Some researchers find higher levels of perceived discrimination among immigrant-origin minorities who recently arrived in their host society, while other studies find the opposite (Portes et al., 1980; Aguirre et al., 1989). One explanation for these conflicting results is the way existing literature measures perceived discrimination. Most research uses cross-sectional surveys that ask about experiences with discrimination or opinions on the prevalence of discrimination in society. That approach is vulnerable to measurement bias from differential item functioning. Questions that explicitly ask about perceived discrimination cannot determine whether subjects with higher levels of perceived discrimination are more likely to experience discrimination or are just sensitive to the issue and more likely to use discrimination...
as a heuristic for interpreting events. In addition, experiences with discrimination and sensitivity to discrimination may influence survey responses in ways that vary across subjects and are unobservable to the researcher. As a result, analysis of the overall sample may yield unreliable relationships between the individual-level characteristics of interest and perceived discrimination. In short, measurement error may help explain the conflicting results across studies.

I propose that different aspects of discrimination be approached through distinct research strategies. The most reliable way of studying when minorities are more likely to experience discrimination is by using experiments that manipulate minority characteristics (e.g., skin color, national origin, or religion) in a given situation (e.g., job application or social interaction) and then observe majority individuals' responses (Sen and Wasow, 2014). In contrast, studies of minorities are more appropriate for determining which minorities are more likely to view life through the lens of racial discrimination. In this article, I focus on the latter task with an online survey of non-Whites in the United Kingdom.

I build on previous studies by proposing a new strategy to measure when minorities use discrimination as a heuristic for understanding society. Instead of posing questions that explicitly ask respondents to reflect on discrimination, I provide vignettes that describe racial inequality in education, employment, politics, the arts, and business, and then ask respondents to generate their own explanation for each form of inequality. Previous research has asked minorities about their views on general racial inequality. My approach has implications for debates about racial minorities in the United Kingdom and perceived discrimination in general. Most notably, my focus on variation across institutional fields implies that all minorities have the capacity to view life through racialized or non-racialized heuristics. This complicates the search for which type of minority is more or less likely to view society in racialized terms and has both optimistic and pessimistic implications for social cohesion.

### Generating Hypotheses about Perceived Discrimination in the United Kingdom from Existing Literature

Racial discrimination is highly salient in the United Kingdom. The United Kingdom has a long history of racial inequality dating back to the transatlantic slave trade. More recently, non-Whites from around the world immigrated to the United Kingdom in the decades after World War II and often suffered integration difficulties due to their status as racial minorities (Gilroy, 1993; Phillips and Phillips, 1998). There is also a long tradition in the United Kingdom of using the concept of racial discrimination as a framework for understanding the inequalities suffered by non-Whites (as opposed to other European countries where similar inequalities are framed as a function of culture, religion, or national origin) (Bleich, 2003; Givens and Case, 2014). Yet, despite the salience of racial discrimination, non-Whites in the United Kingdom do not always view their lives through the lens of race. In fact, existing literature generates three predictions for why some minorities in the United Kingdom will be more likely than others to use racial discrimination as a heuristic for interpreting events.

The first hypothesis focuses on social class. In some respects, this is an alternative framework for understanding inequality because it is possible that some non-Whites in
the United Kingdom will interpret inequalities as the result of social class differences (Miles, 1982). In addition, research on the interaction between race and class suggests that poorly educated and working-class minorities are the most likely to suffer from racial discrimination (Sivanandan, 1976; Rex and Tomlinson, 1979; Miles, 1993). This imbalance in disadvantage should shape how different minorities view the world (Chong and Kim, 2006).

**H1:** Non-Whites with lower socio-economic status will be more likely to cite racial discrimination as a cause of inequality.

A second argument focuses on generational differences. Most racial minorities in the United Kingdom have immigrant origins, and when immigrants arrive they tend to interpret their place in society through the lens of their foreign origins. In contrast, non-Whites who are born in the United Kingdom will inevitably be socialized into British norms and social categories. As a result, second-generation non-Whites will be more likely to interpret life through the racial categories commonly used in the United Kingdom (Paul, 1997; Goulbourne, 2009). This is consistent with research from across Europe and North America, which finds that first-generation immigrants are often more positive and optimistic about life in the new country, compared with the second generation, which is more likely to be disappointed, alienated, and sensitive to their vulnerability to discrimination (Waters, 1999; Maxwell, 2010a,b).

**H2:** Non-Whites born in the United Kingdom will be more likely to cite racial discrimination as a cause of inequality.

The third argument highlights differences among non-Whites. In contemporary Britain there are many established non-White communities, the largest of which are Bangladeshis, Caribbeans, Indians, Pakistanis, and Sub-Saharan Africans. Some argue that racial discrimination is of particular concern to the Black minorities with origins in the Caribbean and Sub-Saharan Africa. Black minorities are the ones most likely to be defined by ‘racial’ differences because the concept of race comes from the transatlantic slave trade and the distinction between people of African and European descent (Gilroy, 1993). Other non-Whites face different integration challenges. Most notably, for South Asians the primary barrier has been whether their religious needs will be respected by a British society constructed around Christian norms (Modood and Berthoud, 1997; Modood, 2010).

**H3:** Black non-Whites should be the most likely to cite racial discrimination as a cause of inequality.

### Institutional Fields and Perceived Discrimination

The main theoretical proposition in this article is that individual-level attributes matter less than institutional fields for predicting perceptions of discrimination. Institutional fields are societal environments with specific norms and ideological principles (Fligstein, 2001; Martin, 2003). Existing research argues that institutional fields are rich with symbolic meaning that shape our attitudes, behavior, and perceptions of social situations (Blumer, 1969; Bourdieu, 1989). Given the fact that we should expect different social logics across institutional fields, I claim that evaluations of racial discrimination should also vary across fields.

**H4:** The relative importance of individual-level factors for predicting perceived discrimination will vary according to the field.

**H5:** There is more variation in perceived discrimination across fields than across individual-level factors.

To predict the fields in which minorities will be most likely to perceive discrimination, I draw on research about the strategies minorities use to preserve their self-esteem when confronted with evidence of potential discrimination (Crocker and Major, 1989). When minorities have less control over the outcome, they are more likely to use discrimination to explain negative results and protect their self-esteem by not blaming themselves. But when minorities have more control over the outcome they will avoid using discrimination to explain negative results. This strategy protects minorities’ agency and allows them to avoid being categorized in a lower social status (Crosby, 1984; Kaiser and Miller, 2001).

**H6:** Non-Whites will be more likely to cite discrimination as a cause of racial inequality in fields where they have less control over the outcome.

### Data

The data in this article are from a survey conducted during 24–27 February 2012 by the market research agency YouGovUK. At the time of the study, YouGov maintained a panel of approximately 350,000 potential survey respondents in the United Kingdom. YouGov recruits panel members through standard (online and offline) advertising campaigns and partnerships with a broad set of websites. On completion of a survey, respondents are compensated with points that are
In your opinion, what is the most important explanation for why there are few BME CEOs of large corporations in Britain?

These fields were selected to test H6 by providing variation in the extent of minority control over the outcomes. Minorities in the United Kingdom have the most control (and therefore should have the least perceived discrimination) in secondary education where graduation outcomes are largely driven by meritocratic testing and there is no limit on the number of people who can succeed. This does not imply that minorities have complete control over their educational outcomes, as research suggests there are several structural barriers that hinder the educational attainment of minorities in Europe (Borgna and Contini, 2014). However, research also finds that the UK educational system allows minorities more access to post-secondary education than other European countries (Griga and Hadjar, 2014). Moreover, the key to my research design is that minorities have less control in the other fields. As such, minorities should have the least control (and therefore the most perceived discrimination) in politics, arts, and CEO positions. All three fields involve elements of merit but are highly competitive and dependent on networks and luck. Existing research on minority political candidates suggests that complex internal party dynamics are more important than any objective measure of candidate quality for determining whether immigrant-origin minorities are selected as candidates for winnable seats (Dancygier, 2013; Street, 2014). Similarly, there is extensive research on the importance of networks and connections for securing high-level positions in business and accessing resources in the art world (Granovetter, 1973; Ostrower, 2002; Hwang and Kim, 2009). Finally, unemployment is in-between. Getting hired is not as meritocratic as passing secondary school exams, as there is ample opportunity for employer discretion and discrimination (Riach and Rich, 2002). However, unlike accessing specific high-level political offices, artistic funding, or CEO positions, individuals have some control over the extent to which they obtain some sort of job and avoid unemployment.

I code responses to the open-ended questions into three general categories: racial discrimination, blaming minorities, and socio-economic status. I also code whether responses are a mixture of these categories, whether they pose an ‘other’ explanation, or whether they should be classified as ‘don’t know’. I limit coding to three main substantive categories because they were the most common responses and the most general way of organizing responses.8 The coding scheme is
summarized in Table 1 and produces 12 response categories. Full details on coding for the independent variables can be found in the appendix.

Perceived Discrimination across Individuals and Institutional Fields

To evaluate H1–H5, Table 2 presents multinomial logistic regression models that estimate the likelihood of explaining racial inequality in each of the fields by racial discrimination, socio-economic factors, blaming minorities, a mixture of the explanations, or ‘other’/‘don’t know’. For each model the baseline category is ‘Discrimination’, so the coefficients indicate the likelihood that respondents choose the respective classification as opposed to discrimination. In an ideal world I would estimate models that account for each of the 12 classifications in my coding scheme. However, that would require a significantly larger sample size to have enough cases in each response option for all values of each covariate. Given that constraint, I select these five categories as the most substantively meaningful.

The results in Table 2 support H1 because having no educational qualifications is consistently associated with being more likely to cite discrimination as opposed to a mixture of explanations for inequality. In addition, having a higher education degree is associated with being more likely to cite a mixture of explanations as opposed to discrimination in four of the five fields. There is limited support for H2 as being born in the United Kingdom is consistently associated with being more likely to cite discrimination as opposed to blaming minorities. However, for neither H1 nor H2 is the predicted relationship consistent across each of the coding category comparisons. There is very little support for H3, as the relationship between being Black and citing discrimination is uneven across fields and categorical comparisons. Overall, the most striking pattern in Table 2 is that no covariate has a consistent relationship with perceived discrimination across all fields and each categorical comparison. This supports H4, as it suggests that the individual-level factors associated with perceived discrimination vary across fields.

Across the models in Table 2, few covariates are statistically significant at conventional levels and the r-squared statistics are low. This suggests that the standard explanations for perceived discrimination are not good predictors of whether non-Whites interpret inequality through the lens of discrimination. I now turn to H5 and ask whether institutional fields are better predictors of perceived discrimination.

The first evidence supporting H5 is the fact that few individuals interpret inequality the same way in each field. Less than 1 per cent of non-Whites give the same explanation for each of the five examples of inequality. Even if I collapse the coding scheme to six options (Only discrimination, Only blame, Only economic difficulties, a Mixture, Other, Do not know), only 2 per cent of respondents answer the same way across each question.

For a formal comparison of variation across individuals and fields, I estimate multilevel logistic regression models without any covariates and in which the variation in citing discrimination is decomposed across the five fields and across individuals. I expand the data set to create five observations (one for each open-ended question) per respondent. The likelihood of citing discrimination is the outcome variable, the question-level grouping variables are categorical variables with five values corresponding to the values for each of the five inequality questions, and the individual-level grouping variable is the unique respondent identification code.

Table 3 summarizes results from the multilevel models and indicates that when predicting the likelihood of citing only discrimination as opposed to all other responses, 80 per cent of the variation is across individuals and 20 per cent is across fields. The next column indicates the exact same results for a model predicting the likelihood of citing any discrimination. However, when I exclude those who answered ‘Do not know’ and estimate models only among respondents who offered an interpretation of the inequality, roughly two-thirds of the variation is across individuals and one-third is across fields. The final column limits the analysis to those who answered either Discrimination only or Blame only and here the variation is split evenly across individuals and across fields. These results suggest that among non-Whites who are able to provide a heuristic for interpreting inequality, much may depend on the field.

| Table 1. Coding scheme for responses to the open-ended questions about explanations for racial inequality |
|-------------------------------------------------|-------------------------------------------------|-----------------|
| Single-factor | Mixed-factors | Other |
| Racial discrimination | Discrimination and economic | Other |
| Economic factors | Discrimination and blame | Do not know |
| Blame minorities | Economic and blame | |
| | Disc/econ/blame | |
| | Discrimination and other | |
| | Economic and other | |
| | Blame and other | |
Table 2. Multinomial logistic regression results for responses to open-ended questions about inequality

<table>
<thead>
<tr>
<th>Response</th>
<th>Variable</th>
<th>Education</th>
<th>Unemployment</th>
<th>MPs</th>
<th>Arts</th>
<th>CEOs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Socio-economic</td>
<td>Higher education</td>
<td>$-0.646 \ (0.261)^{**}$</td>
<td>$0.297 \ (0.404)$</td>
<td>$0.208 \ (0.289)$</td>
<td>$0.251 \ (1.14)$</td>
<td>$0.363 \ (0.460)$</td>
</tr>
<tr>
<td></td>
<td>No qualifications</td>
<td>$-1.46 \ (1.17)$</td>
<td>$-0.362 \ (1.09)$</td>
<td>$0.209 \ (0.712)$</td>
<td>$-9.96 \ (1.31)^{***}$</td>
<td>$0.747 \ (1.13)$</td>
</tr>
<tr>
<td></td>
<td>Professional</td>
<td>$0.589 \ (0.263)^{**}$</td>
<td>$-0.264 \ (0.400)$</td>
<td>$-0.664 \ (0.324)^*$</td>
<td>$1.27 \ (1.43)$</td>
<td>$-0.647 \ (0.477)$</td>
</tr>
<tr>
<td></td>
<td>Manual</td>
<td>$0.991 \ (0.471)^{**}$</td>
<td>$-0.040 \ (0.575)$</td>
<td>$0.240 \ (0.395)$</td>
<td>$1.55 \ (1.37)$</td>
<td>$-0.721 \ (0.778)$</td>
</tr>
<tr>
<td></td>
<td>Born in the United Kingdom</td>
<td>$-0.039 \ (0.233)$</td>
<td>$0.229 \ (0.346)$</td>
<td>$-0.170 \ (0.259)$</td>
<td>$-0.124 \ (1.15)$</td>
<td>$0.214 \ (0.413)$</td>
</tr>
<tr>
<td></td>
<td>Black</td>
<td>$-0.080 \ (0.265)$</td>
<td>$-0.213 \ (0.374)$</td>
<td>$0.430 \ (0.261)$</td>
<td>$0.002 \ (1.20)$</td>
<td>$0.131 \ (0.409)$</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>$0.045 \ (0.259)$</td>
<td>$-2.55 \ (0.455)^{**}$</td>
<td>$-1.47 \ (0.305)$</td>
<td>$-5.89 \ (0.164)^{***}$</td>
<td>$-3.18 \ (0.521)^{***}$</td>
</tr>
<tr>
<td>Blame minorities</td>
<td>Higher education</td>
<td>$0.052 \ (0.215)$</td>
<td>$-0.015 \ (0.186)$</td>
<td>$0.067 \ (0.175)$</td>
<td>$-0.066 \ (0.200)$</td>
<td>$-0.116 \ (0.220)$</td>
</tr>
<tr>
<td></td>
<td>No qualifications</td>
<td>$0.164 \ (0.704)$</td>
<td>$-0.533 \ (0.555)$</td>
<td>$-0.629 \ (0.562)$</td>
<td>$-0.466 \ (0.599)$</td>
<td>$-1.52 \ (1.05)$</td>
</tr>
<tr>
<td></td>
<td>Professional</td>
<td>$0.088 \ (0.215)$</td>
<td>$0.007 \ (0.187)$</td>
<td>$-0.258 \ (0.175)$</td>
<td>$0.028 \ (0.202)$</td>
<td>$-0.106 \ (0.233)$</td>
</tr>
<tr>
<td></td>
<td>Manual</td>
<td>$0.990 \ (0.393)^{**}$</td>
<td>$-0.115 \ (0.300)$</td>
<td>$0.289 \ (0.268)$</td>
<td>$0.059 \ (0.280)$</td>
<td>$0.260 \ (0.314)$</td>
</tr>
<tr>
<td></td>
<td>Born in the United Kingdom</td>
<td>$-0.049 \ (0.182)$</td>
<td>$-0.137 \ (0.166)$</td>
<td>$-0.254 \ (0.152)^*$</td>
<td>$-0.038 \ (0.176)$</td>
<td>$-0.001 \ (0.202)$</td>
</tr>
<tr>
<td></td>
<td>Black</td>
<td>$-0.044 \ (0.203)$</td>
<td>$0.149 \ (0.182)$</td>
<td>$-0.092 \ (0.170)$</td>
<td>$0.148 \ (0.193)$</td>
<td>$0.136 \ (0.218)$</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>$1.03 \ (0.210)^{***}$</td>
<td>$-0.576 \ (0.194)^{***}$</td>
<td>$0.328 \ (0.174)^*$</td>
<td>$-0.963 \ (0.208)$</td>
<td>$-1.42 \ (0.231)^{***}$</td>
</tr>
<tr>
<td>Mixed</td>
<td>Higher education</td>
<td>$0.078 \ (0.222)$</td>
<td>$0.172 \ (0.152)$</td>
<td>$0.095 \ (0.200)$</td>
<td>$0.018 \ (0.212)$</td>
<td>$-0.015 \ (0.152)$</td>
</tr>
<tr>
<td></td>
<td>No qualifications</td>
<td>$-0.235 \ (0.745)$</td>
<td>$-0.979 \ (0.491)^{**}$</td>
<td>$-0.503 \ (0.580)$</td>
<td>$-2.20 \ (1.05)^{**}$</td>
<td>$-0.563 \ (0.489)$</td>
</tr>
<tr>
<td></td>
<td>Professional</td>
<td>$0.276 \ (0.222)$</td>
<td>$0.065 \ (0.153)$</td>
<td>$-0.154 \ (0.196)$</td>
<td>$0.079 \ (0.211)$</td>
<td>$-0.106 \ (0.153)$</td>
</tr>
<tr>
<td></td>
<td>Manual</td>
<td>$1.38 \ (0.394)^{***}$</td>
<td>$0.304 \ (0.216)$</td>
<td>$0.434 \ (0.291)$</td>
<td>$0.020 \ (0.292)$</td>
<td>$-0.136 \ (0.220)$</td>
</tr>
<tr>
<td></td>
<td>Born in the United Kingdom</td>
<td>$0.169 \ (0.189)$</td>
<td>$0.122 \ (0.131)$</td>
<td>$-0.242 \ (0.171)$</td>
<td>$0.074 \ (0.183)$</td>
<td>$0.205 \ (0.131)$</td>
</tr>
<tr>
<td></td>
<td>Black</td>
<td>$0.338 \ (0.205)^*$</td>
<td>$-0.009 \ (0.146)$</td>
<td>$-0.074 \ (0.190)$</td>
<td>$-0.029 \ (0.200)$</td>
<td>$-0.023 \ (0.145)$</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>$0.472 \ (0.224)^{**}$</td>
<td>$0.004 \ (0.156)$</td>
<td>$-0.167 \ (0.203)$</td>
<td>$-1.07 \ (0.214)^{***}$</td>
<td>$-0.313 \ (0.150)^{**}$</td>
</tr>
<tr>
<td>Other/ Don’t Know</td>
<td>Higher education</td>
<td>$-0.244 \ (0.209)$</td>
<td>$0.050 \ (0.148)$</td>
<td>$-0.094 \ (0.156)$</td>
<td>$-0.168 \ (0.133)$</td>
<td>$-0.052 \ (0.134)$</td>
</tr>
<tr>
<td></td>
<td>No qualifications</td>
<td>$-0.225 \ (0.689)$</td>
<td>$-0.606 \ (0.413)$</td>
<td>$-0.704 \ (0.452)$</td>
<td>$-0.657 \ (0.374)^*$</td>
<td>$-0.155 \ (0.400)$</td>
</tr>
<tr>
<td></td>
<td>Professional</td>
<td>$0.213 \ (0.216)$</td>
<td>$-0.038 \ (0.150)$</td>
<td>$-0.089 \ (0.154)$</td>
<td>$0.031 \ (0.135)$</td>
<td>$-0.073 \ (0.134)$</td>
</tr>
<tr>
<td></td>
<td>Manual</td>
<td>$0.958 \ (0.387)^{**}$</td>
<td>$0.142 \ (0.213)$</td>
<td>$0.354 \ (0.238)$</td>
<td>$-0.039 \ (0.189)$</td>
<td>$0.069 \ (0.189)$</td>
</tr>
<tr>
<td></td>
<td>Born in the United Kingdom</td>
<td>$0.125 \ (0.179)$</td>
<td>$0.049 \ (0.128)$</td>
<td>$-0.103 \ (0.134)$</td>
<td>$-0.074 \ (0.113)$</td>
<td>$0.110 \ (0.115)$</td>
</tr>
<tr>
<td></td>
<td>Black</td>
<td>$0.081 \ (0.196)$</td>
<td>$-0.002 \ (0.142)$</td>
<td>$-0.025 \ (0.146)$</td>
<td>$0.059 \ (0.126)$</td>
<td>$-0.040 \ (0.126)$</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>$1.31 \ (0.210)^{***}$</td>
<td>$0.296 \ (0.147)$</td>
<td>$1.02 \ (0.160)^{***}$</td>
<td>$0.899 \ (0.129)$</td>
<td>$0.284 \ (0.135)$</td>
</tr>
</tbody>
</table>

|       | N                  | 2,008            | 2,008          | 2,008          | 2,008           | 2,008           |
|       | Pseudo R²          | 0.01             | 0.00           | 0.00           | 0.00            | 0.00            |

Notes: Weighted data. Cells provide coefficients with robust standard errors in parentheses. Baseline category is 'Discrimination only'.

* $P < 0.10$; ** $P < 0.05$; *** $P < 0.01$. 

N 2,008 2,008 2,008 2,008 2,008

Pseudo R²
The results in Table 3 do not support H5, as there is more variation in perceived discrimination across individuals than fields for most specifications. Yet, the models summarized in Table 3 decompose variation across all individual-level characteristics, including those that are unobserved, poorly understood by the literature, and random noise. A more focused test of H5 would compare the importance of fields with the key independent variables cited in H1, H2, and H3. For this test, I again estimate logistic regression models on the expanded data set. I include individual-level covariates as well as dummy variables for four of the five open-ended questions about inequality. Full results are in Supplementary Table A2, but the relationship between each covariate and the likelihood of citing discrimination is summarized with a graph of average marginal effects in Figure 1.

Figure 1 provides strong evidence in favour of H5, as the average marginal effects are much larger for the question variables than they are for the individual-level characteristics. In the top graph, the average marginal effect for the fields ranges from 0.13 to 0.26, while the only effect for the individual covariates that is statistically significant at the 5-per cent level is 0.09 for having no qualifications. Similarly, in the graph for responses that have any mention of discrimination, the average marginal effect for the fields spans from 0.11 to 0.26, while the largest effect for an individual-level covariate is 0.09 for having no qualifications. In summary, results thus far offer limited support for H1, H2, or H3 but provide stronger support for H4 and H5. Institutional fields may be at least as important as all individual-level factors, but they are much more important than the individual-level variables cited in existing literature as explanations for why minorities are more or less likely to view life through the lens of racial discrimination.

### Table 3. Individual-level and field-level variation in responses

<table>
<thead>
<tr>
<th>Variation</th>
<th>Disc. only (per cent)</th>
<th>Any disc. (per cent)</th>
<th>Disc. only (w/o dk) (per cent)</th>
<th>Any disc. (w/o dk) (per cent)</th>
<th>Disc. vs. Blame (per cent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual</td>
<td>80</td>
<td>80</td>
<td>62</td>
<td>64</td>
<td>51</td>
</tr>
<tr>
<td>Field</td>
<td>20</td>
<td>20</td>
<td>38</td>
<td>36</td>
<td>49</td>
</tr>
</tbody>
</table>

*Note*: Results are calculated from multilevel logistic regression models with variation across individuals and across questions specified as random effects. The first two columns include all respondents. The third and fourth columns exclude respondents who answered with a form of ‘I do not know’. The fifth column includes only respondents who answered Racial discrimination only or Blame minorities only.

### Variation in Perceived Discrimination across Institutional Fields

Figure 2 presents graphs of the percentage of respondents who mention discrimination as either the only explanation or as one of multiple explanations for inequality across the five fields. In each graph the pattern is the same. Discrimination is more likely to be cited as an explanation for inequality among CEOs, artists, and politicians than as an explanation for educational inequality. This supports H6 as it suggests non-Whites are more likely to perceive discrimination in fields where they have less control over the outcomes. Moreover, Supplementary Figure A1 indicates that ‘Blaming minorities’ is a more common response to the question about educational inequality than the other four fields. This is also consistent with the logic behind H6, as minorities should be more likely to emphasize their own responsibility (as opposed to discrimination).
in fields like education where they have more control over the outcome.

Although the overall pattern in Figure 2 is generally supportive of Figure 6, there are two results that are inconsistent with H6. One is the higher number of mentions for discrimination as an explanation for employment inequality as opposed to political inequality. The second is that discrimination is mentioned by roughly the same percentage of respondents to explain employment and arts inequality. I expected fewer mentions of discrimination for employment as opposed to political and arts inequality because I claimed that minorities have more control over employment outcomes than political and art outcomes. Yet results in Supplementary Figure A1 suggest that this may not be the case, as respondents are more likely to blame minorities for inequality in politics than for inequality in employment and the arts, where there are similar levels of blame. It is also important to note that there may be other forms of variation across fields that are unrelated to minority control and which may explain some of the patterns in Figure 2. For example, public debates about anti-discrimination strategies in the United Kingdom have focused on the labour market and politics but not as much on education and this may influence how non-Whites interpret inequalities in the different fields (Givens and Case, 2014). In addition, respondents may have personal beliefs about the fairness of the power structures in each field (independent of the extent to which minorities have control over those power structures), which then shapes perceptions of discrimination across the fields. Future research should explore these possibilities more closely.

Robustness Checks

To ensure that my results are not dependent on coding decisions, I explore alternate specifications of the independent variables. In the main analysis I coded mixed-race respondents as ‘black’ because mixed-race individuals in Britain are likely to be treated by society as Black and are vulnerable to racial discrimination (Song, 2003). Yet, mixed-race individuals may be less sensitive to racial issues than other Blacks, so I conduct additional analyses with an operationalization of ‘black’ that excludes all mixed individuals. A second issue is that socialization into the use of British racial categories may occur within generations as immigrants spend more time in the United Kingdom. Therefore I conduct additional analyses among non-Whites born abroad and include a control variable for how long respondents have been in the United Kingdom. Finally, in the previous models I did not account for interactions between non-White subgroups and socio-economic outcomes or generational status. This may be an oversight because being Black and having no qualifications or between being Black and being born in the United Kingdom may be more important for perceived discrimination than merely being Black, having no qualifications, or being born in the United Kingdom (Modood and Berthoud, 1997).

I use the expanded data sets to estimate a series of logistic regression models with the alternate specifications. I estimate models predicting the likelihood of citing only discrimination and models predicting the likelihood of citing any discrimination. Full details are in Supplementary Table A3, but the main result is that none of these alternate specifications challenge my earlier findings. The narrower definition of Black, the amount of time spent in the United Kingdom among first-generation immigrants, and the interaction terms all fail to achieve a statistically significant relationship (at the 5 per cent level) with perceiving discrimination. In short, my earlier findings are robust to several alternate specifications.12

Another concern is that although I provide all subjects with the same stimuli in an effort to obtain a common benchmark, individuals may have different experiences with discrimination that influence how they respond to
questions about inequality. If this were true, omitted variable bias might distort the results in Table 2 and Supplementary Table A2 and lead me to underestimate the support for H1, H2, and H3. To test for this possibility, I use a survey item that asks how frequently subjects experience discrimination and then re-estimate the models from Table 2 and Supplementary Table A2.13

Full results from the models with an additional covariate for self-reported discrimination are in Supplementary Tables A4 and A5, and they suggest that the results are similar to models without a covariate for personal discrimination. In all models, all of the previously documented relationships are the same. In the multinomial logistic regression models, having more personal experience with discrimination is mostly associated with being less likely to cite discrimination as an explanation for inequality, although the relationships are generally not statistically significant at the 10-per cent level. In the logistic regression models using the expanded data set, having more experience with discrimination is also associated with being less likely to mention discrimination as an explanation for inequality, and in this case the relationships are statistically significant at the 1-per cent level.

These findings are counterintuitive as one might have expected individuals who report more experience with discrimination to be more likely to interpret inequality through the lens of discrimination. One possibility is that non-Whites’ views on discrimination in their personal lives and in public are two distinct dynamics. However, one should not over-interpret results based on the closed-ended question about discrimination. As discussed earlier, closed-ended questions that explicitly ask about discrimination measure multiple dynamics that are difficult to disentangle. Nonetheless, at a minimum these robustness checks suggest that the results in this article are not biased by variation in personal experiences with discrimination.

The final area of concern is survey effects. Open-ended questions are more challenging than closed-ended questions because they require subjects to formulate their own response. As a result, subjects are more likely to not answer open-ended questions (Geer, 1988). As seen in Supplementary Figure A1, ‘Do not know’ ranges from 27 to 45 per cent across the five questions about inequality and it is the modal response for each question. In comparison, ‘Do not know’ was <8 per cent of responses to the closed-ended question about discrimination. In some respects, these greater cognitive demands are appropriate for my study because they mirror the real-world challenge of appraising an outcome and determining whether it involves discrimination (Essed, 1991). However, there are two ways in which the cognitive demands of open-ended questions may bias my results.

One possibility is that variation in perceived discrimination across individuals is primarily about who is sufficiently cognitively engaged to answer the questions. This could depress the relationships between other individual-level covariates and perceived discrimination in the overall sample. To explore this possibility, I re-estimated the models in Table 2 only among non-Whites who did not answer ‘Do not know’ for each question (i.e., the most cognitively engaged sub-set of the sample) and the results were the same as in Table 2. In addition, if cognitive demands were the main factor driving ‘Do not know’ responses (as opposed to ambivalence or indecision) we would expect a large and consistent amount of ‘Do not know’ responses to all five questions because people who are vulnerable to the cognitive demands should immediately opt out of all open-ended questions. Yet, while 70 per cent of the sample answered ‘Do not know’ at least once, <5 per cent of the sample answered ‘Do not know’ to all five questions. Finally, if I use educational attainment as a proxy for cognitive sophistication, it is not a statistically significant predictor at the 10-per cent level of responding ‘Do not know’ for any of the open-ended questions.14

The other potential survey effect is that variation in perceived discrimination across fields may not be owing to the fields themselves but rather the effect of answering a series of challenging questions. This could lead to increasing numbers of ‘Do not know’ responses as subjects progressed through the questions and became more vulnerable to the cognitive demands. Or, it could lead to decreasing numbers of ‘Do not know’ responses as subjects became more habituated to the challenge and better able to answer. Future work should randomize the order of open-ended questions to fully mitigate this concern, but my results indicate that response patterns do not change in a consistent way across questions. As seen in Supplementary Figure A1, the number of ‘Do not know’ responses is fairly constant across the first three questions, peaks at the fourth, and drops for the final question.

Conclusion

This article offers a new way of studying perceived discrimination. I posit that the standard practice of explicitly asking minorities about discrimination is likely to produce inconclusive and misleading results because it cannot distinguish between the extent to which minorities are responding based on their actual experiences with discrimination or their levels of sensitivity to the
issue of discrimination. To address this concern, I focus on the latter dynamic and provide a series of open-ended questions that measure the use of racial discrimination as a heuristic for understanding society.

My results break new theoretical ground by suggesting that the individual-level variables cited in the existing perceived discrimination literature are less important than variation across institutional fields. Furthermore, I argue that non-Whites are more likely to cite discrimination as a cause of racial inequality in fields where they have less control over the outcome. This builds on literature that connects minorities’ perceptions of discrimination to strategies for preserving self-esteem.

A major implication of this article is that institutional fields are underappreciated predictors of how minorities interpret events. For better or worse, this does not provide easy answers for concerns about social cohesion in the United Kingdom and elsewhere. This article suggests that all minorities—irrespective of socio-economic status, generational status, or the particular non-White group—have the capacity to view life through racialized or non-racialized heuristics. This raises new challenges, but the extent that it is an accurate representation of how perceived discrimination operates, it is a useful contribution.

Notes

1 In part this focus reflects the ongoing debate mentioned earlier about the relationship between assimilation and perceived discrimination. There have also been a series of counterintuitive findings in the United States about the positive relationship between socio-economic attainment and perceived discrimination, which have sparked ongoing research into individual-level predictors of perceived discrimination (Cose, 1993; Chong and Kim, 2006).

2 These groups account for 66 per cent of the non-White population in England and Wales according to the 2011 Census. There are smaller non-White groups from across Asia and the Middle East (Office for National Statistics, 2012).

3 During the 1960s and 70s British activists tried to unite all non-Whites under the ‘black’ label to maximize their political power, but by the 1990s that unified classification had failed (Modood, 1988; Modood and Berthoud, 1997).

4 YouGovUK uses a ‘turbo sampling’ method in which members of their panel are invited to participate in a survey and then assigned to a specific survey once they have accepted the invitation. The overall panel response rate is approximately 20 per cent. Of those who started taking the survey, 10.5 per cent did not complete the survey and were not included in the final sample.

5 For more details on the polling methodology: http://yougov.co.uk/publicopinion/methodology/.

6 The vignettes were consistently presented in this order.

7 ‘BME’ stands for Black minority ethnic, a common British term for non-Whites.

8 Most ‘other’ responses were idiosyncratic and could not be grouped into a category. All coding was done by the author. All responses were coded twice for reliability. Automated coding was inappropriate because computers can code for subject matter but not meaning and cannot distinguish between ‘it’s all about race’ and ‘it’s definitely not about race’.

9 A potential concern with multinomial logistic regression is the independence of irrelevant alternatives (IIA) assumption, which requires that the odds of choosing between two response options do not depend on the presence or absence of the other options. Several tests (e.g. the Hausman-McFadden test and the Small-Hsiao test) attempt to test whether the IIA assumption has been violated, but research suggests they are unreliable and should be avoided (Cheng and Long, 2007). In this case, there are reasons to believe that the IIA assumption was not violated because my survey respondents did not have a formal choice among concrete response options. Although there is no way of knowing exactly what came into each subject’s head before answering, a reasonable assumption would be that each subject (consciously or subconsciously) surveyed the range of possible answers before responding.

10 Full results with the percentage of respondents in each of the 12 coding categories for each of the five fields are in Supplementary Figure A1.

11 These models are a useful overview of relationships with perceived discrimination but results are similar when I estimate models predicting the likelihood of citing discrimination in each of the five fields.

12 I also explored the possibility of gender differences in perceived discrimination. Non-White women in the sample are generally more likely than men to cite discrimination as an explanation for inequality, although the differences are fairly small and only statistically significant at the 10 per cent level.
for the question about education. Moreover, the inclusion of a control variable for gender does not change any of the results presented in this article.

13 In an ideal world I would also have controlled for variation in personal experiences with discrimination across the five fields, but those questions were not included in the survey.

14 This is based on a series of logistic regressions predicting the likelihood of answers being coded ‘Do not know’ as opposed to all other categories. I model education in three different ways. One is as the dummy variable: Higher education degree/No higher education degree. A second is as the dummy variable: Some higher education/No higher education. The third is No qualifications/Some qualifications.

Acknowledgements
Previous versions were presented at the Council for European Studies Conference of Europeanists, the Comparative Approaches to Immigration and Religious and Ethnic Diversity workshop (Princeton University), and ‘Identity Politics: The New World versus New (and Old) Europe’ at the University of Texas, Austin. The author would like to thank Rodolfo Espino, Marc Helbling, Daniel Hopkins, Tatishe Nteta, Brian Schaffner, and Alex Street for helpful comments on earlier drafts.

Funding
The research for this article was funded by the University of Massachusetts, Amherst Faculty Research Grant/Healey Endowment Grant.

Supplementary Data
Supplementary data are available at ESR online.

References


