Do Name-based Treatments Violate Information Equivalence? Evidence from a Correspondence Audit Experiment

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Online Appendix A – Constituent Name Perceptions

On November 14th 2018, we conducted a survey with Amazon MTurk workers where we randomly presented them with six names out of a pool of several dozen and asked them what characteristics they associated with them. A total of 539[3] respondents were used, however only 446 rated at least one of the twelve aliases used in the present audit study. The unused names were rated to help select names for use in future audits. Each alias was rated approximately 65 times. We asked MTurk respondents what race and ethnicity, gender, nativity, and SES they perceived when presented with a name, see **Appendix A Figure 1** for wording. Results are presented below in **Appendix A Tables 1 – 4**.

Appendix A Figure 1 – Name Perception Prompt

Based on the message above, please answer the following questions about the individual named **[NAME]**.

- What is the likely gender of the individual? [Choices: Male/Female/Other]
- What is the likely race of the individual? [Choices: White/Black/Hispanic/Asian/Native American/Middle Eastern/Mixed/Other]
- What is the likely nativity status of the individual? [Choices: Natural born citizen/Naturalized citizen/Non-citizen migrant]
- What is the likely socio-economic class of the individual? [Choices: Working Class/Lower Middle Class/Middle Class/Upper Class]

Names were selected by using a mixture of common surnames reported by the US Census and common first names reported by the Social Security Administration. For Black names we

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[3] We filtered our survey so that only MTurk workers living in the United States were eligible. We did not otherwise exclude MTurk workers and our sample size reflects our monetary budget restrictions.

relied on distinct first names to signal race, and for Hispanics we selected based on distinct last names. Notably, we paired Hispanic surnames with English first names. We did this because our audit was primarily designed to test for ethnic/racial discrimination in helping constituents to vote and we were concerned that Spanish first names paired with Hispanic surnames would be more likely to signal a noncitizen migrant. Noncitizen migrants are ineligible to vote in contemporary federal elections. As we show below in **Appendix A Table 5**, Spanish first names paired with Hispanic surnames are more likely, compared to English first names paired with Hispanic surnames, to signal a migrant (p-value= 0.050) and a noncitizen (p-value= 0.001). Perceived whiteness and working-class status are indistinguishable across condition.

A limitation of the results reported herein is that we rely on the perceptions of MTurk respondents instead of state legislators. We attempt to elicit state legislators' perceptions but, as noted in the main manuscript, they were unwilling to answer explicitly racial questions. Ideally, we would wish to compare state legislators' perceptions with those of the general public. If no or few differences were found, this would justify our use of MTurk respondents. A 2nd best solution is to compare for differences in perceptions among our MTurk respondents, which we report in Appendix A Table 7. With the exception that Republican respondents are more likely to identify names as being of migrant status, we find little statistically significant evidence that name perceptions differ by respondents' demographic characteristics.

Appendix A Table 1 - Perceived Race and Ethnicity by Name

	White Names				Black Names				Hispanic Names			
	Nicholas Smith	Ethan Miller	John Ryan	Daniel Schmitz	Tyreke Brown	Jamal Gaines	DeMar Washington	Kobe Jefferson	Joe Garcia	Joe Martinez	Michael Gonzalez	John Chavez
White (%)	86.15	91.3	92.65	89.71	3.08	3.08	4.41	4.48	13.64	11.76	1.49	8.82
Black	6.15	1.45	1.47	2.94	84.62	84.62	92.65	82.09	0	0	0	0
Hispanic	0	0	0	0	0	1.54	1.47	0	80.3	80.88	82.09	80.88
Asian	1.54	1.45	1.47	0	0	1.54	0	1.49	0	0	1.49	0
Native American	1.54	0	1.47	0	1.54	0	0	1.49	0	0	2.99	1.47
Middle Eastern	1.54	0	0	1.47	6.15	4.62	1.47	1.49	0	1.47	1.49	1.47
Mixed	1.54	5.8	2.94	4.41	3.08	4.62	0	10.45	6.06	5.88	10.45	7.35
Other	1.54	0	0	1.47	1.54	0	0	0	0	0	0	0
N	65	69	68	68	65	65	68	67	66	68	67	68

Appendix A Table 2 - Perceived Gender by Name

	White Names				Black Names				Hispanic Names			
	Nicholas Smith	Ethan Miller	John Ryan	Daniel Schmitz	Tyreke Brown	Jamal Gaines	DeMar Washington	Kobe Jefferson	Joe Garcia	Joe Martinez	Michael Gonzalez	John Chavez
Male (%)	93.85	95.65	98.53	98.52	87.69	96.92	95.59	98.51	93.94	95.59	97.01	97.06
Female	1.54	1.45	0	1.47	10.77	3.08	4.41	1.49	6.06	1.47	1.49	0
Other	4.62	2.9	1.47	0	1.54	0	0	0	0	2.94	1.49	2.94
N	65	69	68	68	65	65	68	67	66	68	67	68

Appendix A Table 3 - Perceived Nativity by Name

	White Names				Black Names				Hispanic Names			
	Nicholas Smith	Ethan Miller	John Ryan	Daniel Schmitz	Tyreke Brown	Jamal Gaines	DeMar Washington	Kobe Jefferson	Joe Garcia	Joe Martinez	Michael Gonzalez	John Chavez
Natural-born citizen (%)	78.46	84.06	79.41	89.55	81.54	80	91.18	91.04	60	64.71	52.24	60.29
Naturalized citizen	20	11.59	17.65	7.46	16.92	15.38	5.88	8.96	30.77	27.94	34.33	38.24
Non-citizen migrant	1.54	4.35	2.94	2.99	1.54	4.62	2.94	0	9.23	7.35	13.43	1.47
N	65	69	68	68	65	65	68	67	66	68	67	68

Appendix A Table 4 - Perceived SES by Name

	White Names				Black Names				Hispanic Names			
	Nicholas Smith	Ethan Miller	John Ryan	Daniel Schmitz	Tyreke Brown	Jamal Gaines	DeMar Washington	Kobe Jefferson	Joe Garcia	Joe Martinez	Michael Gonzalez	John Chavez
Working class (%)	16.92	11.59	16.42	16.18	20	44.62	29.41	22.39	22.73	20.59	40.3	33.82
Lower middle class	4.62	5.8	10.45	10.29	27.69	13.85	20.59	17.91	25.76	13.24	19.4	13.24
Middle class	64.62	50.72	61.19	47.06	46.15	35.38	42.65	49.25	36.36	52.94	32.84	41.18
Upper class	13.85	31.88	11.94	26.47	6.15	6.15	7.35	10.45	15.15	13.24	7.46	11.76
N	65	69	68	68	65	65	68	67	66	68	67	68

In addition to the twelve aliases used, we tested two aliases which share the same surname (Garcia and Martinez respectively) as two of the used Hispanic aliases but used Spanish first name instead of an English first name (Jose [Spanish first name] vs Joe [English first name]). This allows us to estimate the "Jose" effect or, more generally, the effect of pairing an English first name versus a Spanish first name with a Hispanic surname. Like the main manuscript's **Table 1**, the outcome variables are binary variables indicating whether an MTurk respondent identified the name as White, Working-class, Migrant. We add a fourth outcome variable, noncitizen. The independent variable is a binary variable indicating whether the alias is paired with an English first name (=0, Joe) or a Spanish first name (=1, Jose). As shown in **Appendix A Table 6**, the "Jose" aliases are more likely to be perceived as belonging to a migrant (p-value= 0.052) and a noncitizen (p-value= 0.047).

Appendix A Table 5 – Names used to test the "Jose" effect

	Joe	Jose
Garcia	Joe Garcia	Jose Garcia
Martinez	Joe Martinez	Jose Martinez

Trivially this data also allows us to compare the Garcia (=0) surname with the Martinez surname (=1). Martinez is less likely to be perceived as a non-citizen compared to Garica.

Appendix A Table 6 – Name Perceptions of Hispanic Surnames Paired with English vs Spanish First names

VARIABLES	(1) Perceived White	(2) Perceived Working-Class	(3) Perceived Migrant	(4) Perceived Noncitizen
Jose First name	-0.022	0.088	0.119*	0.189***

	(0.022)	(0.059)	(0.061)	(0.046)
Martinez Surname	0.037*	-0.088	-0.090	-0.085**
	(0.022)	(0.057)	(0.057)	(0.042)
Constant	0.033**	0.415***	0.482***	0.117***
	(0.017)	(0.052)	(0.052)	(0.038)
Observations	268	268	268	268
R-squared	0.012	0.016	0.022	0.077

Standard errors in parentheses and are clustered by MTurk respondent.

*** p<0.01, ** p<0.05, * p<0.1

In **Appendix A Table 7** we compare the race, party ID and gender of state legislators with MTurk respondents. A team of undergraduate research assistants coded state legislator's characteristics based on legislative website, newspapers and other authoritative sources. As noted by the different sample sizes across characteristics, some attributes like party id were more readily available than other. MTurk respondents' demographics are self-reported. Both groups are predominantly white. MTurk respondents are less likely to be Republican and more likely to be female than state legislators. The average MTurk respondent was 37 years of age (mean: 37.456, SD: 11.829); we were unable to gather data on legislator's age. A 2015 report by the National Conference of State Legislatures finds that the average state legislator is 56 years old (Kurtz 2015)

Given these differences and given that our focus is on perceived race/ethnicity and SES, we should be concerned if we find differences in how those attributes are perceived by party ID or gender. In **Appendix A Table 8**, we fail to find evidence that either perceived whiteness or perceived working-class status are influence by MTurk respondents' demographics. We do find that Republican respondents are more likely to identify a given name as being migrant in origin (p-value= 0.019).

Appendix A Table 7 – State Legislators and MTurk Respondents' Demographics

	State Legislators	N	MTurk Respondents	n
White	87.03%	3,793	75.37%	475
Republican	56.57%	4,343	27.31%	476
Female	26.62%	3,801	47.15%	473

Appendix A Table 8 – Name Perceptions by MTurk Respondents' Demographics

	(1)	(2)	(3)	(4)
	Perceived White	Perceived Working-Class	Perceived Migrant	Perceived Female
VARIABLES				
White Respondent	-0.002	-0.052	0.026	-0.025
	(0.039)	(0.045)	(0.042)	(0.018)
Republican Respondent	-0.009	-0.009	0.097**	0.026
	(0.038)	(0.042)	(0.041)	(0.018)
Respondent Age	-0.001	0.002	-0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Female Respondent	-0.013	0.046	-0.057	0.022
	(0.034)	(0.038)	(0.035)	(0.014)
Constant	0.380***	0.199***	0.246***	0.028
	(0.057)	(0.071)	(0.058)	(0.025)
Observations	787	787	787	776
R-squared	0.001	0.008	0.014	0.011

Standard errors in parentheses and are clustered by MTurk respondent.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

References

Kurtz, Karl. 2015. "Who We Elect: The Demographics of State Legislatures." National Conference of State Legislatures. https://www.ncsl.org/research/about-state-legislatures/who-we-elect.aspx.

Online Appendix B – Audit Composition

Fielded: October 2018

Email Subject: [Constituency Help/Voter Registration Help]

Email Body:
[Formal – A] Representative [Legislator's Full Name],

My name is [Constituent Name]. I think you're my representative, but I'm sorry if I'm mistaken. We had to look up our representatives in [Class] last semester, but since I moved for college I'm not sure what address to use.

[Electoral] I was hoping you could help me register to vote. Do you know if I can register with my parent's address? Or do I have to use my dorm address? Can I vote for local elections in both? [Partisan] This is the first time I'm old enough to vote. As a citizen, I feel it's my obligation to make my voice heard.

[Formal – B] [Formal – C],
[Constituent Name, Formal – D]

PS [Post]

White Names	Nicholas Smith	Ethan Miller	John Ryan	Daniel Schmitz
Black Names	Tyreke Brown	Jamal Gaines	DeMar Washington	Kobe Jefferson
Hispanic Names	Joe Garcia	Joe Martinez	Michael Gonzalez	John Chavez
Electoral**	As someone who hopes to vote for you, As a voter, Although I don't intend to vote for you,			
Partisan**	I look forward to voting Republican! I look forward to voting Democrat! I look forward to voting Libertarian! I look forward to voting!			
Post	You would think a college would better explain how voter registration works! It should be mandatory for colleges to cover basic voter registration info.			
Class	civics	poli-sci		
	Part A	**Part B**	**Part C**	**Part D**
Formal	Dear	Thank you	Leg.'s Full Name	Cons. Full Name
Informal	Hi	Thanks	Leg.'s First Name	Cons. First Name

**Only one electoral/partisan treatment applied per email.

Online Appendix C – Additional Analysis and Miscellaneous Information on Audit Study

We herein report additional analysis and miscellaneous information on the reported audit study. There are 7,383 state legislators in the fifty respective state legislatures. We collected the publicly available emails of 5,735 state legislators in 43 states. States were only excluded when no publicly available set of emails was available. After excluding invalid observations (e.g. cases where emails bounced indicating an invalid email address, cases where the legislator was deceased, etc. etc.), and excluding a small portion used for a colleague's separate audit, we were left with 4,460 observations. In some analysis sample size may be lower due to the limited availability of covariates. All randomization was done using Microsoft Excel's simple randomization feature. In **Appendix C Table 1** we display subjects' characteristics by purported race/ethnicity of alias.

Appendix C Table 1 – Subject Characteristics by Purported Race/Ethnicity

Purported Race/Ethnicity	Total N by Race/Ethnicity	District Per Capita Income, in 10,000s USD (2017 USD ACS)		Percent White Legislator	Percent Hispanic Legislator	Percent Black Legislator	Percent Female Legislator
All Aliases	4460	3.13		87.03%	1.77%	8.73%	26.62%
		(N= 4398)	(SD = 1.06)	(N= 3793)	(N= 3793)	(N= 3793)	(N= 3801)
White Aliases	1862	3.14		87.29%	1.29%	8.77%	26.32%
		(N= 1833)	(SD = 1.09)	(N= 1550)	(N= 1550)	(N= 1550)	(N= 1554)
Black Aliases	1302	3.11		87.49%	2.36%	8.07%	26.75%
		(N= 1285)	(SD = 1.01)	(N= 1103)	(N= 1103)	(N= 1103)	(N= 1103)
Hispanic Aliases	1296	3.15		86.23%	1.84%	9.30%	26.92%
		(N= 1280)	(SD = 1.06)	(N= 1140)	(N= 1140)	(N= 1140)	(N= 1144)

The audit was conducted on the first week of October 2018, shortly before the 2018 midterm elections. Emails were sent from Gmail accounts reflecting the respective aliases used. Example: Nicholas Smith's emails were sent from Nicholas.Smith.Business.College@gmail.com. Tyreke Brown's came from Tyreke.Brown.Business.College@gmail.com. And so forth and so forth. We used yet another mail merge (YAMM) to aide in sending our emails.

In the following table we investigate how a number of different name characteristics are associated with reply rates from state legislators. We find that low SES is consistently associated with a lower reply rate from legislators (**Appendix C Table 2 column 1 and 5**), and we also find a consistently lower reply rate for names associated as being Hispanic (**columns 2 and 5**).

Appendix C Table 2 – Reply Rate by Name's Perceived Characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Perceived as Black		-0.034			0.020
		(0.022)			(0.040)
Perceived as Hispanic		-0.073***			-0.144***
		(0.023)			(0.052)
Perceived as Low SES	-0.290***				-0.300**
	(0.077)				(0.150)
Perceived as Female			0.253		0.621
			(0.263)		(0.387)
Perceived as Migrant				-0.125**	0.328
				(0.062)	(0.211)
Constant	0.552***	0.511***	0.478***	0.513***	0.492***
	(0.019)	(0.012)	(0.010)	(0.016)	(0.031)
Observations	4,460	4,460	4,460	4,460	4,460
R-squared	0.003	0.002	0.000	0.001	0.006

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In **Appendix C Table 3** we find that district per capita income is associated with a greater likelihood of a legislator reply. The coefficients for low SES in columns 1 & 2 indicate that including district per capita income barely changes the relationship between low SES and legislative reply rates.

Appendix C Table 3 – Reply Rate, SES Discrimination Moderated by District Per Capita Income

VARIABLES	(1)	(2)	(3)
Perceived as Low SES	-0.290***	-0.288***	-0.162
	(0.077)	(0.077)	(0.246)
District Per Capita Income, 2017 10k USD		0.021***	0.031*
		(0.007)	(0.019)
Perceived as Low SES x District Per Capita Income			-0.040
			(0.074)
Constant	0.552***	0.488***	0.459***
	(0.019)	(0.030)	(0.061)
Observations	4,460	4,398	4,398
R-squared	0.003	0.005	0.005

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As others have noted (Brambor, Clark, and Golder 2005), it is difficult to interpret moderation by tables alone. For ease for interpretation we plot **Appendix C Table 3 column 3** in **Appendix C Figure 1** below. The mean state legislative district has per capita income of $31,338.47 (SD: $10,571). The results indicate that the relationship between low SES and reduced reply rates, occurs across the range of per capita district income.

Appendix C Figure 2 – Reply Rate, SES Discrimination Moderated by District Per Capita Income

SES Discrimination by State Legislative District Income
95% CI

State Legislative District Per Capita Income (10,000 USDs, 2017 ACS)
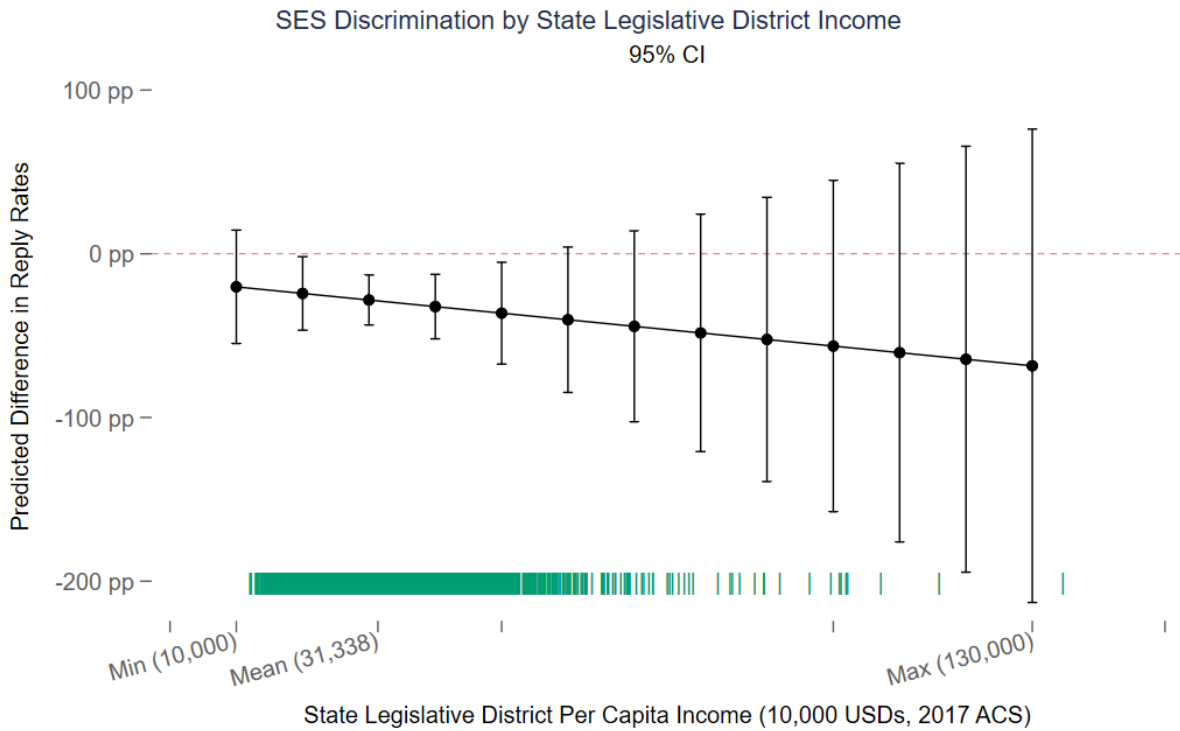
Negative values indicate fewer responses for lower SES names.

In **Appendix C Table 4** we examine a new outcome -- whether a respondent provides information about where to register. We coded this outcome as a 1 if the respondent provided information on where to register (e.g. usually providing a hyperlink or physical address) and a 0 otherwise. We cannot observe what those who do not respond would have done, and therefore we need to address post-treatment bias concerns. We do so by assuming that all non-responses would not have provided helpful information, and we code them as a zero in the data (Coppock 2018). As we found with reply rates, we find that whether a response includes information about registration is associated with low SES and whether a name is perceived to be from a Hispanic individual.

Appendix C Table 4 – Reply Rate by Name's Perceived Characteristics

DV: Did respondents explain where to register?

VARIABLES	(1)	(2)	(3)	(4)	(5)
Purportedly Black Name	-0.006		0.026		
	(0.016)		(0.020)		
Purportedly Hispanic Name	-0.033**		-0.001		
	(0.016)		(0.020)		
Perceived as Low SES		-0.186***	-0.231**		-0.236**
		(0.067)	(0.093)		(0.095)
Perceived as Hispanic				-0.041**	0.001
				(0.020)	(0.026)
Perceived as Black				-0.007	0.033
				(0.019)	(0.025)
Constant	0.261***	0.293***	0.296***	0.261***	0.296***
	(0.010)	(0.017)	(0.017)	(0.010)	(0.017)
Observations	4,460	4,460	4,460	4,460	4,460
R-squared	0.001	0.002	0.002	0.001	0.002

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C References

Brambor, Thomas, William Roberts Clark, and Matt Golder. 2005. "Understanding Interaction Models: Improving Empirical Analyses." *Political Analysis* 14 (1): 63–82.

Coppock, Alexander. 2018. "Avoiding Post-Treatment Bias in Audit Experiments." *Journal of Experimental Political Science*, 1–4.

Online Appendix D – Quasi Pre-Analysis Plan

The following is excerpted from our IRB application (HS 18 – 065, approved May 18th 2018). We did not submit a formal pre-analysis plan for the audit but hope that this serves as a quasi-pre-analysis plan, albeit less comprehensive than would be expected in a formal pre-analysis plan.

We diverged from the quasi pre-analysis in two aspects when we fielded the audit study. We changed the request wording slightly for technical reasons (and had IRB approval to make technical wording changes as necessary), but the substantive nature of the request (voter registration help) remained the same. Secondly, we initially proposed testing an ethno-racially "ambiguous" name alongside the white, black and Hispanic names. While ethno-racially ambiguous names may exist, we did not find any among the names we tested in our name perception study.

IRB Excerpt beings here –

<u>IRB Appendix A – Constituent Requests</u>

Below are sample constituent requests that will be sent out as part of the 2018 North American Election Audit Studies project. Exact wording may change for technical purposes (e.g. translation from English to Spanish), but these samples are reflective of the substantive nature of requests to be made. For convenience all samples are in English, but the requests sent to Mexican state legislators will of course be in Spanish. The exact names used are not yet decided, but likely names are provided in {{IRB}} Appendix C – Names for Audits. We will first conduct an experiment where subjects will be presented with various aliases and asked about the perceived

characteristics (we will submit a separate IRB application for this experiment). Based off these results we will use the names which signal the desired characteristics (e.g. race, gender, partisanship etc.).

Email Request:

Dear [Representative/Senator] [Legislator's Surname],

My name is [White/Black/Hispanic/Ambiguous Name] and I'm trying to figure out how to register to vote for the upcoming elections. I heard that the voter registration deadline is soon.

Who should I contact to register? I look forward to voting [{blank}/for the Republican party/for the Democratic party].

Thank you,

[White/Black/Hispanic/Ambiguous Name]

IRB Appendix B – Pre-Analysis Plans for Audit Studies

DV: Reply Rate

Main Treatment: Correspondent's Perceived Ethno-Race [White/Black/Hispanic/Ambiguous]

Secondary Treatment: Partisanship [Unknown/Republican/Democrat]

To be fielded: Early October 2018

To be fielded with: US state legislators

Summary:

The first audit study we propose is a direct replication of Butler and Broockman (2011)'s field experiment, fielded on October 2008. The original paper found evidence of discrimination against purportedly black constituents when partisanship was unknown (Butler and Broockman 2011). A more recent audit study, fielded in 2014, was unable to detect discrimination against black correspondents, but did find evidence of discrimination against Hispanics and Asians (Gell-Redman et al. 2017). The latter authors brought up the possibility that a secular change in racial attitudes explained their null results, but meta-analysis of economic audit studies have

found no evidence for this hypothesis (Quillian et al. 2017). This audit study's primary purpose is to verify if there has been a secular change in discriminatory actions against purportedly black constituents by state legislators in the past ten years.

In this audit study, we intend to send state legislator offices emails from hypothetical constituents asking for help in voter registration. We modify the design of Butler and Broockman (2011) in only one major respect: we include a third ethno-race (Hispanic). Otherwise the modifications we employ are technical; we intend to pretest the names of correspondents to ensure they only differ in signaled ethno-race and we will employ various methods to reduce detection (multiple aliases, differing {{miscellaneous}} text).

Primary Tests To be Conducted & Predictions:

$$Reply\ Rate_i = B_1\ White_i + B_2\ Black_i + B_3\ Hispanic_i$$

$$H_o: B_1 = B_2$$
$$H_a: B_1 \neq B_2$$

Prediction: H_a {{the White and Black coefficients will not be equal}}

$$H_o: B_1 = B_3$$
$$H_a: B_1 \neq B_3$$

Prediction: H_a {{the White and Hispanic coefficients will not be equal}}

Online Appendix E – Reporting Standards for Experiments

In this appendix we report how the present research meets the standards described in Gerber et al. (2014).

1. Hypotheses

Hypotheses are discussed in the manuscript's main text. As noted in our IRB excerpt (Appendix D), this study was designed as a conceptual replication to test the hypotheses of Gell-Redman et al. (2018) and Butler and Broockman (2011)

2. Subjects and Context

The recruitment of participants and the context of the two studies are discussed in the manuscript's main text and in Appendix A (for the name perception study) and Appendix C (for the audit study component). We here reiterate the key points.

For the name perception study, we recruited MTurk workers on November 2018 as part of a larger name perception study, but subset to the 446 Mturk workers who rated the names used in the present study. MTurk workers. Each Mturk worker rated approximately six names and could perform the task only once. Our recruitment was restricted to U.S. residents. MTurk workers performed the task online through Qualtrics.

For the audit study we attempted to recruit all 5,735 (out of a universe of 7,383) state legislators with a valid email address. After excluding responses that were invalid (e.g. emails bounced, autoreplies) and those used in a separate study, we were left with 4,460 observations.

3. Allocation Method

Randomization of names in the name perception study was conducted within Qualtrics. No restrictions were placed on the randomization process other than having each name appear the same number of times.

Randomization in the audit study, as further discussed in Appendices A and B, was conducted using Microsoft Excel's randomization function.

Block randomization was not employed in either study.

4. Treatments

In addition to their discussion in the main manuscript, detailed treatment explanations for the name perception study are reported in Appendix A. Treatment explanations, including wording, for the audit study are reported in Appendix B.

5. Results

a. Outcome Measures and Covariates

Full question wording and coding procedures are available in Appendices A, B, and C.

In the main analysis we do not employ pre-treatment measures. Descriptive tables of pre-treatment variables used in auxiliary analyses (Appendices A and C) are located within the respective appendices.

b. Statistical Analysis

We report our principal analysis in the main manuscript, with auxiliary analyses in the appendices. We primarily rely on comparisons of means and OLS/LPM as appropriate.

6. Other Information

The University of California, Riverside's Institutional Review Board approved both the name perception study (approval number: HS-18-060) and audit study (approval number: HS-18-065).

The name perception study was supported by a small grant awarded by the University of California Institute for Mexico and the United States (UCMEXUS).

The authors are not aware of any conflict of interest regarding this research.

References

Butler, Daniel M., and David E. Broockman. 2011. "Do Politicians Racially Discriminate against Constituents? A Field Experiment on State Legislators." *American Journal of Political Science* 55 (3): 463–477.

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Gerber, Alan, Kevin Arceneaux, Cheryl Boudreau, Conor Dowling, Sunshine Hillygus, Thomas Palfrey, Daniel R. Biggers, and David J. Hendry. 2014. "Reporting Guidelines for Experimental Research: A Report from the Experimental Research Section Standards Committee." *Journal of Experimental Political Science* 1 (1): 81–98.