Mental representations of immigrants encode racialized expectations of socio-structural positions

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Abstract

Illegalized immigrants are mentally associated with specific visual expectations (e.g., dark-skinned threats) and classifications (e.g., Latin American, Syrian, poor, economic drains). However, these findings provide only partial accounts of how migrant illegality is represented: visual representations could shift depending on the various societal positions or categories illegalized immigrants occupy. We therefore introduce a factorial cross-categorical reverse correlation design where online participants ($N = 480$) visualized immigrants simultaneously associated with certain documentation statuses (documented or undocumented), economic circumstances (job or welfare), and nationalities (Mexican, Irish, Chinese, or Nigerian). The resulting images and evaluations by naïve samples ($N = 345$) highlighted that: 1) illegality is not always visually encoded as darker skin, 2) affective face expressions hint at racialized expectations of European vs. non-European immigrants' societal positions in the U.S., and 3) disaggregation of a target category is critical for understanding the relationship between categorical and visual mental representations.

Keywords: *Face Representations, Illegalized Immigrants, Racialization, Economic Position, Cross-Category Reverse Correlation*

Documentation statuses (e.g., “undocumented immigrant”, “documented immigrant”, “U.S. citizen”) have been shown to conjure differentially racialized mental representations (Martinez, Oh, et al., 2021). The average visual representation of illegalized immigrants in the minds of U.S. residents is a dark-skinned person who elicits evaluations of being relatively dangerous, incompetent, un-American and likely to be racially classified as black. Research that instead examines the public’s demographic associations with illegality suggests that illegalized migrants are presumed to be from Mexico, Central American countries, Syria, or Africa (Flores & Schachter, 2018; Lee & Fiske, 2006).

These separate findings raise questions about the relationship between visual and categorical representations of illegalized immigrants: are associated categories accompanied by visual expectations (e.g., dark-skinned Mexicans) or are there multiple logics in operation captured by different modalities (e.g., any dark-skinned person *or* any Mexican)? Measuring visual expectations or categorical associations without attending to the other provides only a partial account of representations of illegalized migrants. This study aims to address this ambiguity by capturing how illegalized immigrants are visualized across linked social categories: nationalities and economic circumstances.

Visual representational features of migrant illegalization

A combination of racialized phenotypicality (i.e., facial features or skin color) along with facial expressions related to impressions of trustworthiness (Oosterhof & Todorov, 2008), competence (Lee & Fiske, 2006), and American-ness (Devos & Banaji, 2005) distinguish visual representations of illegalized immigrants from documented immigrants or U.S. citizens (Martinez, Oh, et al., 2021). Illegalized immigrants are visualized as darker and more threatening. A related

line of research finds that similar visual features or racialized perceptions arise when targets are criminals (Avery et al., 2021; Funk et al., 2016), welfare recipients (Brown-Iannuzzi et al., 2017), or in conditions of scarcity (Krosch & Amodio, 2014).

Together these findings suggest that cues of criminality and low status should increase darker racialized and moralized features, akin to a bad-is-black effect (Alter et al., 2016). However, visual darkening only makes sense if we consider that the visualization is meant to represent a particular kind of immigrant (e.g., a dark-skinned Nigerian or Mexican immigrant). Unfortunately, knowing the intended identity of a visualization is difficult because typical reverse correlation tasks do not ask visualizers to explicitly characterize the target so as not to disturb the intended implicitness of the procedure. Instead, interpreting the intended identity of a visualization relies on naïve raters' perceptions, which can introduce classification distortions (Nicolas et al., 2019). Visualizations of general social categories (e.g., undocumented immigrant) thus contain interpretive ambiguities. We propose that disaggregating social categories can clarify the relation(s) between visual and categorical representations of illegality.

Nationality, economic circumstances, and ascriptions of migrant legality

Immigrants are not all treated or perceived the same. Colonial and political projects ensure that migrants from different nationalities experience various racializing processes within the U.S. (Treitler, 2013). One key racializing mechanism is exclusion from “legal status”, a social position which has been increasingly criminalized (Waters & Kasinitz, 2015). Tracing the history of U.S. migration suggests that illegality as a status developed across time in ways that favored Northwestern European countries and restricted migration from various geographic regions and countries, particularly Mexicans due to proximity (Ngai, 2004). Illegality has since been

reconfigured and bolstered through policies on the war on terror, national security, and border militarization, which marked immigrants from Latin America and the Middle East as threats (Rivera, 2014; Warner, 2005). It is then no surprise that national origin is an important cue in ascriptions of illegality: U.S. residents mainly associate Mexican, Central American, and Syrian immigrants with being “illegal” relative to Canadian, Italian, or Polish immigrants (Flores & Schachter, 2018). Likewise, associations between immigrants and general criminality also depend on their national origin: immigrants framed as criminals are differentially represented based on whether they originate from European vs. non-European countries (Martinez, Feldman, et al., 2021). Even people occupying the same racial category can be evaluated differently based on their status as native-born citizens or immigrants, suggesting racialization, in turn, makes use of immigrant status (Schachter, 2021).

An economic dimension underlies these patterns. Immigrants’ economic need and membership of exploited countries is seen as an essential component of non-white racialization through global capitalism (Golash-Boza et al., 2019; Provine & Doty, 2011). Not only does economic status feed into racialization, but racialization, in turn, has economic consequences that mark immigrants as moral and economic liabilities. Criminal law and immigration law have increasingly merged with time, leading to similar sanctions for anyone deemed outside of the protection and “deservingness” of citizenship (Stumpf, 2006). For instance, criminalized citizens and immigrants are barred from access to welfare, a consequence reflecting the belief in a social contract that grants exclusive rights to public goods for (moral) citizens only. Evidence of U.S. residents’ fears of immigrants’ undeserving intrusion into exclusive resources can even be found in data-driven investigations of immigrant stereotypes. Such research has found two main factors related to impressions of immigrants: being a national drain (vs. asset) and being vulnerable (vs.

hardworking), with illegalized immigrants being marked as semi-vulnerable drains (Savaş et al., 2021). Likewise, research assessing economic associations found that illegalized immigrants are believed to either be unemployed, hold low status employment, or receive welfare (Flores & Schachter, 2018).

These findings suggest that the category of “undocumented immigrants” tacitly conjures immigrants from specific nationalities and economic circumstances. In other words, all these dimensions are interrelated. However, phenotypic variation exists within every socially constructed category; they cannot neatly capture the contours of an always in-flux world. This means that even if one semantically associates Mexicans with illegality, it is unlikely that one could identify all Mexicans, and thus “illegals”, by appearance. Instead, it is more likely that some Mexicans (and immigrants from other countries) will better match a prototypical representation of illegalized immigrants than others (Maddox & Perry, 2018). However, we cannot assume that representations of illegalized immigrants will always contain racialized features such as darker skin. Visual representations of illegality may shift across social categories or when categories are further partitioned or intersected. Understanding the psychological encoding of migrant illegalization thus requires characterizing two forms of representational patterns: 1) how representations of immigrants within suspected categories become visually marked by illegalization (e.g., Mexicans or immigrants on welfare) and 2) how immigrants from categories that are less associated with illegality, yet contain actual illegalized immigrant populations, are also visually marked by illegalization (e.g., Irish or employed immigrants).

Current Project

A critical issue for representations of migrant illegality is that visualizations cannot straightforwardly inform us about intended categories and associated categories cannot straightforwardly inform us about visual expectations. We also cannot assume that insights from research in both modalities can easily be integrated due to the possibility that visual representations of illegality may shift across social categories. We attempt an integration by employing a novel cross-categorical reverse correlation task that prompts participants to visualize immigrants who embody a combination of nationality (i.e., Mexican, Nigerian, Chinese, Irish), documentation (i.e., documented, undocumented), and economic (i.e., having a steady job, on welfare) positions. The factorial combinations are such that the target immigrants have favorable, unfavorable, or mixed documentation and economic circumstances and are from countries with undocumented populations in the United States, but that vary in associated salience with migrant illegalization. Reverse correlation tasks typically study single category targets, however, assessing how nationality and economic information shifts representations of illegalized immigrants is critical to understanding the psychological encoding of migrant illegality.

This exploratory investigation proceeds in two stages: a standard reverse correlation task where classification face images of the multiple immigrant targets are collected and subsequently evaluated on various dimensions by naïve samples, followed by three main analyses on the face ratings. The ratings are on the following traits for their salience in immigrant discourse: dangerous, trustworthy, competent, and American (Martinez, Oh, et al., 2021). The first analysis functions as a manipulation check. Before examining the combined cross-category representations, it is important to check if documentation status and economic circumstances independently contain reliable signal as “main effects” in the expected directions. If aggregate visualizations of immigrants who are documented vs. undocumented or who are on welfare vs. have a job do not

differ in ratings as previous research has found, that could suggest a problem with the task design or data quality. The next analysis characterizes the ratings of the sample-averaged classification image for each cross-categorical target. The last analysis functions as a robustness check on the evaluative patterns found for the average images. Using ratings of average classification images can increase false positives compared to ratings of the individual-level classification images (Cone et al., 2020), so we also characterize ratings of the participant-level images on the same four traits.

Method

The following Open Science Framework archive contains the data, analysis scripts, and preregistration: https://osf.io/fkuj6/?view_only=1d9d5234ef53433d83f2b43c5ad8cc5c. The project was approved by the Princeton University IRB #7301.

Image generation task

Participants

Participants from Amazon Mechanical Turk completed our study, 30 in each of the 16 visualization conditions ($N = 480$). The data were collected in November 2018. Across the full sample ($N = 480$), the average age was 35.9 ($SD = 10.6$) and 200 were women and 280 were men. The sample was largely white ($N = 365$), followed by Latinx ($N = 36$), black ($N = 38$), Asian or Pacific Islander ($N = 29$), multiracial ($N = 10$), and other ($N = 2$). Most were born in the U.S. ($N = 459$), some were not ($N = 20$), and one preferred not to say. While all participants lived in the U.S., there was larger representation from Texas ($N = 41$), California ($N = 36$), Florida ($N = 33$), Pennsylvania ($N = 27$), North Carolina ($N = 27$), New York ($N = 24$), and Michigan ($N = 24$). See the online archive materials for the complete table with descriptive statistics for each condition.

Target Conditions

The 16 conditions that were visualized for this project included all combinations of four nationalities (Mexico, China, Nigeria, Ireland), two documentation statuses (documented, undocumented), and two economic circumstances (on welfare, has a job). The specific nationalities were chosen for two reasons. The first is that these countries are commonly perceived to be racially distinct as Latinx-, (East) Asian-, black-, and white-majority countries, respectively. In this way, we can disentangle whether illegality differentially visually racializes immigrants from countries that vary in their presumed positions within the U.S. racial hierarchy and in how strongly they are associated with illegality (e.g., Latinx-undocumented vs. white-undocumented). The second reason is that illegalized immigrants from the four chosen countries constitute a relatively large population size compared to countries in the same or neighboring region and thus should be at least somewhat familiar to the public. We assessed population size at the level of nationality and not race because the logics of racial classifications can shift across borders. Still, population size estimates of undocumented immigrants' national origins are fraught with complications (e.g., dangers of visibility, choices in reporting aggregates vs. specific estimates); therefore we gathered multiple estimates from various years and sources (see **Supplementary Table S1** and Warren, 2021). Between the four countries, the population size of illegalized immigrants in the U.S. is greatest for immigrants from Mexico, followed by China, Nigeria, then Ireland. Each country was represented by an individual. Names were selected from online lists of the most popular names for men in each country: José from Mexico, Li from China, Abaeze from Nigeria, and Connor from Ireland. We focused on immigrant men because they have been considered the current deportation regime's main targets (Golash-Boza, 2015).

It should be noted that the cross-section of documentation and economic circumstances leads to category combinations that are more and less possible under current immigration, welfare, and employment policies. Immigrants with documentation gain access to employment authorization and can legally obtain jobs. Illegalized immigrants may gain access to employment authorization if eligible for programs that grant liminal legal status (e.g., Deferred Action for Childhood Arrivals). Otherwise, many do find work without authorization through “under the table” employment. Moreover, while documented immigrants can access forms of welfare after remaining in the U.S. for at least five years, illegalized immigrants are barred from obtaining federal welfare, although they may be eligible for local aid programs or very restricted forms of assistance (e.g., supplemental nutrition program for Women, Infants, and Children, WIC). This legislative obstacle makes the category combination of undocumented and on welfare unlikely, yet it has been treated as a real widespread threat in public discourse. An oft-stated worry is that immigrants are in the U.S. to steal jobs and simultaneously abuse welfare (Abrajano & Hajnal, 2015). In fact, a month before our data collection in September 2018, Donald Trump announced intentions to institute a policy where immigrants who accessed government assistance programs would be considered public charges and could be denied green cards (Alamillo et al., 2019). Thus, while this category combination is unlikely, it remains politically and socially salient and treated as a real threat.

Procedure

After providing consent, participants were instructed that they would be presented with details about an individual. Their task was to try to visualize that individual in their mind. Afterwards, they were told that they would be presented with two face images and to choose the face that most looked like their visualization: they pressed the “0” key for the image on the right

and the “1” key for the image on the left. Each trial displayed the images side-by-side in the center of the screen with each image being 9 cm x 9 cm. There was a 1 second fixation cross between trials and each trial was self-paced. Underneath was the description of the target individual. Every individual was described using a template sentence that simply replaced key descriptive words depending on the target condition: “[José, Li, Abaeze, Connor] was born in [Mexico, China, Nigeria, Ireland]. He is financially [helped through a welfare program, stable through a steady job] and he has been living in the United States [with, without] legal immigrant status.” Participants completed 350 trials, the last 50 trials were repeated trials to assess test-retest reliability as the percentage of matching choices on the same face pairs (average test-retest = 56%, range = [32%, 98%]). Afterwards, the participants completed demographic surveys.

Stimulus generation

The stimuli for the reverse correlation task were generated using the *rcicr* package in R (Dotsch, 2017; R Core Team, 2015). Random sinusoid noise was repeatedly overlayed on a base face image to create 770 noisy face pairs for the trials. Each pair consisted of one face that depicts the noise pattern while the other depicts the opposing noise pattern. The base face was a grey-scale morph of all the men in the London Face Database (DeBruine & Jones, 2017) (**Figure 1**). Due to the difficulties of running longer experiments online (e.g., attrition, inattention), we restricted the stimulus set to the first 300 face pairs.

Classification image generation

The classification images were generated using the *rcicr* package. Individual classification images are generated by averaging the noise patterns of the chosen face stimuli across the 300 non-repeated trials per participant and overlaying the average noise pattern over the base face. The

sample average classification image averages over all the participants' classification image noise patterns and overlays that sample-averaged noise over the base face.

Image rating task

Participants

Based on a simulation power analysis, 20 participants were enough for 99.9% power for an effect size of $f = .77$, however we collected more data to account for simulation inaccuracies and reliability exclusions. Raters evaluated the sample average classification images on one of four traits: dangerous ($N = 40$, $M_{\text{age}} = 40.4$, $SD = 11.5$, 19 women and 21 men), trustworthy ($N = 40$, $M_{\text{age}} = 35.8$, $SD = 8.17$, 21 women and 19 men), competent ($N = 40$, $M_{\text{age}} = 38.3$, $SD = 12.4$, 16 women and 24 men), American ($N = 40$, $M_{\text{age}} = 36.3$, $SD = 12.7$, 12 women, 26 men, and 2 non-binary people). Over 65% of each sample was white. To account for heterogeneity of the individual classification images within each condition (Cone et al., 2020), the individual faces were also rated on the same four traits: dangerous ($N = 42$, $M_{\text{age}} = 39.1$, $SD = 11.5$, 24 women, 17 men, and 1 preferred not to say), trustworthy ($N = 43$, $M_{\text{age}} = 38.4$, $SD = 11.5$, 15 women and 28 men), competent ($N = 53$, $M_{\text{age}} = 41.8$, $SD = 12.6$, 30 women, 22 men, and 1 preferred not to say), American ($N = 47$, $M_{\text{age}} = 35.1$, $SD = 11$, 24 women and 23 men). Each trait rating sample for the individual images originally contained a total of 60 raters ($N = 240$ total), deviations from this sample size are due to unreliability exclusions (i.e., test-retest reliability was less than 0). Ratings for the average images were collected in January 2019 and ratings for the individual images were collected in March 2019. We collected many individual difference measures that were not analyzed here, however, see **Supplementary Table S2** and **S3** for descriptive characteristics.

Procedure

Participants first provided consent before starting the task. The instructions stated that they would see a series of faces that they would evaluate “how [trait] each face looks” by pressing a key between 1 (not at all) to 9 (extremely). Each face image was displayed at 300 pixels x 300 pixels. All trials were self-paced and there was a 250 ms delay between trials. Face variation in classification images is restricted to that allowed by the base face, thus participants were instructed to treat each face as a different person when responding. Participants who rated the average classification images rated the average faces from the 16 conditions along with the 4 additional faces we consider main-effect averages that represent each documentation and economic circumstance in isolation. To make these main-effect faces, we averaged all the individual faces that contained each documentation or economic circumstance (e.g., we averaged undocumented immigrants with a job or on welfare to create the “undocumented” face; $N = 240$ for each average). We do not assume that these main effect faces reflect the representations that would appear if we had asked participants to visualize those statuses directly. Rather, the purpose of investigating these faces was to ensure that evaluations of the average documentation status and economic circumstance faces differ in the expected directions, a sign that they contain meaningful signal. The average classification images were only rated once.

Participants who rated the individual faces encountered only a subset of the full stimulus set. The complete set of individual faces ($N = 480$) were grouped into three batches of 160 faces (10 from each condition); participants evaluated only one of the three batches. Additionally, we randomly sampled three faces from each condition from each batch for a total of 48 faces to repeat within the rating task to assess test-retest reliability. Test-retest reliability was calculated as the correlation between each participant’s first and second rating of the same stimuli (see

Supplementary Table S3 for sample averages). Overall, the rating task for the individual faces included 208 trials. The rating task ended with demographic surveys.

Analyses

All ratings were analyzed using mixed models that were estimated using maximum likelihood within the “lme4” package in R (Bates, 2010). Model specification aimed to maximally account for the study design (Barr et al., 2013). To help with convergence, models were optimized using the “bobyqa” algorithm. Estimated marginal means, effect sizes, and confidence intervals were calculated using the “emmeans” package in R (Lenth, 2020). Degrees of freedom were estimated using the Satterthwaite approximation (Luke, 2016). The summed variance components and residuals were used for the effect size estimation to approximate Cohen’s d (Westfall, 2016). Comparisons were corrected for false discovery rate. For clarity, we report a subset or summary of all the analyses as appropriate. Full statistics can be found on the Open Science Framework archive (https://osf.io/fkuj6/?view_only=1d9d5234ef53433d83f2b43c5ad8cc5c).

Status average main effect ratings. While the 4 main effect average faces (i.e., documented, undocumented, job, welfare) were intermixed with the 16 condition faces during the rating task, their ratings were analyzed separately. Since each face was rated only once, the ratings were analyzed using mixed models that contained a stimulus dummy variable as a predictor and allowed random intercepts by participants. Comparisons of interest were documented vs. undocumented and job vs. welfare.

Average face ratings. Predictors of the ratings for the 16 condition average faces (separate from the 4 main effect faces) included the three-way interaction between documentation status, economic circumstance, and nationality. These average faces were only rated once, therefore

random effects included intercepts and slopes for the main effects of documentation status, economic circumstance, nationality per participant along with random intercepts for stimuli.

Individual face ratings. Ratings for the individual faces were predicted by the three-way interaction between documentation status, economic circumstance, and nationality. Since many of the faces were repeated, the random effects included random intercepts and slopes for documentation status, economic circumstance, and nationality by participants, random intercepts by stimuli, and random intercepts by the interaction between participants and stimuli to account for repeated measures.

Results

Documentation and economic circumstance average main effects

The main average face images and ratings of each status can be seen in **Figure 1**. Better evaluations for the documented vs. undocumented average faces were significant for the following dimensions: *dangerous* ($b = -1.35$ CI[-2.27, -.43]; $d = -.71$ CI[-1.08, -.34]), *trustworthy* ($b = .95$ CI[.25, 1.65]; $d = .51$ CI[.23, .79]), and *American* ($b = .93$ CI[.17, 1.68]; $d = .44$ CI[.17, .71]). The *competence* ratings showed the expected pattern, but only descriptively ($b = .55$ CI[-.27, 1.37]; $d = .31$ CI[-.03, .65]). Rating differences between the job and welfare average faces were significant for all dimensions: *dangerous* ($b = -2.63$ CI[-3.55, -1.70]; $d = -1.39$ CI[-1.78, -.99]), *trustworthy* ($b = 1.55$ CI[.85, 2.25]; $d = .83$ CI[.54, 1.12]), *competent* ($b = 1.15$ CI[.33, 1.97]; $d = .64$ CI[.29, .99]), and *American* ($b = .70$ CI[-.06, 1.46]; $d = .33$ CI[.06, .60]).

These initial results show that the average documented and job faces contained more smiling features and were rated as more trustworthy, American, competent, and less dangerous than their counterpart undocumented and welfare faces. The expected main effects of

documentation status and economic circumstances were present, meaning the faces contained meaningful signal and thus examining the cross-category conditions *would* be informative.

Figure 1. Main effects of documentation and economic circumstance. The top face panel depicts the base face along with average faces for each overall status category. The bottom violin plot panels are the ratings of the average faces. The y-axes are the rating values, the x-axes are the different statuses. Violin plots reflect the density of the data and the lines within the violin plots reflect data quartiles. Error bars are 95% confidence intervals.

Average classification images for all conditions

The average faces are shown in **Figure 2**. The clearest visual variation across conditions was how nationalities were represented relative to each other in terms of skin colors and phenotypical facial features. Variation in affective expressions also existed in how documentation and economic circumstance combinations were visually represented within nationality. To understand what evaluations these various features elicited, we examined three-way interactions between nationality, economic, and documentation status in trait ratings (**Figure 3**). The three-way interactions were significant for dangerous ($F(3,440)=22.5$, $p<.0001$), trustworthiness ($F(3,440)=14.1$, $p<.0001$), competence ($F(3,440)=4.88$, $p=.002$), and American ($F(3,440)=2.62$, $p=.050$). We explore these interactions in two ways: 1) how nationality affects status representations as the main question of interest and 2) how documentation and economic circumstance affect nationality representations.

Figure 2. Average classification images at the intersections of nationality, economic circumstance, and documentation status. The rows depict the four different nationalities. The columns represent the various combinations of economic and documentation statuses. The left-most column represents a combination of favorable statuses, the center two columns reflect mixed statuses, and the right-most column shows a combination of difficult statuses.

How do nationalities shift status representations? Dangerous and trustworthy ratings exhibited similar patterns. There were no significant average nationality differences for immigrants who were documented with a job ($bs_{\text{range}} = [.08, .53]$, $ds_{\text{range}} = [.02, .19]$, $ps_{\text{range}} = [.230, .812]$). The Irish immigrant was perceived as less dangerous ($bs_{\text{range}} = [.90, 2.0]$, $ds_{\text{range}} = [.27, .61]$, $ps_{\text{range}} =$

[<.0001, .032]) and more trustworthy ($b_{\text{range}} = [.52, 1.5]$, $ds_{\text{range}} = [.22, .62]$, $ps_{\text{range}} = [<.0001, .027]$) than the three other nationalities (Mexican, Nigerian, Chinese) when they were either documented and on welfare or undocumented with a job. The one exception was the difference between the Irish and Mexican immigrants' trustworthiness ratings when documented and on welfare ($b = .525$ CI[-.14, 1.19], $t(222) = 2.09$, $p = .074$). Lastly, when the immigrants were undocumented and on welfare, the Irish immigrant was perceived as more dangerous than the immigrants from the other three nationalities ($b_{\text{range}} = [.80, 1.5]$, $ds_{\text{range}} = [.23, .44]$, $ps_{\text{range}} = [.0004, .042]$) and less trustworthy than the Mexican and Chinese immigrants ($b_{\text{range}} = [.60, .73]$, $ds_{\text{range}} = [.25, .30]$, $ps_{\text{range}} = [.041, .052]$), though not the Nigerian immigrant ($b = .48$ CI[-.22, 1.17], $t(184) = 1.82$, $p = .140$).

Competence ratings exhibited no significant nationality differences for immigrants in the following conditions: documented with a job ($b_{\text{range}} = [.13, .57]$, $ds_{\text{range}} = [.03, .20]$, $ps_{\text{range}} = [.331, .805]$), documented on welfare ($b_{\text{range}} = [.08, .45]$, $ds_{\text{range}} = [.03, .16]$, $ps_{\text{range}} = [.513, .774]$), and undocumented on welfare ($b_{\text{range}} = [.03, .65]$, $ds_{\text{range}} = [.01, .23]$, $ps_{\text{range}} = [.173, .935]$). For immigrants who were undocumented with a job, the Nigerian immigrant was perceived as less competent than the Irish and Chinese immigrants ($b_{\text{range}} = [.92, 1.3]$, $ds_{\text{range}} = [.32, .44]$, $ps_{\text{range}} = [.0004, .008]$) and the Mexican immigrant as less competent than the Irish immigrant ($b = .90$ [.03, 1.77], $t(134) = 2.76$, $p = .013$). Lastly, the American ratings exhibited the same pattern across all status conditions: The Irish immigrant was perceived as the most American ($b_{\text{range}} = [1.3, 4.3]$, $ds_{\text{range}} = [.35, 1.14]$, $ps_{\text{range}} = [<.0001, .001]$), while Chinese immigrants were perceived as the least American ($b_{\text{range}} = [1.6, 4.3]$, $ds_{\text{range}} = [.43, 1.14]$, $ps_{\text{range}} = [<.0001, <.0001]$) compared to the other nationalities.

How do status combinations shift nationality representations? The Irish undocumented immigrant on welfare was perceived as less trustworthy ($b_{\text{range}} = [1.6, 2.2]$, $ds_{\text{range}} = [.65, .92]$,

$p_{\text{range}} = [<.0001, <.0001]$), less competent ($b_{\text{range}} = [1.3, 1.5]$, $d_{\text{range}} = [.43, .50]$, $p_{\text{range}} = [<.0001, <.0001]$), and more dangerous ($b_{\text{range}} = [2.4, 3.1]$, $d_{\text{range}} = [.73, .93]$, $p_{\text{range}} = [<.0001, <.0001]$) than when he had any of the other three status combinations. Conversely, the Mexican, Nigerian, and Chinese immigrants instead were less dangerous ($b_{\text{range}} = [.93, 1.6]$, $d_{\text{range}} = [.28, .49]$, $p_{\text{range}} = [<.0001, .003]$) and more trustworthy ($b_{\text{range}} = [.70, 1.4]$, $d_{\text{range}} = [.29, .56]$, $p_{\text{range}} = [<.0001, .003]$) when they were documented with a job compared to their three counterpart status combinations. Only the Mexican immigrant exhibited a rating pattern where they were perceived as less American when they were undocumented and on welfare compared to the other Mexican status counterparts ($b_{\text{range}} = [.65, .73]$, $d_{\text{range}} = [.17, .19]$, $p_{\text{range}} = [.017, .024]$). Other comparisons were either not significant (e.g., American ratings of different statuses or circumstances within Chinese or Irish immigrants) or exhibited a less interpretable pattern.

To summarize, evaluations of the average faces revealed a clear racialized pattern in how nationality and economic circumstances shift representations of illegalized immigrants. There was a double standard within moral evaluations (i.e., dangerous and trustworthy) whereby the Irish immigrant was perceived as less dangerous as long as there was one favorable circumstance (a job *or* documentation) and the other immigrants were only perceived as not dangerous if they had both a job and documentation. The Irish undocumented immigrant on welfare was perceived as the most dangerous immigrant, indicative of a severe expectation violation. The pattern in the competence ratings was harder to discern. Lastly, American ratings seemed to mostly track nationality (as race). However, there was one nationality where documentation status and economic circumstance seemed to matter. The Mexican representation was less American when both undocumented and on welfare, suggesting that Mexican immigrants are potentially marked as legal vs. illegal through skin color – a possibility we elaborate further in the discussion.

Figure 3. Rating results of the average classification images. The x-axis represents the various combinations of documentation and economic circumstances (*from left to right*: documented with job, documented on welfare, undocumented with job, undocumented with welfare). The nationalities are represented by colors and line styles: Ireland in red solid line, Mexico in green small-dashed line, China in blue dashed line, and Nigeria in purple spaced-out dashed line. Shaded areas reflect 95% confidence intervals for the estimated marginal means.

Individual classification images for all conditions

To check if the trait ratings for the individual faces replicated the patterns found for the average faces, we first examined whether the three-way interactions between nationality, documentation status, and economic circumstance remained significant (**Figure 4**). None of the three-way interactions were significant ($p_{\text{range}} = [.327, .779]$). Instead, we highlight the simple effects across the traits to understand what evaluations *were* elicited from the individual faces based on the main manipulations of documentation status, nationality, and economic circumstance.

Documented immigrants were perceived as more trustworthy than undocumented immigrants ($b = .16$ CI[.05, .26], $d = .09$, $t(136) = 3.00$, $p = .003$), but only descriptively less dangerous ($b = -.10$ CI[-.21, .005], $d = .05$, $t(234) = -1.88$, $p = .062$), more competent ($b = -.07$ CI[-.01, .16], $d = .03$, $t(102) = 1.66$, $p = .099$), and more American ($b = .09$ CI[-.03, .21], $d = .04$, $t(258) = 1.43$, $p = .154$). Immigrants with jobs were perceived as less dangerous than immigrants on welfare ($b = .09$ CI[-.03, .21], $d = .04$, $t(258) = 1.43$, $p = .154$), but only descriptively more trustworthy ($b = .09$ CI[-.01, .20], $d = .05$, $t(205) = 1.87$, $p = .063$), more competent ($b = .03$ CI[-.06, .12], $d = .01$, $t(104) = .69$, $p = .491$), and more American ($b = .05$ CI[-.06, .17], $d = .02$, $t(245) = .85$, $p = .394$). The status effects were in the expected direction yet small in magnitude. In contrast, nationality was a stronger predictor of all trait ratings with a consistent pattern. The Irish immigrants were perceived as less dangerous ($b_{\text{range}} = [-.33, -.22]$, $d_{\text{range}} = [.10, .15]$, $p_{\text{range}} = [.004, .053]$), more trustworthy ($b_{\text{range}} = [.28, .44]$, $d_{\text{range}} = [.15, .23]$, $p_{\text{range}} = [<.0001, .004]$), more competent ($b_{\text{range}} = [.30, .39]$, $d_{\text{range}} = [.13, .17]$, $p_{\text{range}} = [<.0001, .0009]$), and more American ($b_{\text{range}} = [.49, 1.01]$, $d_{\text{range}} = [.21, .43]$, $p_{\text{range}} = [<.0001, <.0001]$) than the Mexican, Nigerian, and Chinese immigrants. Moreover, the Chinese immigrants were also perceived as less American than the other nationalities ($b_{\text{range}} = [.42, 1.01]$, $d_{\text{range}} = [.18, .43]$, $p_{\text{range}} = [<.0001, .0002]$).

The results provided convergent evidence at the individual-level images of the main effects of documentation status and economic circumstance from the first set of reported analyses. Representations of documented immigrants were more positively evaluated than representations of undocumented immigrants. Representations of immigrants with a job were more positively evaluated than representations of immigrants on welfare. Lastly, the nationality (as race) main effect was clear; representations of Irish immigrants were more positively evaluated than

representations of the other immigrants. However, the complex three-way interactive patterns in the ratings of the full set of average faces did not hold at the individual level.

Figure 4. Rating results of the individual classification images. The x-axis represents the various combinations of documentation and economic circumstances (*from left to right*: documented with job, documented on welfare, undocumented with job, undocumented with welfare). The nationalities are represented by colors and line styles: Ireland in red solid line, Mexico in green small-dashed line, China in blue dashed line, and Nigeria in purple spaced-out dashed line. Shaded areas reflect 95% confidence intervals for the estimated marginal means.

Discussion

To better integrate visual and categorical representations of migrant illegality, we employed a novel cross-categorical reverse correlation design where participants visualized immigrants who embodied a combination of social positions. Once the category of “undocumented immigrant” was

disaggregated by nationality and economic circumstances, the encoding of illegality shifted in ways that revealed racialized expectations of immigrants' socio-structural positions. However, these patterns only occurred in ratings of average classification images, not individual-level images. We discuss the theoretical and methodological implications of both findings for characterizing representations of migrant illegality.

Visual marking of illegality

Affective expressions (e.g., frowns, smiles, or “neutral”) tended to better track documentation status and economic circumstances in this study suggesting that illegality is not always marked by skin color and facial phenotype as found in previous research (Martinez, Oh, et al., 2021). Instead, skin color and facial phenotype marked nationality as these features seemed to stay consistent within a nationality no matter the associated documentation status and economic circumstances (**Figure 2**). The one exception was the Mexican immigrant, who seemed to be darker skinned (**Figure 2**) and was perceived as less American (**Figure 3**) when on welfare and undocumented. Since ascriptions of Americanness are associated with skin tones (Martinez, Oh, et al., 2021), this is suggestive that Mexicans become encoded as illegal and economic drains through darker skin. These results show how research on visual and category associations cannot be easily combined because illegality is encoded differently across social categories and through different features. Future work attempting an integration of visual-category mental representations should therefore consider cross-categorical reverse correlation designs.

Racialized expectations

An alternative way to understand the results is to reframe the question from representations of illegality to representations of nationality and race. For each nationality, affective facial

expressions marked the social-structural position each immigrant was expected to have (i.e., documentation and economic circumstances). The non-European immigrants (i.e., Mexican, Nigerian, and Chinese) were visualized with neutral expressions when they were associated with one or two negative circumstances (welfare or undocumented or both) but were smiling and non-threatening when they had a job and documentation. The Irish immigrant instead was visualized as smirking and non-threatening when they were associated with one or two positive circumstances (documentation or job or both) but showed a threatening expression when both undocumented and on welfare. These patterns are indicative of a racist double standard: the Irish immigrant is given leniency and the benefit of a doubt while the non-European immigrants are only redeemable through excellence (Martinez, Feldman, et al., 2021; Moffitt et al., 2019). Moreover, the undocumented Irish immigrant on welfare was perceived as *more* threatening than the other Irish immigrants with better circumstances and than the non-European immigrants, evidence of an expectation violation for European immigrants that marked that Irish immigrant as a “black sheep” (Marques & Paez, 1994).

This expectancy pattern is reminiscent of early 1930s associations whereby the deportation of Europeans was used as a more shocking migration reformist case than deportations of non-Europeans (Ngai, 2004, p. 2). The pattern also aligns with aspects of the Racial Position Model whereby U.S.-based stereotypes of various racial categories are derived from their positions along two dimensions of inferior and foreign (Kim, 1999; Zou & Cheryan, 2017). While the Racial Position Model focused on Americans and our data on immigrants, we replicated the expected perceived foreign-ness of the Asian category and the American-ness of the white category. However, while the Racial Position Model suggests Latinxs are perceived as foreign and black people as American, visual representations of Mexican and Nigerian immigrants held an in-

between location. These divergent results further highlight the need to incorporate categorical and visual modalities and migrant status when mapping racial stereotypes.

Representations as socio-structural thinking

These socio-structural expectations of immigrants from various nationalities suggest that representations of social groups are actually representations of social structure (Fiske et al., 2002; Vasilyeva et al., 2018; Vasilyeva & Lombrozo, 2020). Rather than representing information about target groups' behaviors or traits as *essences*, those perceived characteristics instead index the group's expected societal positions (Eagly & Koenig, 2021). In other words, immigrant features (e.g., national origin, phenotype) are tracked by people to confer societal statuses (e.g., illegal, white) upon immigrants that restrict or allow modes of living (Ásta, 2018). Representations of illegalized immigrants in the U.S. thus are a reflection and product of the criminalizing and racist colonial structures that they are embedded in that make these associations socially significant.

This structural interpretation is bolstered by the fact that the boundaries of who constitutes various “groups” are dynamic and constantly in motion (Brubaker et al., 2004; Cikara, 2020). Although we often treat demographic “groups” as stable and coherent entities (Rodríguez-Muñiz, 2021), “groups” are instead contingent events made possible by shifting assemblages of human, discursive, and material elements (Price-Robertson & Duff, 2016). For instance, illegalized immigrants are not a homogenous agentic entity as they each experience shifting forms of incorporation and exclusion across institutional and community contexts (Chauvin & Garcés-Mascareñas, 2012; Menjívar & Kanstroom, 2014). Yet, they can temporarily become a coherent “group” through encounters between external pressures (e.g., ICE raids, restrictive policies) that impose similar conditions and material and discursive resources that help mobilize connections and

political goals (Brown, 2013; Costanza-Chock, 2014). Symbolic positions within hierarchical social structures may be more stable (although may manifest in context-specific ways) than the groups that embody those positions because those structures help create groups in the first place (Treitler, 2013). Thus, socio-structural positioning is a more stable source of information from which mental representations about groups can be developed.

This interpretation aligns with a historical, relational, and structural understanding of race whereby “race is not in the eye of the beholder or on the body of the objectified” (Hesse, 2016), but is rather a collection of continuing colonial practices that distinguish Europeans vs. non-Europeans (Hesse, 2007). These practices create colonially inherited environments that shape who gets to comfortably exist within them through repeated racial logics (Ahmed, 2007). From this understanding, a race is not something one is or possesses. When scholars and the public alike discuss these practices in the language of identity (e.g., “their/my race” or “race relations”), a sleight of hand is performed that “transforms racism, something an aggressor *does*, into race, something the target *is*” (Fields & Fields, 2012). These racism-to-race transformations mark immigrants once they enter into the U.S. and are forced into its hierarchical racial logics – “no one in the United States is allowed to be without a race” (Treitler, 2013). Racialized immigrant representations can therefore be interpreted as perceptions of expected positions within racist economic hierarchies that force economic precarity and restriction from rights rather than accurate encodings of an immigrant’s “race” as an individualized identity.

Inferences from average vs. individual images

The expected main effects of documentation status, economic circumstance, and nationality were shown in ratings of the average and individual faces; however, the interactive effects mainly

occurred in ratings of the average faces. Does this mean the pattern of racialized expectations is unreliable? This discrepancy strikes at the heart of two competing interpretations of the relationship between average and individual classification images. On one hand, individual images can be seen as noisy and thus aggregation across individual images accentuates the relevant representational features of a target (Dotsch & Todorov, 2012). From this view, ratings of average images are more informative than ratings of the individual level images. On the other hand, average images can be seen to neglect variation that exists in the individual images, thus ratings done at the average image level can inflate false positives (Cone et al., 2020). The first view would imply that the racialized expectation patterns in the average face ratings are reliable, the second view would imply that the lack of racialized expectation patterns in the individual face ratings is more reliable.

A relevant detail here is that these perspectives were mainly developed from studies that focused on representations of single-category targets (e.g., immigrants). The introduction of multicategory individual targets may engage these perspectives differently. At the individual-level, a multicategory target may provide an especially noisy image, as a target within overlapping intersections may be difficult to visualize, especially if those intersections are socially rendered invisible (Crenshaw, 1991). This means that averaging across people would accentuate the relevant features amidst very noisy images, in line with the first perspective. For multicategorical targets, aggregation may be ideal to capture the interactive effects. However, the second perspective may still be relevant whereby the average representation continues to neglect individual-level variation. How these perspectives operate for multicategorical targets remains an open question.

Limitations

One limitation is that we focused on representations of *individual* immigrants from each cross-category position. Given the hypothesized role that visualization difficulty plays in inferences made from average or individual classification images, future work could instead examine on representations of cross-category positions as collectives. Likewise, we focused on three non-exhaustive dimensions (i.e., documentation status, nationality, and economic circumstance), future research could characterize additional intersections (i.e., gender, age).

Conclusions

This study sought to improve upon previous research that examined restricted representations of illegalized immigrants- *either* visual *or* categorical associations. We introduced a cross-categorical reverse correlation design to study the relationship between visual and categorical representations of illegalized immigrants. The results showed that representations of illegality continue racialized, this time not by skin color but by affective face expressions that reveal the social positions that European vs. non-European immigrants are expected to occupy in the United States. These findings provide a view into how modern-colonial practices link racialization and migrant illegalization, resulting in the reification of those practices in the public's mind.

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Mental representations of immigrants encode racialized expectations of socio-structural positions – Supplementary Material

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2. **Supplementary Table S2:** Demographic characteristics of the raters for the average classification images.
3. **Supplementary Table S3:** Demographic characteristics of the raters for the individual classification images.

Supplementary Table S1. Population size estimates in the United States for illegalized immigrants from various countries

Region	Country	2012 ^a	2012 ^b	2013 ^c	2016 ^b	2017	2018 ^f
<i>Latin and Central America and the Caribbean</i>	<i>Combined</i>	8.8 M		8.75 M			8.6 M
	Mexico	5.85 M	6.7 M	6.2 M	5.45 M		5.57 M
	El Salvador	675K	690 K	436 K	725 K		750 K
	Guatemala	520 K	560 K	704 K	575 K		588 K
	Honduras	350 K	360 K	317 K	425 K		402 K
	Dominican Republic	170 K		123 K	210 K		
	Colombia	150 K		137 K			
	Ecuador	130 K	170 K	146 K			
	Peru	120 K		105 K			
	Haiti	110 K					
	Brazil	100 K		117 K	130 K		
	Jamaica	100 K		77 K			
	<i>Asia</i>	<i>Combined</i>		1.5 M			1.5 M
	India	450 K	260 K	284 K	475 K		469 K
	China	300 K	210 K	285 K	325 K		
<i>Middle East, Africa</i>	Philippines	200 K	310 K	197 K	140 K		
	S. Korea	180 K	230 K	192 K	130 K		
	Vietnam		160 K	116 K			
	<i>Combined</i>	400 K		342 K			230 K
	Nigeria			45 K			
	Ghana			36 K			
<i>Europe, Canada</i>	Ethiopia			35 K			
	Kenya			24 K			
	<i>Combined</i>	600 K		423 K			648 K
	Ireland					10^d-50^e K	

Note: M = million, K = thousand.

^a <https://www.pewresearch.org/hispanic/2014/11/18/chapter-2-birthplaces-of-u-s-unauthorized-immigrants/>

^b <https://immigration.procon.org/demographics-of-immigrants-in-the-united-states-illegally/>

^c <https://www.migrationpolicy.org/sites/default/files/publications/Unauth-COB-Report-FINALWEB.pdf>

^d <https://www.thejournal.ie/factcheck-undocumented-irish-usa-3559047-Aug2017/>

^e <https://www.cnn.com/2017/03/16/us/white-irish-undocumented-trnd/index.html>

^f <https://www.migrationpolicy.org/data/authorized-immigrant-population/state/US>

Supplementary Table S2. Demographic characteristics of the raters for the average classification images.

	Dangerous (N=40)	Trustworth y (N=40)	Competent (N=40)	American (N=40)	Overall (N=160)
Age					
Mean (SD)	40.4 (11.5)	35.8 (8.17)	38.3 (12.4)	36.3 (12.7)	37.7 (11.4)
Median [Min, Max]	39.0 [22.0, 62.0]	34.0 [25.0, 66.0]	35.5 [20.0, 71.0]	32.5 [21.0, 65.0]	35.0 [20.0, 71.0]
Gender					
Female	19 (47.5%)	21 (52.5%)	16 (40.0%)	12 (30.0%)	68 (42.5%)
Male	21 (52.5%)	19 (47.5%)	24 (60.0%)	26 (65.0%)	90 (56.2%)
Non-binary/Other	0 (0%)	0 (0%)	0 (0%)	2 (5.0%)	2 (1.2%)
Race					
Asian/Pacific Islander	3 (7.5%)	6 (15.0%)	4 (10.0%)	5 (12.5%)	18 (11.2%)
Black or African	3 (7.5%)	2 (5.0%)	4 (10.0%)	4 (10.0%)	13 (8.1%)
Latinx/o/a or Hispanic	2 (5.0%)	1 (2.5%)	3 (7.5%)	1 (2.5%)	7 (4.4%)
Multiracial	2 (5.0%)	4 (10.0%)	3 (7.5%)	1 (2.5%)	10 (6.2%)
White or European	30 (75.0%)	27 (67.5%)	26 (65.0%)	29 (72.5%)	112 (70.0%)
Born in U.S.					
No	2 (5.0%)	3 (7.5%)	4 (10.0%)	2 (5.0%)	11 (6.9%)
Yes	38 (95.0%)	37 (92.5%)	36 (90.0%)	37 (92.5%)	148 (92.5%)
Prefer not to say	0 (0%)	0 (0%)	0 (0%)	1 (2.5%)	1 (0.6%)
U.S. Citizen					
Yes	40 (100%)	39 (97.5%)	39 (97.5%)	37 (92.5%)	155 (96.9%)
No	0 (0%)	1 (2.5%)	1 (2.5%)	2 (5.0%)	4 (2.5%)
Prefer not to say	0 (0%)	0 (0%)	0 (0%)	1 (2.5%)	1 (0.6%)
Lives in U.S.					
I am living in the U.S.	40 (100%)	40 (100%)	40 (100%)	40 (100%)	160 (100%)
Social Dominance Orientation ^a					
Mean (SD)	2.35 (1.69)	2.68 (1.56)	2.38 (1.22)	2.16 (1.15)	2.40 (1.42)
Median [Min, Max]	1.50 [1.00, 6.63]	2.50 [1.00, 7.00]	1.88 [1.00, 5.13]	1.75 [1.00, 4.38]	1.88 [1.00, 7.00]
Missing	4 (10.0%)	2 (5.0%)	2 (5.0%)	3 (7.5%)	11 (6.9%)

	Dangerous (N=40)	Trustworth y (N=40)	Competent (N=40)	American (N=40)	Overall (N=160)
Social & Economic Conservatism Scale ^b					
Mean (SD)	58.3 (19.3)	56.4 (18.1)	57.3 (18.0)	57.2 (18.3)	57.3 (18.3)
Median [Min, Max]	56.3 [20.2, 96.0]	57.0 [10.7, 96.7]	59.2 [19.3, 86.3]	56.2 [16.7, 89.3]	57.8 [10.7, 96.7]
Immigrant Contact ^c					
Mean (SD)	3.23 (2.03)	3.98 (2.09)	3.65 (1.86)	3.78 (1.98)	3.66 (1.99)
Median [Min, Max]	3.00 [1.00, 7.00]	4.00 [1.00, 7.00]	3.00 [1.00, 7.00]	4.00 [1.00, 7.00]	3.00 [1.00, 7.00]
Undocumented Contact ^d					
Mean (SD)	2.48 (1.69)	2.40 (1.30)	2.23 (1.25)	2.15 (1.51)	2.31 (1.44)
Median [Min, Max]	2.00 [1.00, 7.00]	2.00 [1.00, 6.00]	2.00 [1.00, 6.00]	2.00 [1.00, 6.00]	2.00 [1.00, 7.00]

^a Participants responded whether they strongly oppose (1) or strongly favor (7) eight items related to preferences for group hierarchies (e.g., “Some groups of people are simply inferior to other groups.”) (Ho et al., 2015). Item scores are reverse-corrected and averaged to compute a single score where higher numbers reflect greater dominance orientation.

^b The Social and Economic Conservatism Scale (SECS) was used to assess political orientation (Everett, 2013). The scale presents 12 political topics (e.g., military, abortion, gun ownership, patriotism). Participants respond on a temperature-like scale (0 (negative) to 100 (positive)) how they feel about each issue. Scores are reverse-corrected and averaged across topics to produce a final score where closer to 0 is more liberal and closer to 100 is more conservative.

^{c,d} Participants self-reported on a scale of 1 (never) to 7 (all the time) how often they are in contact with immigrants in general and with undocumented immigrants specifically on a daily basis.

Supplementary Table S3. Demographic characteristics of the raters for the individual classification images.

	Dangerous (N=42)	Trustworth y (N=43)	Competent (N=53)	American (N=47)	Overall (N=185)
Age					
Mean (SD)	39.1 (11.5)	38.4 (11.5)	41.8 (12.6)	35.1 (11.0)	38.7 (11.9)
Median [Min, Max]	37.0 [21.0, 66.0]	37.0 [19.0, 67.0]	40.0 [23.0, 67.0]	31.0 [19.0, 66.0]	36.0 [19.0, 67.0]
Gender					
Female	24 (57.1%)	15 (34.9%)	30 (56.6%)	24 (51.1%)	93 (50.3%)
Male	17 (40.5%)	28 (65.1%)	22 (41.5%)	23 (48.9%)	90 (48.6%)
Prefer not to say	1 (2.4%)	0 (0%)	1 (1.9%)	0 (0%)	2 (1.1%)
Race					
Black or African	3 (7.1%)	4 (9.3%)	4 (7.5%)	5 (10.6%)	16 (8.6%)
East Asian	2 (4.8%)	4 (9.3%)	3 (5.7%)	2 (4.3%)	11 (5.9%)
Multiracial	3 (7.1%)	1 (2.3%)	0 (0%)	1 (2.1%)	5 (2.7%)
Other	1 (2.4%)	0 (0%)	0 (0%)	0 (0%)	1 (0.5%)
South Asian/Indian	3 (7.1%)	0 (0%)	2 (3.8%)	0 (0%)	5 (2.7%)
White or European	30 (71.4%)	29 (67.4%)	39 (73.6%)	32 (68.1%)	130 (70.3%)
Latinx/o/a or Hispanic	0 (0%)	4 (9.3%)	4 (7.5%)	2 (4.3%)	10 (5.4%)
Middle Eastern	0 (0%)	1 (2.3%)	0 (0%)	1 (2.1%)	2 (1.1%)
Indigenous/Native American	0 (0%)	0 (0%)	1 (1.9%)	2 (4.3%)	3 (1.6%)
Prefer not to say	0 (0%)	0 (0%)	0 (0%)	2 (4.3%)	2 (1.1%)
Born in U.S.					
No	2 (4.8%)	3 (7.0%)	2 (3.8%)	6 (12.8%)	13 (7.0%)
Prefer not to say	1 (2.4%)	0 (0%)	1 (1.9%)	0 (0%)	2 (1.1%)
Yes	39 (92.9%)	40 (93.0%)	50 (94.3%)	41 (87.2%)	170 (91.9%)
U.S. Citizen					
Prefer not to say	1 (2.4%)	0 (0%)	1 (1.9%)	0 (0%)	2 (1.1%)
Yes	41 (97.6%)	42 (97.7%)	52 (98.1%)	46 (97.9%)	181 (97.8%)
No	0 (0%)	1 (2.3%)	0 (0%)	1 (2.1%)	2 (1.1%)
Lives in U.S.					
I am living in the U.S.	42 (100%)	43 (100%)	53 (100%)	47 (100%)	185 (100%)
Social Dominance Orientation ^a					
Mean (SD)	2.30 (1.41)	2.31 (1.25)	2.65 (1.39)	2.70 (1.49)	2.50 (1.39)

	Dangerous (N=42)	Trustworth y (N=43)	Competent (N=53)	American (N=47)	Overall (N=185)
Median [Min, Max]	1.75 [1.00, 7.00]	2.00 [1.00, 5.13]	2.63 [1.00, 7.00]	2.06 [1.00, 6.38]	2.13 [1.00, 7.00]
Missing	2 (4.8%)	1 (2.3%)	4 (7.5%)	3 (6.4%)	10 (5.4%)
Social & Economic Conservatism Scale ^b					
Mean (SD)	55.6 (20.4)	58.3 (18.8)	58.3 (20.2)	53.3 (18.8)	56.4 (19.5)
Median [Min, Max]	58.1 [13.5, 87.3]	59.1 [21.2, 95.9]	57.6 [4.00, 100]	51.0 [5.42, 94.8]	56.8 [4.00, 100]
Immigrant Contact ^c					
Mean (SD)	3.69 (1.88)	3.79 (2.10)	3.74 (1.94)	3.53 (1.95)	3.69 (1.96)
Median [Min, Max]	3.00 [1.00, 7.00]	4.00 [1.00, 7.00]	4.00 [1.00, 7.00]	3.00 [1.00, 7.00]	3.00 [1.00, 7.00]
Undocumented Contact ^d					
Mean (SD)	2.19 (1.25)	2.65 (1.86)	2.87 (1.86)	2.89 (1.73)	2.67 (1.72)
Median [Min, Max]	2.00 [1.00, 6.00]	2.00 [1.00, 7.00]	2.00 [1.00, 7.00]	2.00 [1.00, 7.00]	2.00 [1.00, 7.00]
Test-Retest Reliability					
Mean (SD)	0.259 (0.149)	0.310 (0.174)	0.274 (0.176)	0.337 (0.194)	0.295 (0.176)
Median [Min, Max]	0.241 [0.0214, 0.642]	0.293 [0.0283, 0.594]	0.267 [0.00379, 0.644]	0.325 [0.00951, 0.790]	0.295 [0.00379, 0.790]

^{a,b,c,d} See Supplementary Table S2 for more information on the tagged individual difference measures.