Worries about Appearing Prejudiced Decreased among Conservatives after the 2016 Election of Donald Trump

Abstract

Donald Trump frequently makes racist remarks. Did his public example change the acceptability of racial prejudice among his supporters? To investigate the relationship between Trump's political rise and a potential decrease in worry about appearing racially prejudiced, we used four years of data from visitors to the Project Implicit website (2015-2018, $N = 90{,}703$). In a set of preregistered analyses, we found that the external motivation to respond without prejudice toward Black people (EMS; Plant & Devine, 1998) decreased among conservatives, but not among liberals, after Trump's 2016 election to the presidency. This change in external motivation mediated the relationship between political orientation and explicit racial attitudes. These results indicate that Trump's election is associated with conservatives' weakened external motivation to control prejudice and, to an extent, their explicit attitudes.

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Expressing prejudice against racial minorities is considered socially unacceptable in the United States. National surveys, for example, no longer find it useful to ask whether respondents support racial equality in the abstract, as few people in contemporary American society report anything less than full support (Krysan & Moberg, 2016). Most Americans report believing that it is inappropriate to even hold prejudice against racial groups (Crandall et al., 2002) and often find racist messages more offensive than other forms of discrimination, such as sexist or anti-gay messages (Cowan & Hodge, 1996). Americans, on the whole, do not feel comfortable expressing racial prejudice.

These nonprejudiced reactions may have two primary (non-exclusive) sources of motivation (Plant & Devine, 1998). Some may believe that expressing racial prejudice violates their own value system and therefore do not express prejudice so as to live up to their ideal selves (i.e., internal motivation). Others, however, may present themselves as egalitarian (or hide their prejudice) largely to avoid the disapproval of others (i.e., external motivation). Although perceived changes in social norms affect both self-reported prejudiced attitudes (e.g., Blanchard et al., 1991; Blanchard et al., 1994) and behaviors (e.g., Paluck, 2009; see Paluck & Green, 2009 for a review on prejudice-reduction, and see Legros & Cislaghi, 2020 for a review of reviews on social norms and their influence), one's motivations for suppressing one's own prejudice affect how norms moderate expression. That is, prejudice expression for individuals who are primarily internally motivated should not be affected by changes in perceived cultural norms, as their standard is internal. Whereas individuals who are primarily externally motivated are affected by social context, perceived norms, and cultural changes (e.g., Walker et al., 2015). For example, when cultural prohibitions on expressing racial prejudice are unambiguous, even highly prejudiced individuals worry about sanction from friends and neighbors and regulate their prejudice to conform to the egalitarian norm. However, if individuals perceive that sanctions against expressing racial prejudice are weakening, then those primarily driven by an external motivation may be less motivated to suppress prejudiced expression (though see Crandall et al., 2002, who argue that internal and external motivations are a consequence of social approval, not a moderator of their effect). The perception of changing norms can be a powerful signal, leading individuals to believe that previous barriers to certain actions or beliefs are crumbling, even if the existing norm is still widely agreed-upon (i.e., *dynamic norms*, Sparkman & Walton, 2017; Sparkman & Walton 2019). Accordingly, perceiving that norms related to expressing racial prejudice are changing may lead externally motivated people to worry less about being 'politically correct' and, in turn, more likely to express their prejudices freely.

One reason this question is of particular interest is that our political situation has led to a sense that norms against expressing prejudice are, in fact, changing. During the 2016 presidential campaign, then-candidate Donald Trump repeatedly and openly made statements and comments many found racist, a practice that has continued throughout his Presidency. This open expression is changing the perception of norms. In a recent survey, 45% of Americans reported that, since the election of Donald Trump, it has become more acceptable to express racist or racially insensitive views, and 65% said that the expression of such views has become more common (against 23% saying that it has become less acceptable, and just 5% saying that it has become less common; Horowitz et al., 2019). Moreover, norms may be shifting especially quickly around groups frequently denigrated by Trump, with people perceiving that it has become more acceptable to express prejudice towards groups Trump targeted during his campaign (e.g., Mexicans, immigrants), but not towards groups not targeted by Trump (e.g., porn stars, rich people; Crandall et al., 2018).

These changes in norms may be particularly salient for certain groups in society. People take their cues about norms from ‘role models,’ especially those who are prominent and powerful within a valued ingroup identity (see e.g., Cialdini & Trost, 1998; Etzioni, 2000; Sunstein, 1996; Young, 2015 for reviews). Therefore, Donald Trump, as the leader of the Republican party may have a stronger influence on the attitudes and beliefs of conservatives compared to liberals (see e.g., Sides et al., 2018). People also take cues from the behavior of their friends and neighbors (see e.g., Lapinski & Rimal, 2005; Young, 2015 for reviews). A cluster of conservatives may reinforce changes in shared norms more strongly than a more politically heterogeneous group that is less in agreement about changes in the norm (see e.g., Miller & Walton, 2013; Payne et al., 2017 for the creation and maintenance of ‘prejudiced places’). Taken together, we expect the norm-breaking rhetoric of Donald Trump to be especially influential on conservatives living and working in spaces dominated by other conservatives.

To study whether the rise of Donald Trump is associated with a decrease in the external motivation to control racial prejudice, we used data from Project Implicit (2015 through 2018, $n \sim 90{,}000$), a widely-used website where people can take tests about their implicit and explicit biases. As part of an ongoing project, a subset of participants who took the Race implicit association test (IAT) were then asked about their motivations for not expressing prejudice toward Black people, as well as their attitudes towards Black and White individuals. We predicted that people’s external motivation to regulate their own racial prejudice would decrease after the political rise to prominence of Donald Trump, and that this decrease would be especially concentrated among conservatives living in counties that voted for Trump.

Additionally, we predicted that this decrease in external motivation would be associated with a rise in explicit anti-Black attitudes.

Method

Disclosures

Preregistration

For all planned analyses, we first randomly-reshuffled the dependent variable scores among participants in order to break the relationship between predictors and our dependent variables (and therefore prevent us from learning anything about our hypotheses). Next, we refined model specifications and registered our analyses. After the registration, we ran the full models and checked model assumptions.

Our registrations can be found at https://osf.io/6q25d?view_only=bbec18e6f8c14d058d3800381e146f9d and https://osf.io/mjwtn?view_only=bbec18e6f8c14d058d3800381e146f9d. All differences between the registrations and the final models are tracked at https://osf.io/zvwrd/?view_only=bbec18e6f8c14d058d3800381e146f9d.

Data and Materials

All data, scripts, codebooks, and model-objects can be found at https://osf.io/wvenk/?view_only=bbec18e6f8c14d058d3800381e146f9d.

Reporting

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

Participants and Materials

We analyzed data from 90,703 individuals who participated in a Race Implicit Association Test on the Project Implicit website between January 5, 2015 and December 31, 2018 (see Table 1 for demographics). As part of the experimental session, a subset of participants were randomly assigned to complete both the External Motivation to Respond Without Prejudice Scale (EMS) and the Internal Motivation to Respond Without Prejudice Scale (IMS; Plant & Devine, 1998). Sample items for EMS include “Because of today’s PC (politically correct) standards, I try to appear nonprejudiced toward Black people” and “If I acted prejudiced toward Black people, I would be concerned that others would be angry with me,” alpha = .78 [.77, .78]. Sample items for IMS include “I attempt to act in nonprejudiced ways toward Black people because it is personally important to me” and “I am personally motivated by my beliefs to be nonprejudiced toward Black people,” alpha = .78 [.78, .79]). Participants completed the EMS and IMS scales on a 9-point scale, from 1 = “Very Strongly Disagree” to 9 = “Very Strongly Agree”). EMS and IMS scores were summed, with case-wise deletion in the case of missing values. To measure explicit racial attitudes, participants completed 11-point feeling thermometer scale items related to Black and White people (asking how warm or cold they felt toward the relevant group, from 1 = “very cold” to 11 = “very warm”), and a one item explicit racial preference measure (from 1 = “I strongly prefer African Americans to European Americans” to 7 = “I strongly prefer European Americans to African Americans.”). To create a one-item aggregate measure of explicit racial attitudes we subtracted feeling thermometer scores towards Black people from thermometer scores towards White people such that higher, positive scores would mean greater anti-Black attitudes in comparison with attitudes toward White people, and combined the resulting scores with the explicit racial preference item by standardizing each and averaging them together, $r(82701) = .62$ [.61, .62].

Due to missingness of demographics or location data, our sample varies between models, but even our smallest sample size (38,069) gives us 99% power to detect an effect of $f = .00048$ in our models. See https://osf.io/h93s5/?view_only=1fc9f391b0d144808913d0cbe61a0938 for all relevant codebooks.

Table 1

Demographics of the Sample

	2015	2016	2017	2018	Full Sample
Mean Birth Year	1989.10 (11.59) *n* = 19,520	1987.56 (30.64) *n* = 20,064	1988.86 (12.75) *n* = 20,921	1989.83 (12.96) *n* = 19,091	1988.82 (18.80) *n* = 79,596
% Female	60.8% *n* = 18,861	50.4% *n* = 22,941	59.1% *n* = 21,785	60.3% *n* = 20,183	57.4% *n* = 83,770
% White	67.8% *n* = 18,410	70.1% *n* = 18,836	69.8% *n* = 19,902	67.2% *n* = 18,063	68.8% *n* = 75,211
% Black	9.7%	9.9%	9.7%	11.2%	10.1%
% Asian	8.5%	7.4%	7.5%	7.9%	7.8%
% Hispanic	12.6% *n* = 18,918	11.9% *n* = 19,389	12.8% *n* = 20,236	14.9% *n* = 18,516	13.0% *n* = 77,059
Median Education	Some College *n* = 19,966	Some College *n* = 20,434	Some College *n* = 20,906	Some College *n* = 19,123	Some College *n* = 80,429
Mean Political Orientation	4.81 (1.60) *n* = 19,560	4.82 (1.66) *n* = 20,060	4.73 (1.67) *n* = 11,579	4.73 (1.67) *n* = 19,322	4.78 (1.65) *n* = 70,521
Mean Religiosity	2.03 (1.01) *n* = 19,461	2.07 (1.02) *n* = 20,526	2.06 (1.01) *n* = 21,406	2.11 (1.00) *n* = 19,534	2.07 (1.01) *n* = 80,927
Total *n*	23,756	23,099	22,952	20,896	90,703

Note. Political orientation from 1 = "Strongly conservative" to 7 = "Strongly liberal"; Religiosity from 1 = "Not at all religious" to 4 = "Strongly religious." All percentages based on number of participants reporting the demographic in the sample

Analytic Strategy

Most people who visit Project Implicit and participate in an IAT only do so once - of the participants who can be identified across multiple sessions in the data[1], only 6 of the 1,707 (0.35%) completed the Race IAT multiple times. This independence across data points led us to model changes over time using an OLS-based-regression-discontinuity approach, as opposed to using models that track changes in individuals over time.[2] We chose to analyze two important moments when Trump gained significant political power as potential points of change: the day that Donald Trump officially accepted the nomination of the Republican Party and the day of his election.

Changes in Motivation

Since the composition of visitors to the Project Implicit website has changed over time, we built a series of hierarchical regressions to control for demographic change and potential seasonality issues (see Sawyer & Gampa, 2018; Schmidt & Axt, 2016; Westgate et al., 2015 for similar approaches). Since we tested two separate dates with the same data, we divided our alpha level in half for all models in order to control the false-positive rate.

In Model 1 for each timepoint, we regressed EMS scores on a discontinuity dummy coded as 0 if the date was before our discontinuity date and coded as 1 if the date was on or after the discontinuity point. In Model 2, we added in covariates for the set of demographics which were consistently asked across all four years of data: participants' age, gender, race, Latinx status, political orientation, religiosity, and level of education. We then added controls for seasonality in Model 3: the day of the week of participation and the month of the year. Finally, in

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[1] Project Implicit only tracks the repeat visits across days of people who have signed up for their participant pool, and so the actual rate of repeat-visits is impossible to estimate with more precision.
[2] Bolstering this analytic choice, we find that the residuals for all models, save those with no covariates, are uncorrelated, suggesting no temporal dependence (i.e. a Durbin-Watson test fails to reject the null).

Model 4 we interacted the regression dummy with each covariate, to model potential moderation by demographics or seasonality.

To test whether the change in motivation was particularly concentrated among self-identified conservatives living in counties which voted for Donald Trump, we supplemented the Project Implicit data with county-level voting data from the 2016 Presidential election (Leip, 2016). Project Implicit does not collect party affiliation directly, so we used participants' self-reported political orientation (from 1 = Strongly conservative to 7 = Strongly liberal). We used a multilevel model with EMS predicted by the changepoint dummy, interacted with participant's own self-reported political orientation and the percentage of voters in their county who voted for Donald Trump, using the same demographic and seasonality controls as in the flat models and with a random intercept for each county. We attempted to fit the interaction of the changepoint dummy, and individual-level political orientation as a random slope (e.g., Brauer & Curtin, 2018). All models were fit using the *lme4* package in R, with *p*-values for the fixed effects generated from Satterthwaite approximations using the *lmerTest* package (Kuznetsova et al., 2017).

To demonstrate the specificity of the effect to External Motivation to Respond Without Prejudice, and not changes in motivation to respond without prejudice more generally, we ran an additional set of models, using the same hierarchical strategy across the same two changepoints, looking instead at changes in Internal Motivation to Respond Without Prejudice.

Changes in Explicit Attitudes

After running the analyses on changes in motivation, we then registered a follow-up analysis to test whether changes in motivation were associated with changes in explicit attitudes. We fit a moderated-mediation model, using the *mediation* package (Tingley et al., 2014) with

EMS (and then IMS) mediating the relationship between political orientation (dichotomized, for the sake of interpretability, as conservative or liberal, dropping any self-identified political-neutrals) and explicit racial attitudes, testing for changes in the mediation before and after the election of Donald Trump.

Results

Deviations from Registered Analyses

In inspecting model diagnostics, we discovered that there were a few individuals of high leverage who misunderstood the free-response age variable. We therefore excluded 22 people who indicated that they were older than 90 in 2015 (mean reported age of dropped participants = 362 years old). Our results do not meaningfully differ based on this exclusion.

Changes in Motivation

Main Effects

While, in our simplest model, we did find that external motivation to respond without prejudice (EMS) was lower after the nomination of Donald Trump than before (Model 1), b = -0.15 [-0.27, -0.04], $t(89361) = -2.66$, $p = .0078$; the effect did not survive our extensive controls (Model 4), b = 18.40 [-9.74, 46.54], $t(55963) = 1.28$, $p = .20$. In our simplest model, we also found an increase in the internal motivation to respond without prejudice (IMS) after the nomination of Donald Trump (Model 1), b = 0.19 [0.088, 0.29], $t(89626) = 3.63$, $p < .001$; which however, after controlling for demographic and compositional changes to the sample, flipped signs to indicate an overall decrease in IMS (Model 4): b = -40.62 [-64.81, -16.43], $t(56121) = -3.29$, $p = .001$.

We did not find changes in EMS after the election of Donald Trump, either in our simplest (Model 1): b = .072 [-0.037, 0.180], $t(89361) = 1.29$, $p = .20$; or most complex (Model

4) specification: $b = 7.94$ [-18.97, 34.86)], $t(55963) = 0.56$, $p = .56$. We did not find evidence for changes in IMS in our simplest model (Model 1) $b = -0.087$ [-0.19, 0.013], $t(89626) = -1.71$, $p = .087$; but we did find an overall decrease in IMS after controlling for demographic and compositional changes (Model 4), $b = -55.27$ [-78.42, -32.12], $t(56121) = -4.68$, $p < .001$.

Interaction by Political Orientation

We did, however, find evidence, controlling for changes in demographics and the composition of the sample across our changepoint (required for proper interpretation of interaction models with controls, see Yzerbyt et al., 2004), that the relationship between political orientation and EMS changed from before to after the election of Donald Trump (Model 4), $b = 0.11$ [0.023, 0.20], $t(55963) = 2.47$, $p = .013$.

Post-hoc comparisons looking at the difference for each political orientation scale point found that conservatives, whether identifying as Strongly Conservative, Moderately Conservative or Slightly Conservative, were all less externally-motivated to control their prejudice after the election of Donald Trump, while independents and liberals showed no difference across timepoints. See Table 2 for statistics. Collapsing across self-identified conservatives and liberals, conservatives on the whole were less externally motivated to control their prejudice after the election of Donald Trump: pre-election marginal $M = 24.3$, $se = 0.18$, post-election $M = 23.7$, $se = 0.21$, $t(41003) = 2.31$, $p = .021$, $d = 0.080$ [0.012, 0.14]; while liberals did not change their self-reported motivation: pre-election $M = 23.4$, $se = 0.14$, post-election $M = 23.1$, $se = 0.18$, $t(41003) = 1.02$, $p = .31$, $d = 0.029$ [-0.026, 0.084], nor did political neutrals: pre-election $M = 23.8$, $se = 0.12$, post-election $M = 23.4$, $se = 0.16$, $t(55963) = 1.65$, $p = .10$, $d = 0.041$[-0.0078, 0.090]. See Figure 1.

Table 2

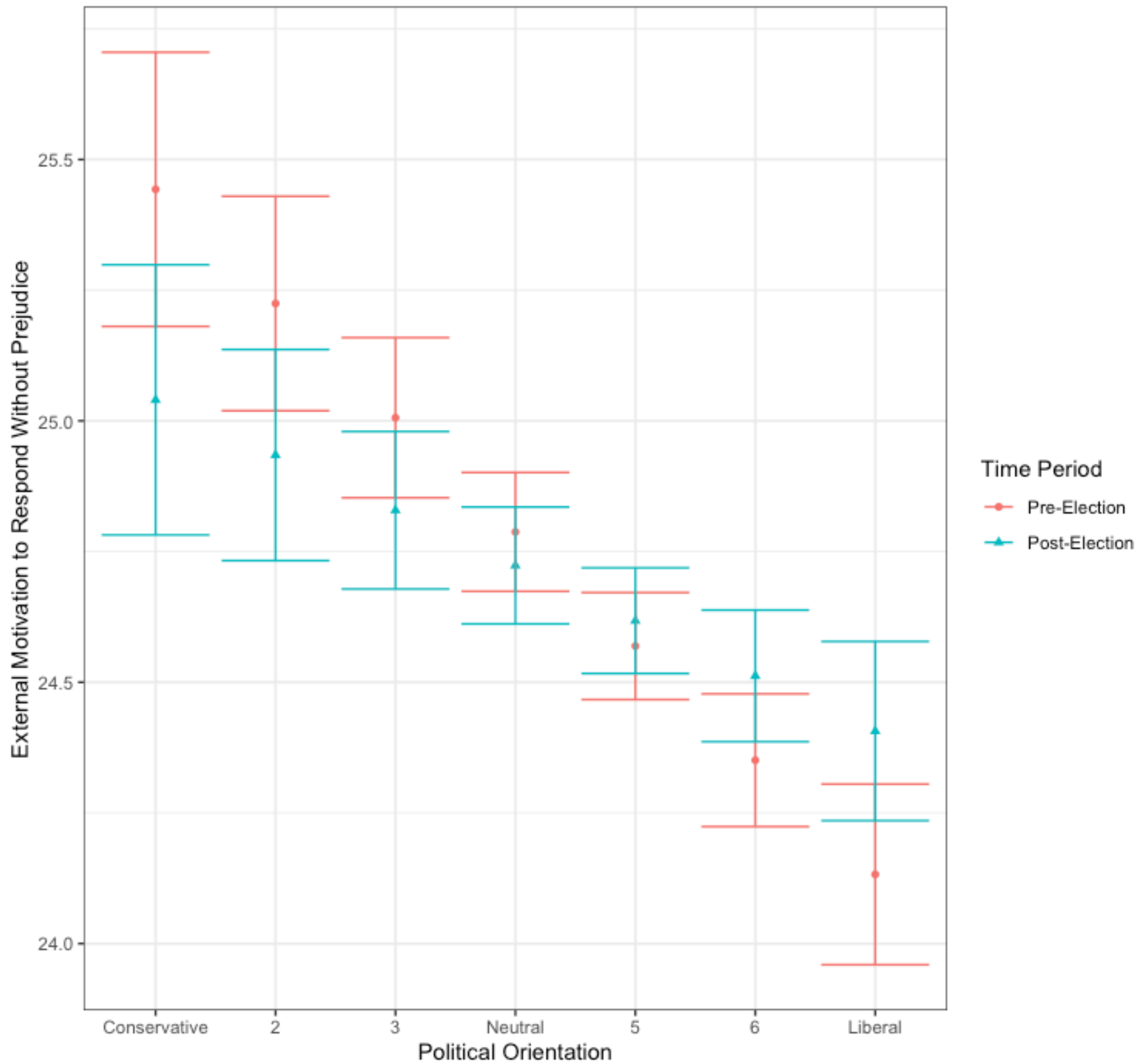
Changes in External Motivation to Respond Without Prejudice (EMS) Pre- vs. Post-Election of Donald Trump across Political Orientation

Political Orientation	Pre-Election *M* (se)	Post-Election *M* (se)	*d* [95% CI]	*p* -value
Strongly Conservative	24.4 (0.17)	23.8 (0.21)	0.083 [0.018, 0.15]	.013*
Moderately Conservative	24.2 (0.15)	23.6 (0.19)	0.069 [0.011, 0.13]	.020*
Slightly Conservative	24.0 (0.13)	23.5 (0.17)	0.055 [0.0024, 0.11]	.040*
Neutral	23.8 (0.12)	23.4 (0.16)	0.041 [-0.0078, 0.090]	.10
Slightly Liberal	23.6 (0.11)	23.3 (0.16)	0.027 [-0.020, 0.075]	.26
Moderately Liberal	23.3 (0.12)	23.2 (0.16)	0.013 [-0.035, 0.062]	.59
Strongly Liberal	23.1 (0.13)	23.1 (0.17)	-0.00071 [-0.053, 0.052]	.98

* $p < .05$

Figure 1

Changes in External Motivation to Respond Without Prejudice Pre- vs. Post-Election of Donald Trump across Political Orientation



Note. Error bars indicate 95% confidence intervals.

This pattern is not apparent in the matching analysis of IMS before and after the election, *b* = -0.059 [-0.14, 0.018], t(56121) = -1.50, *p* = .13, nor does it appear looking across the nomination changepoint for either EMS, *b* = 0.012 [-0.081, 0.10], *t*(55963) = 0.25, *p* = .81; or for IMS, *b* = -0.079 [-0.16, 0.0012], *t*(56121) = -1.92, *p* = .053. See Table 3 for the regression output for EMS changing across the election, and see the Online Supplement for regression outputs for all other models.

Table 3

Regression Output for Changes in External Motivation to Respond without Prejudice (EMS) across the Election of Donald Trump

	Dependent Variable			
	External Motivation to Respond Without Prejudice (EMS)			
	[1]	[2]	[3]	[4]
Post-Election	.072 [-.037, .180] p = .198	.054 [-.081, .189] p = .432	.038 [-.104, .180] p = .603	7.944 [-18.974, 34.862] p = .563
Birth Year		.145 [.138, .152] $p < .001^{***}$	.144 [.137, .150] $p < .001^{***}$	.145 [.136, .155] $p < .001^{***}$
Male		-.617 [-.760, -.475] $p < .001^{***}$	-.620 [-.762, -.478] $p < .001^{***}$	-.661 [-.863, -.458] $p < .001^{***}$
Other Gender		-.359 [-.745, .026] p = .068	-.344 [-.731, .042] p = .081	-.227 [-.671, .217] p = .317
Black		-3.054 [-3.284, -2.823] $p < .001^{***}$	-3.057 [-3.287, -2.826] $p < .001^{***}$	-3.286 [-3.618, -2.953] $p < .001^{***}$
Asian		.026 [-.232, .284] p = .843	.033 [-.224, .291] p = .801	-.030 [-.393, .333] p = .873
Other Race		-1.752 [-1.980, -1.525] $p < .001^{***}$	-1.752 [-1.980, -1.525] $p < .001^{***}$	-1.756 [-2.076, -1.435] $p < .001^{***}$
Hispanic		-.805 [-1.035, -.576] $p < .001^{***}$	-.804 [-1.033, -.575] $p < .001^{***}$	-.698 [-1.030, -.366] $p = .00004^{***}$
Education		.122 [.092, .153] $p < .001^{***}$	.125 [.094, .156] $p < .001^{***}$	.129 [.089, .169] $p < .001^{***}$
Political Orientation		-.166 [-.211, -.122] $p < .001^{***}$	-.164 [-.209, -.119] $p < .001^{***}$	-.218 [-.282, -.155] $p < .001^{***}$
Religiosity		.262 [.189, .335] $p < .001^{***}$	.258 [.185, .330] $p < .001^{***}$	.236 [.133, .339] $p < .001^{***}$
Monday			.357 [.108, .606] $p = .005^{**}$	.503 [.145, .861] $p = .006^{**}$
Tuesday			.290 [.044, .537]	.365 [.009, .721]

	$p = .022^{*}$	$p = .045^{*}$
Wednesday	.289 [.043, .535]	.292 [-.059, .643]
	$p = .022^{*}$	$p = .104$
Thursday	.217 [-.034, .467]	.258 [-.098, .614]
	$p = .090$	$p = .156$
Saturday	-.009 [-.321, .303]	.129 [-.293, .550]
	$p = .957$	$p = .550$
Sunday	.117 [-.167, .402]	.151 [-.239, .541]
	$p = .420$	$p = .448$
January	-.379 [-.714, -.045]	-.152 [-.660, .355]
	$p = .027^{*}$	$p = .557$
February	-.367 [-.689, -.046]	-.337 [-.742, .068]
	$p = .026^{*}$	$p = .104$
March	-.189 [-.514, .136]	-.216 [-.614, .182]
	$p = .255$	$p = .288$
May	-.450 [-.806, -.095]	-.556 [-1.005, -.107]
	$p = .014^{*}$	$p = .016^{*}$
June	-.290 [-.687, .107]	-.299 [-.782, .183]
	$p = .153$	$p = .224$
July	-.802 [-1.147, -.457]	-1.070 [-1.508, -.633]
	$p < .001^{***}$	$p < .001^{***}$
August	-.265 [-.605, .076]	-.026 [-.482, .430]
	$p = .128$	$p = .911$
September	-.362 [-.642, -.083]	-.622 [-.971, -.272]
	$p = .012^{*}$	$p < .001^{***}$
October	-.257 [-.562, .048]	-.530 [-.981, -.079]
	$p = .100$	$p = .022^{*}$
November	-.227 [-.528, .074]	-.378 [-.847, .091]
	$p = .140$	$p = .114$

December	-.310 [-.661, .042] p = .085	.044 [-.542, .629] p = .885
Birth Year*Post-Election		-.004 [-.018, .009] p = .529
Male*Post-Election		.088 [-.197, .372] p = .546
Other Gender*Post-Election		-.661 [-1.578, .255] p = .158
Black*Post-Election		.429 [-.033, .890] p = .069
Asian*Post-Election		.126 [-.390, .642] p = .632
Other Race*Post-Election		.005 [-.451, .461] p = .982
Hispanic*Post-Election		-.208 [-.668, .251] p = .375
Education*Post-Election		-.015 [-.077, .048] p = .647
Political Orientation*Post-Election		.113 [.023, .202] p = .014*
Religiosity*Post-Election		.037 [-.109, .183] p = .619
Monday*Post-Election		-.296 [-.796, .203] p = .245
Tuesday*Post-Election		-.176 [-.670, .319] p = .486

Wednesday*Post-Election	-.002 [-.494, .491] p = .996
Thursday*Post-Election	-.066 [-.567, .436] p = .798
Saturday*Post-Election	-.333 [-.963, .297] p = .300
Sunday*Post-Election	-.070 [-.643, .503] p = .811
January*Post-Election	-.227 [-.931, .477] p = .528
February*Post-Election	-.047 [-.716, .621] p = .890
March*Post-Election	.086 [-.605, .777] p = .808
May*Post-Election	.299 [-.439, 1.038] p = .427
June*Post-Election	.033 [-.819, .885] p = .940
July*Post-Election	.748 [.032, 1.463] p = .041*
August*Post-Election	-.390 [-1.087, .307] p = .273
September*Post-Election	.703 [.119, 1.288] p = .019*
October*Post-Election	.523 [-.119, 1.165] p = .111
November*Post-Election	.332 [-.315, .980] p = .315

December*Post-Election				-.363 [-1.129, .404] p = .354
Constant	24.473 [24.394, 24.551] p < .001***	-263.306 [-276.589, -250.024] p < .001***	-260.629 [-273.989, -247.269] p < .001***	-263.974 [-282.773, -245.176] p < .001***
Observations	89,363	56,019	56,019	56,019
Adjusted R^2	.00001	.056	.056	.057

$^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$

Localization to Place

As we had issues with multilevel models converging, we iteratively simplified our random-effects terms, ending up with just a random intercept for county. For models looking at EMS, we use data from 40,763 individuals nested within 2051 counties; and for models looking at IMS, we use data from 40,876 individuals nested within 2052 counties. We did not find evidence for the predicted three-way-interaction between changepoint, individual political orientation, and 2016 county-level voting patterns for EMS either across the nomination, *b* = -0.39 [-0.99, 0.20], *t*(40703) = -1.29, *p* = .20; or across the election: *b* = -0.21 [-0.78, 0.35], *t*(40703) = -0.74, *p* = .46. We additionally found no evidence for the predicted three-way interaction for IMS either across the nomination, *b* = -0.31 [-0.82, 0.20], *t*(40815.79) = -1.19, *p* = .23; or across the election: *b* = -0.25 [-0.74, 0.24], *t*(40815.79) = -1.00, *p* = .32. See Online Supplement for full regression output.

Changes in Explicit Attitudes

As predicted, using data from 38,069 participants with explicit attitude data, we did find evidence that EMS mediated the relationship between political orientation and explicit attitudes, and that the mediational pathways were significantly different before and after the election of

Donald Trump: test of moderation in the indirect effect (*ab* path) = .0080 [.0025, .014], $p = .016$; test of moderation in the direct effect (*c'* path) = -0.017 [-0.059, 0.024], $p = .42$. Specifically, we found evidence for moderation of the relationship between political orientation and EMS (*a* path): interaction $b = -0.46$ [-0.87, -0.049], $t(38013) = -2.20$, $p = .028$, whereby political orientation predicted EMS more weakly after the election of Donald Trump; but we found no moderation in the relationship between EMS and explicit attitudes across the election (*b* path): interaction $b = -0.0018$ [-0.0037, 0.00017], $t(38011) = -1.79$, $p = .074$.

Prior to the election, political orientation (coded as 0 if liberal and 1 if conservative), controlling for demographics and seasonality, predicted EMS (*a* path), $b = 0.99$ [0.69, 1.28], $t(19504) = 6.58$, $p <.001$, and EMS predicted explicit attitudes (*b* path), $b = 0.015$, [0.014, 0.017], $t(19503) = 23.52$, $p <.001$; average causal mediation effect (*ab* path) = 0.015 [0.010, 0.02], $p < .001$; total effect (*c* path) = 0.38 [0.35, 0.41], $p < .001$; direct effect (*c'* path) = 0.36 [0.34, 0.39], $p < .001$.

After the election, political orientation predicted EMS (*a* path), $b = 0.53$ [0.24, 0.81], $t(18509) = 3.61$, $p < .001$, and EMS predicted explicit attitudes (*b* path), $b = 0.014$, [0.012, 0.015], $t(18508) = 18.10$, $p < .001$; average causal mediation effect (*ab* path) = 0.0072 [0.0030, 0.01], $p < .001$; total effect (*c* path) = 0.39 [0.36, 0.42], $p < .001$; direct effect (*c'* path) = 0.38 [0.35, 0.41], $p < .001$.

We also find evidence for moderated mediation of political orientation on explicit attitudes through IMS: test of moderation in the indirect effect (*ab* path) = 0.032 [0.015, 0.047], $p = .002$; test of moderation in the direct effect (*c'* path) = -0.040 [-0.083, 0.0020], $p = 0.062$. Unlike with EMS however, we find no evidence for moderation in the *a* path: interaction $b =$ 0.24 [-0.11, 0.59], $t(38100) = 1.37$, $p = .17$; but rather we find evidence for moderation in the *b* path: interaction $b = 0.0056$ [0.0033, 0.0078], $t(38098) = 4.85$, $p < .001$, whereby IMS predicted explicit attitudes more weakly after the election of Donald Trump: pre-election, $b = -0.026$ [-0.028, -0.025], $t(19535) = -33.35$, $p < .001$; post-election, $b = -0.020$ [-0.022, -0.019], $t(18563) = -23.84$, $p < .001$. See Online Supplement for more details.

This change in IMS may have counteracted changes in EMS, as the relationship between political orientation and explicit attitudes, controlling for changes in demographics and seasonality, did not significantly differ before and after the election of Donald Trump,: $b = 0.007$ [-0.033, 0.048], $t(38246) = 0.367$, $p = .71$, with conservatives just as pro-White, relative to liberals, pre-election $b = 0.38$ [0.35, 0.41], $t(19599) = 27.47$, $p < .001$; and post-election $b = 0.39$ [0.36, 0.42], $t(18647) = 25.85$, $p < .001$.

Discussion

In a set of preregistered analyses, using data from a large, demographically-diverse sample, we observe that the election of Donald Trump was associated with a decrease in the external motivation to avoid responding with prejudice among self-identified conservatives. Worries about appearing prejudiced mediated the relationship between political orientation and explicit pro-White attitudes, and we found that whether a participant participated in our study before or after the election of Donald Trump moderated this mediation. Specifically, conservatives were less concerned with appearing prejudiced after the election, but one's external motivation to avoid responding with prejudice was just as predictive of one's actual explicitly-reported racial attitudes both before and after Trump's election.

We found that this pattern was not attributable to changes in overall motivation to avoid responding with prejudice; rather it was unique to external motivation, as matched analyses of changes in internal motivation only showed a main-effect decrease from before to after the election of Donald Trump, with no moderation by political orientation. Similarly, while we found evidence for moderation by time-period of the relationship between political orientation and explicit attitudes mediated by internal motivation to avoid responding with prejudice, here we found that it was the relationship between internal motivation and explicit attitudes that weakened from before to after the election of Donald Trump, not the relationship between politics and one's self-reported motivation to live up to one's internal values of being non-prejudiced.

Our work corroborates a growing body of evidence that suggests that Donald Trump's racist rhetoric has indeed loosened the social norms around suppressing prejudice (Crandall et al., 2018) and emboldened some Americans to express their underlying racist views (Bursztyn et al., 2020; Newman et al., 2021). Notably, our work extends this literature beyond prior findings that people's perceptions about *other people's* prejudice expressions changed after the election of Trump; we show here that people's *own* motivations to control prejudice also changed. Specifically, we find evidence that this change is unique to conservatives, not liberals, and that this change is primarily in decreased worries about *appearing* prejudiced, not in internal motivations to actually avoid responding with prejudice.

The overall effects we identified were relatively small. Due to our sample, this is likely an underestimate of the relationship between the election of Donald Trump and the motivation to control prejudice. Volunteers who participate in studies on Project Implicit are, by definition, those who are interested in interrogating their own biases. Therefore, there are selection effects that suggest caution in uncritically extending these findings to individuals who may not be as interested in understanding and potentially controlling their own racial biases (e.g., Nosek et al., 2007). Our findings are also limited by the cross-sectional nature of the data collection -

participants generally visited Project Implicit only once, and so we are therefore limited in extrapolating to change over time within individuals.

Even taking estimates at face value, however, this may be a prime case for when small effects may compound to create meaningful real-world outcomes (e.g., Abelson, 1985; Funder & Ozer, 2019; Greenwald et al., 2015). If biases are widely shared, then even a small increase, multiplied by, say the entire population of a country, may lead to large effects. Similarly, if the outcomes of those biases are disparately focused on a subset of the population, then the effects of these small increases can rapidly accumulate. Greenwald et al. (2015) show, for example, that even if the correlation between a NYC police officer's IAT score and their likelihood of racial profiling is very small ($r = .148$), if the entire department moved from 1 SD above the mean on implicit bias to 1 SD below the mean, it would predict almost 10,000 fewer racially-motivated stops. And, similarly, if bias only reduces the likelihood of a group getting a positive outcome from 99% to 98%, just 25 repetitions of the process will lead to a 17.4% cumulative disadvantage.

Even if small changes in external motivation only slightly increases the likelihood of responding with prejudice, over time, given the number of potentially questionable utterances, that slight increase will cumulatively lead to an increase in prejudiced responses. If only one or two more prejudiced responses are uttered per person over the course, say, of a year, it only takes one such prejudiced remark to cause harm, and when that small increase in likelihood is shared across an entire political party, the odds of an increase in prejudiced speech (and potentially prejudiced action) is high.

There may, in fact, be evidence that this unshackling is causing real-world damage. There is ample evidence that racial discrimination leads to worsened mental and physical health outcomes for racial minorities (e.g., Pascoe & Richman, 2009; Schmitt et al., 2014). Self-reported perceptions and experiences of racism is linked to negative health outcomes and poor health-related choices (Paradies, 2006), and the explicit bias of White community members is related to worsened health outcomes for Black members residing in the same county (Leitner et al., 2016).

It is especially worrying, therefore, that counties that hosted Trump rallies during the 2016 election saw a greater than 200% increase in hate-crimes across the rest of the year (Feinberg et al., 2019), with a similar analysis finding that hate crimes meaningfully increased in 2017 relative to previous years, an increase that was most concentrated in counties that voted for Trump (Edwards & Rushin, 2019; though see Siegel et al., 2019, who find no increase in racist speech on Twitter after Trump's election). If acts and expressions of prejudice are increasing, especially in places where the attitudes of Donald Trump may carry special weight, then the well-being of a significant proportion of Americans may be under threat.

Future work, then, should more directly investigate the links between changing views of the restraining power of "political correctness" and the well-being of minority members of those communities where fear of sanction by one's fellow community-members has eroded. The present data may not have been geographically distributed enough to get reliable estimates of changes in external motivation across US counties (median response per county = 4 people, with only 131 of the 2201 counties represented (5.9%) containing more than 100 participants across the full four years of data), which therefore may have left us without enough data to identify place-based changes over time. However, this question is a vital one, and more robust sampling, along with potentially using alternate operationalizations for the concern that one's community may be judging one's speech for racist content, will help researchers understand the true impact of the erosion of external motivations to avoid responding with prejudice in Donald Trump's America.

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Contributions

Contributed to conception and design: NB, HB

Contributed to acquisition of data: NB

Contributed to analysis and interpretation of data: NB, HB, JM

Drafted and/or revised the article: NB, HB

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Competing Interests

The authors declare that they have no competing interests.

Data Accessibility Statement

All data, scripts, codebooks, and model-objects can be found at

https://osf.io/wvenk/?view_only=bbec18e6f8c14d058d3800381e146f9d

Online Supplement for “Worries about Appearing Prejudiced Decreased among Conservatives after the 2016 Election of Donald Trump”

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Table S1.
Regression output for changes in External Motivation to Respond without Prejudice across the nomination of Donald Trump

	Dependent variable:			
	External Motivation to Respond Without Prejudice			
	[1]	[2]	[3]	[4]
Post-Nomination	-.153 [-.265, -.040]	-.036 [-.174, .103]	.022 [-.125, .170]	18.401 [-9.740, 46.541]
	p = .008**	p = .614	p = .767	p = .200
Birth Year		.145 [.139, .152]	.144 [.137, .150]	.150 [.139, .162]
		p < .001***	p < .001***	p < .001***
Male		-.618 [-.760, -.476]	-.620 [-.762, -.478]	-.570 [-.802, -.337]
		p < .001***	p < .001***	p < .001***
Other Gender		-.376 [-.760, .007]	-.353 [-.738, .032]	.101 [-.508, .710]
		p = .055	p = .073	p = .745
Black		-3.053 [-3.284, -2.822]	-3.056 [-3.287, -2.826]	-3.184 [-3.564, -2.804]
		p < .001***	p < .001***	p < .001***

Asian	.025 [-.233, .282] p = .852	.033 [-.224, .291] p = .799	.127 [-.284, .539] p = .545
Other Race	-1.755 [-1.983, -1.528] p < .001***	-1.753 [-1.980, -1.525] p < .001***	-1.803 [-2.168, -1.438] p < .001***
Hispanic	-.801 [-1.031, -.572] p < .001***	-.803 [-1.032, -.574] p < .001***	-.575 [-.955, -.195] p = .004**
Education	.123 [.093, .154] p < .001***	.125 [.094, .156] p < .001***	.135 [.088, .182] p < .001***
Political Orientation	-.167 [-.211, -.122] p < .001***	-.164 [-.209, -.119] p < .001***	-.169 [-.243, -.095] p < .001***
Religiosity	.263 [.190, .336] p < .001***	.258 [.185, .330] p < .001***	.312 [.194, .431] p < .001***
Monday		.357 [.108, .607] p = .005**	.356 [-.061, .772] p = .095
Tuesday		.291 [.044, .538] p = .021*	.338 [-.076, .753] p = .110

Wednesday	.290 [.044, .536] p = .022*	.302 [-.108, .711] p = .149
Thursday	.217 [-.034, .467] p = .090	.168 [-.247, .583] p = .428
Saturday	-.010 [-.322, .302] p = .950	.024 [-.465, .514] p = .923
Sunday	.116 [-.169, .401] p = .424	.094 [-.354, .542] p = .682
January	-.374 [-.709, -.039] p = .029*	-.160 [-.668, .348] p = .537
February	-.366 [-.688, -.045] p = .026*	-.340 [-.745, .065] p = .101
March	-.189 [-.514, .136] p = .255	-.209 [-.607, .189] p = .304
May	-.457 [-.818, -.096] p = .014*	-.257 [-.867, .353] p = .409

June	-.299 [-.700, .102] p = .145	-.015 [-.697, .667] p = .966
July	-.811 [-1.163, -.458] p < .001***	-.709 [-1.410, -.009] p = .048*
August	-.268 [-.613, .077] p = .129	-.199 [-.796, .399] p = .515
September	-.367 [-.650, -.084] p = .012*	-.795 [-1.192, -.397] p < .001***
October	-.252 [-.557, .054] p = .107	-.518 [-.969, -.066] p = .025*
November	-.222 [-.524, .081] p = .151	-.476 [-.958, .007] p = .054
December	-.304 [-.656, .048] p = .091	.055 [-.531, .641] p = .855
Birth Year*Post-Nomination		-.009 [-.023, .005]

	p = .201
Male*Post-Nomination	-.083 [-.377, .211] p = .581
Other Gender*Post-Nomination	-.842 [-1.630, -.053] p = .037*
Black*Post-Nomination	.209 [-.270, .687] p = .393
Asian*Post-Nomination	-.132 [-.660, .396] p = .624
Other Race*Post-Nomination	.095 [-.372, .563] p = .690
Hispanic*Post-Nomination	-.357 [-.833, .120] p = .143
Education*Post-Nomination	-.020 [-.082, .042] p = .522

Political Orientation*Post-Nomination	.012 [-.081, .104]
	p = .807
Religiosity*Post-Nomination	-.098 [-.249, .052]
	p = .202
Monday*Post-Nomination	.004 [-.516, .524]
	p = .988
Tuesday*Post-Nomination	-.091 [-.607, .426]
	p = .731
Wednesday*Post-Nomination	-.004 [-.517, .508]
	p = .987
Thursday*Post-Nomination	.097 [-.424, .617]
	p = .717
Saturday*Post-Nomination	-.045 [-.682, .591]
	p = .889
Sunday*Post-Nomination	.049 [-.533, .632]

	p = .868
January*Post-Nomination	-.218 [-.922, .486] p = .544
February*Post-Nomination	-.041 [-.710, .628] p = .905
March*Post-Nomination	.075 [-.615, .766] p = .831
May*Post-Nomination	-.121 [-.912, .670] p = .765
June*Post-Nomination	-.251 [-1.125, .623] p = .574
July*Post-Nomination	.014 [-.837, .864] p = .975
August*Post-Nomination	.047 [-.721, .816] p = .904

September*Post-Nomination				.789 [.197, 1.381]
				p = .010**
October*Post-Nomination				.508 [-.134, 1.150]
				p = .122
November*Post-Nomination				.457 [-.199, 1.114]
				p = .172
December*Post-Nomination				-.378 [-1.144, .389]
				p = .335
Constant	24.605 [24.516, 24.694]	-263.646 [-276.912, -250.380]	-260.714 [-274.069, -247.359]	-273.760 [-296.453, -251.066]
	p < .001***	p < .001***	p < .001***	p < .001***
Observations	89,363	56,019	56,019	56,019
Adjusted R^2	.0001	.056	.056	.057

*p<.05; **p<.01; ***p<.001

Table S2.
Regression output for changes in Internal Motivation to Respond without Prejudice across the nomination of Donald Trump

	Dependent variable:			
	Internal Motivation to Respond Without Prejudice			
	[1]	[2]	[3]	[4]
Post-Nomination	.190 [.088, .293]	.125 [.006, .244]	.144 [.017, .271]	-40.620 [-64.810, -16.430]
	$p < .001^{***}$	$p = .040^{*}$	$p = .026^{*}$	$p = .001^{***}$
Birth Year		-.010 [-.016, -.005]	-.010 [-.015, -.004]	-.022 [-.031, -.012]
		$p < .001^{***}$	$p = .002^{**}$	$p < .001^{***}$
Male		-2.326 [-2.448, -2.204]	-2.323 [-2.446, -2.201]	-2.340 [-2.540, -2.140]
		$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Other Gender		-.770 [-1.099, -.440]	-.806 [-1.136, -.475]	-.815 [-1.339, -.292]
		$p < .001^{***}$	$p < .001^{***}$	$p = .003^{**}$
Black		-1.028 [-1.227, -.830]	-1.031 [-1.229, -.833]	-.939 [-1.266, -.612]
		$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$

Asian	-1.260 [-1.482, -1.038] p < .001***	-1.268 [-1.490, -1.046] p < .001***	-1.257 [-1.611, -.902] p < .001***
Other Race	-.336 [-.532, -.140] p = .001***	-.336 [-.532, -.140] p = .001***	-.348 [-.662, -.034] p = .030*
Hispanic	-.527 [-.725, -.330] p < .001***	-.529 [-.726, -.332] p < .001***	-.205 [-.531, .122] p = .220
Education	.120 [.094, .146] p < .001***	.118 [.092, .144] p < .001***	.044 [.004, .085] p = .033*
Political Orientation	1.422 [1.383, 1.460] p < .001***	1.420 [1.382, 1.458] p < .001***	1.469 [1.406, 1.533] p < .001***
Religiosity	.739 [.676, .802] p < .001***	.740 [.677, .803] p < .001***	.772 [.669, .874] p < .001***
Monday		-.162 [-.376, .052] p = .139	-.274 [-.633, .084] p = .134
Tuesday		-.098 [-.311, .114]	-.167 [-.523, .190]

	p = .365	p = .360
Wednesday	-.071 [-.283, .140]	-.074 [-.427, .278]
	p = .510	p = .680
Thursday	.008 [-.207, .224]	-.057 [-.414, .301]
	p = .940	p = .757
Saturday	.185 [-.083, .454]	.280 [-.142, .701]
	p = .176	p = .194
Sunday	.009 [-.236, .254]	-.015 [-.400, .371]
	p = .944	p = .941
January	-.123 [-.411, .164]	-.105 [-.541, .332]
	p = .401	p = .638
February	-.346 [-.623, -.069]	-.419 [-.767, -.070]
	$p = .015^{*}$	$p = .019^{*}$
March	-.223 [-.502, .057]	-.311 [-.653, .031]
	p = .119	p = .075

May	-.399 [-.710, -.089] p = .012*	-.354 [-.879, .172] p = .188
June	.056 [-.290, .401] p = .753	-.236 [-.823, .351] p = .431
July	.056 [-.248, .359] p = .719	-.416 [-1.018, .187] p = .177
August	-.195 [-.492, .102] p = .199	-.720 [-1.233, -.206] p = .007**
September	-.215 [-.458, .029] p = .084	-.515 [-.857, -.173] p = .004**
October	-.229 [-.492, .034] p = .089	-.051 [-.440, .338] p = .799
November	-.298 [-.558, -.038] p = .025*	-.025 [-.440, .390] p = .907
December	-.483 [-.787, -.180]	-.174 [-.679, .330]

	$p = .002^{**}$	$p = .498$
Birth Year*Post-Nomination		.020 [.008, .032]
		$p = .001^{***}$
Male*Post-Nomination		.029 [-.224, .281]
		$p = .825$
Other Gender*Post-Nomination		-.032 [-.709, .645]
		$p = .927$
Black*Post-Nomination		-.135 [-.546, .276]
		$p = .520$
Asian*Post-Nomination		.002 [-.453, .457]
		$p = .995$
Other Race*Post-Nomination		.020 [-.382, .422]
		$p = .924$
Hispanic*Post-Nomination		-.509 [-.919, -.100]
		$p = .015^{*}$

Education*Post-Nomination	.129 [.075, .182] $p = .00001^{***}$
Political Orientation*Post-Nomination	-.079 [-.158, .001] p = .054
Religiosity*Post-Nomination	-.056 [-.185, .074] p = .401
Monday*Post-Nomination	.188 [-.260, .635] p = .411
Tuesday*Post-Nomination	.122 [-.322, .566] p = .590
Wednesday*Post-Nomination	.017 [-.424, .458] p = .940
Thursday*Post-Nomination	.113 [-.335, .561] p = .622

Saturday*Post-Nomination	-.184 [-.731, .364] p = .512
Sunday*Post-Nomination	.034 [-.467, .535] p = .893
January*Post-Nomination	.083 [-.522, .688] p = .788
February*Post-Nomination	.251 [-.324, .827] p = .392
March*Post-Nomination	.283 [-.310, .877] p = .350
May*Post-Nomination	.061 [-.620, .742] p = .862
June*Post-Nomination	.535 [-.217, 1.288] p = .164
July*Post-Nomination	.689 [-.043, 1.420]

				p = .065
August*Post-Nomination				.801 [.140, 1.462]
				p = .018*
September*Post-Nomination				.560 [.051, 1.069]
				p = .032*
October*Post-Nomination				-.156 [-.709, .397]
				p = .582
November*Post-Nomination				-.238 [-.802, .327]
				p = .410
December*Post-Nomination				-.306 [-.966, .353]
				p = .363
Constant	34.862 [34.781, 34.943]	47.889 [36.479, 59.300]	46.472 [34.984, 57.960]	70.900 [51.401, 90.399]
	p < .001***	p < .001***	p < .001***	p < .001***
Observations	89,628	56,177	56,177	56,177

Adjusted R^2	.0001	.134	.134	.135

Note: $^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$

Table S3.
Regression output for changes in Internal Motivation to Respond without Prejudice across the election of Donald Trump

	Dependent variable:			
	Internal Motivation to Respond Without Prejudice			
	[1]	[2]	[3]	[4]
Post-Election	-.087 [-.186, .013]	-.027 [-.143, .088]	.015 [-.107, .137]	-55.265 [-78.414, -32.115]
	p = .087	p = .643	p = .807	$p < .001^{***}$
Birth Year		-.010 [-.016, -.004]	-.009 [-.015, -.004]	-.022 [-.030, -.014]
		$p = .0005^{***}$	$p = .002^{**}$	$p < .00100^{***}$
Male		-2.326 [-2.448, -2.203]	-2.322 [-2.445, -2.200]	-2.268 [-2.442, -2.094]
		$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Other Gender		-.781 [-1.112, -.450]	-.802 [-1.134, -.470]	-.794 [-1.175, -.412]
		$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Black		-1.028 [-1.226, -.829]	-1.031 [-1.229, -.832]	-.919 [-1.205, -.632]

	$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Asian	-1.263 [-1.485, -1.042]	-1.270 [-1.492, -1.048]	-1.199 [-1.512, -.886]
	$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Other Race	-.342 [-.538, -.146]	-.341 [-.537, -.144]	-.323 [-.599, -.048]
	$p = .001^{***}$	$p = .001^{***}$	$p = .022^{*}$
Hispanic	-.521 [-.719, -.324]	-.524 [-.722, -.327]	-.281 [-.566, .004]
	$p < .001^{***}$	$p < .001^{***}$	$p = .054$
Education	.122 [.096, .148]	.119 [.093, .146]	.059 [.025, .094]
	$p < .001^{***}$	$p < .001^{***}$	$p = .001^{***}$
Political Orientation	1.422 [1.383, 1.460]	1.420 [1.382, 1.458]	1.446 [1.392, 1.501]
	$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Religiosity	.740 [.677, .803]	.742 [.679, .804]	.779 [.690, .867]
	$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Monday		-.161 [-.375, .054]	-.285 [-.594, .023]
		$p = .142$	$p = .070$

Tuesday	-.096 [-.308, .116]	-.141 [-.448, .165]
	p = .376	p = .366
Wednesday	-.071 [-.283, .141]	-.093 [-.395, .209]
	p = .512	p = .546
Thursday	.009 [-.207, .224]	-.079 [-.385, .228]
	p = .938	p = .616
Saturday	.177 [-.092, .445]	.257 [-.106, .620]
	p = .198	p = .166
Sunday	-.001 [-.247, .244]	-.046 [-.382, .290]
	p = .992	p = .789
January	-.080 [-.368, .207]	-.107 [-.543, .330]
	p = .585	p = .633
February	-.338 [-.614, -.061]	-.426 [-.775, -.078]
	p = .017*	p = .017*
March	-.223 [-.502, .057]	-.315 [-.657, .027]

	p = .119	p = .071
May	-.342 [-.648, -.036]	-.364 [-.751, .022]
	p = .029*	p = .065
June	.111 [-.231, .454]	.375 [-.040, .791]
	p = .525	p = .077
July	.127 [-.170, .424]	.150 [-.226, .527]
	p = .401	p = .435
August	-.136 [-.429, .156]	-.178 [-.570, .215]
	p = .362	p = .375
September	-.171 [-.411, .069]	-.340 [-.641, -.040]
	p = .164	p = .027*
October	-.184 [-.447, .078]	-.046 [-.435, .342]
	p = .169	p = .815
November	-.243 [-.502, .016]	-.130 [-.533, .274]
	p = .066	p = .528
December	-.432 [-.734, -.129]	-.173 [-.676, .331]

	$p = .006^{**}$	$p = .503$
Birth Year*Post-Election		.028 [.016, .039] $p < .001^{***}$
Male*Post-Election		-.102 [-.347, .143] $p = .414$
Other Gender*Post-Election		.152 [-.633, .937] $p = .705$
Black*Post-Election		-.197 [-.594, .201] $p = .333$
Asian*Post-Election		-.123 [-.568, .321] $p = .586$
Other Race*Post-Election		-.025 [-.418, .367] $p = .899$
Hispanic*Post-Election		-.461 [-.856, -.066] $p = .023^{*}$

Education*Post-Election	.148 [.095, .202] $p < .001^{***}$
Political Orientation*Post-Election	-.059 [-.136, .018] $p = .134$
Religiosity*Post-Election	-.080 [-.206, .045] $p = .211$
Monday*Post-Election	.251 [-.178, .681] $p = .252$
Tuesday*Post-Election	.096 [-.329, .522] $p = .658$
Wednesday*Post-Election	.061 [-.363, .485] $p = .778$
Thursday*Post-Election	.174 [-.258, .605] $p = .431$

Saturday*Post-Election	-.205 [-.747, .337] p = .458
Sunday*Post-Election	.087 [-.407, .580] p = .731
January*Post-Election	.091 [-.514, .696] p = .769
February*Post-Election	.259 [-.317, .834] p = .379
March*Post-Election	.291 [-.302, .885] p = .337
May*Post-Election	.074 [-.562, .709] p = .821
June*Post-Election	-.812 [-1.545, -.079] p = .030*
July*Post-Election	-.043 [-.658, .572] p = .893

August*Post-Election				.133 [-.467, .733]
				p = .665
September*Post-Election				.463 [-.040, .966]
				p = .072
October*Post-Election				-.159 [-.712, .393]
				p = .572
November*Post-Election				-.101 [-.658, .456]
				p = .724
December*Post-Election				-.301 [-.961, .358]
				p = .371
Constant	35.026 [34.955, 35.097]	47.525 [36.100, 58.950]	46.118 [34.625, 57.611]	71.024 [54.862, 87.185]
	$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$	$p < .001^{***}$
Observations	89,628	56,177	56,177	56,177
Adjusted R^2	.00002	.134	.134	.135

Note: $^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$

Table S4.
Regression output for place-based analyses across the nomination of Donald Trump

	Dependent variable:	
	EMS	IMS
	[1]	[2]
Post-Nomination	23.895 [-8.676, 56.466]	-45.914 [-73.906, -17.922]
	$p = .151$	$p = .002^{**}$
Birth Year	.157 [.143, .170]	-.023 [-.034, -.011]
	$p < .001^{***}$	$p = .0001^{***}$
Male	-.674 [-.955, -.393]	-2.060 [-2.301, -1.818]
	$p < .001^{***}$	$p < .001^{***}$
Other Gender	.058 [-.703, .819]	-.508 [-1.164, .147]
	$p = .882$	$p = .129$
Black	-3.459 [-3.899, -3.020]	-.982 [-1.360, -.604]
	$p < .001^{***}$	$p < .001^{***}$

Asian	.110 [-.454, .674] p = .703	-1.458 [-1.944, -.973] p < .001***
Other Race	-2.240 [-2.696, -1.783] p < .001***	-.283 [-.675, .109] p = .158
Hispanic	-.465 [-.924, -.005] p = .048*	-.257 [-.652, .137] p = .202
Education	.159 [.100, .217] p < .001***	.087 [.037, .137] p = .001***
Political Orientation	-.142 [-.361, .077] p = .205	1.399 [1.210, 1.587] p < .001***
% of County Voting for Trump	-1.857 [-4.313, .598] p = .139	-.503 [-2.610, 1.604] p = .640
Religiosity	.270 [.126, .414] p < .001***	.839 [.715, .962] p < .001***
Monday	.386 [-.117, .889] p = .133	-.258 [-.690, .174] p = .243

Tuesday	.244 [-.257, .744] p = .340	-.171 [-.601, .260] p = .438
Wednesday	.150 [-.348, .649] p = .555	-.135 [-.564, .295] p = .540
Thursday	.221 [-.283, .725] p = .390	.155 [-.279, .588] p = .485
Saturday	.098 [-.520, .716] p = .756	.428 [-.104, .959] p = .115
Sunday	.193 [-.357, .743] p = .492	.176 [-.297, .648] p = .467
January	-.330 [-.938, .277] p = .287	-.007 [-.529, .515] p = .980
February	-.537 [-1.008, -.065] p = .026*	-.408 [-.813, -.002] p = .049*
March	-.323 [-.791, .144] p = .176	-.265 [-.667, .137] p = .196
May	-.625 [-1.340, .091] p = .088	-.378 [-.995, .238] p = .229

June	-.100 [-.893, .692]	-.425 [-1.106, .257]
	p = .805	p = .223
July	-.818 [-1.637, .001]	-.335 [-1.039, .368]
	p = .051	p = .351
August	-.702 [-1.387, -.017]	-.800 [-1.389, -.211]
	p = .045*	p = .008**
September	-.612 [-1.121, -.102]	-.415 [-.853, .023]
	p = .019*	p = .064
October	-.472 [-1.029, .086]	.087 [-.393, .567]
	p = .098	p = .723
November	-.731 [-1.311, -.151]	-.100 [-.598, .398]
	p = .014*	p = .695
December	.492 [-.241, 1.225]	-.148 [-.778, .482]
	p = .189	p = .646
Birth Year*Post-Nomination	.139 [-.132, .409]	.100 [-.132, .333]
	p = .315	p = .398

Male*Post-Nomination	1.878 [-1.151, 4.907]	2.592 [-.013, 5.196]
	p = .225	p = .052
Other Gender*Post-Nomination	-.057 [-.235, .121]	-.116 [-.270, .037]
	p = .532	p = .139
Black*Post-Nomination	-.064 [-.548, .420]	-.023 [-.439, .392]
	p = .795	p = .913
Asian*Post-Nomination	-.392 [-.987, .204]	-.310 [-.822, .201]
	p = .198	p = .235
Other Race*Post-Nomination	-.012 [-.029, .004]	.023 [.009, .036]
	p = .134	p = .002**
Hispanic*Post-Nomination	.014 [-.335, .362]	-.042 [-.342, .258]
	p = .938	p = .784
Education*Post-Nomination	-.859 [-1.835, .118]	-.005 [-.845, .834]
	p = .085	p = .990
Political Orientation*Post-Nomination	.206 [-.340, .752]	-.151 [-.621, .318]
	p = .460	p = .527
% of County Voting for Trump*Post-Nomination	-.120 [-.817, .576]	.370 [-.229, .970]
	p = .735	p = .227

Religiosity*Post-Nomination	.462 [-.106, 1.030]	.082 [-.406, .570]
	p = .111	p = .743
Monday*Post-Nomination	-.555 [-1.119, .009]	-.582 [-1.067, -.097]
	p = .054	p = .019*
Tuesday*Post-Nomination	-.028 [-.103, .047]	.100 [.035, .164]
	p = .457	p = .003**
Wednesday*Post-Nomination	-.095 [-.710, .520]	.138 [-.390, .667]
	p = .762	p = .608
Thursday*Post-Nomination	-.038 [-.816, .741]	-.202 [-.871, .468]
	p = .925	p = .555
Saturday*Post-Nomination	.168 [-.528, .865]	-.011 [-.609, .588]
	p = .636	p = .973
Sunday*Post-Nomination	-.068 [-.686, .550]	-.032 [-.564, .499]
	p = .829	p = .906
January*Post-Nomination	.010 [-.600, .621]	.107 [-.418, .632]
	p = .975	p = .690
February*Post-Nomination	.177 [-.433, .787]	.081 [-.444, .605]

	p = .570	p = .764
March*Post-Nomination	.455 [-.418, 1.327]	.770 [.020, 1.521]
	p = .307	p = .045*
May*Post-Nomination	-.820 [-1.742, .102]	-.429 [-1.222, .363]
	p = .082	p = .289
June*Post-Nomination	.188 [-.567, .943]	.148 [-.501, .797]
	p = .626	p = .655
July*Post-Nomination	-.075 [-.889, .739]	-.198 [-.897, .502]
	p = .857	p = .580
August*Post-Nomination	.218 [-.766, 1.201]	.395 [-.450, 1.240]
	p = .665	p = .360
September*Post-Nomination	-.275 [-1.287, .737]	.584 [-.287, 1.455]
	p = .595	p = .189
October*Post-Nomination	.160 [-.621, .941]	-.044 [-.715, .628]
	p = .688	p = .899
November*Post-Nomination	.470 [-.447, 1.386]	-.105 [-.893, .684]
	p = .316	p = .795

December*Post-Nomination	.687 [-.075, 1.450]	-.375 [-1.031, .280]
	p = .078	p = .262
Political Orientation*% of County Voting for Trump	.437 [-.317, 1.192]	-.390 [-1.039, .259]
	p = .256	p = .239
Political Orientation*% of County Voting for Trump*Post-Nomination	.462 [-.244, 1.167]	.240 [-.367, .846]
	p = .200	p = .439
Constant	-285.488 [-312.089, -258.888]	72.996 [50.149, 95.844]
	p < .001***	p < .001***
Observations	40,763	40,876
Log Likelihood	-142,653.300	-136,933.000
Akaike Inf. Crit.	285,430.500	273,990.000
Bayesian Inf. Crit.	285,964.700	274,524.300

Note: EMS = External Motivation to Respond Without Prejudice; IMS = Internal Motivation to Respond Without Prejudice

*p<.05; **p<.01; ***p<.001

Table S5.
Regression output for place-based analyses across the election of Donald Trump

	Dependent variable:	
	EMS	IMS
	[1]	[2]
Post-Election	4.144 [-26.696, 34.983]	-59.969 [-86.485, -33.453]
	$p = .793$	$p < .001^{***}$
Birth Year	.150 [.139, .161]	-.022 [-.032, -.013]
	$p < .001^{***}$	$p < .001^{***}$
Male	-.706 [-.949, -.462]	-2.023 [-2.233, -1.814]
	$p < .001^{***}$	$p < .001^{***}$
Other Gender	-.290 [-.844, .264]	-.535 [-1.012, -.059]
	$p = .306$	$p = .028^{*}$
Black	-3.542 [-3.926, -3.158]	-.928 [-1.259, -.598]
	$p < .001^{***}$	$p < .001^{***}$

Asian	.0001 [-.495, .496] p = 1.000	-1.256 [-1.682, -.830] p < .001***
Other Race	-2.023 [-2.421, -1.625] p < .001***	-.252 [-.594, .090] p = .149
Hispanic	-.734 [-1.134, -.334] p < .001***	-.366 [-.709, -.023] p = .037*
Education	.133 [.085, .182] p < .001***	.089 [.047, .132] p < .001***
Political Orientation	-.126 [-.314, .062] p = .190	1.419 [1.258, 1.580] p < .001***
% of County Voting for Trump	-1.330 [-3.448, .787] p = .219	-.142 [-1.960, 1.676] p = .879
Religiosity	.214 [.090, .338] p = .001***	.845 [.738, .951] p < .001***
Monday	.517 [.088, .946] p = .019*	-.243 [-.611, .126] p = .198

Tuesday	.301 [-.126, .729] p = .167	-.095 [-.462, .273] p = .614
Wednesday	.154 [-.271, .578] p = .479	-.143 [-.508, .222] p = .444
Thursday	.272 [-.157, .701] p = .214	.121 [-.248, .490] p = .521
Saturday	.273 [-.251, .798] p = .308	.379 [-.072, .830] p = .100
Sunday	.237 [-.239, .712] p = .330	.132 [-.277, .541] p = .527
January	-.324 [-.931, .283] p = .296	-.003 [-.525, .518] p = .991
February	-.533 [-1.004, -.061] p = .027*	-.414 [-.819, -.009] p = .046*
March	-.331 [-.798, .136] p = .165	-.265 [-.667, .137] p = .197
May	-.664 [-1.202, -.125] p = .016*	-.318 [-.781, .145] p = .179

June	-.472 [-1.054, .111] p = .113	.289 [-.213, .790] p = .259
July	-1.167 [-1.679, -.654] $p < .001^{***}$	.249 [-.192, .689] p = .270
August	-.386 [-.914, .142] p = .152	-.137 [-.591, .317] p = .554
September	-.609 [-1.034, -.185] $p = .005^{**}$	-.220 [-.585, .145] p = .238
October	-.478 [-1.035, .079] p = .093	.090 [-.389, .570] p = .713
November	-.596 [-1.158, -.034] $p = .038^{*}$	-.211 [-.694, .272] p = .392
December	.476 [-.257, 1.208] p = .204	-.150 [-.779, .480] p = .642
Birth Year*Post-Election	.141 [-.117, .399] p = .284	.073 [-.149, .295] p = .519
Male*Post-Election	1.362 [-1.530, 4.255] p = .357	2.446 [-.042, 4.934] p = .055

Other Gender*Post-Election	.037 [-.134, .207] p = .671	-.149 [-.296, -.003] $p = .046^{*}$
Black*Post-Election	-.209 [-.623, .205] p = .323	-.088 [-.444, .267] p = .626
Asian*Post-Election	-.213 [-.780, .353] p = .461	-.248 [-.735, .240] p = .319
Other Race*Post-Election	-.003 [-.018, .013] p = .725	.030 [.016, .043] $p < .001^{***}$
Hispanic*Post-Election	.085 [-.248, .418] p = .617	-.119 [-.405, .168] p = .417
Education*Post-Election	-.723 [-1.826, .381] p = .200	.480 [-.468, 1.428] p = .322
Political Orientation*Post-Election	.398 [-.125, .922] p = .136	-.276 [-.726, .174] p = .230
% of County Voting for Trump*Post-Election	.059 [-.607, .725] p = .862	.078 [-.495, .652] p = .790
Religiosity*Post-Election	.151 [-.394, .695] p = .588	.043 [-.425, .511] p = .857

Monday*Post-Election	-.177 [-.715, .360] p = .519	-.482 [-.945, -.020] p = .041*
Tuesday*Post-Election	.014 [-.060, .088] p = .704	.137 [.074, .201] p < .001***
Wednesday*Post-Election	-.361 [-.942, .220] p = .224	.152 [-.348, .652] p = .552
Thursday*Post-Election	-.433 [-1.185, .320] p = .260	-.142 [-.789, .505] p = .667
Saturday*Post-Election	.125 [-.549, .800] p = .716	.060 [-.520, .640] p = .839
Sunday*Post-Election	-.183 [-.769, .403] p = .541	.010 [-.494, .514] p = .969
January*Post-Election	-.095 [-.671, .481] p = .748	-.008 [-.504, .487] p = .974
February*Post-Election	.213 [-.363, .789] p = .470	.127 [-.369, .623] p = .616
March*Post-Election	-.143 [-.933, .647] p = .723	-.022 [-.701, .657] p = .950

May*Post-Election	-.796 [-1.717, .126] p = .091	-.421 [-1.213, .371] p = .298
June*Post-Election	.183 [-.572, .937] p = .636	.152 [-.497, .801] p = .647
July*Post-Election	-.081 [-.895, .733] p = .846	-.196 [-.895, .503] p = .583
August*Post-Election	.923 [.100, 1.746] p = .029*	-.419 [-1.127, .289] p = .247
September*Post-Election	.089 [-.886, 1.064] p = .858	-.641 [-1.480, .198] p = .135
October*Post-Election	.175 [-.606, .956] p = .661	-.045 [-.717, .626] p = .895
November*Post-Election	.584 [-.267, 1.434] p = .179	-.164 [-.896, .568] p = .661
December*Post-Election	.519 [-.231, 1.269] p = .176	-.230 [-.875, .415] p = .485
Political Orientation*% of County Voting for Trump	.448 [-.306, 1.202] p = .244	-.394 [-1.042, .255] p = .234

Political Orientation*% of County Voting for Trump*Post-Election	.502 [-.170, 1.174]	.103 [-.474, .681]
	p = .143	p = .726
Constant	-271.282 [-293.285, -249.279]	71.950 [53.039, 90.861]
	$p < .001^{***}$	$p < .001^{***}$
Observations	40,763	40,876
Log Likelihood	-142,652.600	-136,935.900
Akaike Inf. Crit.	285,429.200	273,995.700
Bayesian Inf. Crit.	285,963.400	274,530.000

Note: EMS = External Motivation to Respond Without Prejudice; IMS = Internal Motivation to Respond Without Prejudice

$^{*}p<.05$; $^{**}p<.01$; $^{***}p<.001$

Moderated mediation results for IMS

Prior to the election, political orientation predicted IMS (*a* path), $b = -4.87$ [-5.11, -4.62], $t(19530) = -39.26$, $p < .001$, and IMS predicted explicit attitudes (*b* path), $b = -0.026$ [-0.028, -0.025], $t(19535) = -33.35$, $p < .001$; average causal mediation effect (*ab* path) = 0.13 [0.11, 0.14], $p < .001$; total effect (*c* path) = 0.38 [0.35, 0.41], $p < .001$; direct effect (*c'* path) = 0.25 [0.23, 0.28], $p < .001$.

After the election, political orientation predicted IMS (*a* path), $b = -4.62$ [-4.87, -4.37], $t(18558) = -36.31$, $p < .001$, and IMS predicted explicit attitudes (*b* path), $b = -0.020$ [-0.022, -0.019], $t(18563) = -23.84$, $p < .001$; average causal mediation effect (*ab* path) = 0.095 [0.083, 0.11], $p < .001$; total effect (*c* path) = 0.39 [0.36, 0.42], $p < .001$; direct effect (*c'* path) = 0.29 [0.26, 0.32], $p < .001$.