Race, Prejudice and Attitudes toward Redistribution: A Comparative Experimental Approach

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Abstract: Past work suggests that support for welfare in the US is heavily influenced by citizens' racial attitudes. Indeed, the idea that many Americans think of welfare recipients as poor Blacks (and especially as poor Black women) has been a common explanation for Americans' lukewarm support for redistribution. Here, we draw on a new online survey experiment conducted with national samples in the US, UK and Canada, designed to extend research on how racialized portrayals of policy beneficiaries affect attitudes toward redistribution. We designed a series of innovative survey vignettes that experimentally manipulate the ethno-racial background of beneficiaries for various redistributive programs. The findings provide, for the first time, cross-national, cross- domain, and cross-ethno-racial extensions of the American literature on the impact of racial cues on support for redistributive policy. Our results also demonstrate that race clearly matters for policy support, although its impact varies by context and by the racial group under consideration.

Keywords: redistributive policy; racial prejudice; survey experiments
As countries become more ethnically and racially diverse, there is increasing concern over continued public support for a shared social safety net (Van Parisj 2004, Soroka et al., 2006, Banting and Kymlicka, 2006, Goodhart 2006, Banting et al., 2007, Crepaz, 2007, Koopmans 2010). There is nevertheless relatively little comparative research that examines the direct impact of citizens’ attitudes about diverse others on support for specific welfare state policies, at least outside of the US context.

Racial attitudes have long played an important role in shaping Americans’ policy preferences (Hutchinson 2009; Banks 2013; Kinder and Sears, 1981). This is especially true for programs designed to address poverty, in particular, “welfare.” There is a considerable body of work suggesting welfare is “race-coded,” i.e., Americans tend to think welfare recipients are disproportionately Black, and support for welfare is significantly lowered among people who hold negative attitudes toward Blacks (Iyengar 1990; Gilens 1995, 1996a, 1996b, 1999; Mendelberg 2001; Nelson 1999; Federico 2005; Lee and Roemer 2006; Schram et al. 2003; Winter 2006, 2008).

This conflation of race and “welfare” is often discussed – in US work at least – as a uniquely American phenomenon. There are growing signs that it is not, however. Recent work points to the racialization of welfare in the Canadian context (Harell et al. 2014) and in Europe (Ford 2006, 2015; Wright and Reeskens 2013). This complements a longstanding body of work on welfare-chauvinistic parties in Western Europe (e.g., Freeman 2009; Van Der Wall et al. 2013); and growing literatures on the tension between diversity and support for the welfare state as well (for recent reviews see Nannestad 2007; Sticknoth and Straeten 2013; Soroka et al. 2015; though also see Evans 2006.). Much of this work points to the generalizability of what is sometimes viewed as a distinctive American story.
The overlap between findings in the US and elsewhere is limited by the fact that US work on welfare support typically focuses on Blacks, whereas work elsewhere focuses on the diversity introduced by recent immigration, which may or may not be directly linked to race. Indeed, much of the European literature focuses on the impact of diverse immigration – not directly on support for welfare policies currently available to racially-different minorities. The aim of this paper is thus to offer one of the first directly comparable tests of the impact of racial bias on social welfare preferences, focused on specific welfare state policies in a cross-national context. The analysis covers multiple racial groups, a variety of social welfare programs, and several liberal welfare states. Drawing on a unique parallel online experiment conducted in the UK, Canada and the US, we focus on one relatively simple, but fundamentally important, research question: How do racial cues and racial attitudes influence support for welfare state benefits?

Our findings suggest that support for redistribution is indeed racialized. Unlike most past research that focuses on Blacks in the US, we show that the racialization of welfare attitudes extends beyond this racial minority, beyond welfare, and beyond the US context. Indeed, our evidence indicates that relative to the US, recipient race affects support for social programs equally if not more so in the UK, and to a lesser extent in Canada as well; that the effects are evident for different races/ethnicities, and hold across a range of welfare state policies. There is heterogeneity in the impact of racial cues: they are particularly powerful for individuals with pre-existing racial prejudice. Racial bias thus not only exerts powerful direct effects on welfare attitudes, but also moderates the impact of racial cues in our experimental treatments. The end result is, we believe, a powerful demonstration of the relevance of racial bias for understanding attitudes toward social policy.
**Race and Welfare**

One of the recurring themes in the US debate around support for welfare, defined in terms of means-tested social assistance programs, concerns the racial composition of the beneficiary class. Unlike programs like social security that promoted integration among White middle class (male) workers through a national, universal program structure; programs for the poor like AFDC targeted an increasingly feminized and disproportionately Black underclass (Lieberman 1998; Williams 2004). Public support for welfare in the US is thus inextricably inter-twined with the racial cleavage between whites and Blacks (Gilens 1995, 1996a, 1999; Mendelberg 2001; Schram et al. 2003; Winter 2006).

When whites associate welfare benefits with race (by identifying beneficiaries as Black) they tend to be less generous toward welfare recipients and to view them as less deserving (Iyengar 1991; Gilens 1999). The reason for this association is two-fold. First is an underlying intergroup dynamic. Work in social psychology has consistently pointed to people’s tendency to favor their own group members and to express hostile and negative attitudes toward out-group members (Allport 1958; Blumer 1958; Sherif et al. 1961; Tajfel and Turner 1986). When recipients of welfare are viewed as representing an out-group, evaluations of their deservingness and eligibility are colored by feelings and stereotypes about that out-group (Nelson 1999). When it comes to welfare, we know that citizens tend to overestimate the number of Blacks on welfare (Gilens 1999: 68). We also have extant evidence that outgroup prejudice towards Blacks is correlated with less support for welfare among the White majority (Gilens 1995; 1996b; 1999; Nelson 1999; Federico 2005; Lee and Roemer 2006; Winter 2008).

In addition to the in-group-out group dynamic, there is a more program-specific discourse in American culture that intersects with the racial divide. The norms of rugged individualism in
the US stigmatize welfare recipients who are perceived as able but unwilling to work (Golding and Middleton 1982; Katz 1989; Gilens 1996; Clawson and Trice 2000; Misra et al 2003; Somers and Block 2005; Kluegel and Smith 1986). As Katz (1989, 10) notes, “The issue [in poverty discourse] becomes not only who can fend for themselves without aid, but more important, whose behavior and character entitle them to the resources of others.” The issue of deservingness is further exacerbated because welfare is also seen as a program that creates perpetual welfare recipients by creating perverse incentives not to work (Somers and Block 2005).

Racial perceptions, at least in the US context, come into play when deservingness arguments are evoked. While old-fashioned racial stereotypes often focused on Blacks’ perceived biological differences related to capacity (e.g. lower intelligence), more recent forms of racism tend to focus on cultural values, such as the work ethic (e.g. laziness). When asked to explain economic inequalities between Whites and Blacks, citizens often reject structural explanations in favor of individualistic ones (Kleugel 1990, Bobo 2001). And individualistic explanations tend to cite Blacks’ lack of motivation or willingness to work hard, rather than their innate ability (Bobo 2001, 282-283), reflecting a shift away from (at least overt) expressions of old-fashioned racist attitudes.

Recipient deservingness is thus often assessed through the lens of racial schemas that activate underlying predispositions about group characteristics. According to Winter (2008, 37-40), racial schemas in the US – in keeping with the underlying distinction between in and out-groups – characterize the Black out-group as “lazy, dependent and poor,” in comparison with hardworking Whites (38). For Gilens (1999), these stereotypes are key in understanding low levels of support for welfare among White Americans. Because they think welfare recipients are overwhelmingly Black, and because they tend to view Blacks as lacking in work ethic, they tend
to be hostile to welfare programs. Fox (2004) has further shown that concerns about work ethic extend to Whites support of welfare benefits directed at Latinos. In other words, racial prejudice is likely to activate, accentuate and distort considerations of deservingness, which themselves are more likely to motivate policy support when means-tested programs are under consideration.

The racialization of welfare argument thus relies on the perpetuation of racial stereotypes, alongside a continued over-representation of Blacks in news media coverage of welfare programs. Gilens (1996a; 1999) shows that the news media over-represent Black welfare recipients relative to their actual program usage. Furthermore, Blacks are especially over-represented in the least sympathetic stories: stories about unemployed adults and the cycle of welfare dependency (Gilens 1996; Clawson and Trice 2000; Misra et al 2003). This is in contrast to stories that focus on groups viewed as more deserving, such as the elderly and the working poor (Iyengar 1990; Cook and Barrett 1992), which tend to under-represent Black recipients.

Work on race and policy attitudes in the US extends beyond social assistance programs. There are related literatures focusing on affirmative action (e.g., Bobo and Kleugel 1993; Krysan,; 2000; Feldman and Huddy 2005), health care (Tesler 2012), and crime (e.g., Peffley et al. 1997; Hurwitz and Peffley 1997; Mendelberg 2001; Peffley and Hurwitz 2002; Gilliam et al. 2002; Federico and Holmes 2005). As with welfare, media coverage of crime paints it as a disproportionately Black problem; and consistent evidence suggests that when Blacks are portrayed as violent criminals, Whites support harsher punishments (Gilliam and Iyengar 2000). Racial attitudes are thus related to a host of policy domains that feature visible racial cues. So while the literature on welfare points to the intersection of racial attitudes with assessments of deservingness, other literatures point toward the pervasiveness of racial attitudes in shaping policy judgments.
The comparative literature – across policy domains, or across countries – has remained relatively silent on the role of racial attitudes in support for social welfare policies.¹ Much of the comparative European literature on the welfare state focuses on the impact of immigration and ethnic diversity on support for the welfare state (for recent reviews, see Nannestad 2007; Sticknoth and Straeten 2013; Soroka et al. N.d.). For example, Crepaz (2007) argues that population homogeneity allowed for the development of generous European welfare states, because intergroup competition for resources was less likely when shared ethnic identity overlapped national identity. Interestingly, Wright and Reeskens (2013) show that strong ethnic conceptions of national identity have a negative impact on support for welfare. Luttmer (2001), Finseraas (2008), and Mau and Burkhardt (2009) further show that ethnic heterogeneity has a negative impact on support for welfare state redistribution, while Reeskens and van Oorschot (2012) show that higher levels of immigration are related to citizens’ willingness to place more restrictions on immigrants’ access to welfare benefits. This body of literature is focused on the impact of actual diversity (rates or levels of immigration, or measures of ethnic heterogeneity), however, and much less on the impact of attitudes about diverse others.

Work on the connections between racial and ethnic prejudice and support for redistribution is much more limited. Faist (1995), in a comparison between the US and Germany, has argued that while welfare state support has always been racialized in the US, rising levels of immigration in Germany has led to a shift from a class-based to an ethno-class based cleavage around support for

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¹ This is not to say that there is no work on racial and ethnic prejudice and policy – there is certainly work on other policies such as immigration and support for accommodation. See, for example, McLaren and Johnson (2007) and Blinder, Ford and Ivarsflaten (2013).
the welfare state. Ford (2006) shows that prejudice has a negative effect on general support for the welfare state in the UK. He also shows that when confronted with ethnic minority or immigrant welfare claimants, Britons consistently show less support (Ford, 2015), as Soroka, Harell and Iyengar (2012) found in a previous working paper based on the data used here. Hjorth (2015) finds that cues about ‘cross-border’ welfare recipients within the European framework leads to greater welfare chauvinism and that this interacts with pre-existing ethnic attitudes. Other work also finds evidence that racial cues and racial prejudice decrease support for Aboriginals on social assistance in the Canadian context based on separate data (Harell, Soroka and Ladner 2014). To the best of our knowledge, these are the only studies to directly test the influence of racial cues on support for specific welfare state policies outside the US context, and there is no study that looks at the combined roles of racial prejudice and racial cues across policy domains. These prior studies nevertheless suggest that there is good reason to think that racial cues and racial attitudes will influence people’s attitudes toward welfare state policies.

This expectation is further supported by research showing that there are important ethno-racial hierarchies outside of the United States that put ethnic and national majorities at the top, although there is some debate about how exactly various minority groups rank (Bleich 2009; Ford 2008). What is clear is that prejudicial thinking toward ethno-racial and religious minorities is not unique to the US context, and it is reasonable to assume that such attitudes, at least some of the

2 Note that an early version of our work is available as in the EUI working paper series (Soroka, Harell and Iyengar 2012). The working paper provides results from a single vignette that manipulates program type (EI versus social assistance) and only shows the impact of racial cues. Racial prejudice was not included in the analysis.
time, can be activated to influence public opinion elsewhere (see, for example, Blinder, Ford and Ivarsflaten 2013). Furthermore, there is reason to believe that policy domains that are means-tested are particularly likely to link recipient characteristics, and particularly their deservingness, to public support (Larsen and Dejgaard 2013, Rothstein 1998, though see Aarøe and Petersen 2014).

Some explanatory factors have been studied in considerable detail: for instance, self-interest and political predispositions have been shown to be powerful drivers of attitudes about redistributive policy (Hasenfeld and Rafferty 1989; Bobo 1991; Cook and Barrett 1992; Feldman and Zaller 1992; Sniderman and Carmines 1997); those who espouse more egalitarian values also tend to be more supportive of the welfare state (Bobo 1991). But thus far we know very little about how racial biases affect policy support cross-nationally, even though the intergroup dynamic that underpins this relationship is broadly generalizable.

**Data and Methods**

Our analyses explore how racial cues and racial attitudes influence public support for welfare state policies. In the first case, we examine the direct effect of a racial cue on support for redistribution across five policy domains. Consistent with research on stereotypes and intergroup dynamics, we expect that a beneficiary perceived as a racial minority will be awarded lower levels of cash benefits as compared to a white beneficiary, especially when dominant stereotypes associated with that racial group include negative traits related to the work ethic, as in the case of Black stereotypes in the US. Conversely, “model” minority groups, whose stereotype is more favorable (e.g. Asians in the US), will be treated less harshly. In the second case, we not only assess the effect of racial stereotypes on redistributive policy attitudes, but also consider the extent to which
racial prejudice interacts with recipient race. We expect those with higher levels of racial bias to be less willing to dispense cash benefits in general and that the effects of the beneficiary’s race will be stronger among respondents with higher levels of racial bias.

The data used for this analysis are drawn from the Race, Gender and the Welfare State (RGWS) survey, which was fielded online in July 2012 in the US, Canada, and the UK (n=1200 per country). An additional subsample of 600 respondents was collected in the US in May 2013, and we were also able to include 509 “incompletes” from the US, bringing that sample up to 2309 for some analyses. Each survey was fielded by YouGov-PMX, which uses a matching methodology for delivering online samples that mirror target populations on key demographics. For details on the sampling procedures and composition of the YouGov online panels, see Vavreck and Iyengar (2011).

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3 The additional US sample was identical to the original, except Asian and Native American beneficiaries in the vignettes were replaced with Hispanics, allowing for an additional ethno-racial cue for the US.

4 The vignettes (described below) were early in the survey, so for most of our analyses even the “incompletes” (those who did not finish the survey) have provided the responses we need.

5 While YouGov does not provide a true probability sample, research suggests that analyses of causal effects tend not to be influenced by potential selection biases (e.g. the tendency of online panelists to be more politically interested (Simmons and Bobo 2015.) Moreover, the YouGov matched samples have achieved impressive rates of predictive validity, accurately predicting the outcome of several national, statewide, and local elections, with an average error rate comparable to what would be expected given random sampling (Rivers and Bailey 2008; Vavreck and Rivers 2011).
The selection of these three countries reflects a “most similar systems” design. All three are considered liberal welfare states, each has significant levels of racial and ethnic diversity, and each has experienced significant economic retrenchment (albeit to varying degrees) in recent years. These countries also have the practical commonality of having large English-speaking populations, meaning that the survey instrument can be conducted in a common language in each country, minimizing the risk of inter-country differences resulting from survey instrument translation. (That said, in Canada the survey was conducted in both English and French to ensure national representativeness.) In addition, there is reason to believe that negative attitudes toward the poor are prevalent in all three nations, although most of the evidence derives from the US (see, though, Golding and Middleton 1982; Harell, Soroka and Mahon 2008; Harell, Soroka and Ladner 2013).

Measuring Racism

We know that racial attitudes are an important factor in understanding support for redistribution. Yet, measuring racial prejudice is not an easy task. There are numerous approaches to defining and operationalizing racial prejudice, and associated debates over its causes and consequences. (For an overview see Bobo and Fox 2003.) While a detailed review of the relevant literature is beyond the scope of this paper, we note that all of these approaches view racial prejudice as resulting from an underlying inter-group dynamic. An out-group is viewed as a collectivity rather than a set of individuals, and the group is perceived negatively vis-à-vis one’s in-group. Simply

cuing group identity, in many cases, is sufficient to activate out-group hostility (Sherif et al., 1961, Tajfel and Turner, 1986).

In the US, one of the most contentious debates in the racial attitudes literature addresses whether prejudice against Blacks has decreased over time, or – alternatively – whether their public expression has simply become more subtle (e.g. McConahay and Hough 1976; Kinder and Sears 1981; Schuman et al. 1997; Pettigrew and Meertens 1995). Blatant forms of racism, such as the expression of explicitly negative racial stereotypes, may have declined, not because the stereotypes have changed, but because it has become socially unacceptable to express them. In response to the diffusion of egalitarian norms, Whites have adopted “modern” or “symbolic” forms of prejudice based on beliefs that Blacks violate mainstream American values such as individual achievement and the work ethic (Henry and Sears 2002).

There is a further debate over whether indicators of modern racism are valid measures of prejudice (Sniderman and Carmines 1997; Carmines et al. 2011). While we take no position on this issue, the debate highlights the importance of measuring racism in all its forms. For the sake of parsimony, we begin with just one measure of “overt” racism here. An Appendix includes a replication of our findings using three different measures of racism (overt, modern and implicit); the evidence given there suggests that, at least for the effects on which we focus, the various measures of racism all point in the same direction.

“Overt” or “blatant” racism is measured here using a 0-1 scale based on two questions that tap negative racial stereotypes. Using the example of Canada, the questions are worded as follows

1. Where would you rate each of the following groups in Canada on a scale of 1 to 7, where 1 means HARDWORKING and 7 means LAZY?
2. Where would you rate each of the following groups in Canada on a scale of 1 to 7, where 1 means DEPENDENT and 7 means SELF RELIANT?

These items are a subset of the standard racial stereotypes battery used in the General Social Survey and the American National Election Surveys. We rely here on two traits that the race and welfare literature (as well as the modern racism literature) identify as particularly important to the link between Blacks and welfare due to their relationship to the deservingness frame. These overt racism questions also have the benefit that we are able to target different racial groups of interest: Aboriginals/Native Americans, Asians (e.g. Chinese), Blacks, South Asians (e.g. Indians, Pakistanis), and Hispanics.

*Experimental Vignettes*

To examine the effects of racial cues and racial attitudes on support for redistributive policy, we developed seven experimentally-manipulated policy vignettes, using a factorial design (Rossi and Nock 1982). Each vignette is treated as the unit of analysis in a repeated, or within-subject, experimental design. In total, we have as many as 32,963 respondent-vignette pairs (4709 respondents* 7 vignettes each), and 21,082 respondent-vignette pairs when we limit the analyses to White, non-foreign born respondents (with non-missing data on the variables of interest).

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6 Note we use these terms interchangeably. Aboriginal is the term most often used in the Canadian context, while Native Americans is used in the US (and our surveys reflect these differences in terminology.) Both refer to descendants of the peoples that populated the continent prior to European settlement. To simplify the tables, we use the term Aboriginal in both the US and Canada.
The vignettes are short stories about individual policy recipients, including a photo, that describe the fictional recipients’ personal situation and the amount they would be eligible to receive as cash benefits. (See the Appendix for the full text of all vignettes.) The eligible amount is calculated as the average amount of support for a person in the described situation, based on actual benefits in place in each country as of 2012. Following presentation of the vignette, the respondent is asked what level of benefits the target recipient should receive on a scale ranging from $0 to twice the eligible amount, where the starting point for the slider is the middle of the scale, so that respondents can drag benefit levels either up or down from the midpoint representing the present amount received. For the analyses below, we focus on the percentage change in support based on the amount offered in the vignette, allowing us to combine and compare results across countries and domains on a similar metric.

The vignette approach provides a useful alternative to establish attitudes compared to traditional survey items, despite its less common use in political science. Vignettes allow people to make specific judgments that are often easier to report compared to feelings about abstract values (Alexander and Becker 1978). They have the added benefit of being ideally suited to experimental manipulation because respondents can be randomly assigned to different versions of the scenario (as well as randomly assigned to the order of presentation to minimize sequence effects). This is especially important when racial attitudes are considered. As we have noted, overt

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Note that for parental leave in the US, no comparable public program exists. Here, we rephrase the vignette to say the recipient is eligible for a new parental leave benefits based on the approximate levels available under temporary disability benefits in the five states in the US that offer such programs.
racial animosity has decreased over time, yet people continue to express more subtle forms of racism (Kinder and Sears 1981). Given increasing social pressure to refrain from overt forms of racism, asking directly about racial attitudes can induce social desirability bias in responses. The online vignette has the additional advantage of allowing us to take advantage of visual cues not normally available in traditional survey methodology.

Our seven vignettes (presented in a random order) focus on five policy domains: welfare, benefits for low-income seniors, unemployment insurance, parental leave benefits, and disability benefits. Each vignette experimentally manipulates the race of the recipient. In the US and Canada, we include White, Black, Asian, and Native recipients. The US study also included Latino recipients. In the UK, we included White, Black, Asian, and South Asian recipients.\(^8\) White is treated as the control category in all analyses. The ethno-racial categories were selected in each country to include Blacks for direct comparison to the US context. Asians (and South Asians in the UK) were selected to represent a large immigrant population within each country that is relatively well-off and not necessarily linked with welfare discourses. Finally, Native Americans (Aboriginals) were included as a non-immigrant ethno-racial minority in both Canada and the US. Like US Blacks, native populations in both countries face important issues surrounding poverty (Cornell 2006), and are targets of pernicious stereotypes related to the work ethic (Tan, Fujioka, and Lucht 1997; Harell, Soroka and Ladner 2014). Finally, an additional subsample was collected in the US which included Latino cues across vignettes. Given the size of the Latino/Hispanic community in the US as well as recent work on the link between attitudes

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\(^8\) To be clear, we use “Asian” here to refer to, e.g., Chinese, Vietnamese, and Korean immigrants; and “South Asian” with reference to, e.g., Indians, Pakistanis, Sri Lankans.
toward Latinos and welfare support (Fox 2004), this category was viewed as essential for understanding the power of diverse “racial” cues in the US context.

We cue the race of the recipient in two ways. First, using a face-morphing program (FaceGen Modeler), we start with a base photo and then blend in prototypical ethnic morphs. The resulting photos are edited further to add in age characteristics, hair and clothing that are identical across morphs. We rely on morphed photos because it is important that we control for other facial characteristics (such as attractiveness) known to affect social judgments (see, for example, Eberhardt et al. 2004; Eagly et al. 1991). By beginning with the same base face, blending this face with identical morphs, and adding other identical features, we largely eliminate the influence of these potential confounds. In addition to race, several of the vignettes also vary the gender of the recipient, so models include controls for this attribute.

In addition to the non-verbal manipulation, the vignettes vary the name of the recipient, using common ethnicized male and female names associated with the different ethno-racial groups. For instance, one vignette uses the following male names: Jay Smith (White), Jamal Williams (Black), and Jiang Lee (Chinese); and the following female names: Laurie Smith (White), Latoya Williams (Black), and Lian Lee (Chinese). We examine the independent effects of the race manipulations – both verbal and visual – on respondents’ level of generosity toward the target recipients. We are also able to assess the joint effects of racial cues and racial attitudes by interacting the racial manipulations with our indicators of prejudice. The bulk of this latter

9 Note that a proto-typical face for Native Americans/Aboriginals is not available in FaceGen. The authors used a combination of morphs to achieve a stereotypical Native recipient.
analysis uses the measure of overt racism, since it was asked of each racial group in all countries. Parallel analyses of symbolic and implicit measures of racism are available in the Appendix.

Our analyses of variation in benefits awarded to the target recipients include several control variables. We control for the order in which the respondent sees the vignettes (numbered 1 to 7), as well as a set of dummy variables for each of the seven vignettes. These variables soak up whatever effects are attributable to policy domains and other sources of cross-vignette variance. The result is that the coefficients for all other variables capture their within-vignette impact. Finally, in the US, we add an additional dummy variable (Wave) to separate the respondents who completed the study in May 2013.

We present a pooled analysis in which each respondent-vignette combination is a separate case. This allows for a panel estimation that is ideally suited for capturing the impact of racial cues, alongside other factors, averaged across vignettes.

**Analysis**

We include the full results of all estimations in the Appendix. Here, we focus on the most important (for our purposes) results — the impact of racial cues, both alone and alongside measures of overt racial bias.

[Figure 1 about here]

Figure 1 presents the effect of racial cues for each country separately. (Based on models included in Appendix Table A1.) The Figure shows the average percentage change in financial support awarded to the target recipient, where 0 represents the actual level of support received, derived from a basic model including no measures of racial bias. Our expectation is that recipients representing racial minorities will be treated as less deserving of support than Whites. Based on the literature, this should be particularly true for Black recipients in the US context.
In fact, we find very little evidence of racial bias in the amounts awarded by US participants. While the estimated percentage change in financial support awarded is highest for Whites (who receive a slightly positive increase in support), none of the differences across racial groups are significant. US respondents, on average, defer to the status quo giving recipients amounts very similar to current levels, no matter the ethnicity of the recipient.

Canada and Britain both provide stronger evidence of race-based judgments of deservingness. The effect is clearest in the UK where Black, Asian and South Asian recipients all receive significantly less in relation to the White baseline condition. While participants cut the White recipient’s benefits by about four percent from the status quo, they treat minority recipients even more harshly, cutting their benefits by between seven and ten percent, with Blacks receiving the lowest levels of support. Canadian respondents proved more generous to recipients across the board, with all recipients allocated higher levels of support than the current level. Nonetheless, there are traces of racial bias; Canadians are less generous (award smaller increases over the current benefit) toward Asian recipients and, to a lesser extent, Aboriginal Canadians.  

The results in Figure 1 thus provide some support for the hypothesis that White respondents are less supportive of welfare assistance directed at racial minorities. We are faced with a puzzling result, however: in spite of the large US-focused literature motivating our analysis, we find that racial cues matter in the UK and Canada but not in the US.

[Table 1 about here]

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10 Note that only the Asian estimate is significantly different than for Whites. The Aboriginal estimate is similar to Asians, but the large margin of error around the estimate - due to the fact that we have a much smaller sample size (n=393) for Aboriginal vignettes - is quite large.
We are not inclined to believe that race does not matter to welfare attitudes in the US. Table 1 shows the mean scores on our measure of overt racism by country. Recall that this measure consists of two questions tapping the extent to which each minority group is perceived to have two negative qualities (lazy and dependent) that have traditionally been associated with Blacks in the US. On this measure, racism is clearly strongest for Blacks in the US (mean = .45), and weakest for Asians (mean = .19). South Asians, Hispanics and Native Americans receive overt racism scores in between. Thus, the racial hierarchy in the US clearly places Blacks at the bottom when it comes to explicitly negative stereotypes.

The UK overt racism scores exhibit a similar pattern: on average, Blacks receive almost an identical score as in the US (.45); South Asians and Asians are rated more favorably than Blacks, although they are viewed somewhat more negatively than in the US. In Canada, Blacks elicited more favorable trait ratings than in either the US or the UK (.36), but the racial hierarchy vis-a-vis Asians and South Asians remained intact, i.e. Asians and South Asian stereotypes are less negative. As past research has suggested (Harell, Soroka and Ladner, 2013), Aboriginal peoples in Canada face significant prejudice. They are, in fact, the only group across the three countries for whom the mean overt racism score is above .5.

Given the considerable individual-level variance in these measures of prejudice, it follows that the impact of racial cues on support for welfare policies might be particularly strong for some (overtly racist) respondents, but weak for other (less racist) respondents. Overt racism may also directly impact policy support with more racist respondents favoring less generous benefits. Recall that we have overt racism scores for each racial category, and can thus explore both possibilities by interacting particular racial cues with relevant racism scores (e.g. Black
beneficiary x overt racism toward Blacks). Table 2 present results speaking just to the second issue: what is the direct impact of overt racism on policy support?

[Table 2 about here]

The table shows coefficients for overt racism, drawn from the full estimations in Appendix Table A2. In brief, the results suggest that the small differences in support across racial groups in Figure 1 are the product of countervailing tendencies among high- and low-prejudice respondents. First, let us consider the American case. Table 2 makes clear the significant relationship between overt racism and policy support: those who express overt prejudice consistently award less support across the five redistributive policy domains. In the US, the effects of overt racism hold for both Black and Native American recipients and the impact is strongest for the former. This is exactly as we should expect given the literature: there is a link between racism toward Blacks and Americans’ support for redistributive policies, even independent of whether the target recipient is perceived as Black. (Note that the coefficients are easily interpreted: a move across the scale in overt racism toward Blacks is associated with an average 43-point decrease in the percentage change in support offered by respondents.) In the UK too, there is a powerful negative effect of overt racism toward Blacks, and a smaller one for South Asians. In Canada, it is only overt racism toward Aboriginals that affects policy support.

The impact of both racial cues and overt racism is clearer still when we take the interaction effects into account. Figures 2 through 4 show results for the US, UK and Canada, respectively.

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11 Note as well that the US results are not dependent on the measure of racism here. Indeed, using a modern racism scale, we find very similar results. See the Appendix for models using various measures of racial prejudice.
(Again, results are based on models in Appendix Table A2.) Each figure graphs the estimated percentage change in support based on the race of the recipient (as compared with White recipients) interacted with the respondents’ overt racism (toward the relevant race). The solid line represents respondents with a high level of overt racism, and the dashed line represents those with low overt racism scores.

[Figures 2-4 about here]

The pattern for Black recipients in the US sets out the expected relationships clearly. There is a direct, negative impact of overt racism (toward Blacks) on the benefits awarded. In addition, when presented with a Black recipient, those with lower overt racism tend to increase benefits above and beyond current levels, while those with higher levels of racism tend to cut benefits. This results in a widening of the gap between Black and White recipients by nearly 30 points. This result is not contingent on our measure of racism, either – parallel analyses using a modern racism scale or an implicit measure of bias against Blacks yield similar results.\(^{12}\)

A similar dynamic is evident for Native recipients. For Asians, however, the results are more complex. We skipped over the positive coefficients for Asians in Table 2 — they are a little misleading, but Figure 2 helps clarify this relationship. Those who are openly prejudiced against Asians give markedly more money to Whites, but less to Asians. We suspect this reflects the perceived economic position of Asians vis-a-vis the other ethnic groups — concerns about Asian economic success leads prejudiced respondents to give Whites more money. Those who express low levels of overt racism toward Asians, however, treat White and Asian recipients no differently. Finally, the benefits awarded to Hispanic recipients are not moderated by expressed

\(^{12}\) These results are provided in Appendix Table A3.
racism toward Hispanics, though a small (but insignificant) direct effect of racism is evident here. These null results may be a function of a smaller sample size; it may also suggest something distinctive about the impact of racial bias toward Hispanics.

Figure 3 presents results for the UK, where we find a pattern with Black recipients that is similar to the US. Again, when the recipient is Black, non-racist individuals increase the level of support over current funding, whereas racists recommend reduced support. As we have already seen, the measure of prejudice has a powerful direct effect as well. Also in keeping with the US results, the moderating effects of prejudice are weaker for the two other racial minority groups. For Asians and South Asians, the racial cue matters only for racists; those with low racism scores make no distinction between White and Asian/South Asian recipients. Canada is unlike the US and the UK in that Canadians do not discriminate against Black recipients. Nor is there any apparent bias against Asian recipients. The solitary case of Canadian prejudice is directed toward Aboriginal recipients; overtly racist attitudes toward Aboriginals have a substantial effect on the support awarded to an Aboriginal recipient. The 65-point gap in support is the largest penalty incurred by any minority group across the three countries — although roughly the same as the reduction in support for Blacks in the US and UK. In other words, while Canadians appear to behave in an egalitarian manner when supporting redistribution for immigrant racial minorities, they are by no means benevolent and unprejudiced toward Aboriginal peoples.

**Conclusions**

Race matters when it comes to public support for redistribution. Yet, as our analysis clearly demonstrates, the influence of racial cues and racial prejudice varies by context and across particular racial minority groups. In the US, we find that racial cues directly affect support for
redistribution to individual recipients with Black recipients being subjected to discriminatory treatment. This “racialization” effect is conditional on respondents’ pre-existing racial biases, where higher levels of racism dramatically enlarge the effects of the racial cues. Blacks are not the only group subject to discrimination, though: White respondents with high levels of prejudice also display bias against Native American and Asian American welfare recipients.

We find parallel evidence in the UK and, to a lesser extent, in Canada. Those in the UK tend to be less generous than their American counterparts, especially toward racial minorities, and this support is especially low when prejudiced individuals are confronted with a minority recipient. In Canada, citizens tend to be relatively generous in their support to immigrant-based racial groups, although their generosity does not extend to Aboriginal recipients.

Do the results obtained above matter for general attitudes towards redistribution, or are they specific to attitudes directed towards (hypothetical) individual recipients? Our use of vignette-based experiments gives us a good deal of leverage over the specific characteristics of recipients, and it allows us to be very precise in our description of benefits as well. We regard the vignettes as a particularly powerful way of getting at the impact of race on welfare-state attitudes. But it is reasonable to ask whether the connections between racial bias and support for social policy evident in these experimental data also apply at a more general level. This spillover is testable. Indeed, the Appendix includes a detailed comparison of our individual-level results and results where general support for social programs is the dependent variable. These models make clear the degree to which our experimental results spillover to models of welfare state support more broadly: overt racism not only has an impact on (a) support for spending on particular beneficiaries (from experiments), but also a direct and significant negative impact on (b) support for generalized government action (from survey questions).
This study has several implications for understanding the relationship between group identity, group stereotypes, and support for welfare state policies. Most importantly, our results suggest that the largely American literature about the racialization of welfare attitudes among Whites towards Blacks is more generalizable than some past work suggests. The relationship between welfare attitudes and racial attitudes in the US is certainly tied in part to its unique history, but our evidence makes clear that other racial groups in other nations are stereotyped similarly and subject to the same form of discrimination. This is of real significance: immigration is clearly changing the racial and ethnic composition of European and North American populations, and this has raised serious debates about the state of social solidarity in diverse societies (Crepaz, 2007, Koopmans 2010). Redistributive policies are one of the key ways in which the state addresses economic inequality, yet this study suggests that racial bias is a major impediment to public support for such programs, and this is not limited to social assistance programs, nor specifically to the unique history of slavery and racial discrimination that characterizes race relations in the US.

The significance of these findings is underscored by the fact that US media coverage of redistributive policy domains is often both personalized and racialized (Iyengar 1991; Gilens 1999). We suspect that such racialized coverage is not limited to this context or to this particular group – issues around immigration and the welfare state in the European context also regularly draw on racialized discourses around deservingness. And our results make clear the extent to which simply cuing the racial background of recipients can influence support for an essential component of the welfare state.

The variation observed in this study, across groups, policies and countries may in part be explained by how dominant such associations are between each group and policy across these
three liberal welfare states. Explaining this variation will be the focus of future work. So too will a consideration of the degree to which our findings extend beyond liberal welfare states. There is reason to believe that liberal welfare states that rely primarily on means-tested programs will make recipient considerations more likely (e.g., Larsen and Dejgaard 2013, Rothstein 1998). Past work on media coverage also points towards this possibility. For instance, Aarøe and Petersen (2014) show that media coverage of welfare recipients is much more likely to mention stereotypes associated with Black racial stereotypes (e.g. laziness) than similar coverage in Denmark. Larsen (2013) also finds that media coverage in the US and the UK tend to be far more negative about welfare recipients than in Sweden and Denmark. It may be the case that liberal welfare states tend to promote a public discourse that highlights specific characteristics of recipients.

Note that our vignettes were not limited to means-tested programs –indeed, half of the programs were contribution based. Our study thus shows that when associations are made between recipients of various programs, and their ethno-racial background, then we expect racial prejudice to decrease support. While other welfare type regimes might be less likely to draw this association, when it does occur we would expect similar results to emerge. This, of course, is conjecture and requires empirical testing. But with increasing pressure on welfare states, combined with new and increasingly diverse immigration to Europe, there is good reason to expect that media discourse will increasingly link the who with welfare benefits. If this occurs, we expect that a broad range of policies will become racialized. Support for redistributive programs, across a wide range of welfare states, may decline accordingly.
Bibliography


### Table 1: Mean Overt Racism Scores

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<th>US</th>
<th>UK</th>
<th>CA</th>
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<tbody>
<tr>
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<td>0.445</td>
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<tr>
<td>Hispanic</td>
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<tr>
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<tr>
<td>S Asian</td>
<td>0.239</td>
<td>0.312</td>
<td>0.299</td>
</tr>
</tbody>
</table>

Based on white, non-foreign born respondents only (unweighted). Cells contain mean scores for a 0-1 measure combining responses to questions on whether groups are (a) hardworking/lazy and (b) dependent/self-reliant.
Table 2: Direct Impact of Overt Racism on Recipient Support

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>UK</th>
<th>CA</th>
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</thead>
<tbody>
<tr>
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<td>-42.591***</td>
<td>-37.436***</td>
<td>.371</td>
</tr>
<tr>
<td>Hispanic</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>15.448*</td>
<td>1.189</td>
</tr>
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<td>-26.136*** (5.041)</td>
<td></td>
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<tr>
<td>South Asian</td>
<td></td>
<td>-13.271* (6.091)</td>
<td></td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01; *** p < .001. Cells contain multilevel mixed-effects linear regression coefficients with standard errors in parentheses. Based on white, non-foreign born respondents only (unweighted). Full models are included in Appendix Table A2.
Figure 1: Mean Recipient Support, by Recipient Ethnicity

Average within-respondent, within-vignette racial effects, based on white, non-foreign born respondents only (unweighted), all vignettes combined.
Figure 2: Treatment Effects of Recipient Ethnicity Moderated by Overt Racism (US)

Average within-respondent, within-vignette racial effects, based on, based on white, non-foreign born respondents only (unweighted), all vignettes combined. Solid line shows the impact of Race for high-racism respondents. Dashed line shows the impact of Race for low-racism respondents.
Figure 3: Treatment Effects of Recipient Ethnicity Moderated by Overt Racism (UK)

Solid line shows the impact of Race for high-racism respondents, based on white, non-foreign born respondents only (unweighted). Dashed line shows the impact of Race for low-racism respondents.
Solid line shows the impact of Race for high-racism respondents, based on white, non-foreign born respondents only (unweighted). Dashed line shows the impact of Race for low-racism respondents.
Race, Prejudice and Attitudes toward Redistribution: A Comparative Experimental Approach

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Online Appendix

This appendix includes a number of supporting tables for the preceding text, a discussion of (and analyses using) alternative measures of racism, and an extension of our analyses to models of more generalized support for policy.

Supporting Tables

The full regression models referred to in the text are included in Appendix Tables A1-A4. We note the following additional considerations in the specification of these models, not discussed in detail in the text:

Survey Ordering: Note that the survey was fielded with a randomization in the ordering of major components: vignettes appeared at the beginning of the survey (0), before the other survey questions and an Implicit Association Test were completed, between the survey items and the IAT (1) or at the end of the survey (2). The first wave of the survey included some randomization in this regard; the second wave module order was completely randomized.
Preliminary results suggest that including a randomization variable makes no difference to our results.

*Additional Measures of Policy:* We have in some past work (e.g., *Redacted*) included measures of support for government action and views of recipients - two indices intended to capture general attitudes relating to welfare state support. These are useful in accounting for variance in support for individual recipients. As the modern racism literature suggests, however, they are heavily influenced by racism, particularly in the US. Given that our focus here is on the impact of race, we do not include these variables. It is worth considering in future work whether there are general measures of support for redistributive policies that do not partly capture the impact of racism.

[Tables A1-A4 about here]

**Additional Details on the Survey Instrument**

The text includes a brief summary of the experimental treatments and broader survey instrument. We accordingly include some additional details below.

*Language of Interview:* Regarding the Canadian survey, note that approximately 22% of Canadians have French as their mother tongue, concentrated primarily in the province of Quebec. Three graduate students at the Université du Québec à Montréal conducted the French translation. A single student translated each section, and then language and equivalence to the English survey were checked by two other students. In case of disagreement in word choice or phrasing, coder discussion ensued to see if agreement could be reached. Any case where the three coders were not unanimous after discussion was brought to the principal researcher who made a final decision.
Morphed Images: Note that we confirmed the equivalence of the facial images by having a sample of 50 individuals rate the attractiveness and stereotypicality of each face. (Respondents were drawn from Mechanical Turk). The results showed no significant variance across photos on either dimension. Note the Hispanic faces in the US were collected later and were not included in the ratings.

Hypothetical Respondents’ Names: Common names were primarily selected from US Census data based on popularity and racial group, and supplemented, when necessary, by other online databases.

Experimental Vignettes: The set of seven vignettes (in a fully randomized order) was introduced as follows: “In the following section, we would like you to read about people applying for various types of government benefits. Please read about each person’s situation, then tell us what you think about him or her receiving government benefits.” The full text of the seven experimental vignettes was as follows. For the sake of clarity we include only the English-language Canadian versions of each vignette. The UK and US versions (which use different amounts of dollars/pounds), and French-language Canadian versions, are available upon request.

Vignette #1: Employment Insurance

Manipulations: race (3), gender (2)

Male Names: [X]= Jay Smith (White Photo), Jamal Williams (Black Photo), Jiang Lee (Chinese Photo)

Male vignette: [X] is 49 years old and lives in [PROVINCE]. He has worked full-time in the accounts receivable department of Reliable Insurance for the past 3 years. His salary is $3600 a month before taxes. He is a single father with two children, ages 8 and 12. The company he works for decided to lay off some of its employees, and [X] lost his job.
[X] would like to apply for unemployment benefits. The average benefit in this situation is about $1900 a month for up to 10 months.

Female Names: [X] = Laurie Smith (White Photo), Latoya Williams (Black Photo), Lian Lee (Chinese Photo)

Female vignette: [X] is 49 years old and lives in [PROVINCE]. She has worked full-time in the accounts receivable department of Reliable Insurance for the past 3 years. Her salary is $3600 a month before taxes. She is a single mother with two children, ages 8 and 12. The company she works for decided to lay off some of its employees, and [X] lost her job. [X] would like to apply for unemployment benefits. The average benefit in this situation is about $1900 a month for up to 10 months.

Vignette #2: Employment Insurance versus Social Assistance

Manipulations: race (3), program type (2)

Names: [X] = Emily Johnson (White Photo), Ebony Jackson (Black Photo), Jing Nguyen (Chinese Photo)

Vignette: [X] is 37 years old and rents an apartment with her two children. She has worked in the food service industry since graduating high school in [BIGGEST CITY of PROVINCE]. Last year, she earned about $1600 a month before taxes. This year, she has not found suitable employment. She has no savings and has about $2500 in credit card debt.

[X] would like to apply for [unemployment benefits/welfare benefits]. The average benefit in this situation is about $1100 a month.

Vignette #3: Disability Benefits
Manipulations: race (3), cause (2)

Names: [X]= Todd Miller (White Photo), Tyrone Martin (Black Photo), Tao Huy (Chinese Photo)

Vignette: [X] is divorced. He is a single father with 2 children. He worked full-time as a machine operator for CCF Manufacturing for 7 years. He makes about $2800 a month before taxes. [X] has been suffering from chronic back pain caused by [an accident at work/a boating accident] last year, and is unable to work. [X] would like to apply for disability benefits. The average benefit in this situation is about $800 a month.

Vignette #4: Low-Income Seniors

Manipulations: gender (2), race (3)

Male Names: [X]= Matthew Moore (White Photo), Jermaine Roy (Black Photo), Lee Chan (Chinese Photo)

Male vignette: [X] is 68 years old and has worked on and off over her life in customer service at SEA Travel. He is a widower and has three adult children. He is retired, and receives $1000 a month from her Canada Pension Plan [if QC: Quebec Pension Plan] contributions and the Old Age Security program. He does not have any substantial savings. [X] would like to apply for the financial assistance for low-income seniors. The average benefit in this situation is about $400 a month.

Female Names: [X]= Meredith Moore (White Photo), Tanisha Roy (Black Photo), Wen Chan (Chinese Photo)

Female vignette: [X] is 68 years old and has worked on and off over her life in customer service at SEA Travel. S/he is a widow and has three adult children. She is retired, and receives $1000 a month from her Canada Pension Plan [if QC: Quebec Pension Plan] contributions and the Old Age Security program. She does not have any substantial savings. [X] would like to apply for the financial assistance for low-income seniors. The average benefit in this situation is about $400 a month.
$1000 a month from her Canada Pension Plan [if QC: Quebec Pension Plan] contributions and the Old Age Security program. She does not have any substantial savings.

[X] would like to apply for the financial assistance for low-income seniors. The average benefit in this situation is about $400 a month.

Vignette #5: Social Assistance

Manipulations: race (3), gender (2) and deservingness (2) (reason for unemployment)

Male Names: [X]= Brad Williams (White Photo), Duane Davis (Black Photo), Robert Blackhawk (Aboriginal Photo)

Male vignette: [X] is a single father of three children ages 3, 5 and 8. He has some high school education and is unemployed. He is not looking for work because [he has no childcare for his children / has not been able to hold a job because of substance abuse issues]. The children’s mother does not provide any financial support. [X] has no savings and has a hard time paying the rent and bills on his 2 bedroom apartment.

[X] would like to apply for welfare benefits through her province. The average benefit in this situation is about $1200 a month.

Female names: [X]= Nicole Williams (White Photo), Desiree Davis (Black Photo), Linda Blackhawk (Aboriginal Photo)

Female vignette: [X] is a single mother of three children ages 3, 5 and 8. She has some high school education and is unemployed. She is not looking for work because [she has no childcare for her children / has not been able to hold a job because of substance abuse issues]. The children’s father does not provide any financial support. [X] has no savings and has a hard time paying the rent and bills on her 2 bedroom apartment.

[X] would like to apply for welfare benefits through her province. The average benefit in
this situation is about $1200 a month.

Vignette #6: Social Assistance

Manipulations: race (2) and gender (2) and sexual orientation (single, married, same sex partner) (3)

Male names: [X] = Greg Anderson (White Photo), Rasheed Rony (Black Photo)

Male vignette: [X] is 24 years old and [lives alone, shares a small apartment with her spouse/with his/her same sex partner]. He dropped out of high school when he was 15 years old. He has worked previously cleaning hotel rooms and washing dishes at a local restaurant, but he has never held a job for very long. [X] has used the small amount of savings s/he over the past two month and is behind on his rent.

[X] would like to apply for welfare benefits through her province. The average benefit in this situation is about $600 a month.

Female names: [X] = Sarah Anderson (White Photo), Aisha Rony (Black Photo)

Female vignette: [X] is 24 years old and [lives alone, shares a small apartment with her spouse/with his/her same sex partner]. She dropped out of high school when she was 15 years old. She has worked previously cleaning hotel rooms and washing dishes at a local restaurant, but she has never held a job for very long. [X] has used the small amount of savings she over the past two month and is behind on her rent.

[X] would like to apply for welfare benefits through her province. The average benefit in this situation is about $600 a month.

Vignette #7: Parental Leave

Manipulations: gender (2), marital status (2) and race (3)

Male names: [X] = Neil Martin (White Photo), Leroy Henry (Black Photo), Jun Wong (Chinese
Male vignette: [X] is 32 years old and he is [married/single]. He has been working full-time for the past 2 years. He works for a small business designing websites, and he makes about $2400 a month. Recently, [X]’s [wife/ex-girlfriend] found out that she is pregnant. The baby’s mother works part-time in construction.

[X] would like to apply for parental leave benefits to be able to take time off work after the birth of his/her baby. The average benefit in this situation is about $1300 per month for up to 8 months.

Female names: [X]= Kristin Martin (White Photo), Bihanca Henry (Black Photo), Mei Chan (Chinese Photo)

Female vignette: [X] is 32 years old and she is [married/single]. She has been working full-time for the past 2 years. She works for a small business designing websites, and she makes about $2400 a month. Recently, [X] found out that she is pregnant. The baby’s father works part-time in construction.

[X] would like to apply for parental leave benefits to be able to take time off work after the birth of his/her baby. The average benefit in this situation is about $1300 per month for up to 8 months.

**Alternative Measures of Racism**

Analyses above focus on just one measure of overt racism. The RGWS survey includes several measures, however. And as we have noted above, there is some debate about which measure of racism captures racism most directly. This appendix accordingly revisits our results using additional measures of both modern and implicit racism.
Modern racism is measured using a 0-1 scale based on four agree-disagree items drawn directly from the symbolic racism measure as developed by Sears and colleagues (for a recent overview, see Henry and Sears 2002). The four items include:

1. Irish, Italians, Jewish and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors.
2. Over the past few years, Blacks have gotten less than they deserve. [*reversed in the index]
3. It's really a matter of some people not trying hard enough; if Blacks would only try harder they could be just as well off as other Americans.
4. Generations of colonialism, slavery, and discrimination have created conditions that make it difficult for Blacks to work their way out of the lower class.

One of the drawbacks of this scale for cross-national research is that it is rather specific to the US context and Blacks. Although our survey included a version adapted for Aboriginals in Canada, in this appendix, we examine modern racism only in the US.

Our final measure of prejudice is inspired by research in cognitive psychology about automatically activated attitudes. Psychologists view racial prejudice as a deeply ingrained attitude that develops early in life that has both automatic and controlled components (Devine 1989). While citizens may actively try to regulate explicitly-held negative attitudes, as modern or subtle racism scholars suggest, some social psychologists maintain that prejudice can function at a subconscious level (Greenwald et al. 1998; Dovidio et al. 2002; Olson and Fazio 2003, 2004; Gawronski and Bodenhausen 2006). Implicit racial bias, as measured by Implicit Association Tests (IATs), captures unconscious associations between racial groups and positive or negative affect toward these groups using differences in reaction time to stereotypically congruent and
incongruent pairings of racial groups and affective terms.\textsuperscript{13} As with the modern racism scale, this item was only run for Blacks (versus Whites) and is limited to the US survey.

Note that while measures of overt, modern and implicit racial bias are all expected to contribute to lower levels of support for redistribution, they may influence this support to varying degrees, and in distinct ways. Research suggests that controlled responses (which here are responses that are measured through survey responses from respondents, e.g. overt and modern racism) may have different effects on discriminatory behavior than automatic responses (e.g. implicit racial bias) (Fazio and Dunton 1997; Dovidio et al. 1997, 2002). As it becomes less socially acceptable to express racial prejudice, we might expect a divergence between measures of explicit racial attitudes and policy support due largely to the fact that these measures differ in citizens’ motivation to control the expression of their attitudes. The pressure to “under-report” prejudice should be especially true for overt racial bias, whereas the modern racism measure poses a more subtle violation of social norms. We expect that implicit (or automatic) racial bias will prove a stronger predictor of policy support than either indicator of explicit racial attitudes because it is relatively immune to conscious suppression.\textsuperscript{14} We have no a priori assumptions, however, about the relative strength of these different measures across countries or policy domains.

\textsuperscript{13} For a review, see Gawronski and Bodenhausen (2006).

\textsuperscript{14} It should be noted that we often treat controlled measures of racial attitudes within political science as more susceptible to survey response bias. Yet, social psychological research suggests that the very fact that such attitudes can be controlled means that the consequences of such attitudes (such as discriminatory behavior) are also open to intervention.
Most findings in the literature, as well as in this paper, are based on the measure of overt racism. Given the normative pressures facing respondents in democratic, multi-racial societies, blatant prejudice is increasingly being replaced by more subtle forms of racism. And, as we have noted, racial animus also operates at the sub-conscious or implicit level. Table A4 shows correlations between our measures of overt, modern, and implicit racism.

[Table A5 about here]

The three clearly capture some common element of racial prejudice. The correlations are statistically significant, though the strongest link is between the two survey-based measures. Implicit racism appears to be more strongly correlated with modern than with explicit racism (Note the smaller sample sizes for the correlations involving implicit racism. This is because just one half of the first-wave sample took the race IAT. Sample sizes for the models that follow are affected accordingly.)

Figure A1 shows the moderating effects of each measure vis-à-vis our manipulations of racial cues. We do not include all interactions simultaneously, of course – rather, we run three separate models, each of which includes one of the three measures of racism. The full estimates are included in the Appendix. Note that because we have three measures of racism only for Blacks, we use a somewhat simpler model here: we include the direct effect of other minority recipients, alongside a variable capturing Black recipients, prejudice toward Blacks (measured three different ways), and an interaction between the two (alongside the other control variables, discussed above).

[Figure A1 about here]

Both the measure of overt prejudice toward Blacks and the modern racism scale work similarly in moderating the impact of recipient race. Results in Appendix Table 4 make clear
that our results are remarkably similar using either measure: each has a powerfully negative direct impact on policy support, and a moderating effect on the experimental treatment.

The implicit measure of racial bias, as measured by the IAT, is much weaker in both its direct impact on policy support, and its moderation of treatment effects. Both coefficients point in the right direction, but fail to reach statistical significance. Since the implicit measure is based on response latency rather than the selection of survey response categories, it is not surprising that the two survey-based measures are more highly correlated with support for the target recipients. Moreover, the IAT has no policy component whereas the modern racism measure explicitly taps into questions of ideology that are highly predictive of policy preferences (see, e.g., Carmines et al. 2011). It may be that the IAT is better at capturing an element of raw racism that is group specific and independent of policy preferences. This clearly is an avenue for further work. In the meantime, it is clear that the preceding results were not a function of our reliance on the overt racism measure. Modern racism produces nearly identical results; and implicit racism points, at least, in the same direction.

**From Individual Recipients to Generalized Support for Social Policy**

Do the results obtained above matter for general attitudes towards redistribution, or are they particular to attitudes directed towards (hypothetical) individual recipients? Our use of vignette-based experiments gives us a good deal of leverage over the specific characteristics of recipients, and it allows us to be very precise in our description of benefits as well. We regard the vignettes as a particularly powerful way of getting at the impact of race on welfare-state attitudes. But it is reasonable to ask whether the connections between racial bias and support for social policy evident in these experimental data also apply at a more general level. This is relatively easily tested.
One simple test is to use measures of overt racial bias – the same ones used as moderators in our experimental analyses – as independent variables in models of general support for social programs. We capture general support for social programs here using a scale based on five questions capturing the general orientation of the respondent toward state intervention:

Which statement comes closest to your own view?:

1. The free market can handle today's problems without government being involved (0)/ or, We need a strong government to handle today's complex economic problems (1).
2. Less government is better (0)/ There are more things that government should be doing (1).
3. We should cut government spending (0)/ We should expand government services (1)
4. The government should see to it that everyone has a decent standard of living (1)/ The government should leave it to people to get ahead on their own (0).

How much do you agree or disagree with the following statements:

5. Government should redistribute income from the better-off to those who are less well off (0 strongly disagree, 1 strongly agree)

All five questions are equally weighted; the measure is scaled from 0 to 1 where higher scores indicate intervention; the Cronbach’s alpha on the scale is .72. And the model used to predict support for government action includes basic demographics (gender, where female=1; age, in years; education, in three categories: high school or less (0), more than high school (1), and completed university (2); and income, in quartiles (1-4)), alongside each of the measures of overt racial bias examined above.15

15 We run separate models for each measure of racial bias rather than include them all in the same model. To the extent that the measures of bias are positively correlated, using each
The full models are included in Appendix Table A5, where the most important coefficients, capturing the impact of racial bias, are in bold. The most important results: the coefficients for each measure of overt racial bias, capturing the estimated mean impact on our 0-1 measure of support for government action that is a consequence of moving across the entire range of the racial bias scale (from 0 to 1). These coefficients are on a rather different scale (0-1) than our dollar-amount experimental measures; even so, we can easily compare the magnitude of coefficients estimated from our experimental treatment with the magnitude of these coefficients in our models of government intervention. Appendix Figure A2 does exactly this – it plots the coefficient for the former on the x-axis, and the coefficient for the latter on the y-axis.

The figure suggests that the estimated relationships found in the vignettes translate easily onto much more generalized attitudes about social programs. In fact, there is a remarkably strong relationship between the two sets of coefficients; a dashed line shows the plotted relationship between the two; the correlation between them is .87. Dots to the bottom left of the figure indicate cases in which there are particularly powerful negative effects of overt racism on support (both for individuals, and generalized social programs). The case in which race has the most powerful negative effect is Blacks in the US, as we might expect. But this is by no means the only case in which racial bias has a negative impact. Dotted lines on the x- and y-axes indicate the 0-points – all cases to left and bottom of these lines are ones in which the impact of racial bias is systematically negative. Only racism towards Asians, across all three countries individually increases slightly the estimated effect of racial bias. The impact is very slight, however; and the nature of the two-part US sample precludes our including racial bias for Aboriginals and Hispanics in the same model in any case.
(though, nearly, racism towards Blacks in Canada) is not systematically related to decreased support. Clearly, the characteristics of racism towards Asians are quite different than the characteristics of racism towards the other groups investigated here.

We cannot easily explore the “contents” of racism towards each racial group in these data; but the main purpose of this analysis is to link results focused on individual recipients to broader welfare-state attitudes. In this regard, our findings make very clear the relationship between the two. Just as overt racial bias has a direct impact on the allocation of resources to (hypothetical) Black recipients, for instance, so too does it push downwards support for redistributive policy more generally. But, as we have seen in our vignette-based analyses, the direct impact of overt racism is only part of the story. Overt racism increases, markedly, the impact of racial cues on attitudes about social policy recipients. The racialization of social policy attitudes thus has both direct and indirect consequences.
### Appendix Table A1: Treatment Effects on Support

<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>UK</th>
<th>CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recipient: Black</td>
<td>-1.334 (.997)</td>
<td>-5.690** (1.854)</td>
<td>-1.227 (1.061)</td>
</tr>
<tr>
<td>Recipient: Hispanic</td>
<td>-1.273 (1.665)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recipient: Asian</td>
<td>-2.080 (1.310)</td>
<td>-3.465* (1.359)</td>
<td>-3.925** (1.230)</td>
</tr>
<tr>
<td>Recipient: Aboriginal</td>
<td>-.526 (2.697)</td>
<td></td>
<td>-3.220 (2.593)</td>
</tr>
<tr>
<td>Recipient: S Asian</td>
<td></td>
<td>-3.812** (1.231)</td>
<td></td>
</tr>
<tr>
<td>Vignette order</td>
<td>-.172 (.501)</td>
<td>.215 (.224)</td>
<td>-.388 (.210)</td>
</tr>
<tr>
<td>Survey Wave</td>
<td>-2.879 (2.402)</td>
<td></td>
<td></td>
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<table>
<thead>
<tr>
<th></th>
<th>US</th>
<th>UK</th>
<th>CA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-3.847 (2.023)</td>
<td>7.666*** (2.058)</td>
<td>15.139*** (2.110)</td>
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<tr>
<td>N</td>
<td>8866</td>
<td>6567</td>
<td>5649</td>
</tr>
<tr>
<td>N (individuals)</td>
<td>1411</td>
<td>1027</td>
<td>892</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01; *** p < .001. Cells contain multilevel mixed-effects linear regression coefficients with standard errors in parentheses. Based on white, non-foreign born respondents only (unweighted). Models include controls for other manipulations across vignettes, i.e., recipient deservingness, gender, as well as dummy variables for each vignette. These are not shown here, but are available upon request.
Appendix Table A2: Treatment Effects on Recipient Support, Interacted with Overt Racism

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<th>US</th>
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<th>CA</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Combined</td>
<td>Second Wave Only</td>
<td></td>
</tr>
<tr>
<td>Recipient: Black</td>
<td>7.736**</td>
<td>4.748 (4.092)</td>
<td>5.627 (3.552)</td>
</tr>
<tr>
<td>Overt Racism: Black</td>
<td>-42.591***</td>
<td>-47.713***</td>
<td>-37.436***</td>
</tr>
<tr>
<td></td>
<td>- .947 (3.297)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recipient: Hispanic</td>
<td>-11.633 (10.972)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overt Racism: His</td>
<td>2.784 (8.553)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>interaction</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recipient: Asian</td>
<td>1.155 (1.815)</td>
<td>-1.067 (2.021)</td>
<td>-3.810* (1.715)</td>
</tr>
<tr>
<td>Overt Racism: Asian</td>
<td>22.405***</td>
<td>15.448* (6.583)</td>
<td>1.189 (5.901)</td>
</tr>
<tr>
<td>Interaction</td>
<td>-17.936**</td>
<td>-10.221 (6.132)</td>
<td>-1.220 (5.865)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recipient: Aboriginal</td>
<td>5.176 (5.207)</td>
<td></td>
<td>17.946***</td>
</tr>
<tr>
<td>Interaction</td>
<td>-13.900 (11.085)</td>
<td></td>
<td>-40.817***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recipient: S Asian</td>
<td></td>
<td>-.437 (2.000)</td>
<td></td>
</tr>
<tr>
<td>interaction</td>
<td></td>
<td>-11.021* (5.060)</td>
<td></td>
</tr>
<tr>
<td>Vignette order</td>
<td>-.411 (.517)</td>
<td>.225 (.226)</td>
<td>-.374 (.211)</td>
</tr>
<tr>
<td>Constant</td>
<td>22.608***</td>
<td>21.116***</td>
<td>25.009***</td>
</tr>
<tr>
<td></td>
<td>(3.589)</td>
<td>(3.099)</td>
<td>(3.400)</td>
</tr>
<tr>
<td>N</td>
<td>6076</td>
<td>2514</td>
<td>6444</td>
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<tr>
<td>N (individuals)</td>
<td>966</td>
<td>391</td>
<td>1008</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01; *** p < .001. Cells contain multilevel mixed-effects linear regression coefficients with standard errors in parentheses. Based on white, non-foreign born respondents only (unweighted). Models include controls for other manipulations across vignettes, i.e., recipient deservingness, gender, as well as dummy variables for each vignette. These are not shown here, but are available upon request.
Appendix Table A3: Treatment Effects on Support, Interacted with Various Measures of Racism

<table>
<thead>
<tr>
<th></th>
<th>US w/ Overt Racism</th>
<th>US w/ Modern Racism</th>
<th>US w/ Implicit Racism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recipient: Black</td>
<td>6.634** (2.055)</td>
<td>15.574*** (3.590)</td>
<td>1.350 (1.461)</td>
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<tr>
<td>Overt Racism</td>
<td>-54.015*** (4.504)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interaction</td>
<td>-16.612*** (3.830)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Modern Racism</td>
<td></td>
<td>-113.894*** (6.515)</td>
<td></td>
</tr>
<tr>
<td>Interaction</td>
<td></td>
<td>-28.840*** (5.898)</td>
<td></td>
</tr>
<tr>
<td>Implicit Racism</td>
<td></td>
<td></td>
<td>-4.563 (3.994)</td>
</tr>
<tr>
<td>Interaction</td>
<td></td>
<td></td>
<td>-4.335 (3.224)</td>
</tr>
<tr>
<td>Recipient: Hispanic</td>
<td>-1.091 (1.677)</td>
<td>-1.440 (1.663)</td>
<td>-1.463 (1.711)</td>
</tr>
<tr>
<td>Recipient: Asian</td>
<td>-1.914 (1.318)</td>
<td>-2.136 (1.308)</td>
<td>-3.479 (1.932)</td>
</tr>
<tr>
<td>Recipient: Aboriginal</td>
<td>-.831 (2.719)</td>
<td>-.627 (2.697)</td>
<td>-5.532 (3.876)</td>
</tr>
<tr>
<td>Vignette order</td>
<td>-.463 (.510)</td>
<td>-.393 (.491)</td>
<td>.618 (.942)</td>
</tr>
<tr>
<td>Wave</td>
<td>-2.686 (2.293)</td>
<td>-.924 (2.147)</td>
<td>-3.563 (2.853)</td>
</tr>
<tr>
<td>Constant</td>
<td>22.073*** (2.898)</td>
<td>62.292*** (4.260)</td>
<td>.160 (2.892)</td>
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<td>N</td>
<td>8659</td>
<td>8813</td>
<td>5036</td>
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<tr>
<td>N (individuals)</td>
<td>1369</td>
<td>1398</td>
<td>792</td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01; *** p < .001. Cells contain multilevel mixed-effects linear regression coefficients with standard errors in parentheses. Based on white, non-foreign born respondents only (unweighted). Models include controls for other manipulations across vignettes, i.e., recipient deservingness, gender, as well as dummy variables for each vignette. These are not shown here, but are available upon request.
Appendix Table A4: Correlation Matrix - Racism Measures

<table>
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<tr>
<th></th>
<th>Overt</th>
<th>Modern</th>
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<tbody>
<tr>
<td>Modern</td>
<td>.618*  (N=1996)</td>
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</tr>
<tr>
<td>Implicit</td>
<td>.199*  (N=1109)</td>
<td>.267*  (N=1130)</td>
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Based on unweighted RWGS, US data only. Cells contain Pearson correlation coefficients. * p < .01.
Appendix Table A5: Support for Government Action

<table>
<thead>
<tr>
<th>Racial Bias Variable</th>
<th>Black</th>
<th>Hispanic</th>
<th>Asian</th>
<th>Aboriginal</th>
<th>SE Asian</th>
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<td><strong>US</strong></td>
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<td></td>
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<tr>
<td>Racial Bias</td>
<td>-.645*** (.044)</td>
<td>.153* (.061)</td>
<td>-.364*** (.102)</td>
<td>-.455*** (.059)</td>
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<tr>
<td>Female</td>
<td>.069*** (.020)</td>
<td>.096*** (.022)</td>
<td>.084* (.039)</td>
<td>.074** (.026)</td>
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<tr>
<td>Age</td>
<td>-.003*** (.001)</td>
<td>-.003*** (.001)</td>
<td>-.004** (.001)</td>
<td>-.003*** (.001)</td>
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</tr>
<tr>
<td>Education</td>
<td>.035** (.013)</td>
<td>.068*** (.014)</td>
<td>.057* (.026)</td>
<td>.056*** (.017)</td>
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<tr>
<td>Income</td>
<td>-.037*** (.010)</td>
<td>-.038*** (.011)</td>
<td>-.047* (.019)</td>
<td>-.029* (.012)</td>
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<tr>
<td>Constant</td>
<td>.861*** (.048)</td>
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<td>.716*** (.100)</td>
<td>.709*** (.057)</td>
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<tr>
<td>N</td>
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<td>1172</td>
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<td>812</td>
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<td><strong>UK</strong></td>
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<tr>
<td>Racial Bias</td>
<td>-.248*** (.038)</td>
<td>.008 (.043)</td>
<td>-.097* (.039)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>.029 (.016)</td>
<td>.046** (.016)</td>
<td>.044** (.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-.001 (.001)</td>
<td>-.001 (.001)</td>
<td>-.001 (.001)</td>
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<td></td>
</tr>
<tr>
<td>Education</td>
<td>-.014 (.010)</td>
<td>-.004 (.010)</td>
<td>-.009 (.010)</td>
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<tr>
<td>Income</td>
<td>-.016* (.007)</td>
<td>-.016* (.007)</td>
<td>-.015* (.007)</td>
<td></td>
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<tr>
<td>Constant</td>
<td>.802*** (.039)</td>
<td>.685*** (.039)</td>
<td>.726*** (.038)</td>
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<tr>
<td>N</td>
<td>1003</td>
<td>1007</td>
<td>1005</td>
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<td><strong>CA</strong></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>Racial Bias</td>
<td>-.095* (.044)</td>
<td>.025 (.050)</td>
<td>-.246*** (.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>.069*** (.018)</td>
<td>.071*** (.018)</td>
<td>.064*** (.017)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-.002*** (.001)</td>
<td>-.002** (.001)</td>
<td>-.002** (.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>.022* (.011)</td>
<td>.026* (.011)</td>
<td>.020 (.011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td>-.044*** (.008)</td>
<td>-.045*** (.008)</td>
<td>-.040*** (.008)</td>
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</tr>
<tr>
<td>Constant</td>
<td>.817*** (.041)</td>
<td>.765*** (.039)</td>
<td>.895*** (.041)</td>
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</tr>
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<td>N</td>
<td>789</td>
<td>769</td>
<td>799</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p < .05; ** p < .01; *** p < .001. Cells contain linear regression coefficients with standard errors in parentheses. Based on white, non-foreign born respondents only (unweighted).
Appendix Figure A1: Treatment Effects of Recipient Ethnicity Moderated by Various Measures of Racism (US)

Average within-respondent, within-vignette racial effects, based on RGWS survey, all vignettes combined, white non-foreigners only. Solid line shows the impact of Race for high-racism respondents. Dashed line shows the impact of Race for low-racism respondents. In every case, low- and high-racism are defined by the 10th and 90th percentiles for the racism measures. Those measures are: (1) Explicit Racism, based on two questions on whether Blacks are (a) hardworking/lazy and (b) dependent/self-reliant; (2) Modern Explicit Racial Bias: based on four questions, described in the text; (3) results from the race IAT (completed by half the sample only).
Appendix Figure A2: The Impact of Overt Racism in Vignettes, and on Government Action