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Article (Accepted version) (Refereed)

Original citation: Johnston, David W. and Lordan, Grace (2015) *Racial prejudice and labour market penalties during economic downturns.* European Economic Review . ISSN 0014-2921

DOI: 10.1016/j.euroecorev.2015.07.011

Racial Prejudice and Labour Market Penalties during Economic Downturns

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Acknowledgements: We are grateful for the time taken to comment on this work by Steve Pischke, Steve Machin, Alan Manning, Marco Manacorda, Barbara Petrongolo, Carol Propper, Simon Burgess, Stephen Jenkins, Alistair Mcguire, Berkay Ozcan, Joan Costa Font, George Kavetsos, Mikko Myrskylä Nick Powdthavee, Lucinda Platt, Michael Shields, Sonja Kassenboehmer and Frank Windmeijer. We are also grateful to participants of the CMPO seminar series at Bristol, participants of the labour economics workshop at the LSE, participants at the CASE seminar series at the LSE, participants of the social policy empirical reading group at the LSE and participants at the Royal Economic Society Conference 2014.

Abstract

Do economic downturns encourage racist attitudes? Does this in-turn lead to worse labour market outcomes for minorities? We assess these important questions using British attitude and labour force data. The attitude data show that racial prejudice is countercyclical, with the effect driven by large increases for high-skilled middle-aged working men – a 1%-point increase in unemployment is estimated to increase self-reported racial prejudice by 4%-points. Correspondingly, the labour force data show that racial employment and wage gaps are counter-cyclical, with the largest effects also observed for high-skilled men, especially in the manufacturing and construction industries – a 1%-point increase in unemployment is estimated to increase the wage gap by 3%. These results are entirely consistent with the theoretical literature, which proposes that racial prejudice and discrimination are the result of labour market competition among individuals with similar traits, and that the effects of this competition are exacerbated during periods of economic downturn.

Keywords: Prejudice; Recessions; Racism; Discrimination.

”To make matters worse, the current economic and social crises threaten to widen some equality gaps that might have closed in better times.” (Equality and Human Rights Commission, 2010)

1. Introduction

Recent commentary in the popular press and corresponding statements from equality and human rights groups propose that racial prejudice has escalated during the recent Great Recession.[1] If true, this rise in racial prejudice may have led to increased labour market discrimination, widening already existing inequalities in wages and employment. This is in line with predictions from a theoretical literature that highlights the propensity for prejudice and discrimination to increase during periods of economic downturn, due to increased competition for scarce resources (Levine and Campbell, 1972; Frijters, 1998; Smith, 2012; Caselli and Coleman, 2013). In view of the strong public interest in this issue and the important repercussions for policy-makers, this paper provides a detailed analysis of whether self-reported racial prejudice and racial labour market gaps are counter-cyclical.

Our measure of racial prejudice is found in British Social Attitudes Surveys between 1983 and 2010, and is a declaration by a White respondent of being ‘not prejudiced at all’, ‘a little prejudiced’, or ‘very prejudiced’ against people of other races. To identify the effects of macroeconomic conditions we exploit variation across geographic regions and time; a general econometric approach that has been used to analyse attitudes towards immigrants (Mayda, 2006), attitudes towards ethnic minorities (Dustmann and Preston, 2001) and racially motivated crime (Falk et al., 2011). Our findings suggest that prejudice amongst native-born Whites increases with the unemployment rate, with the effect owed mainly to large increases among highly-educated, middle-aged, full-time employed men. For example, it is estimated for this subgroup that a 1%-point increase in the unemployment rate increases self-reported prejudice by approximately 4%-points.

This increase in prejudice may translate into worse labour market outcomes for non-Whites through two main mechanisms. First, increased discrimination could affect non-Whites at all

[1] Examples from the popular press include: The Telegraph, 19 January 2009; Reuters, September 1 2008; The Times 14 January 2009; The New York Times 12 September 12 2009.

levels within firms if there is a general increase in taste-based discrimination[2], or second, it could be concentrated among the highly skilled if the propensity to discriminate arises from increased competition among employees with similar positions. First, assuming that highly-educated middle-aged White men are more likely to be managers and employers, and have political power within organisations, as racial prejudice increases among this group, high-skilled White managers may discriminate against people of all skill levels for whom they have hierarchical power over. Second, it is possible that prejudice and subsequent discrimination arise from increased competition between White and non-White job seekers and workers with similar traits. By forming coalitions based on ethnicity, individuals are more likely to hire and promote persons from within their own coalition in an attempt to capture labour market rents. This second mechanism implies that the negative effects will be concentrated mainly among high-skilled non-Whites. Overall, we expect that counter-cyclical racial prejudice will cause counter-cyclical labour market discrimination. We can explore this hypothesis, and comment on the most likely mechanism, using data on native-born individuals from the 1993-2012 versions of the Quarterly Labour Force Survey (QLFS), and by including in wage and employment models the interaction between local-level unemployment rates and ethnicity. Focusing on native born individuals only, means we avoid composition issues that arise due to the varying inflows and outflows of immigrants across regions and time. Overall, this approach tests whether racial labour market gaps widen during periods of high unemployment under the assumption that differences in unobserved human capital between native Whites and native non-Whites are uncorrelated with shocks in area-level unemployment.

The results suggest that non-Whites are worse off during recessionary periods in terms of employment and earned income. We refer to the increased racial wage gaps during periods of high unemployment as the 'recession wage penalty' (RWP), and correspondingly refer to the increased racial employment gaps as the 'recession employment penalty' (REP). A particularly interesting finding is that the penalties are largest for high-skilled workers, supporting the theoretical predictions. Further disaggregation by ethnicity reveals that Black workers are the most affected. For example, the Black-White wage gap for high-skilled non-manual workers is estimated to increase by 2.4% for every 1%-point increase in unemployment.

[2] In the vein of Becker (1957).

For decades economists have developed theories of racial prejudice (Lang and Lehman, 2012; Altonji and Blank, 1999; Arrow, 1998; Becker, 1957) and have empirically examined its economic consequences (Guryan and Kofi Charles, 2013; Lang and Lehmann, 2012; Fryer and Torelli, 2010; Ritter and Taylor, 2011; Lang and Manove, 2011; Dawkins et al, 2005; Lang et al, 2005; Chay, 1998; Card and Krueger, 1992; Donohue and Heckman, 1991). There are also large independent literatures investigating the determinants of social attitudes, including attitudes towards immigrants and immigration policy (Quillian's, 1995; Dustmann and Preston, 2005; Dustmann and Preston, 2007; Pettigrew 1998; Mayda 2006; Hainmueller and Hiscox 2007; Facchini and Mayda, 2009). However, despite these influential literatures there is little economic research on the determinants of self-reported racial prejudice. Understanding the economic determinants of prejudicial attitudes is therefore academically valuable, as is exploring how racial prejudice may translate into worse labour market outcomes for non-Whites.

Our findings also have implications for policies targeting ethnic minorities residing in Britain. This arises because of already existing inequalities: minorities live in worse housing (Phillips and Harrison; 2010), are taught by lower quality teachers (Clotfelter et al; 2004) and are in worse health (Lordan and Johnston, 2011and Bollini and Harold, 1995). Additionally, the unemployment rate of minorities in Britain has been approximately double that of Whites over the last 40 years, with only half of this gap explained by residential segregation, education differences and other observable factors (Leslie et al, 2001; Blackaby et al, 2002 and Heath and Li, 2007). Higher levels of racial prejudice widen this gap, and thus the recent recession may have reversed some of the gains made during the past decades (Equality and Human Rights Commission, 2010).

The remainder of this paper is organised as follows: In Section 2 we provide a background for our study by discussing theoretical and empirical work related to prejudicial attitudes and discrimination. In Section 3 we describe the British Social Attitudes data, along with our methodology. We also document the results for the empirical work on attitudes. In section 4 we describe the data sources used to consider labour market impacts, methodology and results. The final section is a discussion.

2. Racial Prejudice and Discrimination

For many years economists have been interested in a diverse range of individual attitudes and values (Gentzkow and Shapiro, 2004; Voigtländer and Voth, 2012; O' Rourke and Sinnott, 2001). However, to our knowledge economists have never empirically examined the macroeconomic determinants of self-reported racial prejudice.[3] This is puzzling, because many economic studies examine attitudes towards immigrants and immigration policy (Quillian's, 1995; Dustmann and Preston, 2006; Dustmann and Preston, 2007; Pettigrew 1998; Mayda 2006; Hainmueller and Hiscox 2007; Facchini and Mayda, 2009). Particularly relevant studies include Lahav (2004), who finds that immigration attitudes are related to perceptions of economic conditions, Kesslar and Freeman (2005), who find that as economic conditions worsen so does public opinion towards migrants, and Dustmann and Preston (2007), who demonstrate that racial prejudice and anti-immigration attitudes are strongly related in the UK.

The dearth of economic studies is also puzzling given the evidence that prejudicial attitudes shape the life chances of ethnic minorities. For example, racial prejudice has been suggested as an important causal factor in determining policies that target minorities (Bobo, 1991; Sears, 1988). Additionally, lower levels of racial prejudice have been directly linked to support for the Welfare State in Britain (Ford, 2006). Elsewhere, Dustmann and Preston, (2007) find that racial concerns are an important pathway through which public opinion towards immigration policies are formed. Prejudice and subsequent discriminatory practices have also been linked to residential segregation (Charles, 2000 and Zubrinsky and Bobo, 1996), poor health (Johnston and Lordan, 2012 and Lauderale, 2006) and worse labour market outcomes (Charles and Guryan, 2008 and Goldsmith et al, 2006). Therefore, shifts in racial prejudice during recessionary periods could worsen already existing racial inequalities in a number of domains.

While no economic study investigates the macroeconomic determinants of self-reported racial prejudice, there are several related economic literatures. For instance a number of

[3] Some work outside economics does examine the determinants of self-reported racial prejudice using the British Social Attitudes Survey. However, this work focuses on the correlations between individual and household characteristics and prejudicial attitudes (Evans 2002; Rothon and Heath 2003; Ford 2008). For example, Ford (2008) reports low levels of self-reported prejudice amongst the highly educated, the professional classes and women. There is also a related economic literature that examines how the ethnic composition of geographical areas influences self-reported prejudice (e.g. Dustmann and Preston, 2001).

papers examine the macroeconomic determinants of racially-motivated crime. The closest example to our study is Falk et al. (2011), who find a significantly positive relationship between regional unemployment and the incidence of right-wing extremist crime in Germany. The authors hypothesise that the fear of losing a job increases with unemployment, and that this fear lowers tolerance and altruism. Another close example is Antecol and Cobb-Clark (2010), who in contrast find little evidence that racial hostility towards off-base Army personnel is related to local economic vulnerability (measured by the unemployment rate, poverty rate, and income inequality). This finding of weak relationships with macroeconomic conditions is common in the racially-motivated crime literature. For example, macroeconomic conditions are found to be only weakly related to the incidence of anti-foreigner crime in Germany (Krueger and Pischke, 1997), hate crimes in New York (Green et al. 1998), race riots in the US (DiPasquale and Glaeser, 1998), and racial harassment in Britain (Dustmann et al., 2011). How relevant these results are for our study is unclear, as physical violence is a particular and extreme manifestation of racial prejudice.

Another related literature theoretically models racial discrimination, scarcity and conflict. For example, Frijters (1998) argues that job uncertainty and scarcity encourages groups of individuals to form coalitions based on observed recognizable characteristics, such as ethnicity. Individuals then hire persons from within their own coalition in an attempt to capture all the scarce jobs and ensure future labour market success. Smith (2012) builds on the social identity literature, which finds that people favour members of their own group at the expense of members of other groups, even if securing this outcome creates economic inefficiencies. He finds that the competition for scarce resources can induce agents without discriminatory attitudes to aggressively discriminate. Finally, Caselli and Coleman (2013) consider ethnic conflict. In their model, ethnicity provides a means for group membership and exclusion, which limits the ability of the losing groups to access the spoils of conflict, such as land titles or government jobs. More generally, there are large literatures in sociology and anthropology based on the theory that discrimination is the result of competition over scarce resources, the effects of which are exacerbated during periods of economic downturn (see Green et al. 1998).

A final related literature considers how the business cycle affects racial wage gaps. Early studies relied on aggregate time series data and examined the ratio of annual earnings for the discriminated group compared to the majority group (Ashenfelter, 1970; Freeman, 1973;

O'Neill, 1985). None of these studies found empirical evidence of pro- or counter-cyclical 'pure' wage discrimination. Biddle and Hammermesh (2013) provide the most relevant contribution by considering wage discrimination over the business cycle in the US using the Current Population Survey Merged Outgoing Rotation Groups from 1979 through 2009. They find evidence that there is a counter-cyclical wage gap for African-Americans, but that this is mostly owed to composition effects. They also find an opposite pro-cyclical wage gap for Hispanics, but the effect is only marginally significant. There is also a notable contribution in the immigration literature by Dustmann et al. (2010). The study compares natives and immigrants from OECD and non-OECD countries in Germany and the UK, and highlights counter-cyclical unemployment effects for immigrants that are particularly pronounced for those from non-OECD countries.

Based on this empirical and theoretical research, we hypothesis that macroeconomic conditions can alter an individual's prejudicial attitudes. In particular, we envisage that each individual has a baseline level of prejudice that is affected by the degree to which they are experiencing 'hard economic times' and have to compete over scarce resources. In recessions, when lay-offs and wage cuts are more common, we expect individuals become less tolerant towards people of other ethnicities. This is in line with the Caselli and Coleman (2013) theoretical model, whereby ethnicity provides a means for group membership and exclusion. It is not necessary to make an assumption as to whether steady state baseline prejudice levels are high (becoming low when an individual experiences good economic fortune) or low (becoming high when an individual experiences bad economic fortune). In this work we are simply interested in examining whether racial prejudice is more prevalent in the community during periods of high unemployment.

We also hypothesise that different sub-groups of society alter their attitudes in differing degrees as unemployment rises. This fits with the aforementioned work and the findings of Mayda (2006), who finds that anti-immigration attitudes heighten when an individual's own circumstances are most threatened by immigration. It also fits with our hypothesis that tolerance is a function of one's own individual circumstances. Thus, those who are experiencing good economic times prior to the recession are likely to become relativity more intolerant towards ethnic minorities, particularly if they are competing alongside these groups in a work environment for income and employment opportunities.[4] Thus, high-skilled individuals would become more prejudiced if ethnic minorities were also high-skilled. In the UK, native ethnic minorities have spent more years overall in school and possess a higher number of degree qualifications than native Whites (Blackaby et al, 2002; Gillborn and Gipps, 1996 and Modood et al, 1997). Additionally, Dustmann and Fabbri (2006) highlight that in the UK immigrants have higher levels of skill and education than immigrants in other developed countries. Their work also indicates that the immigration attitudes of the educated are most influenced by economic factors.

To further investigate these educational attainment differences, we use data from the Labour Force Survey (years 1993 to 2012), which we subsequently describe. Multinomial logit models are used to model the relationship between an individual's highest educational attainment (third level degree or equivalent; higher education[5]; A level or equivalent; O level grade a-c or equivalent[6]; other or no qualification[7]) and race, age, gender, year, and region of residence. The marginal effect estimates indicate that native non-Whites have a significantly higher probability of attaining a third level degree (1.6%-points) and A-level (0.9%-points), but a significantly lower probability of attaining an O-level grade a-c (2.5%-points). Effects were statistically insignificant for the remaining categories. Overall, these estimates concur with the aforementioned literature, which concludes that native non-Whites in the UK have a higher number of qualifications than native Whites.

3. Estimating Racial Prejudice over the Business Cycle

3.1. Data

Our data is drawn from the British Social Attitudes (BSA) Survey, which is a mostly annual

[4] The unemployed are unlikely to exhibit the highest responsiveness to business cycle fluctuations, as they are constantly in labour market competition with other White and non-White job-seekers, regardless of the prevailing unemployment rate. Though this competition is more intense when the unemployment rate is high, the change in intensity with the unemployment rate is likely less than that which is experienced by the employed. Unfortunately, our sample size in the BSA is not sufficient to identify the effect of business cycle fluctuations using unemployed persons only, and so we can not test this hypothesis directly.

[5] Tertiary education with a non-degree qualification.

[6] In the context of this data, those who have O and A levels stay in secondary education until the ages of 16 and 18, respectively. Students awarded grade A, B, or C in the current system reached the standard of the former subject pass at Ordinary Level. This system changed in 1975. So, for our sample all grade D's indicate a lower standard of attainment

[7] Includes international non degree qualifications that are not equivalent to O level grades a-c or A-levels in the UK

series initiated in 1983. The exceptions are 1992 and 1998 when the BSA was not conducted. Each year the BSA Survey asks over 3,000 people questions that gauge their social, political and moral attitudes. Participants are selected using random probability sampling which ensures that the survey is representative of the British population. We focus on the responses for White respondents who are in the working-age population (aged 18-64), given our focus on the potential role of labour market competition in generating prejudicial attitudes.

The key racial prejudice question was included in all survey years apart from 1993, 1995 and 1997, and states:

"How would you describe yourself? (1) not prejudiced at all, (2) a little prejudiced, or (3) very prejudiced, against people of other races?".

The relative frequencies of responses (1), (2) and (3) are 67.2%, 30.0% and 2.8%, respectively. Given the low frequencies associated with response (3), we aggregate the responses "a little prejudiced" and "very prejudiced" to create a binary outcome variable measuring any prejudice. Figure 1 presents mean levels of this measure by some key demographics.[8] These graphs demonstrate three interesting features. First, the highly educated report less prejudice. This is consistent with the highly educated being more tolerant (Sullivan and Transue, 1999 and Hello et al, 2006). Second, those not working report less prejudice than those who are working (or equal in the case of highly educated females). Note that the non-working group consists predominantly of home-makers, with the unemployed a relative minority. Third, males report more prejudice than females. This is consistent with Lubbers et al (2002), and Johnson and Marini (1998). Combined, these relationships imply that low-educated working males are the most prejudiced (42%) and high-educated non-working women are the least prejudiced (23%).

It is likely that self-reported prejudice is a biased measure of true prejudice due to people voicing a different attitude publicly (to the interviewer) than they hold privately. That is, self-reported prejudicial attitudes are likely under-reported (Rudman et al, 2001). However, Evans (2002) highlights that the self-reported prejudice variable in the BSA is correlated closely

[8] In Figure 1 those who have achieved a CSE, O level or GCSE are described as having medium education, and those with an A-level or degree are described as highly educated. All others are described as possessing low levels of education.

with other indicators of racial intolerance, and we expect those with the highest level of prejudice to declare. Additionally, the tendency to under-report owing to social desirability is unlikely to be associated with the prevailing unemployment rate, unless the unemployment rate has a strongly significant effect on the level of prejudicial attitudes within the general community. We do note that it is possible that during recessions some media outlets and political groups increasingly discuss ethnic minorities in a critical manner. Subsequently, individuals may be more likely to declare their pre-existing prejudice as they deem such views as more socially acceptable.[9] Here we argue that this still represents a change in levels of racial tolerance, given that being willing to declare one's prejudice also implies an increased probability of acting upon it. Finally, the tendency to under-report should bias the estimated relationship between unemployment rates and attitudes downwards (towards zero).

Another potential issue is that responses to the racial prejudice question may be influenced by individuals' views of immigrants and immigration policy (and vice-versa), implying that the estimated influence of economic downturns on racial prejudice may be confounded by the influence of economic downturns on attitudes towards immigration. Unfortunately, it isn't possible to separately estimate the influence of economic downturns on racial prejudice and immigration attitudes because the BSA does not include a consistently-worded question on immigration attitudes across time. We can however examine the association between these two attitudes for a subset of years (1983, 1984, 1986, 1989, 1990, 1994 and 1996). In these years, BSA respondents were asked: "Britain controls the numbers of people from abroad that are allowed to settle in this country. Please say for each of the groups below, whether you think Britain should allow more settlement, less settlement, or about the same amount as now." First, the correlations between our racial prejudice variable and variables representing less settlement by 'Australians and New Zealanders', 'Indians and Pakistanis', 'West Indians' and 'People from Eastern Europe' equal 0.08, 0.30, 0.27 and 0.14, respectively. Second, in a regression model the proportion of variation in racial prejudice explained by the four immigration variables is around 8%. Third, only the anti-immigration attitudes towards Indians and Pakistanis (t-stat = 14.3) and West Indians (t-stat = 6.0) were statistically significant positive predictors of racial prejudice. This set of results indicate that anti-immigration attitudes are only weakly related to racial prejudice and that the existing weak

[9] Evidence of this occurring is given by Gentzkow and Shapiro (2004) who highlight that media exposure influences attitudes towards whether the 9/11 terrorist attacks were justified.

relationship is driven almost entirely by attitudes towards non-White immigrants. Therefore, our results will more strongly reflect negative attitudes towards non-Whites than attitudes towards immigrants or immigration policy.

Overall the data comprises 23 survey years, and eleven areas within the UK. These areas are: North East England, North West England, Yorkshire and Humber, East Midlands, West Midlands, South West England, East of England, London, South East England, Wales and Scotland. Official unemployment rate data is only available for these areas from 1992, and so to construct area-level unemployment rates for 1983-1991 we use area-level information on the numbers of claimants for Job Seekers Allowance (JSA). The difficulty is that claimant rates are not necessarily equivalent to unemployment rates, because some of the unemployed are ineligible for or may not claim unemployment benefits. To control for this difference, we construct area-level unemployment rates by multiplying the area-level claimant rate with the ratio of national unemployment rates to national claimant rates. That is, for the period 1983-1991 the unemployment rate used in this work is derived as $cr_{ayt} \cdot ur_{yt}/cr_{yt}$, where cr_{ayt} is the area-level claimant rate, and ur_{ty} and cr_{yt} are the national unemployment and claimant rates, respectively.[10]

Figure 2 presents the national self-reported racial prejudice series across time. It shows a general downward trend across the 1980s and 1990s, followed by an upward trend in the 2000s. The upward trend may have been partly caused by the world-wide increase in terrorism during this period. Another interesting feature is the sharp uptake in the early 1990s. This corresponds with a period of high unemployment in Britain; the national unemployment rate peaked at 10.8% in early 1993. Figure 3 presents the estimated cross-sectional relationship between self-reported racial prejudice and unemployment using between area variation (an Epanechnikov kernel function and a rule-of-thumb bandwidth are used). The non-parametric estimates are presented for three labour market groups: employed, unemployed and all others, which are primarily home-makers. The figure shows a strong positive relationship between racial prejudice and unemployment for workers across all UR values. There is also a positive relationship for the unemployed, but this exists only up until an UR of 8%. The relationship is weak for the 'all others' group. This is in line with the

[10] This approach follows advice received from the Office of National Statistics. It assumes that there is no difference between the divergence of claimant and unemployment rates across areas

hypothesis that those who are in competition with ethnic minorities for jobs are more likely to change their levels of prejudice with rising unemployment. Though it is difficult to draw any firm conclusions from cross-sectional correlations, this figure suggests it may be important to consider heterogeneity in the underlying relationship.

3.2. Methodology

To model the effects of macroeconomic conditions on the racial prejudice of White respondents, we use a linear regression model with area-specific intercepts and area-specific linear time trends:

$$RP_{iat} = \delta UR_{at} + X_{iat}\beta' + \mu_t + \alpha_a^1 + \alpha_a^2 t + \varepsilon_{iat} \quad (1)$$

where RP_{iat} is the self-reported racial prejudice of individual i residing in area a in year t, UR_{at} is the area-year-level unemployment rate, X_{iat} is a vector of individual-level control variables, μ_t is a year fixed-effect, α_a^1 is an area-specific intercept, $\alpha_a^2 t$ is an area-specific time-trend, and ε_{iat} is the usual random disturbance term. Standard errors are clustered at the area-year level (229 clusters).[11]

Area-level intercepts (fixed-effects) are included in equation (1) as it is likely that racial prejudice is influenced by local factors. Area-specific linear time trends are also included because it is plausible that there has been a trend across time towards the acceptance of other ethnicities, and that the slope of this trend differs by area. More generally, area-specific trends capture time-variant unobservable factors that are associated with both prejudice and unemployment. Given the inclusion of area-level intercepts and area-specific time trends, the effect of the unemployment rate on prejudice is identified by within-area variation in unemployment in relation to within-area variation in prejudice around its trend.[12]

[11] We've chosen this level because the low number of unbalanced clusters at the area-level (11) and year-level (21) may introduce a downwards-biased cluster-robust variance matrix estimate (Bertrand et al., 2004). In our models, the standard errors clustered at the area-year-level are generally larger than the standard errors obtained when clustered at the area- or year-level.

[12] We have also estimated models with area-specific covariates that control for the effects that the September 11 2001 terrorist attacks and subsequent events may have had on racial prejudice. These covariates amount to the addition of the term $\alpha_a^3 \cdot \mathrm{I}(y > 2001)$ to equation (1), where $\mathrm{I}(\cdot)$ is an indicator function that equals one if the argument is true and zero otherwise.

The vector of individual-level control variables (X_{iat}) includes, gender, age, age-squared, number of children, marital status (married, separated/divorced/widowed or single), employment status (full-time employed, part-time employed, unemployed, retired, full time student, with all others (mostly home-makers) as the control group), log of household income and log of household income squared (in 2010 prices). To the extent that voting preference can capture some propensity of an individual to be more or less liberal (Pallage and Zimmermann, 2006), or indeed their personality in general (Schoen and Schumann, 2007 and Caprara et al, 1999), we include dummies indicating if a person either has no party allegiance or votes for: Labour, Alliance, or 'other party' (Conservative is thus the reference group). Appendix Table A1 reports the sample means of these variables by 'not prejudiced' and 'prejudiced'.

Particularly important covariates are the education variables, which are used to define estimation subgroups. Those with A-levels or a university degree are described as highly educated. In the UK, students completing A-levels stay in school until roughly 18 years and generally aim for third level education. Those who have achieved a certificate of secondary education (CSE), O-levels or a general certificate of secondary education (GCSE) are described as having medium education (CSE and O-levels were replaced by the GCSE in 1988). All three qualifications represent a low-level secondary school qualification that is usually achieved when the student is aged 15. Individuals without any qualification are described as possessing low levels of education. This classification approach generates three education groups of roughly equivalent sample size. Importantly, education information is missing from the BSA Survey in years 1983 and 1984, and therefore the regression sample begins in 1985.

3.3. Results

Table 1 presents coefficient estimates for equation (1), separately by males and females. The coefficient on the unemployment rate equals 0.010 for males and 0.004 for females. These values imply that the probability of self-reported prejudice increases for males and females by 1.0%-points and 0.4%-points when the UR increases by 1%-point; however, neither coefficient is statistically different from zero at the 10% level. We draw similar conclusions if we do not collapse our self-reported prejudice measure (not prejudiced at all, a little prejudiced, very prejudiced) into a binary indicator and instead use an ordered probit model (estimated coefficients for males and females are statistically insignificant with t-statistics equal to 1.58 and 0.49). [13]

The control variables coefficients in Table 1 highlight that male full-time workers, and female full-time and part-time workers are more likely to be racially prejudiced than the control group.[14] Relative to those with low education, the highly educated are less likely to report racial prejudice, and the medium educated are more likely to report racial prejudice. For income our results imply that middle-income households are most likely to be racially prejudiced. This is evidenced by the inverse-U relationship between income and prejudice. Intuitively, voting preference is also indicative of prejudicial attitudes. Table 1 reveals that Labour and Alliance voters report being less racially prejudiced than conservative voters regardless of gender. This is also the case for those who report having no political allegiance.[15]

As discussed in Section 2, we are interested in how the prejudicial attitudes of different sub-groups change with the business cycle. In particular, we hypothesise that the counter-cyclical relationship will be strongest for high-skilled workers (e.g. more experienced and better educated). Ethnic minorities who are native to Britain have higher education than White natives, and therefore in periods of economic downturn the labour market competition between ethnic minorities and Whites will be most intense for high-skilled workers. Note that this dynamic is relatively unique to the UK. For example, in the United States both native and immigrant ethnic minorities are lower skilled than Whites. In this context, studies have concluded that fears about the adverse effects of labour-market competition are the cause of anti-immigration attitudes among low-skilled, blue collar workers (Scheve and Slaughter, 2001; Mayda, 2006).

In Table 2 we present estimated UR coefficients separately by age (18-34, 35-64), education level (low, medium, high) and employment status (full-time, full-time or part-time, not

[13] Including area-specific controls for the sharp increase in racial prejudice post September 11 2001 does not alter these results or any other results presented in the paper.
[14] This gender difference is perhaps owed to it being more common in the UK for females to be part-time employed than in other countries and in comparison to males (Manning and Petrongolo, 2008)
[15] It is possible that political allegiance may be driven by prejudicial attitudes and as such this set of variables may be endogenous. Omitting them from the regression models, however, has very little impact on the remaining estimated coefficients.

employed). Considering age, the only statistically significant effect is for males aged 35-64. For this group, the estimate of 0.017 implies racial prejudice increases by 1.7%-points for every 1%-point increase in UR. Or to put it another way, for a 4%-point increase in UR (as seen in the most recent recessionary period) it is estimated that 7 additional men out of every 100 self-report racial prejudice. The sub-analysis by education reveals that racial prejudice is indeed most strongly counter-cyclical for the high education group. The estimated effects for males and females equal 0.015 and 0.015. With respect to employment status, Table 2 reveals that prejudice attitudes are counter-cyclical for working males. If we consider full-time working males, the results imply that a 1%-point increase in UR increases racial prejudice by 1.8%-points.[16]

To explore this finding further, the bottom panel of Table 2 presents additional sub-group analysis based on interactions between age, education and employment. The results show that for men the UR effect is large and statistically significant for each interacted sub-group. The effect is particular large in the final row, which presents estimates for the highly educated that are full-time employed and aged 35-64. The estimate suggests that a 1%-point increase in UR increases racial prejudice by 3.9%-points. This is a 11% increase relative to the mean racial prejudice for this group of 36%. For females, racial prejudice is also most strongly counter-cyclical for the highly educated that are full-time employed and aged 35-64. The estimate suggests that a 1%-point increase in UR increases racial prejudice by 2.2%-points. Given that the average individual in this sub-group is relatively high-skilled, these findings concur with our hypothesis that racial prejudice is most strongly counter-cyclical for high-skilled workers.[17]

Importantly, an alternative explanation is possible for the results presented in Tables 1 and 2. Prejudice levels amongst workers may increase during recessions if individuals with relatively low levels of racial prejudice are more likely to become unemployed than

[16] Interestingly, the estimated effects of unemployment on prejudice are substantially larger during the recent Great Recession. Using the period 2005-2010, the estimated unemployment rate effects for employed men and for highly-educated men equal 0.050 (t-stat = 2.53) and 0.059 (t-stat = 2.71), respectively.

[17] It's possible that the most relevant measure of labour market competition is not the area-year unemployment rate (as used in Tables 1 and 2), but more individual-specific rates (e.g. based on area, year, education and age). However, it is not possible to use individual-specific rates in the BSA analyses as the areas and survey years in the British Labour Force Survey only partially match those in the BSA. Nevertheless, we can demonstrate that the area-year UR is a significant predictor of employment outcomes for all subgroups and is therefore relevant (results available upon request).

individuals with high levels of racial prejudice. This systematic selection out of employment is plausible if prejudiced workers cooperate together and compete against more tolerant individuals for scarce resources. In this scenario, individual-level prejudice may not have increased during recessions; however, it is still the case that the likelihood of encountering a prejudiced colleague, manager or employer has increased. Thus, we still view this as a worrisome change.

The results in Tables 1 and 2 are also robust to alternative model specifications (see Appendix Table A2). First, the continuous UR was replaced with dummies representing the UR groupings of 5-8%, 8-11% and >11% (<5% was the omitted comparison group). The estimated effects for the high-skilled subgroup (i.e. highly educated, full-time employed and aged 35-64) equal 0.031, 0.080 and 0.169. Second, lagged UR variables (UR_{at-1}, UR_{at-2}) were added to the specification. The dynamic specifications suggest that the UR effect is largely contemporaneous. For the high-skilled subgroup the estimated effects for UR_{at}, UR_{at-1} and UR_{at-2} equal 0.040, -0.004 and 0.006, respectively. Finally, using a three year average of UR, which would reduce any measurement error, counter-intuitively reduces the estimated UR effect for some sub-groups; however, the effect for the high-skilled subgroup remains strong (0.043).

Finally, we can show that the unemployment rate relates to the BSA respondents' expectations of future prejudice rates in Britain. In addition to the question on own racial prejudice, the BSA regularly asks "Do you think there is generally more racial prejudice in Britain now than there was 5 years ago?" with the respondent given the following response options: "less", "more" or "about the same amount"?, and "Do you think there will be more, less, or about the same amount of racial prejudice in Britain in 5 years time compared with now?". In Appendix Table A3 we present the estimated effects of UR on a binary variable indicating that the respondent believes there is less prejudice now than 5 years ago, and on a binary variable indicating that the respondent believes there will be less prejudice in 5 years time. The results show that an increase in UR significantly reduces the probability that the respondent believes there will be less prejudice in 5 years time: the estimated effect for the high-skilled subgroup defined above equals -0.016 (relative to a mean of 0.22). In other words, higher unemployment rates now lead people to expect more racial prejudice in the future.

4. Estimating Labour Market Discrimination over the Business Cycle

The results in the previous section highlight that employed males aged 35-64 that are highly educated have the most pronounced counter-cyclical racial prejudice. Or at least, there are a larger proportion of intolerant high skill males in employment during recessions. Assuming these individuals are more likely to be managers, bosses and have political power within organisations, this may translate into worse labour market outcomes for non-Whites during periods of high unemployment. That is, if this is an increase in taste discrimination, high-skilled White males may discriminate against non-Whites of all skill levels for whom they have any power over. However, if the increase in discrimination is a reaction to heightened job insecurity, the worsening will be concentrated among high skill job-seekers and workers (that is, people ‘like me’). In some sense this may be viewed as ‘rational’ discrimination, given that the propensity to discriminate arises from increased competition with those at their own skill level. It follows, that if successful it results in the person’s own job and the jobs of their group members being more secure (Frijters, 1998). That is, there are economic gains to forming coalitions based on ethnicity.

It is important to note that any racial labour market gaps that we can identify here could be counter-cyclical in the absence of counter-cyclical racial prejudice. An alternative explanation is that the costs of discriminatory behaviour could be lower during periods of high unemployment (Biddle and Hamermesh, 2013; Baert et al. 2013). Hiring a less qualified White applicant generates costs in terms of foregone production, and turning away a qualified non-White applicant generates additional search costs. During economic downturns there is a greater pool of White applicants to employ, and therefore employers with a taste for discrimination can more easily find qualified White workers. Thus, while the analysis that follows can inform on how racial labour market gaps vary with macroeconomic conditions, we cannot with certainty state that these changes are owed to increased racial prejudice. Nevertheless, given the results in Section 3, evidence that high skill non-Whites are especially affected during recessions would be highly suggestive that prejudice (and inter-group competition) is an important pathway. Thus, what follows is arguably a powerful indirect test.

4.1. Data

Our data source for measuring labour market discrimination is the 1993-2012 versions of the Quarterly Labour Force Survey (QLFS). The QLFS is the main survey of individual economic activity in the UK, and provides the official measure of the national unemployment rate. We consider wage and employment differences between native Whites and native non-Whites, and exclude all immigrants from the analysis. We make this selection decision because non-White immigrants have significantly lower observed and unobserved human capital than native Whites and non-Whites; they generally have lower levels of formal education, lack English language skills, are unfamiliar with local customs and work in unskilled jobs (Berthoud, 2000; Heath and Cheung, 2007). In addition, the composition of the immigrant work force is likely to change over the business cycle, with average immigrant human capital levels changing with the needs of the economy. This arises given that natives are likely to have more ties to their area of residence than non-natives. Individuals are identified as being native to the UK based on their country of birth and we include all respondents aged 18-64 years. We choose to focus on both employment and wages as it is plausible that there is heterogeneity in the results for these outcomes across worker groups. For example, the recession wage penalty (RWP) may be worse for highly educated non-Whites whilst the recession employment penalty (REP) may be worse for non-Whites with low education levels. For the purpose of our analysis we generate quarterly unemployment rates specific to 19 geographic regions.[18]

4.2. Methodology

We now consider an indirect test to explore whether the increased prejudice described above may be affecting the labour market outcomes of non-Whites. Specifically, we test whether increases in the area-level UR increases racial employment and wage differentials, especially among those most in competition with high skilled White men. The test is based on estimates of a linear regression model with intercepts specific to each region of residence and quarter:

$$y_{iat} = \delta NW_{iat} + \gamma(UR_{at} \cdot NW_{iat}) + X_{iat}\beta' + \mu_{at} + \varepsilon_{iat} \qquad (2)$$

[18] The geographic regions are: Tyne and Wear; Rest of North East, Greater Manchester, Merseyside, Rest of North West, South Yorkshire, West Yorkshire, Rest of Yorkshire and Humberside, East Midlands, West Midlands Metropolitan County, Rest of West Midlands, East of England, Inner London, Outer London, South East, South West, Wales, Strathclyde, and Rest of Scotland.

where y_{iat} is either log wages or employment of individual i residing in area a in quarter t, NW_{iat} is a dummy variable indicating that individual i is non-White (disaggregated racial identifiers are used in some specifications), X_{iat} is a vector of individual-level control variables, μ_{at} is an area-quarter fixed-effect, and ε_{iat} is a random disturbance term. Standard errors are clustered at the quarter-level (78 clusters), and are generally larger than standard errors obtained when clustering at the area-quarter level. For the wage regressions, the sample is restricted to those who are employed, and the wage variable is equal to the log of real gross weekly wages. Moreover, we include in all wage regressions nine dummy variables representing the first digit of standard occupation codes, along with nine interaction terms between the occupation dummies and the area-quarter unemployment rate. These occupation dummies control for the possibility that non-Whites more frequently work in occupations in which employment and wages are particularly responsive to economic conditions.

Area-quarter intercepts (fixed-effects) are included in equation (2) to control for any differences in wages and employment across areas and time – this approach amounts to the inclusion of 1482 area-quarter dummy variables. This approach is feasible because the main variable of interest is the interaction term $UR_{at} \cdot NW_{iat}$, which varies across individuals within the same area-quarter. The large number of area-quarter terms does however rule out the use of a probit modelling approach for the employment outcome. Consequently, we use linear models for both employment and log wage outcomes. Note also that the pure unemployment rate effect on wages is not identified, as all individuals in the same area-quarter face the same rate. We feel it is preferable to adequately control for differences in outcomes across areas and time, than to include a higher-level fixed-effect term (such as area-level intercepts) and identify the pure unemployment rate effect.[19]

A coefficient of interest in equation (2) is δ, which provides a measure of the wage gap between Whites and non-Whites. Typically, the racial wage gap is negative, indicating that non-Whites earn less than Whites; though, given we have omitted all immigrants this may not hold true in our analysis. Importantly, the interaction term is constructed such that δ represents the wage gap at mean levels of UR. Another coefficient of interest is γ, which

[19] We note that all conclusions are robust to relaxing this assumption, with the estimates from this preferred model being the most conservative.

we've labelled the RWP in the case of wages and the REP in the case of employment. In the case of wages, this term measures how the percentage difference in wages between native Whites and non-Whites (wage gap) changes with each 1%-point change in UR. A negative value of γ means an increase in UR worsens the wage gap between Whites and non-Whites, implying counter-cyclical discrimination. Conversely, a positive value of γ implies pro-cyclical discrimination. In a similar vein, the REP measures how the percentage difference in the probability of being employed between native Whites and non-Whites (employment gap) changes with each 1%-point change in UR.[20]

The vector of individual-level control variables (X_{iat}) includes, age, age squared, education level (low, (control group), medium and high), marital status (single (control group), married, separated/divorced/widowed) and the number of children. For the wage regressions we also include usual hours worked and usual hours worked squared as additional controls. These covariates are included because there is a tendency for ethnic minorities to participate in part-time work more frequently than Whites (Blackaby et al, 2002); though in practice they make little quantitative difference to the estimates of γ. Similarly, our results are robust to the addition of fixed effects representing industry.

4.3. Results

Table 3 presents estimates of equation (2) for the employment and log wage outcomes, separately by males and females.[21] The four coefficients pertaining to the non-White indicator suggest that non-Whites have worse labour market outcomes than Whites overall. Specifically, non-White males are 13.5%-points less likely to be employed and their wages are 9.1% lower than White males (at mean levels of UR). Non-White females are 9.1%-points less likely to be employed and their wages are 2.0% lower than White females. However, these estimated gaps must be interpreted with caution as they may not solely be caused by discrimination (taste-based or statistical), even when considering a sample of natives only. Alternative explanations are that non-Whites have lower levels of unobserved

[20] The potential mechanisms for REPs are increases in the likelihood of non-Whites getting fired and decreases in the likelihood of non-Whites getting hired. The potential mechanisms for RWPs are non-Whites' disproportionally suffering pay cuts, lower starting wages when hired, and less frequent pay increases, bonuses and promotions.

[21] The estimated wage effects of our control variables are all consistent with previous studies. Age has a negative quadratic correlation, and education, marriage and children have a positive correlation.

human capital and that non-Whites are systematically willing to trade salary for non-pecuniary compensation (due to differences in tastes or risk preferences).

Coefficients on the non-White UR interaction term are also significantly negative. For males the employment gap and wage gap increase by 0.6%-points and 1.2% for a 1%-point increase in UR.[22] For females, employment is not affected by UR, while the wage gap increases by 1.1% for a 1%-point increase in UR. For a 4%-point increase in UR (as seen in the recent recession) these estimates imply that relative wages decrease by about 5% for both genders.[23] These estimates are less likely to suffer from omitted variable bias (composition effects) than the estimated average gaps, because unobserved human capital or preference differences between native Whites and non-Whites are unlikely to be associated with differences in area-level unemployment rates.[24] This contrasts with analogous immigration studies in which the systematic self-selection of immigrants into high wage areas is a genuine concern. An approach used in the immigration literature to mitigate the bias is to examine only the sub-group of immigrants who have been living in the country for many years (e.g. Dustmann et al., 2010). This approach is based on the assumption that the current residential location of established immigrants is less likely to be based upon cyclical macroeconomic conditions. This is an assumption similar to our own, given that our analysis focuses exclusively on native ethnic minorities. Another approach is to examine more homogenous groups of employees. The idea is that the likelihood of omitted variable bias (unobserved human capital differences) is lessened if identification comes from comparisons between workers in similar age, education and occupation groups. We implement this approach below.

Before presenting the subgroup analyses, we investigate the possibility that effects differ across regions and time according to the racial diversity of managers. Specifically, we construct, by area-year, a variable that equals the ratio of the proportion of managers who are White to the proportion of the population who are White (based on self-reports of managerial

[22] The employment effects are not contingent on the inclusion of area-quarter fixed-effects. In models of employment with only area fixed-effects, the coefficient on the unemployment rate – non-white interaction term equals -0.005 (t-statistic = -5.07). The results are smaller but still statistically significant if no fixed-effects are included (coefficient estimate = -0.002; t-statistic = -1.91).

[23] Assuming there is negative selection out-of-employment (with respect to productivity and hence wages), the estimated increase in the wage gaps between Whites and non-Whites is an under-estimate of the counterfactual increase in the wage gap in the absence of selection out-of-employment.

[24] More specifically, our estimates would be partly driven by bias if non-White workers with high unobserved human capital systematically move to relatively low UR areas at higher rates than White workers and non-White workers with low unobserved human capital.

status). This variable, which ranges from 0.995 to 1.240, is then interacted with the main interaction term – UR · Non-White – and added to the baseline wage regression models.[25] The estimated coefficients on this new additional interaction term are significantly negative at the 5% level: male and female coefficients equal -0.059 and -0.069, respectively. These negative values indicate that the RWP for ethnic minorities is more highly cyclical in areas that have relatively high proportions of White managers. This result conforms to our hypothesis that an increase in prejudice among highly-educated middle-aged White men translates into worse labour market outcomes for non-Whites.

Table 4 presents the results from a sub-group analysis for men (age, education and work hours). We focus on males given that the employment selection issues are far less problematic than for females. The results between genders are however generally consistent[26]. In Table 4 we report the coefficient on the non-White dummy variable that captures the racial wage/employment gap and the interaction term that captures the RWP or REP. The non-White dummy variable is negative and significant for all sub-groups in both the employment and wage models. For employment it is particularly large for the 18-34 age group (-0.157) and for the medium education group (-0.175). For wages it is particularly large for the 35-64 age group (-0.101), medium and high education groups (-0.083 and -0.084) and for full-time workers (-0.089). More relevant are the estimated coefficients on the interaction term UR · Non-White. For both employment and wages, this interaction term is larger for older (-0.008 and -0.014) and highly educated individuals (-0.012 and -0.014). The difference between part-time and full-time workers is small and not statistically significant.

Table 5 extends the sub-group analysis to occupation, sector and industry in order to consider heterogeneity in the effects. Overall, we may expect the results to be strongest for

[25] Given it is only possible to be a manager if employed, this constructed variable is endogenous to the racial gap in the probability of employment, and therefore was not additionally included in the employment regressions.

[26] Equivalent female results are included in Appendix Tables A4 and A5. Consistent with the results for males it is high-skilled non-manual, highly educated and manufacturing workers that have the highest RWPs. However, there are some differences to the male results. When we disaggregate our non-White indicator into Black, Asian and other ethnicity (see Table A.5) we observe that while the RWP is largest for high-skilled Black males, for females it is high-skilled Asians that have the largest RWP (-0.015 and -0.012 for Asian and Black females respectively). Similarly, among high skill non-manual workers, Asian females do worse than Black females (-0.018 and -0.015 for Asian and Black females respectively). In contrast, for the REP Black females are the worst off in all the sub-groups we consider. Thus, it seems that Black females have a higher tendency to be fired and a lower tendency to be hired during recessions, rather than having lower wages conditional on employment.

manufacturing and administrative public services, which are the areas where entry is difficult in the short-run. Thus, there is an increased propensity for insider-outsider dynamics during a downturn as it is likely to reap rewards. Given that spending on education and health was not curtailed in the recessions that we analyse, we would expect lower effects in these industries. Additionally, we would expect lower effects for the unskilled whose jobs have lower barriers to entry and where racially based insider-behaviour is likely to be less effective. Overall, the results in Table 5 are in line with this intuition. Specifically, the estimated coefficients show that the interaction term UR · Non-White is largest for high-skilled non-manual workers (-0.015), private sector workers (-0.014), and workers in the manufacturing (-0.020) and construction (-0.019) industries. Combined with the results in Table 4, these results suggest that it is high-skilled non-White workers – whether skill is defined by experience (proxied by age), education or occupation – in manufacturing and construction sectors that suffer most during recessions. If we re-estimate the models for the combined group – high-educated, high-skill non-manual workers in manufacturing and construction industries – the estimated RWP equals -0.033 (p-value <0.001). This estimate implies that for this sub-group, non-White relative wages decrease by around 13% with a 4%-point increase in UR, as seen in the recent Great Recession.[27]

In Tables 3-5 the unemployment rate is defined as the average rate of unemployment for all individuals residing in a particular area in a particular quarter. However, it is possible that the relevant measure for a subgroup is not the area-quarter average across all individuals, but the area-quarter average across only those individuals belonging to the subgroup (e.g. unemployment rate for highly educated men aged 35-64). This measure may more adequately capture labour market competition. Given sample size restrictions it isn't possible to calculate highly individual-specific unemployment rates, but can we test this proposition by re-estimating the models with education-area-quarter unemployment rates instead of area-quarter unemployment rates. The results are mixed, with some UR · Non-White coefficient estimates larger than those presented and some smaller; though in all cases they remain statistically significant and the overall conclusions are the same. For example, in male log wage models the new estimate for: all men equals -0.005; highly-educated men equals -

[27] As in the BSA prejudice analysis, results are generally stronger if we re-estimate models for sample years around the recent Great Recession. For example, using years 2005-2012, the estimated UR · Non-White coefficient from male log wage models equals -0.015 (t-stat = -3.96) for all male workers, -0.022 (t-stat = -2.88) for highly-educated workers, and -0.024 (t-stat = -4.10) for high skill non-manual workers.

0.021; construction and manufacturing workers equals -0.008; and the combined high-skill group discussed directly above equals -0.069.

We have chosen not to use education-area-quarter rates as our main measure as we don't feel that it's indisputably the 'best' measure to use. Theoretically, individuals should respond more strongly to the unemployment rate they personally face. But in reality, individuals respond only to perceived labour market competition, and individuals form perceptions based on readily available information, such as published region-specific unemployment rates, not largely unobservable individual-specific unemployment rates. More generally, there is a small economics literature that shows individuals are poor predictors of their 'true' labour market competition. For example, Kassenboehmer and Schatz (2014) show "that a substantial number of the currently unemployed consistently underestimate their re-employment probability and that our econometrician's model performs better on average at predicting re-employment than the individuals stated expectations". Another reason why we don't use education-region-quarter rates as our main measure is that even with the large LFS sample, almost 10% of cells have fewer than 500 observations. Thus, the rates for many cells will contain substantial measurement error, leading to attenuation bias.

Next we explore the potential for heterogeneity across the non-White sub-groups by disaggregating this broad classification into three groupings: Blacks, Asians (Indian, Pakistani or Bangladeshi) and other ethnicities (including Chinese).[28] Practically, we replace the non-White dummy variable in equation (2) with dummy variables representing these three sub-groups. Similarly, we replace the interaction between non-Whites and UR with three interaction terms. The results are documented in Table 6 for our full sample as well as a sub-analysis for highly educated individuals,, workers in high-skill non-manual occupations and workers in manufacturing and construction industries. These subgroups were chosen because their estimated effects in Tables 4 and 5 indicate that the effects for these groups are driving the full-sample effects in Table 3. The disaggregated results reveal that the effect of the unemployment rate (interaction terms) on employment and log wages is larger for Black men (-0.011 and -0.013) than for Asian men (-0.004 and -0.011) and other non-White men (-0.003 and -0.007). The difference between the non-White sub-groups is particularly evident

[28] We follow the common practice used in British surveys of labelling individuals from the Indian subcontinent countries of India, Pakistan and Bangladesh as 'Asian', and treating these individuals separately to those from other countries in Asia (e.g. China).

in the sub-group wage analysis. The estimated coefficients on the UR · Black interaction terms for the high educated, high-skill non-manual, and manufacturing/construction subgroups equal -0.020, -0.024 and -0.023, respectively.

5. Conclusions

This paper investigates whether self-reported racial prejudice increases during economic downturns. There is ample anecdotal evidence that this is the case; but evidence based upon comprehensive statistical analysis is almost non-existent. By exploiting variation in unemployment rates across geographic regions and time, we find only small general population increases in prejudice during periods of high unemployment. However, we find large increases for White males who are full-time employed, have high levels of education and are middle aged. The increase is especially large for the interaction of these groups; a 1%-point increase in unemployment raises self-reported racial prejudice by 4%-points or 10% relative to mean levels. The equivalent effect for females is also statistically significant, albeit half the size of the male effect. This set of results therefore corroborates the popular perception that racial prejudice does increase during recessions. Unfortunately, we do not have a time consistent racial identifier in the BSA with sufficient cell size to allow us to comment on whether racial attitudes changed for any non-White groups.

The second half of the paper examines a potentially harmful consequence of this rise in racism. Given that there is a large increase in racial prejudice among highly-educated, middle-aged, full-time employed men, it may be expected that this would translate into worse labour market outcomes for all non-White workers regardless of their skill level. This is classic ‘taste’ based discrimination. However, if the increase in discrimination is owed to heightened job insecurity the worsening will be concentrated among the highly skilled. This arises if the propensity to discriminate is the result of competition over scarce resources among job-seekers and workers with similar traits. Here, there are gains to forming coalitions based on ethnicity. Our empirical analysis of the LFS highlights that there are significant differences in employment and wages between Whites and non-Whites, and that these gaps increase with the unemployment rate. Specifically, we find the recession employment and wage penalties are the greatest for non-White workers with high skill levels, particularly for men working in manufacturing and construction industries. This suggests that the most likely mechanism is through the increased competition channel. For example, the estimated RWP for high-educated, high-skill non-manual workers in manufacturing and construction industries equals 3.3%, implying that non-White relative wages decrease by around 13% with a 4%-point increase in UR, as seen in the recent Great Recession. Further analysis reveals that Black workers suffer larger RWPs than other non-White workers.

Overall, the attitudes and labour market results support the hypothesis that racial prejudice is driven partly by increased labour market competition between racial groups during periods of high job uncertainty and scarcity.[29] That is, the comparatively large effects for high-skill subgroups with respect to both self-reported racial prejudice and racial labour market gaps suggest that high-skill Whites may be utilising racial discrimination as a means to retain employment and achieve high wages. However, we are unable to conclusively exclude two alternative explanations. First, the costs of discriminatory behaviour could be lower during periods of high unemployment due to the greater pool of qualified White applicants to employ and promote. Second, the QLFS results could be driven by a converse process, in which affirmative action policies are promoted during economic expansions and abandoned during periods of economic recession. This is plausible if the distribution of unobserved productivity differs by race. Both of these explanations imply that racial labour market gaps are counter-cyclical even in the absence of increased racial prejudice. Though possible, in light of our self-reported racial prejudice results, we believe these additional processes could only be partially responsible for our results.

Regardless of the exact underlying processes, we find that during recessions there are relatively more White workers who report being racially prejudiced, and we find that during recessions existing racial inequalities in the labour market widen. The recent commentary in the popular press and the corresponding statements from equality and human rights groups appear correct. Given that non-Whites continue to experience significant inequalities in health, housing and schooling quality, we argue that policy makers must be mindful of how recessions can disproportionately penalise minority individuals, and should develop policies to avoid these harmful effects in the future. What these policies should be is not obvious given that currently the burden of proving discrimination is mostly on workers. We suggest that the government audit medium to large firms and publish the proportion of Non-Whites

[29] These conclusions are robust to the consideration of a number of non-linear specifications, however this dynamic may be specific to the UK where ethnic minorities receive a similar number of third level qualifications in comparison to Whites.

who are in senior roles. This may offer some safeguards for employees in companies that rely on public reputation. Additionally, details of employment discrimination claims could be published annually with a right to reply by employers.

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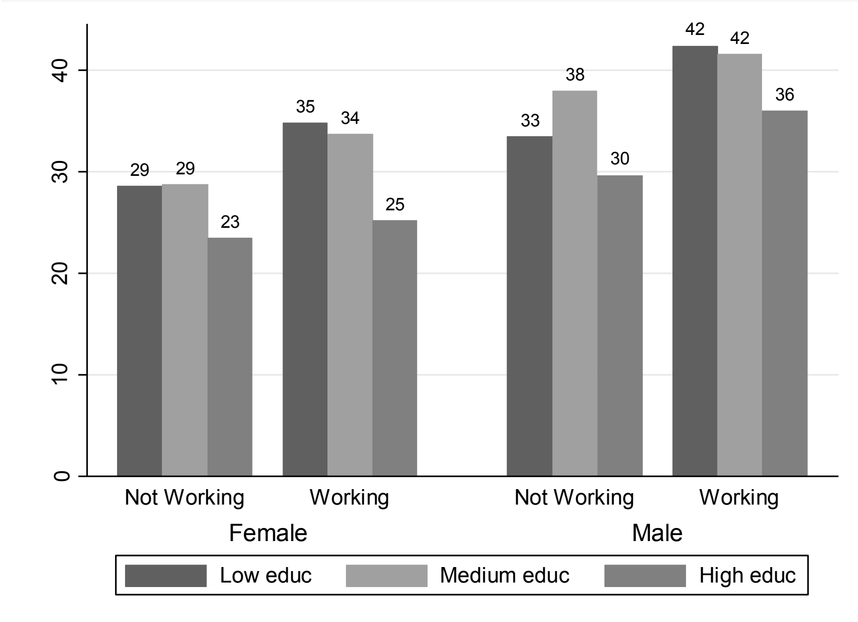
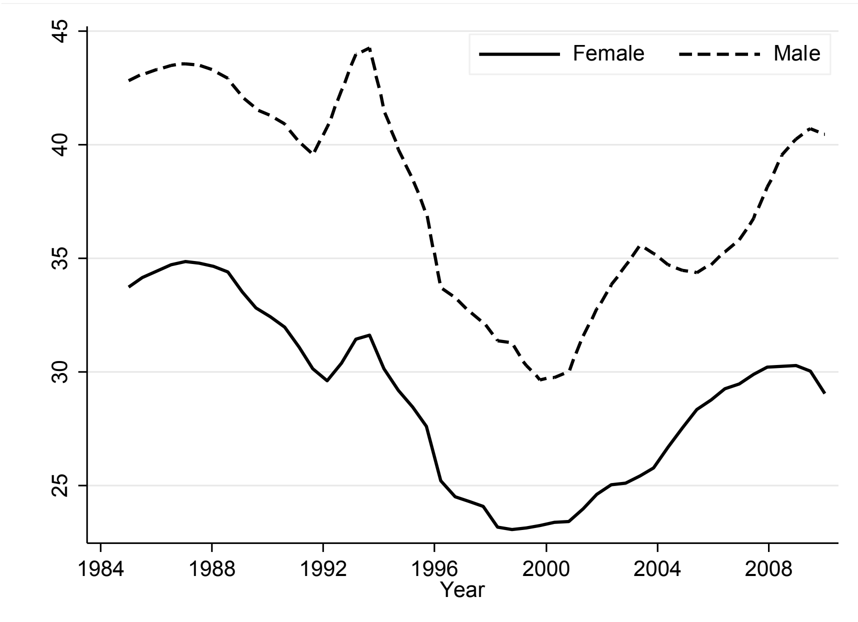
Figure 1: Self-Reported Racial Prejudice by Education, Gender and Employment Status



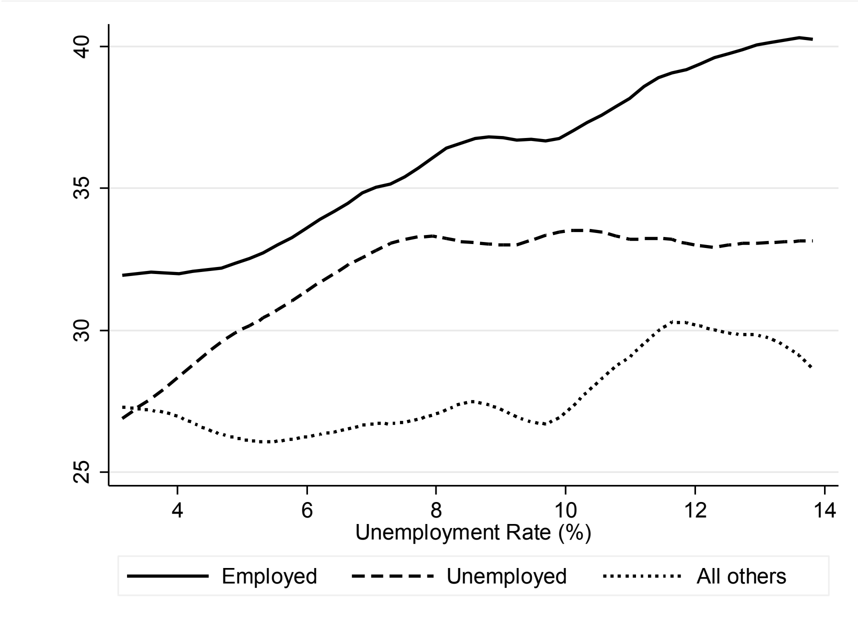
Notes: Based on the responses from White respondents who are in the working-age population (aged 18-64)

Figure 2: Self-Reported Racial Prejudice across Time by Gender



Notes: Based on the responses from White respondents who are in the working-age population (aged 18-64)

Figure 3: Cross-Sectional Relationship between Regional Unemployment Rates and Self-Reported Racial Prejudice



Notes: Based on the responses from White respondents who are in the working-age population (aged 18-64)

Table 1: Linear Probability Models of Self-Reported Racial Prejudice by Gender

	Males		Females	
	ME	SE	ME	SE
Unemployment rate	0.010	(0.006)	0.004	(0.006)
Age	-0.010***	(0.003)	0.000	(0.002)
Age squared / 100	0.011***	(0.003)	0.001	(0.003)
Number of children	-0.007	(0.005)	-0.014***	(0.004)
Married	0.064***	(0.012)	0.006	(0.011)
Separated or divorced	0.028*	(0.015)	0.004	(0.013)
Widowed	0.023	(0.032)	-0.026	(0.020)
Full-time employment	0.044***	(0.016)	0.030***	(0.009)
Part-time employment	-0.002	(0.025)	0.031***	(0.010)
Unemployed	0.016	(0.022)	0.019	(0.015)
Retired	-0.014	(0.022)	0.016	(0.016)
Full-time student	-0.060**	(0.030)	-0.054***	(0.020)
Education medium	0.015	(0.011)	0.012	(0.009)
Education high	-0.037***	(0.013)	-0.061***	(0.011)
Log income	0.167***	(0.036)	0.073**	(0.030)
Log income squared	-0.033***	(0.007)	-0.011*	(0.006)
No party allegiance	-0.031**	(0.015)	-0.038***	(0.013)
Labour voter	-0.108***	(0.010)	-0.094***	(0.010)
Alliance voter	-0.105***	(0.013)	-0.085***	(0.012)
Other party voter	0.072**	(0.031)	-0.014	(0.025)
Mean outcome	0.375		0.289	
R-squared	0.041		0.039	
Sample size	14150		17232	

Note: Figures are OLS coefficient estimates based on the responses from White individuals only aged 18-64. Dependent variable equals one if a little prejudiced or very prejudiced, and zero otherwise. Included in the model but not shown are area-level fixed-effects, area-level linear time trends, and year fixed-effects. Standard errors clustered at the area-year level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Table 2: Estimated Effects of the Unemployment Rate on Self-Reported Racial Prejudice by Subgroups

	Males		Females	
	ME	SE	ME	SE
Age				
(1) 18-34	-0.007	(0.011)	0.007	(0.008)
(2) 35-64	0.017***	(0.006)	0.003	(0.007)
Education				
(3) Low (no qualifications)	-0.004	(0.014)	-0.006	(0.009)
(4) Medium (CSE / o-levels)	0.018	(0.011)	-0.000	(0.010)
(5) High (a-levels / degree)	0.015**	(0.007)	0.015*	(0.008)
Employment				
(6) Full-time	0.018***	(0.007)	0.011	(0.008)
(7) Full-time or part-time	0.014**	(0.007)	0.010	(0.007)
(8) Not employed	0.002	(0.012)	-0.005	(0.009)
Interactions				
(9) 35-64 + high educ	0.029***	(0.010)	0.014	(0.009)
(10) 35-64 + full-time emp	0.027***	(0.007)	0.011	(0.010)
(11) high educ + full-time emp	0.020**	(0.009)	0.014	(0.011)
(12) 35-64 + high educ + full-time emp	0.039***	(0.010)	0.022*	(0.012)

Note: Figures are OLS unemployment rate coefficient estimates based on the responses from White individuals only aged 18-64. Dependent variable equals one if a little prejudiced or very prejudiced, and zero otherwise. Each estimate is from a separate OLS regression model. Included in all models are the covariates shown in Table 1, area-level fixed-effects, area-level linear time trends, and year fixed-effects. Standard errors clustered at the area-year level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Table 3: Employment and Log Wage Regression Models using Data from Labour Force Survey

	Males		Females	
	Employed	Log Wage	Employed	Log Wage
Non-White	-0.135***	-0.091***	-0.091***	-0.020***
	(0.002)	(0.005)	(0.003)	(0.005)
UR · Non-White	-0.006***	-0.012***	0.001	-0.011***
	(0.001)	(0.002)	(0.001)	(0.002)
Age	0.051***	0.067***	0.046***	0.041***
	(0.000)	(0.001)	(0.001)	(0.000)
Age squared	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education medium	0.118***	0.133***	0.151***	0.107***
	(0.001)	(0.002)	(0.002)	(0.002)
Education high	0.166***	0.328***	0.240***	0.307***
	(0.002)	(0.003)	(0.002)	(0.002)
Married	0.152***	0.110***	0.053***	0.015***
	(0.001)	(0.002)	(0.001)	(0.002)
Separated / divorced	0.010***	0.056***	0.006***	-0.001
	(0.002)	(0.003)	(0.001)	(0.002)
Number of children	-0.026***	0.012***	-0.098***	-0.024***
	(0.000)	(0.001)	(0.000)	(0.001)
Occupation controls	×	✓	×	✓
Work hours controls	×	✓	×	✓
Sample size	2234822	435777	2633749	463505

Note: Figures are estimated coefficients from linear regression models with 1482 quarter-region fixed-effects. The sample is restricted to native individuals only. Occupation controls are 9 dummy variables denoting occupation categories and 9 interactions between the occupation dummies and the unemployment rate. Work hours controls are work hours and work hours squared. Standard errors clustered at the quarter level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Table 4: Employment and Log Wage Models for Males by Age, Education and Work hours

	Employed				Log Wage			
	Non-White		UR · Non-White		Non-White		UR · Non-White	
Age								
(1) 18-34	-0.157***	(0.003)	-0.003***	(0.001)	-0.091***	(0.006)	-0.011***	(0.002)
(2) 35-64	-0.069***	(0.004)	-0.008***	(0.001)	-0.101***	(0.011)	-0.014***	(0.004)
Education								
(3) Low	-0.127***	(0.007)	-0.004**	(0.002)	-0.069***	(0.013)	-0.005	(0.005)
(4) Medium	-0.175***	(0.003)	-0.001	(0.001)	-0.083***	(0.007)	-0.011***	(0.003)
(5) High	-0.070***	(0.003)	-0.012***	(0.001)	-0.084***	(0.009)	-0.014***	(0.003)
Work hours								
(6) Part-time	-		-		-0.046***	(0.014)	-0.013**	(0.005)
(7) Full-time	-		-		-0.089***	(0.005)	-0.010***	(0.002)

Note: Each coefficient represents a coefficient estimate from an individual regression that differs by the dependent variable and the sub sample being considered. Figures are estimated coefficients on a non-White dummy variable and on the interaction term UR·Non-White from linear regression models with 1482 quarter-region fixed-effects. The sample is restricted to native individuals only. Also included but not shown are covariates representing age, educational attainment, marital status and children. Occupation and work hours controls are also included in the log wage regressions. Standard errors clustered at the quarter level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Table 5: Log Wage Models for Males by Occupation, Sector and Industry

	Non-White		UR · Non-White	
Occupation				
(1) All manual	-0.059***	(0.010)	-0.004	(0.004)
(2) Low skill non-manual	-0.091***	(0.010)	-0.007**	(0.003)
(3) High skill non-manual	-0.097***	(0.008)	-0.015***	(0.003)
Sector				
(4) Private	-0.096***	(0.006)	-0.014***	(0.003)
(5) Public	-0.071***	(0.009)	-0.006	(0.005)
Industry				
(5) Manufacturing	-0.079***	(0.013)	-0.020***	(0.006)
(6) Construction	-0.077***	(0.027)	-0.019*	(0.011)
(7) Hotels & restaurants	-0.077***	(0.012)	-0.014***	(0.004)
(8) Transport & communication	-0.071***	(0.016)	-0.001	(0.006)
(9) Banking & finance	-0.121***	(0.013)	-0.009	(0.006)
(10) Public admin & social security	-0.115***	(0.017)	-0.006	(0.006)
(11) Education	-0.034	(0.020)	-0.010	(0.009)
(12) Health & social work	-0.031*	(0.019)	-0.010	(0.007)

Note: Each coefficient represents a coefficient estimate from an individual regression that differs by the sub sample being considered. Figures are estimated coefficients on a non-White dummy variable and on the interaction term UR·Non-White from linear regression models with 1482 quarter-region fixed-effects. The sample is restricted to native individuals only.Also included but not shown are covariates representing age, educational attainment, marital status, children, occupation and work hours. Standard errors clustered at the quarter level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Table 6: Disaggregated Racial Employment and Wage Gaps for Males

	Employed		Log Wage			
	All	High Education	All	High Education	High skill Non-manual	Manufacturing & Construction
Black	-0.111***	-0.080***	-0.103***	-0.143***	-0.150***	-0.084***
	(0.004)	(0.007)	(0.009)	(0.015)	(0.013)	(0.017)
Asian	-0.150***	-0.064***	-0.085***	-0.059***	-0.064***	-0.078***
	(0.004)	(0.004)	(0.008)	(0.012)	(0.013)	(0.016)
Other ethnicity	-0.133***	-0.072***	-0.086***	-0.073***	-0.088***	-0.075**
	(0.005)	(0.008)	(0.012)	(0.018)	(0.018)	(0.031)
UR · Black	-0.011***	-0.013***	-0.013***	-0.020***	-0.024***	-0.023***
	(0.001)	(0.003)	(0.003)	(0.006)	(0.005)	(0.007)
UR · Asian	-0.004***	-0.012***	-0.011***	-0.009*	-0.010*	-0.017**
	(0.001)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
UR · Other	-0.003*	-0.009***	-0.007	-0.009	-0.010	-0.009
	(0.002)	(0.002)	(0.005)	(0.007)	(0.007)	(0.009)
Sample size	2234822	557991	435777	131904	196791	141231

Note: Figures are estimated coefficients from linear regression models with 1482 time-region fixed-effects. The sample is restricted to native individuals only. Also included but not shown are covariates representing age, educational attainment, marital status and children. Occupation and work hours controls are also included in the log wage regressions. Standard errors clustered at the quarter level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Appendix Table A1: Description of Covariates Used in Analyses of Self-Reported Racial Prejudice

Variable	Full Sample	Not Prejudiced	Little / very Prejudiced
Male	0.451	0.419	0.516
Age	41.62	41.34	42.18
Age squared / 100	19.03	18.79	19.52
Number of children	0.674	0.691	0.640
Married	0.639	0.622	0.674
Separated or divorced	0.126	0.131	0.114
Widowed	0.033	0.035	0.030
Full-time employment	0.532	0.510	0.578
Part-time employment	0.128	0.131	0.120
Unemployed	0.061	0.062	0.059
Retired	0.068	0.067	0.069
Full-time student	0.023	0.028	0.015
Education medium	0.308	0.295	0.333
Education high	0.419	0.437	0.382
Log income	2.678	2.662	2.709
Log income squared	7.699	7.646	7.806
No party allegiance	0.118	0.117	0.119
Labour voter	0.326	0.351	0.275
Alliance voter	0.119	0.125	0.107
Other party voter	0.028	0.027	0.031
Sample size	31382	21092	10290

Note: All figures are sample means from White respondents only aged 18-64. The omitted (baseline) dummy variables are: never married; looking after the home; no educational qualification; Conservative party preference.

Appendix Table A2: Non-Linear and Dynamic Specifications for Middle Aged, Highly Educated, Full-Time Employed Samples

	All Females (1)	All Males (2)	Males Aged 35-64 (3)	Males with High Education (4)	Males Full-time Employed (5)	Interaction of Groups (3)-(5) (6)
(A) Nonlinear						
$5 < UR_t \leq 8$	0.005	0.034**	0.027	0.017	0.054***	0.031
	(0.016)	(0.013)	(0.017)	(0.016)	(0.012)	(0.037)
$8 < UR_t \leq 11$	0.010	0.037	0.035	0.014	0.079**	0.080
	(0.023)	(0.027)	(0.036)	(0.014)	(0.030)	(0.049)
$11 < UR_t$	0.058**	0.053	0.054	0.057	0.101*	0.169**
	(0.024)	(0.038)	(0.050)	(0.032)	(0.046)	(0.066)
(B) Dynamic						
UR_t	0.001	0.009*	0.011	0.021***	0.019**	0.040*
	(0.006)	(0.004)	(0.006)	(0.005)	(0.008)	(0.019)
UR_{t-1}	0.004	0.003	0.012*	-0.012	-0.001	-0.004
	(0.009)	(0.004)	(0.006)	(0.011)	(0.007)	(0.018)
UR_{t-2}	0.003	-0.004	-0.004	-0.000	-0.003	0.006
	(0.009)	(0.008)	(0.009)	(0.016)	(0.007)	(0.016)
(C) Averaged						
$\left(\Sigma_{k=0}^{2} UR_{t-k}\right)/3$	0.008	0.009*	0.021***	0.008	0.017	0.043**
	(0.008)	(0.005)	(0.004)	(0.012)	(0.010)	(0.014)
Sample size	22066	17641	9245	7346	10433	3352

Note: Estimates are from linear probability regression models and the sample is White respondents only aged 18-64. Figures are regression coefficient estimates for the unemployment rate. Dependent variable equals one if a little prejudiced or very prejudiced, and zero otherwise. Included in all models are the covariates shown in Table 1, area-level fixed-effects, area-level linear time trends, and year fixed-effects. Standard errors clustered at the area-year level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Appendix Table A3: OLS estimates of the Unemployment Rate on Relative Prejudice Rates

	All Females (1)	All Males (2)	Males Aged 35-64 (3)	Males with High Education (4)	Males Full-time Employed (5)	Interaction of Groups (3)-(5) (6)
(A) Less racial prejudice now compared to 5 years ago						
	0.002	-0.007	-0.018*	-0.002	-0.009	-0.016
	(0.007)	(0.005)	(0.009)	(0.011)	(0.006)	(0.013)
(B) Less racial prejudice in 5 years compared to now						
	0.002	-0.006	-0.016***	-0.002	-0.012*	-0.016***
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
Sample size	16588	13697	8951	6413	10056	3267

Note: Estimates are from linear probability regression models and the sample is White respondents only aged 18-64. Figures are regression coefficient estimates for the unemployment rate. Dependent variable equals one if the respondent agrees with the statement and zero otherwise. Included in all models are the covariates shown in Table 1, area-level fixed-effects, area-level linear time trends, and year fixed-effects. Standard errors clustered at the area-year level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Appendix Table A4: Log Wage Models for Females by Subgroups

	Non-White		UR · Non-White	
Age				
18-34	-0.024***	(0.005)	-0.009***	(0.002)
35-64	-0.013	(0.008)	-0.014***	(0.003)
Education				
Low	0.023*	(0.013)	-0.004	(0.005)
Medium	0.004	(0.006)	-0.011***	(0.003)
High	-0.036***	(0.008)	-0.013***	(0.003)
Work hours				
Part-time	-0.008	(0.006)	-0.008**	(0.003)
Full-time	-0.036***	(0.006)	-0.011***	(0.002)
Occupation				
All manual	0.023*	(0.013)	-0.002	(0.007)
Low skill non-manual	0.007	(0.005)	-0.008***	(0.002)
High skill non-manual	-0.041***	(0.008)	-0.017***	(0.003)
Sector				
Private	-0.034***	(0.006)	-0.014***	(0.002)
Public	-0.001	(0.007)	-0.010***	(0.003)
Industry				
Manufacturing	-0.042***	(0.015)	-0.021**	(0.008)
Construction	0.028	(0.049)	-0.008	(0.020)
Hotels & restaurants	-0.033***	(0.010)	-0.012***	(0.004)
Transport & communication	-0.038*	(0.019)	-0.012	(0.011)
Banking & finance	-0.065***	(0.011)	-0.008*	(0.004)
Public admin & social security	-0.056***	(0.012)	-0.013**	(0.006)
Education	0.012	(0.014)	-0.007	(0.005)
Health & social work	0.003	(0.011)	-0.008**	(0.004)

Note: Figures are estimated coefficients on a non-White dummy variable and on the interaction term UR·Non-White from linear regression models with 1482 quarter-region fixed-effects. The sample is restricted to native individuals only. Also included but not shown are covariates representing age, educational attainment, marital status, children, occupation and work hours. Standard errors clustered at the quarter level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.

Appendix Table A5: Disaggregated Racial Employment and Wage Gaps for Females

	Employed		Log Wage			
	All	High Education	All	High Education	High skill Non-manual	Manufacturing
Black	-0.039***	-0.035***	-0.008	-0.064***	-0.068***	-0.007
	(0.004)	(0.005)	(0.007)	(0.012)	(0.011)	(0.028)
Asian	-0.124***	-0.073***	-0.031***	-0.020**	-0.031***	-0.069***
	(0.003)	(0.004)	(0.006)	(0.008)	(0.011)	(0.025)
Other ethnicity	-0.095***	-0.057***	-0.013	-0.025	-0.014	-0.056
	(0.006)	(0.010)	(0.012)	(0.017)	(0.017)	(0.035)
UR · Black	-0.005***	-0.008***	-0.013***	-0.012***	-0.015***	-0.010
	(0.001)	(0.002)	(0.003)	(0.005)	(0.005)	(0.013)
UR · Asian	0.005***	-0.003*	-0.008***	-0.015***	-0.018***	-0.019*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.011)
UR · Other	-0.002	-0.001	-0.015***	-0.004	-0.015**	-0.060***
	(0.002)	(0.002)	(0.005)	(0.006)	(0.006)	(0.017)
Sample size	2633749	587316	463505	138980	162634	39529

Note: Figures are estimated coefficients from linear regression models with 1482 time-region fixed-effects. The sample is restricted to native individuals only. Also included but not shown are covariates representing age, educational attainment, marital status and children. Occupation and work hours controls are also included in the log wage regressions. Standard errors clustered at the quarter level are shown in parentheses. *, ** and *** denote statistical significance at 0.10, 0.05 and 0.01 levels, respectively.