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Contraction as a Response to Group Threat: Demographic Decline and Whites' Classification of People Who are Ambiguously White

Maria Abascal
Columbia University

A. Variable Coding

Individual-level variables. **Age** was recorded using 10 response categories ranging from "18 to 24 years" to "65 years and older." Before they were standardized, responses were midpoint coded, and the final category was assigned a value of 70. **Gender** was recorded using three response categories: "Male," "Female," and "Something else" (selected by just one respondent). Respondents who self-identify as female were assigned a value of 1; all other respondents were assigned a value of 0.

To construct a variable for **college attainment**, respondents who reported having completed a "4-year degree (Bachelor's)" or a "Graduate or professional degree" were assigned a value of 1 and respondents who reported having completed a "2-year degree (Associate's)" or less were assigned a value of 0. **Family income** was recorded using 12 response categories ranging from "Less than $10,000" to "More than $150,000." Before they were standardized, responses were midpoint-coded, and the final category was assigned a value of $200,000. In response to the income item, seven White respondents (1.33 percent) selected "Rather not say." These respondents are omitted from the multivariate analyses.

Party identification was solicited via a series of filter and contingency items modeled after those in the American National Election Surveys. The first item asks, "Do you consider yourself a Republican, an independent, a Democrat or something else?" Respondents then answer, "Would you consider yourself a strong [Republican/Democrat] or not a very strong [Republican/Democrat]" or "Do you think of yourself as closer to the Republican or Democratic Party?" (depending on responses to the first item). Consistent with the amended pre-analysis plan, respondents who identified as Republican were assigned to one category; this includes respondents who first identified as "Independent" or "Something else" before identifying as "closer to the Republican Party."

Supplementary analyses described here utilize three additional measures: perceived White share, voting for Trump, and strength of racial identification. **Perceived White share** is based on responses to the following item, adapted from the 2000 General Social Survey, "Your best guess—what percentage of people in the United States belong to each of the following groups? Whites." Possible responses comprised all integer values between 0 and 100.

Voting for Trump is a binary variable that takes a value of 1 for respondents who selected "Donald Trump" in response to "For whom did you vote for president in 2016?" The variable takes a value of 0 for respondents who selected "Hillary Clinton," "I voted for someone else," or "I did not vote for president in 2016."

Strength of **racial identification** is based on agreement with four items: (1) "Overall, being White has very little to do with how I think of myself," (2) "Being White is an important reflection of who I am," (3) "Being White is unimportant to my sense of what kind of person I am," and (4) "In general, being White is important to the way I think of myself as a person."

Responses to each item were recorded on a seven-point scale ranging from “Strongly disagree” to “Strongly agree.” The first and third items were reverse-coded. Together, the four measures exhibit high internal consistency: Cronbach’s alpha for the standardized measures is .90. One factor alone explains 77.52 percent of all variance. Accordingly, I used a maximum likelihood approach to extract a factor based on the four measures.

County-level variables. County-level variables were sourced from the ACS (2013 to 2017) and linked to respondents using their self-reported five-digit ZIP codes. In cases where a respondent’s ZIP code straddled multiple counties, the respondent was assigned to the county in which the largest share of their ZIP code area’s population resides. Respondents were allowed to leave this field blank, however, none did so. To minimize non-response, respondents were reminded, “Your responses are completely private. We are asking for statistical purposes only.” However, 11 respondents reported ZIP codes that could not be mapped directly to counties, for example, PO Box codes. These respondents were assigned to counties based on the latitude and longitude coordinates corresponding to their IP addresses.

Percent Latino reflects the share of all county residents who identify as “Hispanic/Latino” (of any race). **Percent college-educated** reflects the share of all county residents (25 years and older) with a four-year college degree or higher. **Percent same residence** reflects the share of residents living in the same residence for at least one year. **Median household income** is the fourth county-level variable included in the models.

B. Comparison with the CCES

To compare the MTurk sample to a nationally representative sample of White people in the United States, I rely on an additional source of data: the 2018 Cooperative Congressional Election Study (CCES). The CCES is a national stratified sample survey of U.S. adults. It is administered online by YouGov/Polimetrix, which uses a two-stage, sample matching method to select respondents. In the first stage, YouGov/Polimetrix constructs a stratified random sample of U.S. citizens from the American Community Survey (ACS); in the second stage, they match each ACS respondent to one or more cases from their pool of opt-in respondents.

The CCES has two features that make it ideal for the comparative analyses reported below. First, relevant items are worded similarly and rely on similar response categories. Second, the publicly available version of the CCES reports respondents' FIPS codes, allowing me to compare samples not just in terms of individual characteristics, but also in terms of county ones.

First, I identify differences between the MTurk sample and a representative sample of White people in the United States. Table S1 reports descriptive statistics for the experimental sample and the subset of CCES respondents who identify as White. The MTurk respondents are younger, more likely to be college-educated, and less likely to identify as Republicans. They also have lower family incomes. In addition, they live in more highly educated but slightly less stable areas.

Table S1: Comparison of MTurk Sample and 2018 CCES Sample (weighted): Self-identified Whites

	MTurk Sample		CCES Sample		
	Mean	SD	Mean	SD	*t*
Individual level					
Female	.534	.499	.512	.500	−1.206
Age	38.063	12.632	49.936	18.038	26.086***
College-educated	.494	.500	.329	.470	−9.251***
Family income	62550.125	43884.980	65565.151	49472.285	1.917
Republican	.377	.485	.490	.500	6.489**
County level					
% Latino	13.350	13.205	12.939	13.231	−.872
% College-educated	30.869	11.231	29.832	10.801	−2.585***
Median household income	59244.439	15875.156	58592.166	15264.511	−1.151
% Same residence	84.914	3.783	85.162	3.862	1.842
N	798		45011		

*$p < .05$; **$p < .01$; ***$p < .001$ (two-sided).

The partisanship difference is of special interest. The effect of experimental condition is more pronounced among Republicans and Republicans are underrepresented in the MTurk sample. This suggests the causal estimate in a representative sample would be larger than the one observed in the MTurk sample. To assess this, I reweight the experimental sample to resemble the CCES sample in terms of all nine covariates—both individual and community level. Specifically, I pool the datasets, estimate a logistic regression to predict the odds of being in the CCES as opposed to the MTurk sample, and assign a weight to each experimental observation equal to its rescaled, predicted odds. Finally, I re-estimate Models 1 through 4 (from Table 3) using these weights. In every case, the estimated effect of demographic threat is indeed larger in the reweighted sample. For example, in Model 1, which minimizes the AIC value, White individuals are 3.96 percentage points (versus 3.32 percentage points) less likely to classify a face as White in the demographic threat condition than in the control condition.

The following coding decisions address minor differences in the wording of items or response categories across surveys. The **age** of CCES respondents was calculated from their birth years and recoded to match the values available for the MTurk sample. For both MTurk and CCES respondents, **family income** was midpoint-coded for respondents who reported incomes less than $80,000. Respondents reporting incomes between $80,000 and $100,000 were assigned $90,000, respondents reporting incomes between $100,000 and $150,000 were assigned $125,000, and respondents reporting incomes greater than $150,000 were assigned $200,000. CCES respondents who answered "Not sure" in response to **party identification** were omitted from the analyses, because experiment respondents were not provided with a similar category.

Finally, the analyses are limited to CCES respondents who answered "White" in response to an item soliciting **racial/ethnic identification**. This item included a "Hispanic" response category. A follow-up question asked respondents if they were of "Spanish, Latino, or Hispanic origin or descent." Unlike CCES respondents, experiment respondents did not have a second opportunity to identify as Latinos. Therefore, all CCES respondents who answered "White" in response to the first item were included in the analyses, regardless of how they answered the follow-up.

B. Re-estimation with Logistic Regression

Table S2. Mixed-Effect Logistic Regression Models Predicting Classification as White

	Model 1	Model 2	Model 3	Model 4
Demographic threat	.821*	.822*	.822*	.826*
	(.080)	(.080)	(.079)	(.080)
Individual level				
Female			.830	.821*
			(.081)	(.080)
Age			1.015	1.014
			(.049)	(.049)
College-educated			1.148	1.203
			(.116)	(.124)
Family income			.936	.953
			(.048)	(.050)
Republican			1.251*	1.216
			(.126)	(.122)
County level				
% Latino				.917
				(.045)
% College-educated				.875
				(.077)
Median household income				1.067
				(.093)
% Same residence				1.025
				(.058)
Constant	.449***	.450***	.426***	.420***
	(.078)	(.078)	(.082)	(.080)
Image fixed effects	✓	✓	✓	✓
$\sigma(1)$	1.042	1.041	1.030	1.021
$\sigma(2)$		0.054	0.000	0.000
AIC	7203.471	7205.446	7204.840	7204.841
$N_{participants}$	798	798	798	798
N_{states}		48	48	48

$*p < .05$; $**p < .01$; $***p < .001$ (two-sided); coefficients reported as odds-ratios.

D. Analyses Related to Statistical Inference

Classification of Ambiguously Black–Latino Faces

If the observed effects are due to statistical inference, White respondents in the threat condition should be less likely to classify ambiguously Black–Latino faces as Black, just as they are less likely to classify ambiguously White–Latino faces as White. (The demographic change graph depicts the share of Latinos growing but the share of Blacks remaining stable.) This is not what I observe. Predicting classification as Black for the two ambiguously Black–Latino faces (equivalent to Model 1, Table 3) reveals that White respondents in the demographic threat condition are slightly *more*, not less, likely to classify these faces as Black ($\beta = .038$, $p = .088$).

Mediation by Perceived White Share

The statistical inference account implies that the effect of experimental condition is fully mediated by the perceived share of the U.S. population that is White. I estimate a series of regression models following Baron and Kenny (1986). The first predicts White classification by experimental condition (Model 1, Table 3). The second predicts the percentage of the U.S. population that is believed to be White by experimental condition; the results confirm that being in the demographic threat condition is a significant, negative predictor of perceived White share ($\beta = -4.405$, $p < .001$). The third predicts White classification by both experimental condition and perceived White share. Being in the demographic threat condition is still a negative predictor of White classification, although its magnitude is reduced by 15.09 percent ($\beta = -.028$, $p = .089$). A Sobel's test confirms the reduction is significant ($p < .05$). In summary, approximately 15.09 percent of the observed effect of experimental condition is explained by inferences about the relative size of the White population.

In all likelihood, the true proportion of the experimental effect that is mediated by population inferences is smaller, because standard regression-based mediation analyses "tend to overstate the extent to which a mediator transmits the causal influence of [treatment]" (Gerber and Green 2012:325). A more extended discussion of this issue can be found in Gerber and Green (2012:322–25). In a nutshell, the issue stems from the fact that there is often some overlap between the omitted variables that predict the mediator and those that predict the outcome. In this study, for example, the kinds of White people who think that Whites make up a smaller share of the U.S. population might also be the kinds of White people who classify fewer people as White. An estimate of the mediated effect is equal to its true value plus a bias term that is itself a positive function of the covariance between the omitted variables that predict the mediator and those that predict the outcome. In the scenario I described—and in most scenarios, according to Gerber and Green—this bias term is positive, because the covariance of the omitted variables is positive. As a result, an estimate of the mediated effect will tend to be greater than its true effect.

Moderation by White identification

Is the effect of experimental condition moderated by strength of racial identification? Respondents who identify more strongly as White should react more strongly to information about Whites' demographic decline. Model 4.ID1 in Table S3 reports the results of a linear regression predicting classification as White by experimental condition in interaction with strength of racial identification (a factor variable), as well as individual and county covariates and unmodeled heterogeneity across respondents and images. The effect of demographic threat is marginally stronger among respondents who identify more strongly as White, however, the interaction term is not significant (p = .726).

Table S3. Mixed-Effect Linear Probability Models Predicting Classification as White by Demographic Threat, White Racial Identification, and Republican Identification, Separately and in Interaction

	Model 4.ID1	Model 4.ID2
Demographic threat	−.032*	−.002
	(.016)	(.021)
Racial identification	.009	–.055
	(.027)	(.037)
Republican	.031	.114*
	(.018)	(.056)
Threat x Identification	−.006	.039
	(.017)	(.023)
Threat x Republican		−.055
		(.035)
Identification x Republican		.114*
		(.056)
Threat x Identification x Republican		−.084*
		(.035)
Constant	.298***	.286***
	(.023)	(.038)
Individual-level controls	✓	✓
County-level controls	✓	✓
Image fixed effects	✓	✓
σ(1)	.174	.173
σ(2)	.000	.000
AIC	7550.110	7546.538
N *participants*	798	798
N *states*	48	48

*p < .05; **p < .01; ***p < .001 (two-sided)

One possibility is that the meaning of the identification items differs across respondents, and that for some respondents, agreement is not a valid proxy of ingroup attachment. Consider the case of liberals: asserting that "being White is important to the way I think of myself" might signal a recognition of racial inequality, whereas asserting that "being White has very little to do with how

I think of myself" might signal adherence to a colorblind ideology. The survey did not solicit ideology, but it did solicit partisanship. A three-way interaction between racial identification, experimental condition, and partisanship confirms that racial identification moderates the effect of condition differently across respondents who identify as Republican versus those who do not ($p <$ .05; Model 4.ID2, Table S3). Specifically, among respondents who identify as Republican, agreement with the identification items exacerbates the effect of demographic threat, as initially hypothesized. However, among respondents who do not identify as Republican, agreement with these items mitigates the effect of demographic threat ($p = .092$). The results recommend a reexamination of the meaning of explicit identification with Whiteness in the present day.

Moderation by Partisanship and Trump Support

The following analyses are discussed in the main text. Model 4.R (Table S4) predicts classification as White by experimental condition in interaction with Republican identification, as well as individual and county covariates and unmodeled heterogeneity across respondents and images. Model 4.T (Table S4) predicts classification as White by experimental condition in interaction with voting for Trump in 2016.

Table S4. Mixed-Effect Linear Probability Models Predicting Classification as White by Demographic Threat, Republican Identification, Trump Voting

	Model 4.R	Model 4.T
Demographic threat	−.009	−.005
	(.021)	(.019)
Republican	.123*	
	(.053)	
Threat x Republican	−.061	
	(.033)	
Trump voter		.152**
		(.025)
Threat x Trump voter		−.091*
		(.035)
Constant	.296***	.295***
	(.037)	(.036)
Individual-level controls	✓	✓
County-level controls	✓	✓
Image fixed effects	✓	✓
$\sigma(1)$	.174	.174
$\sigma(2)$	.000	.000
AIC	7544.901	7544.353
$N_{participants}$	798	798
N_{states}	48	48

*$p < .05$; **$p < .01$; ***$p < .001$ (two-sided).

Replication with Non-Whites

The following results are based on a replication with a sample of approximately 200 non-White respondents. To secure a non-White sample, I restricted eligibility to MTurk workers who did not answer "White/Caucasian" in response to "What is your race?" (solicited by TurkPrime).[1] Because TurkPrime uses separate items to solicit racial identification and Latino identification, this restriction excludes Latino workers who identify racially as White (alone).

Two facts mitigate concerns about this exclusion. First, the effect of experimental condition is similar across Latinos and non-Latino non-Whites (Model 6, Table S5). These results are suggestive, although it is not possible with this sample to confirm that the effect is similar among Latinos who identify as White (alone). Second, the findings of previous research suggest the classification choices of Latino respondents are less, not more, sensitive to external cues (Garcia and Abascal 2016).

Table S5. Mixed-Effect Linear Probability Models Predicting Classification as White by Demographic Threat, Race/Ethnicity, Among Non-White Respondents

	Model 5	Model 6
Demographic threat	−.021	−.023
	(.032)	(.044)
Black (ref.)		
Latino	−.019	.051
	(.056)	(.077)
Asian	−.003	−.036
	(.036)	(.052)
Other	−.132	−.091
	(.078)	(.132)
Threat x Latino		−.147
		(.112)
Threat x Asian		.058
		(.072)
Threat x Other		−.061
		(.164)
Constant	.342***	.343***
	(.038)	(.040)
Image fixed effects	✓	✓
$\sigma(1)$	.174	.174
$\sigma(2)$	.000	.000
AIC	1840.706	1851.314
$N_{participants}$	195	195

*p < .05; **p < .01; ***p < .001 (two-sided)

[1] In this case, prospective respondents were not screened out for exceeding quotas for "Democrat," "Independent," or "Something else" responses.

Model 5 in Table S5 reports the results of a linear regression predicting classification as White by experimental condition, racial identification, and unmodeled heterogeneity across non-White respondents and images. Model 6 reports the results of a linear regression predicting classification as White by experimental condition and racial identification, in interaction.

The null results for demographic threat are not due to a lack of statistical power. To capture a simple bivariate difference comparable to the one observed in the non-White sample,[2] I would need substantially more than 800 respondents (the size of the White sample). Indeed, power calculations indicate that the sample size needed to capture the effect size observed in the non-White sample at β = 80 percent power is 8,180; at β = 95 percent, it is 14,318.

References

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Garcia, Denia, and Maria Abascal. 2016. "Colored Perceptions: Racially Distinctive Names and Assessments of Skin Color." *American Behavioral Scientist* 60(4):420–41.

Gerber, Alan S., and Donald P. Green. 2012. "Mediation." Pp. 319–46 in *Field Experiments: Design, Analysis, and Interpretation*. New York: W. W. Norton & Company.

[2] In fact, the difference for Whites satisfies a more stringent test that additionally accounts for clustering across images and respondents.

E. Experimental Instruments

Ambiguously White–Latino Targets

LF-201

LF-206

LF-210

WF-203

LM-212

LM-228

LF-231

WM-233

Ambiguously Black–Latino Targets

BF-207

BM-222