THE EFFECT OF RACIAL AND ETHNIC ATTITUDES ON HISPANIC IDENTITY IN THE U.S *

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NOVEMBER 14, 2022

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ABSTRACT

In this paper, I study the determinants of the choice to identify as Hispanic among those who could—those whose parents, grandparents, or selves were born in a Spanish-speaking country. I find that individuals with Hispanic ancestry are significantly less likely to self-identify as Hispanic if they live in states with high levels of implicit ethnic bias. A one standard deviation increase in bias decreases self-reported Hispanic identity by seven and 13 percentage points for first and second-generation Hispanics, respectively. These effects are more prominent among second-generation immigrants whose mothers and fathers were born in a Spanish-speaking country than among children of inter-ethnic parents.

Keywords: Economics of Minorities, Race, and Immigrants; Discrimination and Prejudice; Well-Being.

JEL Classifications: I310, J15, J71

*I thank Professors Willa Friedman, Chinhui Juhn, Vikram Maheshri, and Yona Rubinstein for their support and advice. I also thank Aimee Chin, Steven Craig, German Cubas, Elaine Liu, Fan Wang, and the participants of the Applied Microeconomics Workshop at the University of Houston for helpful feedback.

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I. INTRODUCTION

How should we count the sizes of various groups defined by race, ethnicity, and gender? Recent Censuses have allowed individuals to check off multiple categories regarding race and ethnicity, reflecting a US population that has become increasingly multi-racial and multi-ethnic.[1] How individuals self-identify into various categories has significant political consequences on policy and economic research focusing on outcome gaps.

In this paper, I examine the determinants of self-identification as "Hispanic" among immigrants from Spanish-speaking countries. I focus on how much prejudice in the place a person lives in impacts their identity decisions. Akerlof and Kranton (2000) posit that actions have benefits and costs that are identity dependent. For example, an individual can engage in seemingly self-destructive behavior such as self-starvation if being thin accords with the proscription of being a woman. Adopting a specific identity then shapes people's decisions, investments, and well-being in potentially profound ways.

Understanding the determinants of self-identification is vital for at least three reasons. First, the rates of self-identification by the group may have consequences for political representation and the distribution of resources. Second, how individuals identify may impact measured changes in labor market outcomes among groups differentiated by race and ethnicity. Antman et al. (2016) show that among Mexican immigrants, the least economically successful self-identify as being of Mexican origin, while the most successful do not. As a result, Mexican immigrants' assimilation rates could appear slower than other groups. Third, to the extent that individuals react to prejudice by not identifying with the group targeted by bias; the standard analyses that attempt to attribute some component of an ethnic gap in outcomes will be biased.

Most research on race and ethnicity relies on self-reported race and ethnic identity measures. Given the prominence of identity in contemporary American society and politics and

1. For a discussion of the implications of multiple ethnic and racial categories and the future of the multi-racial and multi-ethnic demography of the United States see Bratter (2018); Alba (2020).

the increase in the number of Hispanics in the United States, questions on assimilation and mobility (Chetty et al., 2014; Abramitzky et al., 2014), how identity could shift public opinions toward trade (Grossman and Helpman, 2021), and how racial and gender attitudes affect the racial and gender earnings gaps (Charles and Guryan, 2008; Charles et al., 2018) are increasingly important.[2] [3]

In order to explore how individual characteristics and social attitudes toward Hispanics affect the self-reported identity of persons with Hispanic ancestry in the United States, I use identity and ancestry information from the Current Population Survey (CPS), along with a proxy for state-level bias from Harvard's Project Implicit Association Test. I motivate my analysis with a simple model in the vein of Akerlof and Kranton (2000). The model makes explicit a path through which actions affect individuals' utility via their identity. This model also introduces an externality where the actions of others have different effects on a person's well-being and identity. Therefore, if a person has the ability to choose their identity credibly, then they will choose it in order to maximize their outcomes.

Measuring identity choices outside of a laboratory is challenging because I must observe and construct objective and self-reported measures of identity. I use data from the birthplace of a person and their ancestry to construct an objective measure of identity. I find the self-reported measure of identity to be correlated to individual and parental characteristics. I also find that they are associated with variables on discrimination and racial attitudes that reflect the social environment.

Among the people of Hispanic ancestry, I find that higher state-level bias against people with darker skin is correlated to lower self-reported Hispanic identity among Hispanic immigrants. I use data on the Implicit Association Test (IAT), which measures the implicit biases of participants, as a proxy for prejudice. The IAT data is retrieved from Harvard's Project Implicit (Greenwald et al., 1998). The implicit bias toward minorities, as measured

2. The number of Hispanics in the United States almost doubled between 1994 and 2021. Based on data from the Current Population Survey, the number of Hispanics increased from 9% in 1994 to 17% in 2021.

3. For more on mobilityChetty et al. (2016, 2017, 2014) and Abramitzky et al. (2020, 2016); Chetty et al. (2014) for more on assimilation.

by IAT, is widely used by psychologists and is growing in use among economists. IAT scores were shown to be correlated with economic outcomes (Chetty et al., 2020; Glover et al., 2017), voting behavior (Friese et al., 2007), and health (Leitner et al., 2016). I find that a one standard deviation increase in bias is associated with a seven percentage points decrease in the self-reported Hispanic identity among first-generation immigrants. Additionally, a one standard deviation increase in bias is associated with 13 percentage points decrease in the self-reported Hispanic identity among second-generation immigrants. Further, a one standard deviation increase in bias is correlated with a 15 percentage points drop in self-reported Hispanic identity among second-generation Hispanic children with parents born in a Spanish speaking country. Among third-generation Hispanic children with grandparents that were all born in a Spanish speaking country, a one standard deviation increase in bias is associated with 14 percentage points decrease in self-reported Hispanic identity. These results align with the findings of Charles et al. (2018) that sexism experienced by women at the place and time of birth (background sexism) and sexism experienced by women where they currently live (residential sexism) is correlated with lower wages and labor force participation. I also find that state-level bias is uncorrelated with migration decisions and is correlated with a lower probability of interethnic marriage formations.

This paper contributes to three different strands of the literature. First, there is a growing theoretical and empirical economic literature on racial and ethnic identities. Kranton et al. (2020) used an experimental lab design to deconstruct group biases and found significant preferences toward in-group reported identities. Bonomi et al. (2021) posit a model with class and cultural identities. They showed how cultural or class salient issues could increase polarization and affects distributive policies. Fryer and Torelli (2010) introduced a theory where black pupils would punish their peers when they strive for economic success by "Acting White." There is an abundance of empirical studies investigating the effect of identity on many outcomes. Giuliano et al. (2009) found that non-White managers hire more Whites and fewer Black employees. In Giuliano et al. (2011), they found that employees of a certain race experience better outcomes when their manager shares the same race. Bagues et al. (2017) showed that having more women present on hiring committees for academic jobs in Italy and Spain did not decrease the gender gap. Åslund et al. (2014) found that immigrant managers hired more immigrant employees than native managers. Others have looked at the effect of distinct Black names and Hispanic last names on labor market outcomes (Bertrand and Mullainathan, 2004; Fryer and Levitt, 2004; Hadah, 2020). Gershenson et al. (2016) found that non-Black teachers had lower expectations of Black students, and Dee (2005) showed that teachers had different evaluations when teacher and student did not share the same race. [4]

The second strand of the literature this paper fits in is the economics of immigration and assimilation. Abramitzky et al. (2016) measured the speed at which immigrants from Europe, Asia, and Latin America assimilate in the United States. They find that assimilation increases over time.[5] Fouka et al. (2022) investigated the effect of the inflow of Black Americans migrating from the South to the North on the assimilation of European immigrants. The authors found that immigrants in places that received more Black migrants assimilated faster. Meng and Gregory (2005) studied the effect of intermarriage on assimilation and found that immigrants that intermarry earn significantly more than those in an endogamous marriage.

Other researchers studied the assimilation of Hispanic immigrants. Antecol and Bedard (2006) documented an interesting puzzle where non-native-born Hispanics have better health outcomes than native-born Hispanics, and Trejo (1997) showed that Mexican men

4. Other works include Jardina (2019) reported that in the United States, people that identify more with a 'White' identity were more likely to support protectionist policies. Using a large experiment, Alesina et al. (2018) showed that by simply invoking the identity of native *versus* immigrant, voters supported less redistribution. Waters (2001) finds that West Indian immigrants in the US, especially second-generation, that keep their identity and resist assimilation into American culture (Americanization) were more likely to succeed economically. Grossman and Helpman (2021) constructed a theoretical model to explain what led to the recent de-liberalization of trade. More specifically, they investigated whether voters' opinion of globalization is a function of their own self-interest and the self-interest of people that share their identity. The model showed that under some circumstances, as in changes in political and cultural conditions, more people would identify with the 'broad nation.' Their support for trade policies would hinge on the welfare of other members of the 'broad nation' and not their self-interest. Consequently, this increased the support for protectionist policies.

5. For more on immigrant assimilation, see Abramitzky et al. (2020, 2019, 2020, 2014)

earn substantially less than Whites.[6] Smith (2003) offered a more optimistic view of the assimilation of Hispanic immigrants. The longer Hispanic and Latino immigrants spent in the US, the more they could close the educational gap with White men. Moreover, some of the poor showings of how well Hispanic immigrants assimilate in the United States could be explained by ethnic attrition and the use of self-reported Hispanic identity to study Hispanics (Duncan and Trejo, 2017, 2011b; Meng and Gregory, 2005; Duncan and Trejo, 2018a,b; Antman et al., 2016, 2020). The ethnic attrition was driven by the children of inter-ethnic marriages (Meng and Gregory, 2005; Duncan and Trejo, 2005). Once the attrition was accounted for, Hispanic immigrants would appear healthier, and thus more assimilated than previously thought (Antman et al., 2016, 2020).

The third strand this paper fits in is the research on attitudes and discrimination toward minorities. Charles and Guryan (2008); Charles et al. (2018) found that attitudes toward Black people (prejudice) and women (sexism) are correlated with the racial and gender gaps. Chetty et al. (2020) found that higher implicit bias toward Black People, captured by Implicit Association Test (IAT) scores, is associated with lower income ranks and, thus, lower intergenerational mobility. Glover et al. (2017) also found that bias, measured by Implicit Association Test (IAT) scores, of grocery stores' managers negatively affected minority job performance. Bursztyn et al. (2022) showed that the exposure to Arab-Muslims decreased the non-Arab-Muslim Whites' implicit bias toward Arab-Muslims.

This paper is most closely related to Antman et al. (2016); Antman and Duncan (2015, 2021) where the authors studied the ethnic attrition of Hispanic immigrants and how minorities change their self-reported identity to changes in policies.[7] Taking into consideration the ethnic attrition that Antman et al. (2016) document, I investigate the determinants of what drives a person to self-report, or not, their Hispanic identity. I aim to decompose some of the complexity associated with endogenous identity by exploring some of the personal

6. The Hispanic health paradox has led many researchers to try to explain it (Giuntella, 2016; Giuntella and Stella, 2017; Giuntella et al., 2018; Giuntella, 2017; Antman et al., 2016, 2020).

7. Ethnic attrition is when a person with Hispanic ancestry fails to self-identify as Hispanic.

and environmental determinants of identity. The empirical analysis in this paper documents how some observable, i.e., personal characteristics and societal attitudes, affect the self-reported identity of Hispanics.

The rest of this paper will be structured as follows. First, I will introduce a theoretical model in section (II). Second, I will describe the data I use in section (III). Third, I will introduce an empirical model in section (IV). Fourth, I will discuss the results in section (V). Finally, I will conclude in section (VI).

II. Theoretical Model

I introduce a model of identity in the spirit of Akerlof and Kranton (2000). A person belongs to some ethnic group, and their actions either affirm or deny their ethnic identity. Actions that deviate from what is proscribed of the ethnic identity are costly.

Formally, a person i belongs to ethnic group $e_i \in \{H, NH\}$, where H is Hispanic and NH is non-Hispanic. Agent i's utility depends on their actions and the extent to which their actions affirm their identity I_i:

$$U_i = U_i(\boldsymbol{a_i}, \boldsymbol{a_{-i}}, I_i) \tag{1}$$

A person's identity, I_i, is influenced by their own actions, the actions of others, and the behavior proscribed by their ethnicity. I write this as:

$$I_i = I_i(\boldsymbol{a_i}, \boldsymbol{a_{-i}}; \boldsymbol{B}_{e_i}) \tag{2}$$

Where $\boldsymbol{a_i}$ is the actions of person i, $\boldsymbol{a_{-i}}$ is the actions of others, and I_i is the identity function. Each group has an associated set of behaviors that society proscribes them to conform to, which I denote as $\boldsymbol{B}_{e_i}$.[8]

A person i chooses action a_i that maximizes their utility function given ethnic group

8. Akerlof and Kranton (2000) refer to B_{e_i} as proscription.

e_i, proscribed appropriate behavior $\boldsymbol{B}_{e_i}$, and the actions of others $\boldsymbol{a_{-i}}$. This implies the following first-order condition (F.O.C.):

$$\frac{\partial U_i}{\partial a_i} + \frac{\partial U_i}{\partial I_i} \cdot \frac{dI_i}{da_i} = 0 \tag{3}$$

Whose solution $a_i^\star$ yields utility $U_i^\star$. Now, suppose a person can choose their ethnic identity at a cost of c. They will do so if $\tilde{U_i}^\star \geq U_i^\star + c$. Where $\tilde{U_i}^\star$ is the utility obtained from optimal actions $\tilde{a_i^\star}$ under the counterfactual ethnicity.

That is i will change identities when the benefits of doing so $\tilde{U_i}^\star - U_i^\star$ exceed the costs c. These net benefits are non-zero only if $\frac{dI_i}{da_i} \neq 0$. This suggests that an empirical analysis of the determinants of identity choice should focus on: (1) individual characteristics that would lead to different a_i under different identities, (2) contextual characteristics that would lead to different a_{-i} under different identities, and (3) the analysis should focus on a sample of the population with small c. From the empirical analysis, I could investigate the characteristics that would affect i's actions to take different identities from point (1). These characteristics could be the generation immigrants belong to, whether their parents are interethnic or endogamous, etc. I could also investigate how different state-level biases could affect identity. Finally, restricting the sample to people with a small cost of changing identity c guarantees that I do not include populations that would never change identities otherwise—for example, non-Hispanic Whites with no Hispanic ancestry.

III. Data

III.A. Measuring Hispanic Identity

I use multiple datasets to measure Hispanic identity and prejudice. The first dataset I use to measure Hispanic identity is the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) (Flood et al., 2021). The CPS is a comprehensive dataset collected monthly by the United States Census Bureau and the Bureau of Labor Statistics. The survey is of US households to measure unemployment, and the monthly survey is of more than 65,000 households.

The richness of the CPS allows me to link household members with each other. Coupled with the fact that the CPS started asking respondents for the birthplace of their parents beginning in 1994, I could perfectly identify, and construct, a dataset of first-, second-, and third-generation Hispanic immigrants. This will consequently allow me to build an objective measure of the Hispanic identity of minors under the age 17 living with their parents. This objective measure of identity—unlike the self-reported measure where respondents answer affirmatively when asked if they are Hispanic or Latino—depends on the birthplaces of the individual, their two parents, and four grandparents. Thus, the three identifiable generations are: 1) first-generation immigrants that were born in a Spanish-speaking country with both parents also being born in a Spanish-speaking country, 2) second-generation immigrants are native-born citizens to at least one parent that was born in a Spanish-speaking country, 3) third-generation immigrants are native-born citizens to two native-born parents and at least one grandparent that was born in a Spanish speaking country.[9] I restrict the sample to Hispanic Whites, first-, second-, and third-generation immigrants who are 17-year-old and younger and still live with their parents between 2004 and 2021. I present the summary statistics of the sample in table (1).

The overall sample is 49% female, and 91% of the sample self-reportedly identifies as Hispanic—answered yes to the question "are you Latino/Hispanic?". The average age is 8.6-year-old. Almost 14% of mothers have a college degree, and 14% of fathers have a college degree. Finally, the average family income in the sample was $39,882. I provide the rest of the summary statistics for the overall sample and broken down by generation in table (1).

As previously stated, data on the objective Hispanic measure is not readily available. Consequently, it is hard to identify the different generations of Hispanics in the United States using public-use data. Therefore, much of the literature studying Hispanics relied on a self-reported measure of Hispanic identity. A person is identified as Hispanic if they

9. I restrict first-generation immigrants whose parents were born in a Spanish country to avoid including naturally born US citizens that were born abroad to US parents.

answer affirmatively whether they are Hispanic, Spanish, or Latino. Using self-reported identity to check the assimilation and intergenerational mobility of Hispanics in the United States ignores that some immigrants might decide not to identify as Hispanic.

TABLE 1
CPS Summary Statistics

Characteristic	Overall	By Generation		
	All Sample N = 1,131,828	**First** N=119,778	**Second** N=761,450	**Third** N=254,699
Female	0.49	0.48	0.49	0.49
Hispanic	0.91	0.96	0.94	0.82
Age	8.6 (5.1)	11.5 (4.3)	8.3 (5.0)	7.9 (5.0)
College Graduate: Father	0.14	0.15	0.11	0.23
College Graduate: Mother	0.14	0.15	0.11	0.22
Total Family Income (1999 dollars)	39,882 (48,692)	31,927 (38,804)	36,726 (45,353)	53,000 (58,984)

* Mean (SD)

[1] The sample includes children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third-generation Hispanic immigrant children with native born parents and at least one grand parent born in a Spanish speaking country.
[2] Data source is the 2004-2021 Current Population Survey.

To avoid the problem introduced above, I will use the information on the place of birth, parents' place of birth, and place of birth of grandparents to construct an objective Hispanic measure.[10] The advantage is that the Current Population Survey (CPS) asks respondents about their parent's place of birth; I can link children that are 17-year-old and younger that still live with their parents to their parents and identify four generations of Hispanic immigrants.

10. Following the works of Antman et al. (2016, 2020).

Furthermore, I can identify three generations of Hispanic immigrants. Figure (1) offers a visual representation of the algorithm I used to determine the different generations. The different generations are defined according to the following:

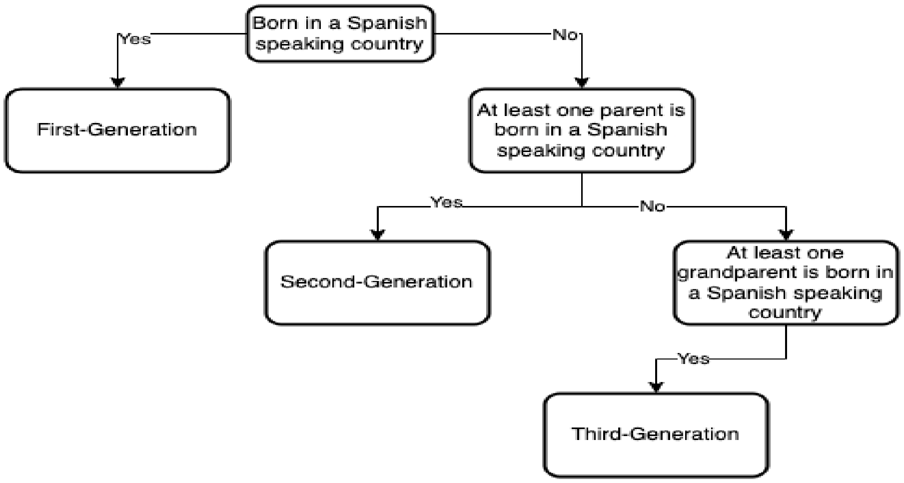
1. A person is a first-generation if they are born in a Spanish-speaking country with non-US-born parents
2. A person is a second-generation Hispanic if they are born in the US and at least one parent is born in a Spanish speaking country
3. A person is a third-generation Hispanic if they are born in the US, both parents are the US born, and they have at least one grandparent that is born in a Spanish speaking country

Moreover, using the place of birth of parents and grandparents, I can objectively identify their ethnic ancestry. Consequently, I can identify different types of parents and grandparents. Using the place of birth of parents data, I can divide parents of second-generation children into three objective types:

1. Objectively Hispanic-father-Hispanic-mother (HH)
2. Objectively Hispanic-father-White-mother (HW)
3. Objectively White-father-Hispanic-mother (WH)

Similarly, using the place of birth of grandparents, I can divide grandparents of third-generation children into 15 objective types: (1) objectively Hispanic paternal grandfather-Hispanic paternal grandmother-Hispanic maternal grandfather-Hispanic maternal grandmother (HHHH); (2) objectively White paternal grandfather-Hispanic paternal grandmother-Hispanic maternal grandfather-Hispanic maternal grandmother (WHHH); (3) objectively Hispanic paternal grandfather-White paternal grandmother-Hispanic maternal grandfather-Hispanic maternal grandmother (HWHH), etc...

FIGURE 1
DIAGRAM OF THE THREE DIFFERENT GENERATIONS OF HISPANIC IMMIGRANTS



My analysis depends on a sub sample of the US population, I show in table (2) that I have enough observations in each generation. Consistent with the literature on ethnic attrition among Hispanics, I find significant attrition among third-generation Hispanic immigrants.[11] These results are displayed in table (2): most first- and second-generation Hispanic immigrants self-reportedly identified as Hispanic. Among first-generation Hispanic immigrants, 96% of the group self-reportedly identified as Hispanic. Among second-generation Hispanic immigrants, 95% of the group self-reportedly identified as Hispanic. Attrition rates increase drastically after the second-generation, with 85% of third-generation Hispanic immigrants identifying as Hispanic. That is more than three folds increase in attrition rates. Most of the attrition among third-generation Hispanics is driven by attrition among the children of inter-ethnic marriages.

11. In Duncan and Trejo (2018a,b); Antman et al. (2016, 2020), the authors find substantial attrition among Hispanics.

TABLE 2

HISPANIC SELF-IDENTIFICATION BY GENERATION

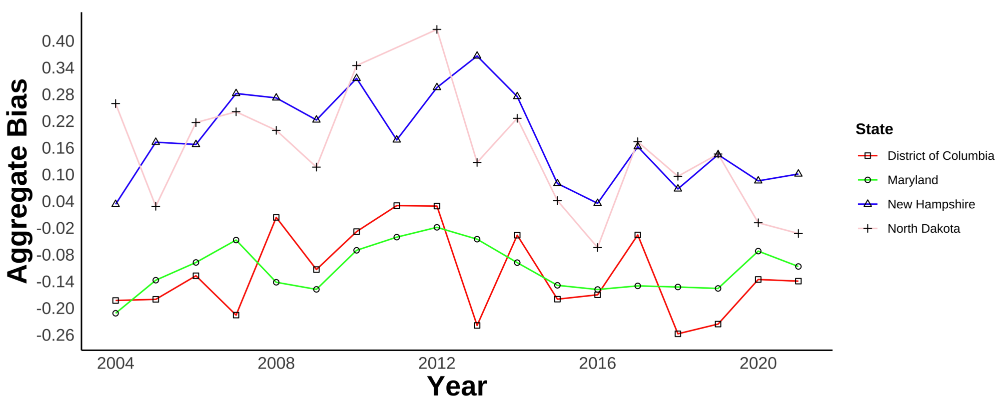
	Self-identify as Hispanic	Self-identify as non-Hispanic	% Self-identify as Hispanic	% Self-identify as non-Hispanic
1st Gen.	114657	5121	0.96	0.04
2nd Gen.	712916	48534	0.94	0.06
Hispanic on:				
Both Sides	516551	19318	0.96	0.04
One Side	196365	29216	0.87	0.13
3rd Gen.	209206	45493	0.82	0.18
Hispanic on:				
Both Sides	55401	2245	0.96	0.04
One Side	52879	17371	0.75	0.25

[1] The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third-generation Hispanic immigrant children with native born parents and at least one grandparent born in a Spanish speaking country.
[2] Data source is the 2004-2021 Current Population Survey.

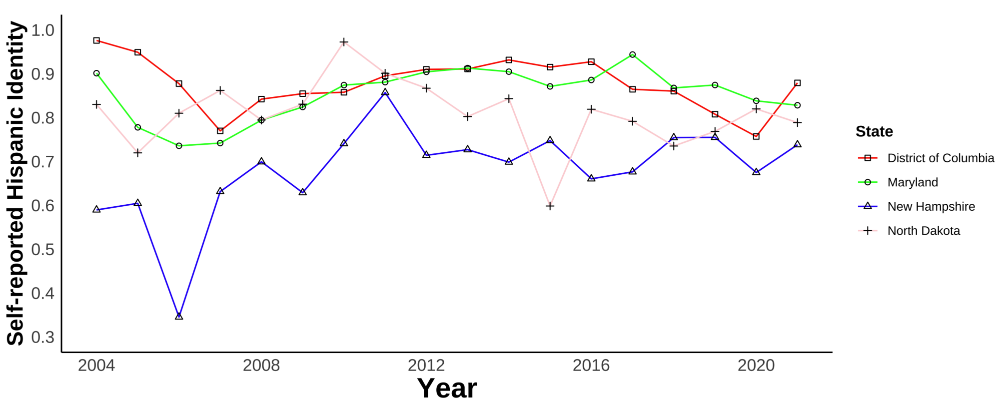
FIGURE 2

BIAS AND SELF-REPORTED HISPANIC IDENTITY IN THE LEAST AND MOST BIASED PLACES

(A) SKIN TONE IMPLICIT ASSOCIATION BIAS OVER TIME



(B) SELF-REPORTED HISPANIC IDENTITY OVER TIME



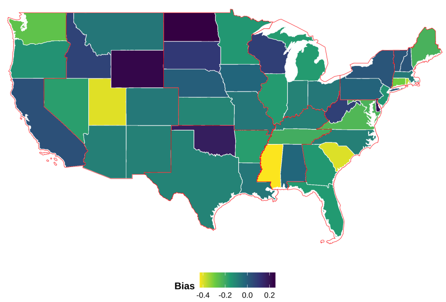
Note. These two panels show the trends in implicit bias (panel a) and self-reported Hispanic identity among Hispanic immigrants (panel b) of the least and most biased places in the data. The District of Colombia is the least biased geographical area, and North Dakota is the most biased. The bias units are in standard deviations. Self-reported Hispanic identity is among first, second, and third-generation Hispanic immigrants aged 17 and younger still living in intact families.

Note. Bias data is from the 2004-2021 Harvard's Project Implicit Association Test scores. Identity data is from the 2004-2021 Current Population Survey (CPS).

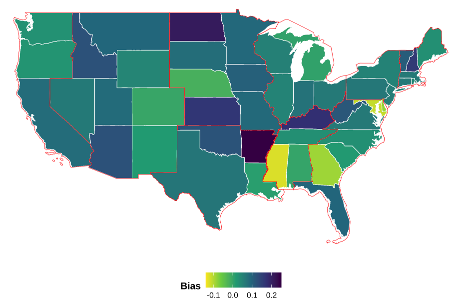
FIGURE 3

MAPS OF STATE-LEVEL IMPLICIT ASSOCIATION TEST BIAS OVER TIME MEASURE WITH CENSUS DIVISION REGIONAL BOUNDARIES

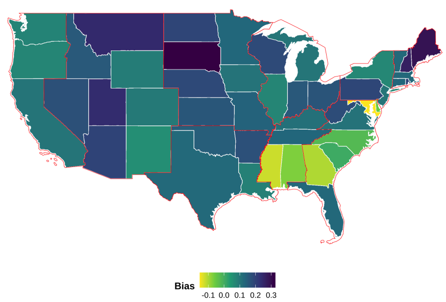
(A) STATE-LEVEL BIAS IN 2004



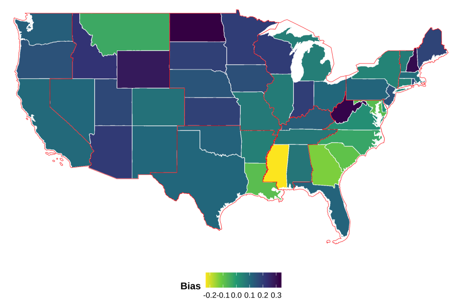
(B) STATE-LEVEL BIAS IN 2006



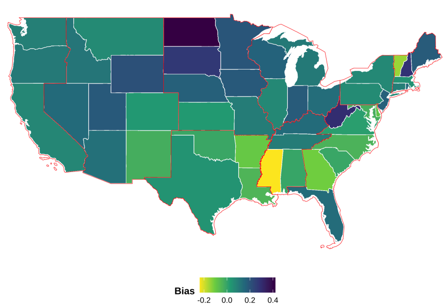
(C) STATE-LEVEL BIAS IN 2008



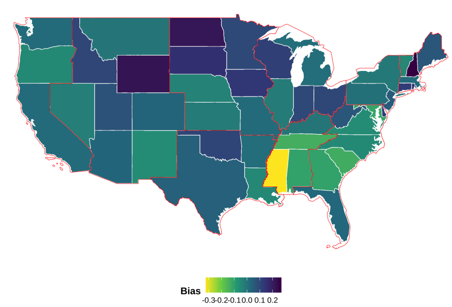
(D) STATE-LEVEL BIAS IN 2010



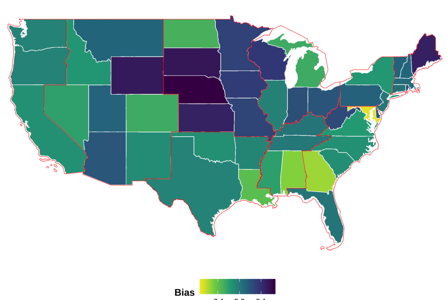
(E) STATE-LEVEL BIAS IN 2012



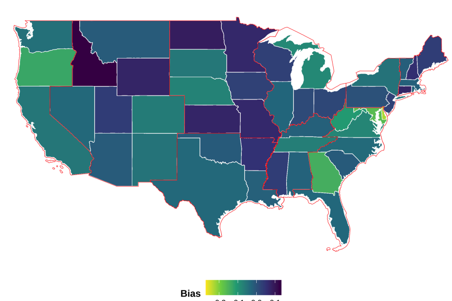
(F) STATE-LEVEL BIAS IN 2014



(G) STATE-LEVEL BIAS IN 2016

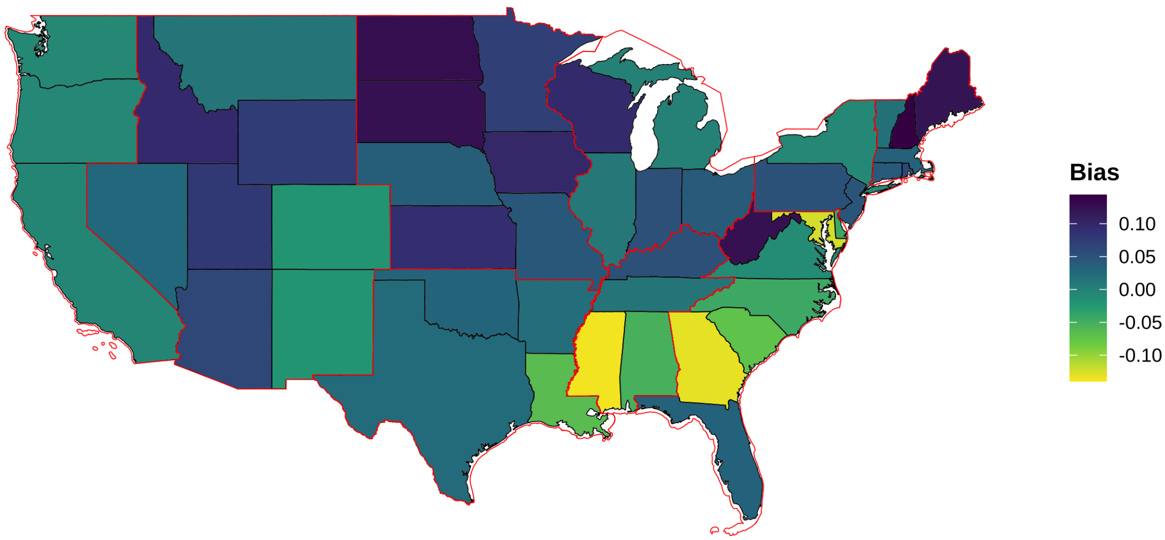


(H) STATE-LEVEL BIAS IN 2018



Note. In this figure, I show the state-level implicit bias in different years in the sample. Each panel presents state-level bias during a certain year. The boundaries in red represent the different Census divisions in the United States. Notice how there is a variation across states with-in a region.

FIGURE 4
MAPS OF STATE-LEVEL IMPLICIT ASSOCIATION TEST BIAS 2004-2021 MEASURE WITH CENSUS DIVISION REGIONAL BOUNDARIES



Note. In this figure, I show the state-level implicit bias in the sample of IAT tests from 2004 to 2021. The boundaries in red represent the different Census divisions in the United States. Notice how there is a variation across states with-in a region.

III.B. Measuring Prejudice

The implicit association test measures how people associate concepts—for example, Black and dark-skinned people—and evaluations—good, bad. Respondents are asked to quickly match words into categories shown on a screen. I provide a few examples of what a test taker would see on a skin tone implicit association test by Harvard's Project Implicit in figure (17).

I use skin tone implicit association test data to construct a state-level prejudice (Greenwald et al., 1998). This measure has been used in the social sciences, especially in psychology. Previous work has shown that IAT test scores are hard to manipulate (Egloff and

Schmukle, 2002) and are correlated to economic outcomes (Chetty et al., 2020; Glover et al., 2017), voting behavior (Friese et al., 2007), and health (Leitner et al., 2016). Moreover, Bursztyn et al. (2022) show that exposure to Arab and Muslim immigrants is predictive of lower IAT scores. I offer a graphical representation of the bias measure over time in the most and least biased places in (2a). A lower score implies less light-skin bias, whereas a higher score implies more discrimination against dark-skinned people. One-half of a standard deviation increase in bias is equivalent to the moving from Washington DC to North Dakota in 2012. I also show the state-level average bias over time in the maps in figure (3) and the overall average from 2004 to 2021 in figure (4).

Participating in the IAT, an online test, is voluntary. Therefore, the samples are not random and might suffer from selection bias in who decides to take the exam. However, bias reflected by Implicit Association Test (IAT) scores has been used as a proxy for prejudiced attitudes in an area Chetty et al. (2020). I provide a summary statistics of the sample in table (3). The average age of an Implicit Association Test (IAT) test taker is 28 years. Of the test takers, 68% are women, and 62% are Whites or 56% non-Hispanic Whites. The test takers are highly educated. I also present the demographics of the representative Current Population Survey (CPS) sample over the same period in table (3). The CPS and IAT samples are different demographically, with the IAT sample being more female, less White, and with higher levels of education.

TABLE 3
SKIN TONE IMPLICIT ASSOCIATION TEST (IAT) SCORES AND CURRENT POPULATION SURVEY (CPS) SAMPLES

	IAT	CPS
Characteristic	N = 1,519,309	N = 29,981,618
Age	28 (11)	38 (23)
Female	0.68	0.51
White	0.62	0.81
Non-Hispanic White	0.56	0.68
Hispanic	0.14	0.13
Education Levels		
Bachelor's degree	0.17	0.14
High school dropout	0.10	0.33
High school graduate	0.09	0.23
Master's degree	0.12	0.06
Other	0.48	0.21
Professional degree	0.05	0.02
Bias	0.30 (0.42)	

[*] Mean (SD)

[a] Data source is the 2004-2021 Harvard's Project Implicit Association Test scores and 2004-2020 Current Population Survey (CPS).

IV. EMPIRICAL STRATEGY

IV.A. The Determinants of Hispanic Identity

I first estimate if state-level bias is correlated with self-reported Hispanic identity. Let H^g be the self-reported Hispanic identity variable for a person from the g^{th} generation, where $g \in \{1,2,3\}$, and X be a vector of controls. I estimate different specifications for each generation g. The regression I will estimate is as follows:

$$\begin{aligned} H^g_{ist} = {} & \beta^g_1 Bias_{st} + \beta^g_2 DadCollegeGrad_{ist} + \beta^g_3 MomCollegeGrad_{ist} + \beta^g_4 Woman_{ist} \\ & + X^g_{ist}\pi + \gamma_{rt} + \varepsilon_{ist}; \text{where } g \in \{1,2,3\} \end{aligned} \tag{4}$$

Where H^g_{ist} is the self-reported identity of person i (whether the answer to "Are you of Hispanic or Latino origin?" was yes or no) that lives in state s and was interviewed in year t, $Bias_{st}$ is the average bias in state s at year t, $DadCollegeGrad_{ist}$ and $MomCollegeGrad_{ist}$ are indicator variables equal to 1 if the parents of person i are college graduates and zero otherwise, and $Woman_{ist}$ is dummy variable that is equal to one if person i is a woman. X^g_{ist} is a vector of controls. Additionally, γ_{rt} is region-time fixed effects that controls for region × year specific shocks. The region × year also controls for systematic differences between regions in the overall Hispanic population, or bias toward Hispanics, even if they vary over time.

The coefficient of interest in equation (4), β^g_1, captures the relationship between state-level bias and self-reported Hispanic identity. If $\beta^g_1 > 0$, then individuals living in a state with higher bias would be more likely to self-report Hispanic identity. The coefficient β^g_1 captures the with-in region and across state variation in bias which could be seen in figures (4), (2a), and (2b). In other words, I am estimating the relationship between bias and self-reported Hispanic identity by comparing states with-in a region to each other.

It could be the case that the desire to self-identify as Hispanic differs depending on the particular type of parents or grandparents. Consequently, I will further explore the relationship between bias and self-reported Hispanic identity by estimating the same equation by parents' and grandparents' types. I present another specification where I estimate the heterogeneous effect of bias on the different kinds of second- and third-generation immigrants by type of parents and grandparents, equation (4). For example, I could estimate a regression on a sample of second-generation immigrants by parental type, where parental types depend on parental place of birth. I first estimate a model on a sample of second-generation immigrants by parents' types, then on third-generation immigrants by grandparents' types:

$$
\begin{aligned}
H^2_{ist} = \beta^2_1 Bias_{st} &+ \sum_n \delta^2_n I_{\{ParentType_{ist}=n\}} \\
&+ \sum_m \alpha^2_m Bias_{st} \times I_{\{ParentType_{ist}=m\}} \\
&+ \beta^2_3 DadCollegeGrad_{ist} + \beta^2_4 MomCollegeGrad_{ist} \\
&+ \beta^2_5 Woman_{ist} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist}
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
H^3_{ist} = \beta^3_1 Bias_{st} &+ \sum_n \delta^3_n I_{\{GrandParentType_{ist}=n\}} \\
&+ \sum_m \alpha^3_m Bias_{st} \times I_{\{GrandParentType_{ist}=m\}} \\
&+ \beta^2_3 DadCollegeGrad_{ist} + \beta^2_4 MomCollegeGrad_{ist} \\
&+ \beta^2_5 Woman_{ist} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist}
\end{aligned} \tag{6}
$$

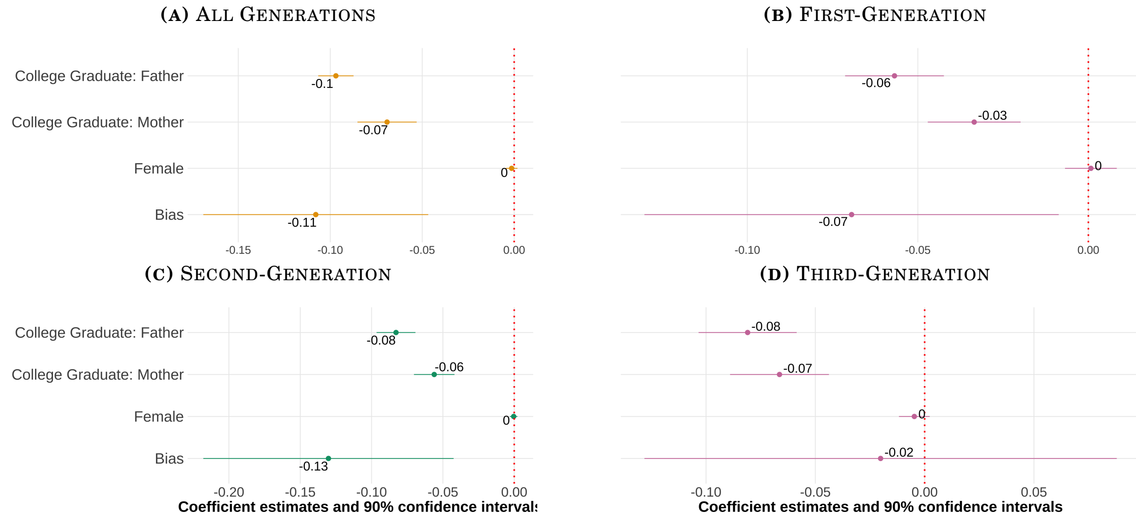
Where H^2_{ist} and H^3_{ist} are the self-reported identity of second and third-generation person i that lives in state s at time t. Regressions (5) and (6) include the state-year average bias, indicator variables $I_{\{ParentType_{ist}=n\}}$ and $I_{\{GrandParentType_{ist}=n\}}$, and the interaction between the bias and parental and grandparent type. The variable $I_{\{ParentType_{ist}=n\}}$ includes three categories of parents: 1) father born in a Spanish Speaking country and mother born in a Spanish-speaking country, or Hispanic-Hispanic (HH) and I will use as the reference category, 2) father born in a Spanish Speaking country and mother born in the US, or Hispanic-White (HW), 3) father born in the US and mother born in a Spanish speaking country, or White-Hispanic (WH). Thus, indicator variable $I_{\{ParentType_{ist}=WH\}}$ is equal to one if the person i has an objectively White father-Hispanic mother, and zero otherwise. The variable $I_{\{GrandParentType_{ist}=n\}}$ includes 15 possible combinations of the types of grandparents: 1) paternal grandfather born in a Spanish-speaking country, paternal grandmother born in a Spanish-speaking country, maternal grandfather born in a Spanish speaking country, and maternal grandmother born in a Spanish speaking country (HHHH) and I will use as the reference category, 2) paternal grandfather born in a Spanish speaking country, paternal grandmother born in a Spanish speaking country, maternal grandfather born in a Spanish speaking country, and maternal grandmother born in the US (HHHW), 3) paternal grandfather born in a Spanish speaking country, paternal grandmother born in a Spanish speaking country, maternal grandfather born in in the US, and maternal grandmother born in the US (HHWW), etc.

The coefficients of interest in equation (5), α_n^2, capture the relationship between state-level bias and self-reported Hispanic identity by parents' type of second-generation immigrants. In other words, α_n^2 estimates the difference in self-reported Hispanic identity between children of Hispanic-White (HW) and White-Hispanic (WH) and the reference group Hispanic-Hispanic (HH) and its relationship with bias. For example, if α_1^2, the coefficient of the indicator variable $I_{\{ParentType_{ist}=White-Hispanic(WH)\}}$, is $\alpha_1^2 > 0$, then the difference between the child of an objectively White father and Hispanic mother (WH) and objectively Hispanic father and Hispanic mother (HH) is positively correlated with state-level bias. Consequently, an increase in bias is associated with higher self-reported Hispanic identity among objectively White father and Hispanic mother (WH) children compared to objectively Hispanic father and Hispanic mother (HH) children.

Furthermore, the coefficients of interest in equation (6), α_m^3, captures the relationship between state-level bias and self-reported Hispanic identity by grandparents' type of third-generation immigrants. For example, if α_1^3, the coefficient of the indicator variable $I_{\{GrandParentType_{ist}=Hispanic-Hispanic-White-White(HHWW)\}}$, is $\alpha_1^3 > 0$. In this case, the difference between the child of objectively Hispanic-Hispanic-White-White grandparents (HHWW) and objectively Hispanic-Hispanic-Hispanic-Hispanic (HHHH) grandparents is positively correlated with state-level bias. Consequently, an increase in bias is correlated with higher self-reported Hispanic identity among objectively Hispanic-Hispanic-White-White (HHWW) children compared to objectively Hispanic-Hispanic-Hispanic-Hispanic (HHHH).

FIGURE 5

RELATIONSHIP BETWEEN SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY GENERATION



Note. I show four panels of estimating equation (4). I include region × year fixed effects with controls for sex, quartic age, and parental education. The dependent variable is self-reported Hispanic identity and the independent variable is state-level bias. Each panel is the results from the same regression but on different samples that are divided by generation. Standard errors are clustered on the state level. The samples include first-, second-, and third-generation Hispanic children ages 17 and below who live in intact families. First-generation Hispanic immigrants are children that were born in a Spanish-speaking county. Native-born second-generation Hispanic immigrants are children with at least one parent born in a Spanish-speaking country. Finally, native-born third-generation Hispanic immigrants are children with native-born parents and at least one grandparent born in a Spanish-speaking country.

IV.B. Estimating the Relationship Between Bias, Interethnic Marriages, and Migration

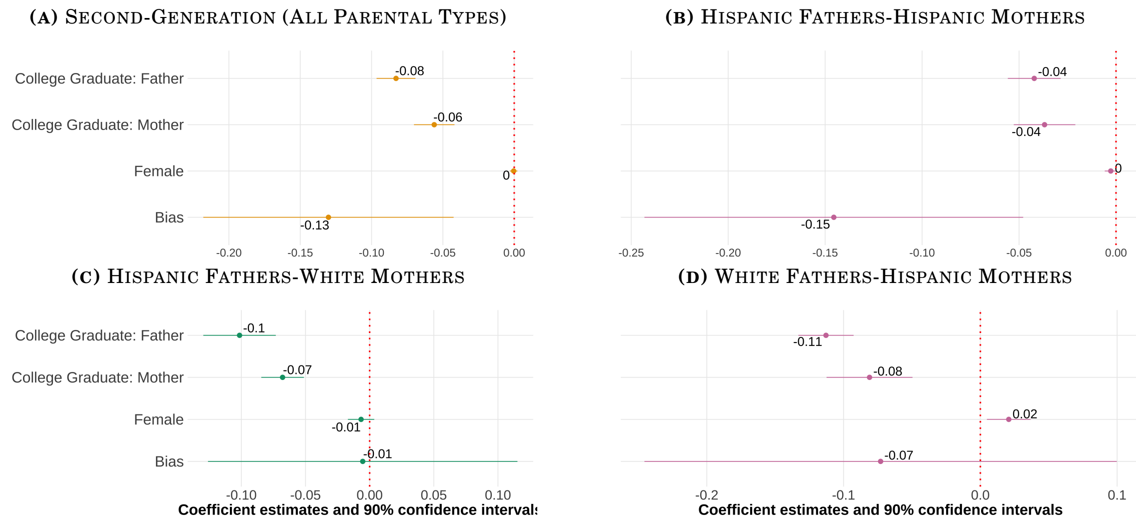
I will investigate the relationship between state-level bias and interethnic marriages. To this scope, the regressions for the estimation will be as follow:

$$
\begin{aligned}
HH^2_{ist} &= \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \\
HW^2_{ist} &= \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \qquad (7) \\
WH^2_{ist} &= \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist}
\end{aligned}
$$

Where HH^2_{ist}, HW^2_{ist}, and WH^2_{ist} are variables representing the type of parents of a second-generation Hispanic immigrant i in state s at time t. HH^2_{ist} represents Hispanic-husband-Hispanic-wife couples, HW^2_{ist} represents Hispanic-husband-White-wife couples, and

FIGURE 6

RELATIONSHIP BETWEEN SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY PARENTAL TYPES



Note. I show four panels of estimating equation (4). I include region × year fixed effects with controls for sex, quartic age, and parental education. The dependent variable is self-reported Hispanic identity and the independent variable is state-level bias. Each panel results from the same regression but on different samples divided by parents' types. Standard errors are clustered on the state level. The samples include second-generation Hispanic children ages 17 and below who live in intact families. Native-born second-generation Hispanic immigrant children with at least one parent born in a Spanish-speaking country.

WH^2_{ist} represents White-husband-Hispanic-wife couples. $Bias_{st}$ is the average bias in state s at time t, and X^2_{ist} is a vector of partner-specific controls that would affect a marriage match that includes the wife's and husband's education, age, and year of immigration to the United States.

There are two ways to estimate the effect of bias on the probability of an interethnic marriage forming. One way is by estimating equations (7) in three separate linear probability models. Another way is by estimating an ordered multinomial logistic regression. The dependent variable in the logistic regression will be an ordinal variable with a value of (1) zero corresponding to an endogenous marriage; (2) one corresponding to an interethnic Hispanic-husband-White-wife marriage; (3) two corresponding to an interethnic White-husband-Hispanic-wife marriage. The coefficient of interest from (7) is β_1, which estimates the effect of bias on the probability of forming an interethnic marriage. If $\beta_1 < 0$, higher bias is correlated with lower log odds of an interethnic marriage forming.

I am also interested in investigating the relationship between state-level bias and migration. For this purpose, I use the following specifications to estimate the relationship between state-level bias and migration:

$$BirthPlaceMigration^2_{ist} = \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{8}$$

$$BirthPlaceMigration^2_{ilb} = \beta^2_1 Bias_{lb} + X^2_{ilb}\pi + \gamma_{lb} + \varepsilon_{ilb} \tag{9}$$

Where $BirthPlaceMigration^2_{ist}$ is an indicator variable equal to one if person i in state s at the interview t lives in a state that is different from their state of birth and zero otherwise. $BirthPlaceMigration^2_{ilb}$ is an indicator variable that is equal to one if person i in birth state l does not currently live in the same state they lived in at the year of birth b and zero otherwise. The analysis of equations (8) and (9) is restricted to second-generation Hispanic immigrants with both parents born in a Spanish speaking country. The coefficient of interest from the regressions is β^2_1, which captures the effect of bias on migration.

Furthermore, to study the relationship between bias and the migration variables introduced above, I use two different ways to define the bias variable. In the first definition from equation (8), I estimate the relationship between the average bias in state s at the time of the interview t and $BirthPlaceMigration^2_{ist}$. In the Second specification from equation (9), I estimate the relationship between the average bias in state of birth l at the year of birth b on $BirthPlaceMigration^2_{ilb}$.

I will also estimate the selection into states based on bias levels. In other words, I want to estimate whether there's a relationship between the difference in state-level bias between the state i is currently living in and their birth state and self-reported Hispanic identity. The estimation equation for the relationship is:

$$Y_{ist} = \beta_0 + \beta^2_1 Hispanic_{ist} + X^2_{ist}\pi + \varepsilon_{ist} \tag{10}$$

Where $Y_{ist} \equiv Bias_{ist} - Bias_{ilb}$, $Bias_{ist}$ is i's state-level bias in state s at the time of interview t, and $Bias_{ilb}$ is i's state-level bias in state of birth l at the birth year b. The analysis is restricted to second-generation Hispanic immigrants with both parents born in a Spanish speaking country ‘that migrated from the state they were born in b to another state s. The coefficient of interest is β_1^2, which captures whether a person that self-reports Hispanic identity self-selects and migrates into states that are more or less biased. For example, if $\beta_1^2 > 0$, then a person who self-reports Hispanic identity, compared to a person that does not, moves from states with less bias to a state with more bias.

V. Results and Discussion

In this section, I will present and discuss the results that I find to answer the following question. Is Hispanic self-identification associated with attitudes toward ethnic minorities in places individuals live in? Is the probability of an interethnic marriage associated with attitudes toward ethnic minorities? Are migration decisions associated with attitudes toward ethnic minorities in places they live in?

V.A. Relationship between Attitudes and Identity

I find that state-level bias is negatively correlated with self-reported Hispanic identity. I find that a one standard deviation increase in state-level bias is correlated with 7 percentage points decrease in self-reported Hispanic identity among first-generation Hispanic immigrants and 13 percentage points decrease in self-reported Hispanic identity among second-generation Hispanic immigrants. I also find a negative correlation between bias and self-reported Hispanic identity in second-generation Hispanic immigrants children of parents born in a Spanish-speaking country and third-generation Hispanic immigrants children of four grandparents born in a Spanish-speaking country.

I show the results of estimating equation (4) using the different specifications by generation in figure (5). Each panel evaluates a different specification with controls for parental education, sex, age, fraction of Hispanic people in a state, and region × year fixed effect. Panel (A) of the figure (5) includes the results of estimating equation (4) on the overall

TABLE 4
RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED HISPANIC IDENTITY: BY GENERATION

	(1) All Gens H_{ist}	(2) First Gen H^1_{ist}	(3) Second Gen H^2_{ist}	(4) Third Gen H^3_{ist}
Bias	−0.10**	−0.07*	−0.13**	−0.02
	(0.04)	(0.04)	(0.05)	(0.07)
Female	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	−0.05***	−0.03***	−0.06***	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.06***	−0.06***	−0.08***	−0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
N	844481	85390	560100	198991
Mean	0.91	0.96	0.94	0.82
Year × Region FE	X	X	X	X

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

[1] Each column is an estimation of a heterogeneous effect of regression (4) by generation with region × year fixed effects. I include controls for sex, quartic age, fraction of Hispanics in a state, and parental education. I also added parents' (HH, HW, and WH) and grandparents' (HHHH, HHHW, HHWH, etc.) type dummy variables to the regression on second and third generation immigrants, where H is objectively Hispanic (born in a Spanish Speaking Country) and W is objectively White (native born). Standard errors are clustered on the state level.
[2] The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third-generation Hispanic immigrant children with native born parents and at least one grandparent born in a Spanish speaking country.
[3] Data source is the 2004-2021 Current Population Survey.

sample—i.e. pooling first-, second-, and third-generations together. I find that state-level bias is associated with a ten percentage points decrease in self-reported Hispanic identity. Panel (B) of figure (5) includes the results of estimating equation (4) on a sample of first-generation Hispanic immigrants. I find a negative relationship between state-level bias and self-reported Hispanic identity. A one standard deviation increase in bias is correlated with a six percentage points decrease in self-reported Hispanic identity. Panel (C) of figure (5) includes the results of estimating equation (4) on a sample of second-generation Hispanic immigrants. I find a negative relationship between state-level bias and self-reported Hispanic identity among second-generation immigrants. A one standard deviation increase in bias is correlated with a ten percentage points decrease in self-reported Hispanic identity. Panel (D) of figure (5) includes the results of estimating equation (4) on a sample of third-generation Hispanic immigrants. I find no statistically significant relationship between bias and self-reported Hispanic identity among third-generation immigrants.

TABLE 5

RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED HISPANIC IDENTITY AMONG SECOND-GENERATION HISPANIC IMMIGRANTS: BY PARENTAL TYPE

Parents Type	All	Both Parents from Spanish Speaking Country (HH)	Father from Spanish Speaking Country (HW)	Mother from Spanish Speaking Country (WH)
	(1) H^2_{ist}	(2) H^2_{ist}	(3) H^2_{ist}	(4) H^2_{ist}
Bias	−0.13**	−0.15**	−0.01	−0.07
	(0.05)	(0.06)	(0.07)	(0.10)
Female	0.00	0.00	−0.01	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)
College Graduate: Mother	−0.06***	−0.04***	−0.07***	−0.08***
	(0.01)	(0.01)	(0.01)	(0.02)
College Graduate: Father	−0.08***	−0.04***	−0.10***	−0.11***
	(0.01)	(0.01)	(0.02)	(0.01)
N	560 100	405 116	88 421	66 563
Year × Region FE	X	X	X	X
Mean	0.94	0.96	0.9	0.83

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

[1] Each column is an estimation of a heterogeneous effect of regression (4) by type of parents with region × year fixed effects. I include controls for sex, quartic age, fraction of Hispanics in a state, and parental education. Standard errors are clustered on the state level.

[2] The samples include second-generation Hispanic children ages 17 and below who live in intact families. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country.

[3] Column (1) includes the results to regression (4) on all second-generation immigrants, column (2) includes the results to regression (4) on second-generation immigrants that who has a father and mother that were born in a Spanish speaking country (HH), column (3) includes the results to regression (4) on second-generation immigrants that who has a father that was born in a Spanish speaking country and a native born mother (HW), and column (4) includes the results to regression (4) on second-generation immigrants that who has a native born father and a mother that was born in a Spanish speaking country (WH).

[4] Data source is the 2004-2021 Current Population Survey.

In table (5), I provide the results of estimating equation (4) on a sample of second-generation immigrants separately for each parent type—Spanish speaking country born father-Spanish speaking country born mother (HH), a native-born father-Spanish speaking country born mother (WH), and Spanish speaking country born father-native born mother (HW)—with region × year fixed effects. I find a significant negative correlation between bias and endogenous Hispanic identity among second-generation Hispanic immigrant children of endogamously Hispanic parents—both the father and mother were born in Spanish speaking country. A one standard deviation increase in bias is correlated with a 15 percentage points reduction in the self-reported Hispanic identity of second-generation Hispanic immigrant children of the Hispanic father-Hispanic mother (HH) (table 5 column 2). The result is statistically significant. A one standard deviation increase in bias is correlated with a one percentage points decrease in the Hispanic identity of second-generation Hispanic immigrant children of the Hispanic father-White mother (HW) (table 5 column 3). The result is statistically insignificant. A one standard deviation increase in bias is correlated with a seven percentage points decrease in the Hispanic identity of second-generation Hispanic immigrant children of the White father-Hispanic mother (WH) (table (5) column 4). The results are statistically insignificant.

The results above indicate that attitudes are not correlated with the self-reported Hispanic identity of third-generation immigrants. One reason for this finding is that first and second-generation immigrants aim to integrate and assimilate into their new community, while third-generation immigrants are already assimilated. The results are consistent with the findings of Abramitzky et al. (2020) where they show that second-generation immigrants would change their foreign-sounding names to fit in and assimilate.

Furthermore, I estimate another specification of equation (4) by the number of grandparents that are objectively Hispanic—born in a Spanish-speaking country—and are third-generation Hispanic immigrants. For example, suppose a person has two grandparents born in a Spanish-speaking country. In that case, they have two 'Hispanic' grandparents, and I will estimate a specification for all of those that belong to this group. The result of evaluating the effect of bias on people with one objectively Hispanic grandparent is in table (6) column

(1), with two objectively Hispanic grandparents is in table (6) column (2), with three objectively Hispanic grandparents is in table (6) column (3), and with four objectively Hispanic grandparents is in table (6) column (4). I find a statistically significant relationship between and self-reported Hispanic identity among third-generation Hispanic immigrants with four objectively Hispanic grandparents. A one standard deviation increase in bias is associated with 14 percentage points decrease in the likelihood of a third-generation Hispanic immigrant with four objectively Hispanic grandparents to self-report Hispanic identity. Bias has no significant effect on children of interethnic grandparents.

TABLE 6

RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED HISPANIC IDENTITY AMONG THIRD-GENERATION HISPANIC IMMIGRANTS: BY GRANDPARENTAL TYPE

	Number of Hispanic Grandparents			
	(1)	(2)	(3)	(4)
	One	Two	Three	Four
Bias	−0.04	0.03	0.19	−0.14*
	(0.11)	(0.09)	(0.26)	(0.07)
Female	−0.01	0.00	−0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Mother	−0.11***	−0.07***	0.02	−0.02
	(0.03)	(0.02)	(0.02)	(0.01)
College Graduate: Father	−0.11***	−0.08***	0.02	−0.03*
	(0.03)	(0.01)	(0.01)	(0.01)
N	55051	74100	12194	57646
Year × Region FE	X	X	X	X

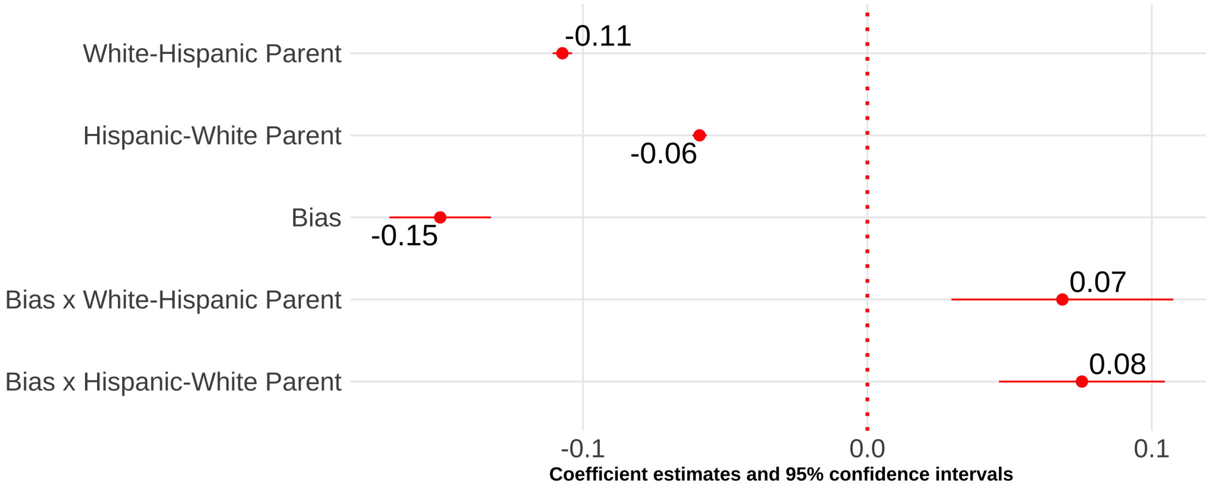
* p < 0.1, ** p < 0.05, *** p < 0.01

[1] Each column is an estimation of equation (4) restricted to third-generation Hispanic immigrants by number of Hispanic grandparents with region × year fixed effects. I include controls for sex, quartic age, fraction of Hispanics in a state, and parental education. Standard errors are clustered on the state level.

[2] The samples include third-generation Hispanic children ages 17 and below who live in intact families. Native born third-generation Hispanic immigrant children with at least one grandparent born in a Spanish speaking country.

[3] Data source is the 2004-2021 Current Population Survey.

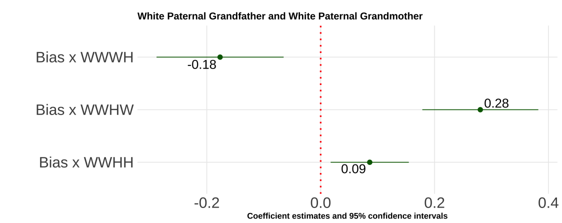
FIGURE 7
RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED IDENTITY ON SECOND-GENERATION HISPANICS: INTERACTION



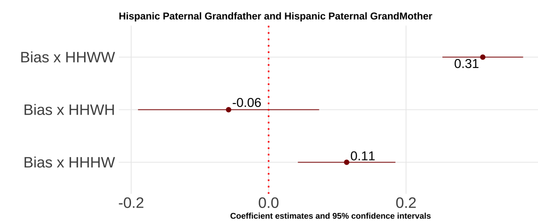
Note. I show four panels of estimating equation (5). I include region × year fixed effects with controls for sex, quartic age, faction of Hispanics in a state, and parental education. Each panel is the results from the same regression but is presented with different combinations of grandparents' types. Robust standard errors are reported. The samples include second-generation Hispanic children ages 17 and below who live in intact families. Native-born second-generation Hispanic immigrant children with at least one parent born in a Spanish-speaking country.

FIGURE 8
RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED IDENTITY ON THIRD-GENERATION HISPANICS: INTERACTION

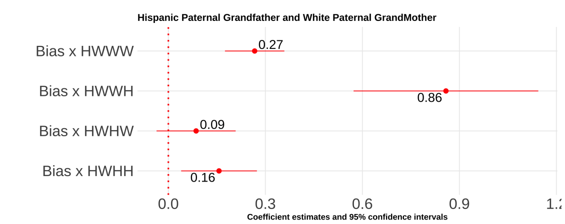
(A) WHITE PATERNAL GRANDFATHER AND WHITE PATERNAL GRANDMOTHER COMBINATIONS



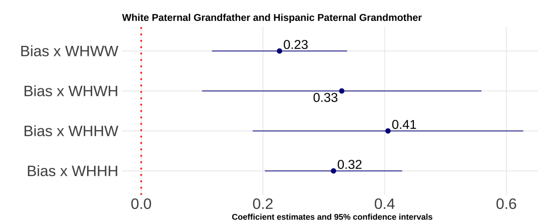
(B) HISPANIC PATERNAL GRANDFATHER AND HISPANIC PATERNAL GRANDMOTHER COMBINATIONS



(C) HISPANIC PATERNAL GRANDFATHER AND WHITE PATERNAL GRANDMOTHER COMBINATIONS



(D) WHITE PATERNAL GRANDFATHER AND HISPANIC PATERNAL GRANDMOTHER COMBINATIONS



Note. I show four panels of estimating equation (6). I include region × year fixed effects with controls for sex, quartic age, and parental education. Each panel results from the same regression but is presented by different combinations of grandparents' types. The syntax of the grandparents' type consists of four letters. The first letter represents the paternal grandfather, the second letter represents the paternal grandmother, the third letter represents the maternal grandfather, and the fourth letter represents the maternal grandmother. A grandparent would be of type H if they were born in a Spanish-speaking country and of type W if they were native-born. Robust standard errors are reported. The samples include third-generation Hispanic children ages 17 and below who live in intact families. Third-generation Hispanic immigrant children with native-born parents and at least one grandparent born in a Spanish-speaking country.

I estimate the heterogeneous relationship between bias and self-reported Hispanic identity by parents' types of equation (5) and show the results in figure (7). This specification estimates the heterogeneous effect of bias on a sample of second-generation immigrants by parental type. Moreover, I find a statistically significant positive heterogeneous relationship between bias and parents on self-reported Hispanic identity. I find that a one standard deviation increase in state-level bias correlates with a seven percentage points increase in Hispanic identity in children with an objectively Hispanic Father-White Mother (HW) compared to the reference group—children of an objectively Hispanic father-Hispanic mother (HH). I find that a one standard deviation increase in bias correlates with an eight percentage points increase in self-reported Hispanic identity in children with an objectively

White Father-Hispanic Mother (WH) compared to children of an objectively Hispanic father-Hispanic mother.

I estimate the heterogeneous relationship between bias and self-reported Hispanic identity by grandparents' types of equation(6) and show the results in figure (8). I mostly find statistically significant positive heterogeneous effect of bias on the different types of third-generation Hispanic immigrants compared to children of objectively Hispanic paternal grandfather-Hispanic paternal grandmother-Hispanic maternal grandfather-Hispanic maternal grandmother (HHHH).[12]

To simplify, I will discuss the results in four groups by the country of origin of the paternal grandparents with the combination of the maternal grandparents. Among third-generation immigrants with objectively White paternal grandfather-White paternal grandmother (figure 8a): (1) those with objectively Hispanic maternal grandparents are nine percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (2) those with objectively Hispanic maternal grandfather and White maternal grandmother are 28 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (3) those with objectively White maternal grandfather and Hispanic maternal grandmother are 18 percentage points less likely than children with HHHH grandparents to self-identify as Hispanic.

Among third-generation immigrants with objectively Hispanic paternal grandfather-Hispanic paternal grandmother (figure 8b): (1) those with objectively Hispanic maternal grandfather and White maternal grandfather are 11 percentage points more likely than children with objectively HHHH grandparents to self-identify as Hispanic; (2) those with objectively White maternal grandfather and Hispanic maternal grandmother are as likely as children with HHHH grandparents to self-identify as Hispanic; (3) those with objectively White maternal grandfather and White maternal grandmother are 31 percentage points

12. The syntax of the grandparents' type consists of four letters. The first letter represents the paternal grandfather, the second letter represents the paternal grandmother, the third letter represents the maternal grandfather, and the fourth letter represents the maternal grandmother. A grandparent would be of type H if they were born in a Spanish-speaking country and of type W if they were native-born.

more likely than children with HHHH grandparents to self-identify as Hispanic.

Among third-generation immigrants with objectively Hispanic paternal grandfather-White paternal grandmother (figure 8c): (1) those with objectively Hispanic maternal grandparents are 16 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (2) those with objectively Hispanic maternal grandfather and White maternal grandmother are as likely as children with HHHH grandparents to self-identify as Hispanic; (3) those with objectively White maternal grandfather and Hispanic maternal grandmother are 86 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (4) those with objectively White maternal grandfather and White maternal grandmother are 27 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic.

Among third-generation immigrants with objectively White paternal grandfather-Hispanic paternal grandmother (figure 8d): (1) those with objectively Hispanic maternal grandparents are 32 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (2) those with objectively Hispanic maternal grandfather and White maternal grandmother are 41 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (3) those with objectively White maternal grandfather and Hispanic maternal grandmother are 33 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (4) those with objectively White maternal grandfather and White maternal grandmother are 23 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic.

V.B. The Relationship Between Bias, Interethnic Marriages, and Migration

In this section, I will discuss the results of estimating the relationship between bias and intermarriages (equation 7), and bias and migration (equations 8, 9, and 10). Since the CPS does not report the state of birth of a person, I use the 2004-2021 Censuses to construct a sample of second-generation Hispanic immigrants (Flood et al., 2021). I construct a mover variable if they moved from their state of birth to another state. I find that bias is not correlated with migration decisions among second-generation immigrants. I find that self-reported Hispanic sort out of state of birth with low bias into states with higher bias. I also find that an increase in bias is associated with a decrease in the likelihood of interethnic marriage formation.

I find no relationship between and the migration decisions objectively Hispanic parents of second-generation Hispanic children make. I show the results of estimating regressions 8, 9 , and 10 in table (7). The results of estimating regression 8 are in column (1) of table (7), where the dependent variable is an indicator variable that is equal to one if a person migrated from the state they were born in, and zero otherwise. $Bias_{st}$ is the average bias in the state the interviewee is currently living s during the year of the survey t. I find that bias is not significantly correlated with the migration decisions. The results of estimating regression 9 are in column (2), where the dependent variable is an indicator variable that is equal to one if a person migrated from the state they were born in, and zero otherwise. $Bias_{lb}$ is the average bias in the state the interviewee was born in l during their year of birth b. I find no statistically significant effect of bias on migration decisions taken by the parents of second-generation Hispanic immigrants.

By estimating equation (10), I find that among second generation Hispanic immigrants movers with objectively Hispanic parents, those that self-report Hispanic identity move from a state of birth with lower bias to a state with higher bias. The results to estimating (10) are shown in table (7) column (3). The dependent variable is the difference in bias between the state person i currently lives in at time t and bias in the state of birth l during birth year b, i.e. $Bias_{ist} - Bias_{ilb}$. Among second-generation Hispanic immigrant movers, those that self-report Hispanic identity live in states that are 0.02 standard deviations more biased than the state they were born. Even though this result shows that there is selection into more biassed states among second-generation immigrants, it does not affect my main results showing correlation between bias and self-reported Hispanic identity. Since those that identify as Hispanics are the movers, this implies that my assessments of the relationship between bias and self-reported Hispanic identity might underestimate the effect of bias.

Moreover, I estimate equations (7) as a multinomial ordered logit and find that a one standard deviation increase in bias decreases the likelihood of interethnic marriages. By estimating (7) as a multinomial ordered logit with an ordinal dependent variable where a value of zero represents a Hispanic father-Hispanic mother, one represents a Hispanic father-White mother, and two represents a White father-Hispanic mother. In table (8) I present the regression results the marginal effects at the mean of the exponentiated estimates since the results of a logit regression cannot be directly interpreted. I find that a one standard deviation increase in bias decreases the probability of having inter-ethnic parents by two percentage points.

TABLE 7
RELATIONSHIP BETWEEN BIAS AND MIGRATION

	(1) Migrated from Birth Place	(2) Migrated from Birth Place	(3) $Bias_{ist} - Bias_{ilb}$
$Bias_{st}$	0.06		
	(0.12)		
$Bias_{lb}$		−0.09	
		(0.26)	
Hispanic			0.02***
			(0.01)
Female	0.00	0.00	0.00*
	(0.00)	(0.00)	(0.00)
College Graduate: Mother	0.03***	0.03***	0.00
	(0.01)	(0.01)	(0.01)
College Graduate: Father	0.02**	0.02***	−0.01
	(0.01)	(0.01)	(0.01)
N	352 712	185 024	12 806
Mean	0.09	0.09	−0.02
Year (t)× Region FE	X		
Birthyear (b)× Birth Region FE		X	

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

[1] Each column is an estimation of equations (8) in column (1), (9) in column (2), and (10) in column (3).
[2] Column (1) is a regression where the left hand side variable is a dummy variable that is equal to one if a person migrated from the state were born in and the right hand side variable is bias the year of survey. Column (2) is a regression where the left hand side variable is a dummy variable that is equal to one if a person migrated from the state were born in and the right hand side variable is bias the year of birth in the state of birth. Column (3) is a regression where the left hand side variable is the difference between state-level bias during the year of the survey in the current state the respondent is living in, and state-level bias during the year of birth in the state of birth and the right hand side variable is self-reported Hispanic identity. This regression captures the selection of those that self-reported Hispanic identity into states with different levels of bias. I include controls for sex, quartic age, parental education, fraction of Hispanics in a state, and region × year fixed effects. Standard errors are clustered on the state level.
[3] The samples include children ages 17 and below who live in intact families. Native born second-generation Hispanic immigrant children with both parents born in a Spanish speaking country. The sample in the column (3) regression is further restricted to only those that migrated from their birth state.
[4] Data source is the 2004-2021 Census Data.

TABLE 8
RELATIONSHIP BETWEEN BIAS AND INTERETHNIC MARRIAGES: MARGINAL EFFECT OF AN ORDINAL MULTILOGIT AND PROBIT REGRESSIONS

	(1) Probit Marginal Effect at Mean	(2) Logistic Marginal Effect at Mean
Bias	−0.04***	−0.02***
	(0.00)	(0.00)
College Indicator: Wife	−0.05***	−0.03***
	(0.00)	(0.00)
College Indicator: Husband	−0.07***	−0.05***
	(0.00)	(0.00)
Wife's Age	0.00***	0.00***
	(0.00)	(0.00)
Husband's Age	0.00	0.00
	(0.00)	(0.00)
Year Immigrated: Wife	0.00***	0.00***
	(0.00)	(0.00)
Year Immigrated: Husband	0.00***	0.00***
	(0.00)	(0.00)

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

[1] This is the result to estimating (7) as a multinomial ordered probit and logit regression.
[2] The results are of regressions where the left hand side variable is an interethnic marriage ordinal variable where a value of: 1) zero is an endogamous marriage with objectively Hispanic-Husband-Hispanic-Wife; 2) one is an interethnic marriage with objectively Hispanic-Husband-White-Wife; 3) two is an interethnic marriage with objectively White-Husband-Hispanic-Wife. I include controls for partners' sex, age, education, and years since immigrating to the United States. Standard errors are clustered on the state level.
[3] Data source is the 2004-2021 Current Population Survey Data.

V.C. Discussion

The results in this paper show that bias is negatively correlated with the self-reported Hispanic identity of Hispanic immigrants. In this paper, my aim is not to establish a causal effect of bias on self-reported Hispanic identity. I aim to establish a correlation between bias and self-reported identity to show that depending on the bias levels in a state, the racial and ethnic gaps that rely on self-reported identity might be overestimating or underestimating the effect of discrimination.

A few questions could arise regarding the validity of the results. First, the self-reported identity in the Current Population Survey (CPS) is reported by a household respondent—

parent or adult caregiver. Thus, the 'self-reported' ethnic identity might not reflect a child's true identity. I view the identity that a parent or a caregiver reports to be a true representation of the child's true identity since parents are essential in shaping the identity of their children. Also, I compare states with a high and low bias for my analysis. The estimates will not be threatened as long as the likelihood of self-reporting does not differ between these states. Moreover, Duncan and Trejo (2011a) show that reported Hispanic identification does not vary with who is the household respondent. Additionally, I present the main effect of self-reported Hispanic identity by the household respondent in table (9) and the results to estimating estimation of equation (4) by the proxy respondent in table (10) on all the generation. The main effect of the reported Hispanic identity of children is 94% when the mother is the proxy, 92% when the father is the proxy, and 96% when the child themselves or another caregiver was the household respondent.[13] The estimation of equation (4) by the proxy respondent, table (10), mostly yields a negative effect of bias on self-reported Hispanic identity for all types of proxy respondents. The relationship between bias and self-reported Hispanic identity is an increase of one percentage point when the objectively White mother is the proxy respondent, but the result is not statistically significant. The relationship between bias and self-reported Hispanic identity is a reduction of six percentage points when the objectively Hispanic mother is the proxy respondent, but the result is not statistically significant. The relationship between bias and self-reported Hispanic identity is a reduction of 13 percentage points when the objectively White father is the proxy respondent, but the result is not statistically significant. The relationship between bias and self-reported Hispanic identity is a reduction of seven percentage points when the objectively Hispanic father is the proxy respondent, and the result is statistically significant. The relationship between bias and self-reported Hispanic identity is a reduction of seven percentage points when the person themselves is the proxy respondent, but the result is not statistically sig-

13. According to the Current Population Survey (CPS), a person can be the household respondent if they are at least 15-year-old with enough knowledge about the household. Thus, when the proxy is 'self', the respondent is between the ages of 15 and 17.

nificant. The relationship between bias and self-reported Hispanic identity is a reduction of 17 percentage points when another caregiver is the proxy respondent, and the result is statistically significant.

TABLE 9
MAIN EFFECT OF PROXY ON SECOND-GENERATION'S HISPANIC SELF-IDENTIFICATION

Parents Type	All	Hispanic-Hispanic	Hispanic-White	White-Hispanic
Proxy:				
Mother	0.94	0.96	0.9	0.84
Father	0.92	0.96	0.86	0.8
Self	0.96	0.97	0.9	0.84
Others	0.96	0.97	0.92	0.9

A second concern is that the Implicit Association Test (IAT) is voluntary and not representative of the population. While I do not claim that the Implicit Association Test (IAT) as a proxy for bias will represent the population, Egloff and Schmukle (2002) show that they are hard to manipulate. Several studies had shown that Implicit Association Test (IAT) are correlated with economic outcomes (Chetty et al., 2020; Glover et al., 2017), voting behavior (Friese et al., 2007), decision-making (Bertrand et al., 2005; Carlana, 2019), and health (Leitner et al., 2016). Another concern could be that the Implicit Association Test (IAT) test takers' characteristics is changing over time and thus, are not the same. I address this concern by including non-parametric region × year fixed effects that would control for the systematic difference in the characteristics of test takers between regions. These changes will be controlled for as long as the differences in the characteristics between test takers do not vary across states within a region.

Moreover, I use different specification and prejudice measures as a robustness check. First, I use the General Security Survey (GSS)—nationally representative survey—to construct a measure of racial prejudice following Charles and Guryan (2008). A downside of using the GSS is that most of the questions used to build the prejudice measure in Charles and Guryan (2008) were discontinued after 1996. Consequently, making it is hard to merge the measure with the CPS data since the CPS only started to ask about the place of birth of parents in 1994. Thus, I use the GSS to construct a residual prejudice 15-20 years before the CPS survey year, which means that it will be a measure of prejudice at roughly the time of birth of the CPS sample. Using the GSS data, I mostly find negative effects of prejudice on self-reported Hispanic identity. However, these results are only significant among second-generation Hispanic immigrant children of native-born fathers and Spanish speaking country born mothers, third-generation Hispanic immigrants, and third-generation Hispanic immigrants with two grandparents that were born in a Spanish-speaking country (see tables 12, 13, and 14.) These results suggest that 'residual' prejudice mainly affects interethnic children.

Another concern could be reverse causality between having more Hispanic people in a state and implicit bias. It could be the case that the number of Hispanic people in a state affects the implicit bias on the residents of that state. For example, having more Hispanics in Florida could affect the implicit bias of the residents of Florida. To show that this is not the case, I provide figures (10) and (11) as evidence. Figure (10) plot the percent of self-reported Hispanics in a state at a specific year on the average implicit bias in the same state during that year. Figure (11) plots the percent of objectively second-generation Hispanic children of endogamous marriages in a state at a certain year on the average implicit bias in the same state during that year. I find no correlation between bias and the number of Hispanics in a state, thus, making the case of reverse causality unlikely.

Finally, estimating the relationship between bias (prejudice) and self-reported Hispanic identity could be biased if those that do not self-report Hispanic identity migrate to more prejudiced states. I have shown in a section above that this is not the case (table 7). I find no evidence that there's a relationship between migration decisions and bias. Additionally, I find that those that report Hispanic identity move out of birth states that are less biases and live in states that are more biased at the time of the survey. Thus, my results might underestimate the relationship between bias.

VI. Conclusion

As the United States becomes more multi-racial and multi-ethnic, self-reported identity will significantly affect representation, distributional politics, and government transfers. The determinants of endogenous identity are particularly important to researchers interested in the role of discrimination on earnings gaps. In this paper, I show how individual characteristics and social attitudes toward racial and ethnic minorities affect the self-reported identity of persons with Hispanic ancestry in the United States. I find that people of Hispanic ancestry are less likely to identify as Hispanic in states with more significant bias. The relationship between self-reported Hispanic identity and bias is more prominent among first- and second-generation immigrants, where a one standard deviation increase in bias correlated with a seven and 13 percentage points decrease in self-reported Hispanic identity. Also, among second-generation immigrants children with Hispanic Fathers-Hispanic Mothers are affected more by state-level bias. A one standard deviation increase in bias is correlated with 15 percentage points decrease in self-reported Hispanic identity among second-generation Hispanic immigrants children of objectively Hispanic parents. I also find that bias is negatively correlated with interethnic marriage matching and is uncorrelated with migration decisions.

The results are important because of the consequences of assimilation and mobility. They could indicate that bias could significantly affect how economists estimate the earnings gap. Most research concerning race and ethnicity relies on self-reported race and ethnic identity measures. Since state-level bias is correlated with less self-reported Hispanic identity, the characteristics of those who do not self-report Hispanic identity would have important consequences. For example, suppose the people whose identities are most likely to be affected by bias are the most educated. In this case, the racial and ethnic gaps will be overestimated in the most biased states. Additionally, the identity decisions will most likely affect people's decisions, investments, and well-being in profound way.

Furthermore, this paper could open the door to other areas where researchers could estimate the relationship of bias on self-reported identities. The analysis of bias on self-reported Hispanic identity could be applied to other groups. For example, we could estimate the effect of bias on the identities of sexual minorities and other ethnic and racial minorities such as Asian, Black, Native American, and Arab populations in the United States. Researchers could also explore the differences in outcomes between the ethnic and racial minorities that self-report to those that do not by using restricted administrative data.

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APPENDIX A: TABLES

TABLE 10

RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED HISPANIC IDENTITY: BY PROXY RESPONDENT

	Proxy Respondent					
	White Mother	Hispanic Mother	White Father	Hispanic Father	Self	Other
	(1)	(2)	(3)	(4)	(5)	(6)
	H_{ist}	H_{ist}	H_{ist}	H_{ist}	H_{ist}	H_{ist}
Prejudice Measure	0.01	−0.06	−0.13	−0.07***	−0.07	−0.17**
	(0.11)	(0.03)	(0.11)	(0.02)	(0.05)	(0.07)
Female	−0.01	0.00	0.01	0.00***	0.00	0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
College Graduate: Mother	−0.02	−0.03***	−0.04***	−0.03***	−0.03*	−0.03***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
College Graduate: Father	−0.09***	−0.05***	−0.01	−0.03***	−0.10***	−0.06***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
First Gen	−0.10*	0.07***	0.03	0.09***	0.13***	0.08***
	(0.06)	(0.01)	(0.05)	(0.02)	(0.02)	(0.02)
Second Gen	0.05*	0.04***	0.06***	0.05***	0.12***	0.07***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
N	64 052	380 625	47 233	267 690	10 472	69 301
Year-Region FE	X	X	X	X	X	X

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

[1] Each column is an estimation of a heterogeneous effect of regression (4) by the proxy household respondent with region × year fixed effects. I include controls for sex, quartic age, fraction of Hispanics in a state, parental education. Standard errors are clustered on the state level.

[2] The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third-generation Hispanic immigrant children with native born parents and at least one grandparent born in a Spanish speaking country.

[3] Data source is the 2004-2021 Current Population Survey.

TABLE 11
RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED HISPANIC IDENTITY

	(1) H_i	(2) H_i	(3) H_i	(4) H_i	(5) H_i
Bias	−0.04	0.00	−0.03***	0.03	−0.10**
	(0.03)	(0.05)	(0.01)	(0.03)	(0.04)
Female	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	−0.05***	−0.06***	−0.05***	−0.05***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.07***	−0.07***	−0.06***	−0.06***	−0.06***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
First Gen	−1.18***	0.13***	0.36***	0.04***	0.26***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Second Gen	−1.19***	0.11***	0.34***	0.02***	0.24***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
N	844 481	844 481	844 481	844 481	844 481
State FE			X	X	
Year FE		X		X	
Mean	0.91	0.91	0.91	0.91	0.91
Year × Region FE					X

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

[1] Each column is an estimation of a regression the following regression (4) with different set of fixed effects. I include controls for sex, quartic age, parental education, fraction of Hispanics in a state, and generational, parents' and grandparents' type dummy variables. Standard errors are clustered on the state level.
[2] The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third-generation Hispanic immigrant children with native born parents and at least one grandparent born in a Spanish speaking country.
[3] Data source is the 2004-2021 Current Population Survey.

TABLE 12

SELF-REPORTED HISPANIC IDENTITY AND CHARLES AND GURYAN (2008) PREJUDICE MEASURE: BY GENERATION

	(1) All Gens H_{ist}	(2) First Gen H^1_{ist}	(3) Second Gen H^2_{ist}	(4) Third Gen H^3_{ist}
Bias	−0.03	−0.02	−0.01	−0.13**
	(0.03)	(0.02)	(0.02)	(0.06)
Female	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	−0.05***	−0.04***	−0.08***	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.07***	−0.04***	−0.10***	−0.10***
	(0.01)	(0.01)	(0.01)	(0.02)
N	906106	111960	605316	188830
Mean	0.89	0.96	0.92	0.76
Year × Region FE	X	X	X	X

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

[1] Each column is an estimation of equation (4) by parents' type with region × year fixed effects with Charles and Guryan (2008) Prejudice measure. Charles and Guryan (2008) use the General Security Survey of the most common racial questions between 1970-2000 for their measure of prejudice. To use the prejudice measure, I take the average of the GSS questions by year groups. The groups I use are as follows: (1) 1977 and 1982, (2) 1985 and 1988, and 1989, (3) 1990, 1991, and 1993, and (4) 1994 and 1996. I link these groups to the following grouped Current Population Survey (CPS) years: (1) 1994-1999, (2) 2000-2005, (3) 2006-2010, and (4) 2011-2016. In other words, I merge CPS data with the residual prejudice measure from 20 years before the survey. I include controls for sex, quartic age, parental education. Standard errors are clustered on the state level.

[2] The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third-generation Hispanic immigrant children with native born parents and at least one grandparent born in a Spanish speaking country.

[3] Data source is the 2004-2021 Current Population Survey.

TABLE 13

Relationship Between Self-Reported Hispanic Identity and Charles and Guryan (2008) Prejudice Measure Among Second Generation Hispanic Immigrants: By Parental Type

Parents Type	All	HH	HW	WH
	(1)	(2)	(3)	(4)
	H^2_{ist}	H^2_{ist}	H^2_{ist}	H^2_{ist}
Bias	−0.01	0.02	−0.01	−0.15**
	(0.02)	(0.02)	(0.08)	(0.07)
Female	0.00	0.00	−0.01	0.02
	(0.00)	(0.00)	(0.01)	(0.01)
College Graduate: Mother	−0.08***	−0.04***	−0.10***	−0.11***
	(0.01)	(0.01)	(0.01)	(0.02)
College Graduate: Father	−0.10***	−0.04***	−0.15***	−0.15***
	(0.01)	(0.01)	(0.02)	(0.01)
N	605316	433135	97699	74482
Year × Region FE	X	X	X	X
Mean	0.92	0.96	0.83	0.77

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

[1] Each column is an estimation of equation (4) by parents' type with region × year fixed effects with Charles and Guryan (2008) Prejudice measure. Charles and Guryan (2008) use the General Security Survey of the most common racial questions between 1970-2000 for their measure of prejudice. To use the prejudice measure, I take the average of the GSS questions by year groups. The groups I use are as follows: (1) 1977 and 1982, (2) 1985 and 1988, and 1989, (3) 1990, 1991, and 1993, and (4) 1994 and 1996. I link these groups to the following grouped Current Population Survey (CPS) years: (1) 1994-1999, (2) 2000-2005, (3) 2006-2010, and (4) 2011-2016. In other words, I merge CPS data with the residual prejudice measure from 20 years before the survey. I include controls for sex, quartic age, parental education. Standard errors are clustered on the state level

[2] The samples include second-generation Hispanic children ages 17 and below who live in intact families. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country.

[3] Data source is the 1994-2021 Current Population Survey.

TABLE 14
RELATIONSHIP BETWEEN SELF-REPORTED HISPANIC IDENTITY AND CHARLES AND GURYAN (2008) PREJUDICE MEASURE AMONG THIRD-GENERATION HISPANIC IMMIGRANTS: BY GRANDPARENTENTAL TYPE

	Numer of Hispanic Grandparents			
	(1) One	(2) Two	(3) Three	(4) Four
Bias	−0.14	−0.19***	−0.13	−0.02
	(0.10)	(0.07)	(0.19)	(0.03)
Female	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.00)
College Graduate: Mother	−0.10***	−0.08***	0.02	−0.04***
	(0.02)	(0.02)	(0.01)	(0.02)
College Graduate: Father	−0.13***	−0.09***	0.00	−0.01
	(0.03)	(0.02)	(0.02)	(0.02)
N	62 969	68 431	12 111	45 319
Year × Region FE	X	X	X	X

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

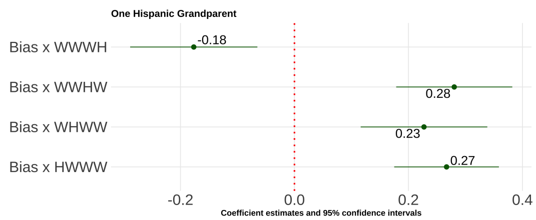
[1] Each column is an estimation of equation (4) by grandparents' type with region × year fixed effects with Charles and Guryan (2008) prejudice measure. Charles and Guryan (2008) use the General Security Survey of the most common racial questions between 1970-2000 for their measure of prejudice. To use the prejudice measure, I take the average of the GSS questions by year groups. The groups I use are as follows: (1) 1977 and 1982, (2) 1985 and 1988, and 1989, (3) 1990, 1991, and 1993, and (4) 1994 and 1996. I link these groups to the following grouped Current Population Survey (CPS) years: (1) 1994-1999, (2) 2000-2005, (3) 2006-2010, and (4) 2011-2016. In other words, I merge CPS data with the residual prejudice measure from 20 years before the survey. I include controls for sex, quartic age, parental education. Standard errors are clustered on the state level.
[2] The samples include third-generation Hispanic children ages 17 and below who live in intact families. Native born third-generation Hispanic immigrant children with at least one grandparent born in a Spanish speaking country.
[3] Data source is the 2004-2021 Current Population Survey.

Appendix B: Figures

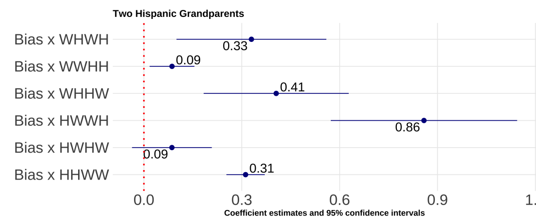
Figure 9

Relationship Between Bias and Self-reported Identity on third-generation Hispanics: Interaction

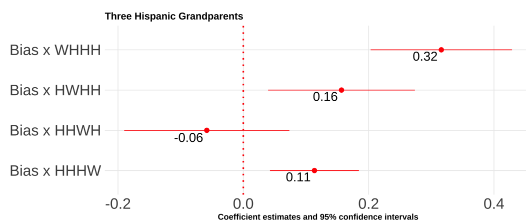
(a) Grandparents Combinations with One Objectively Hispanic Grandparent



(b) Grandparents Combinations with Two Objectively Hispanic Grandparents



(c) Grandparents Combinations with Three Objectively Hispanic Grandparents

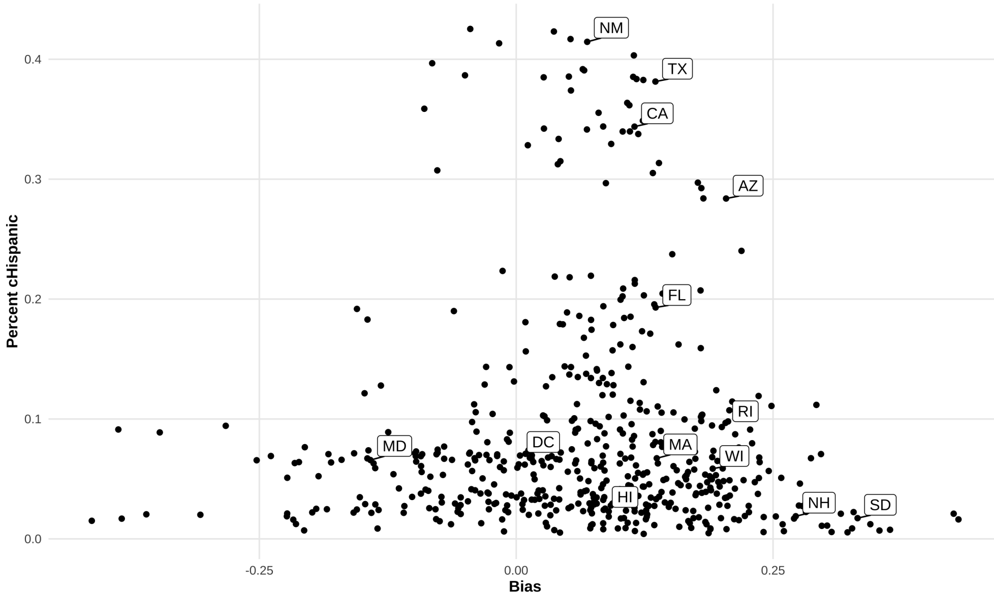


Note. I show four panels of estimating equation (6). I include region × year fixed effects with controls for sex, quartic age, and parental education. Each panel results from the same regression but of a different combination of grandparents types. Robust standard errors are reported. The samples include third-generation Hispanic children ages 17 and below who live in intact families. Third-generation Hispanic immigrant children with native-born parents and at least one grandparent born in a Spanish-speaking country.

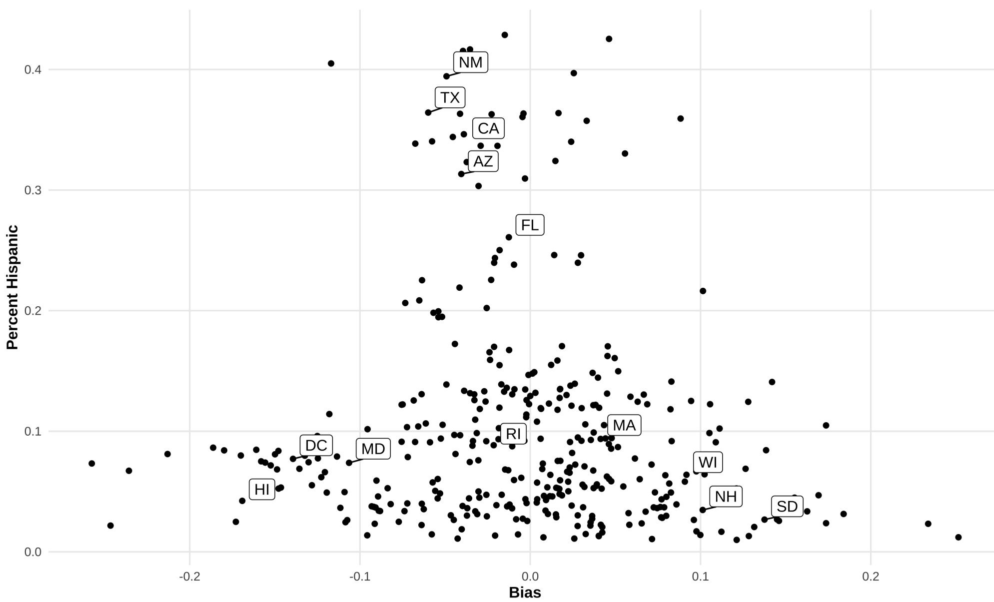
FIGURE 10

SCATTER PLOT OF PROPORTION SUBJECTIVELY HISPANIC ON BIAS

(A) YEAR < 2015



(B) YEAR ≥ 2015



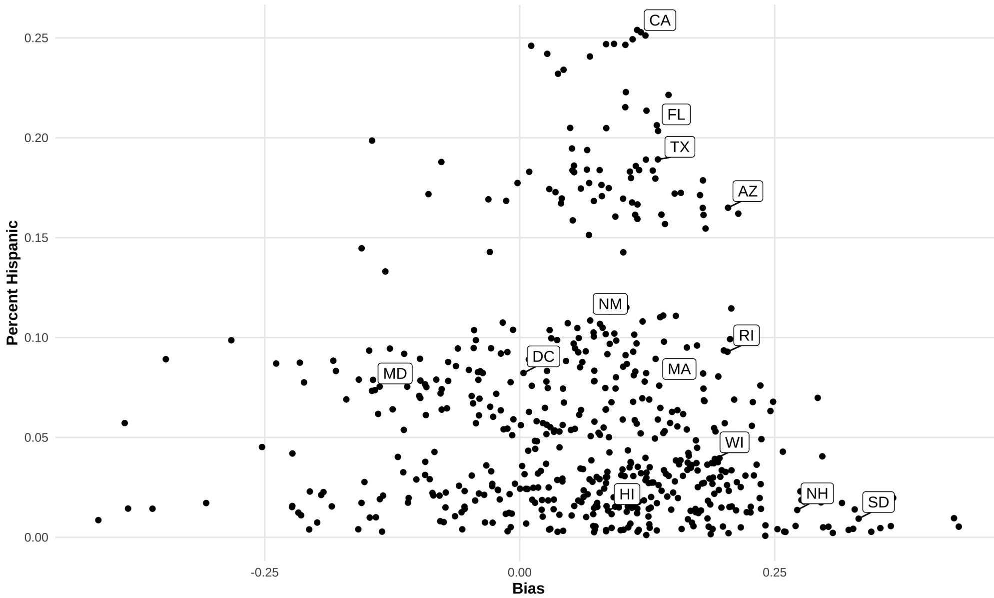
Note. Here are two scatter plots of bias on subjective Hispanic population in a state. Each dot represents a state in a certain year. Percent subjectively Hispanic = $\frac{\#\text{Hispanics}}{\text{Population}}$

Source. 2004-2021 Current Population Survey and 2004-2021 Implicit Association Test as a proxy for bias.

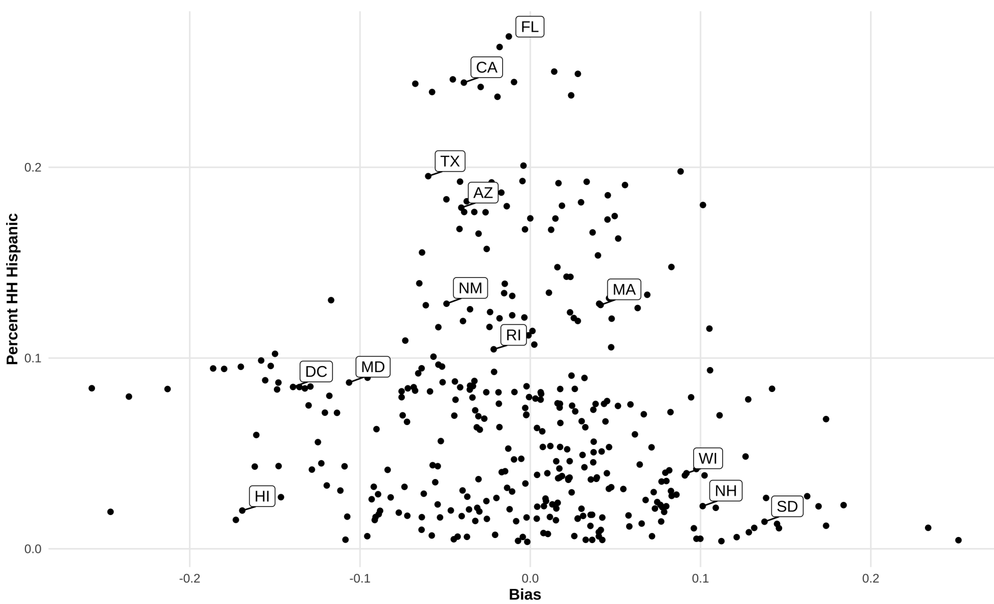
FIGURE 11

SCATTER PLOT OF PROPORTION SECOND-GENERATION AND BOTH PARENTS BORN IN A SPANISH-SPEAKING COUNTRY ON BIAS

(A) YEAR < 2015



(B) YEAR ≥ 2015



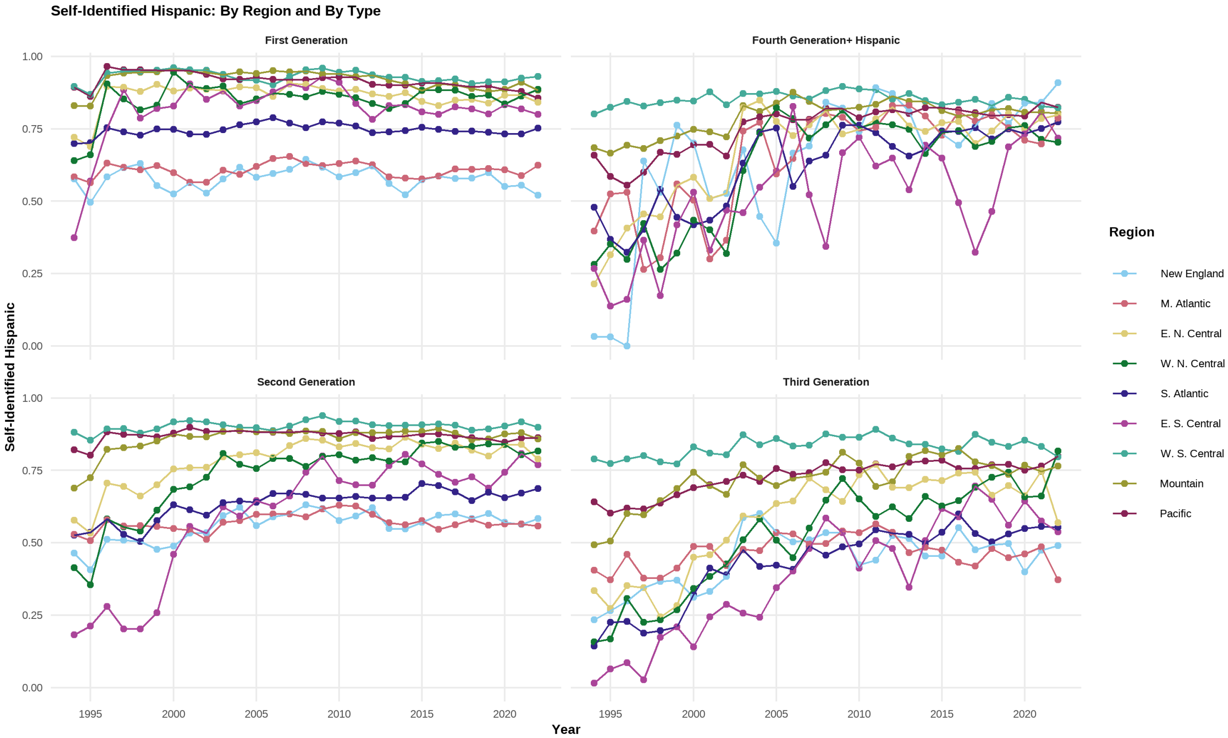
Note. Here are two scatter plots of bias on subjective Hispanic population in a state. Each dot represents a state in a certain year.

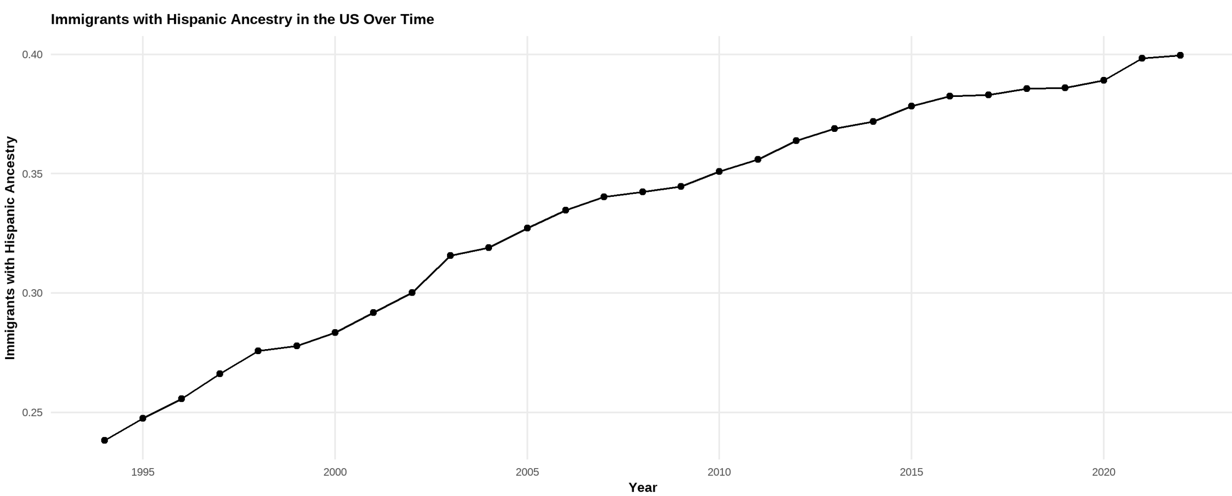
$$\text{Percent HH Hispanic} = \frac{\text{\#Hispanics with two parents born in a Spanish speaking country}}{\text{Population}}.$$

Source. 2004-2021 Current Population Survey and 2004-2021 Implicit Association Test as a proxy for bias.

FIGURE 12

HISPANIC IDENTIFICATION AMONG HISPANIC IMMIGRANTS: BY GENERATION





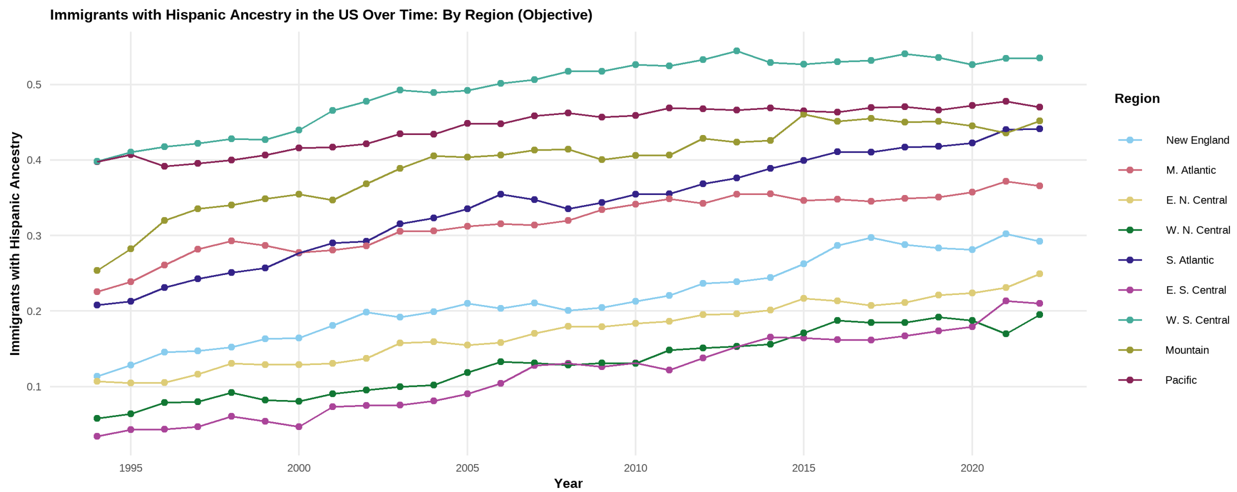

Immigrants with Hispanic Ancestry in the US Over Time: By Region (Objective)
Immigrants with Hispanic Ancestry
0.5
0.4
0.3
0.2
0.1
1995
2000
2005
2010
2015
2020
Year
Region
New England
M. Atlantic
E. N. Central
W. N. Central
S. Atlantic
E. S. Central
W. S. Central
Mountain
Pacific

FIGURE 13

CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: IAT EXPLICIT BIAS QUESTION

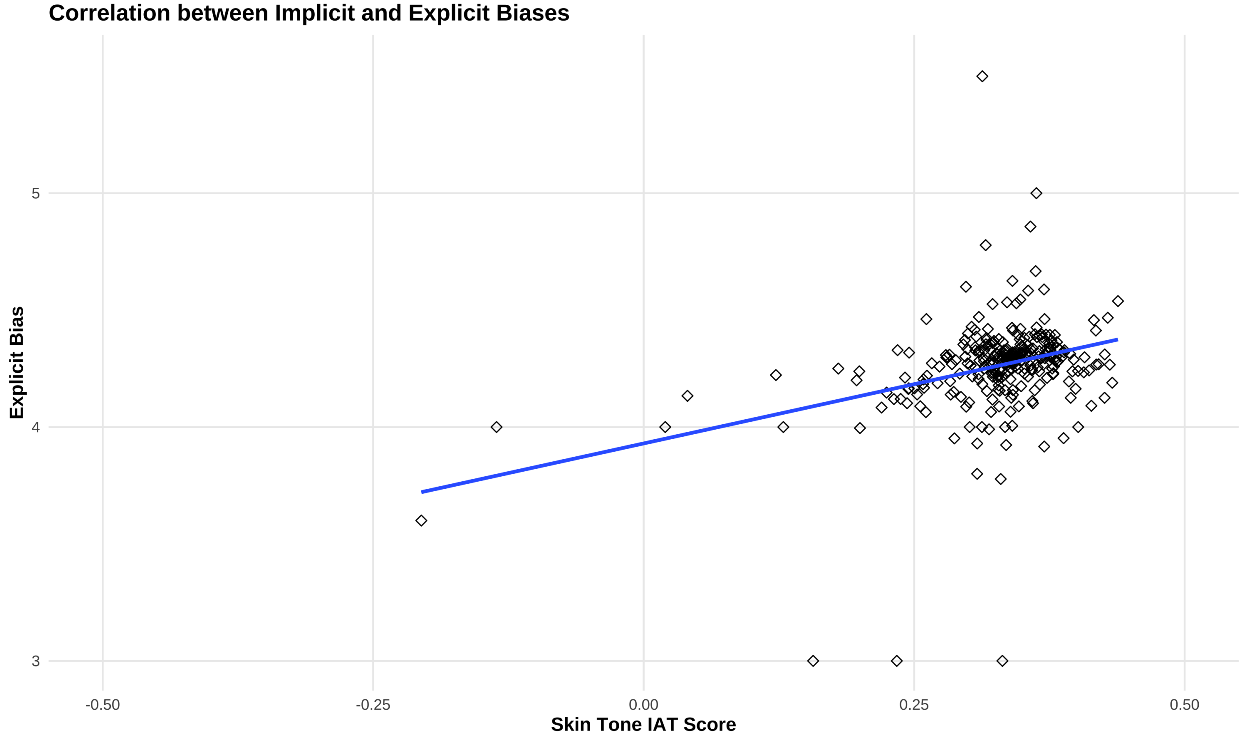


FIGURE 14

CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: GSS CLOSE TO BLACK PEOPLE QUESTION

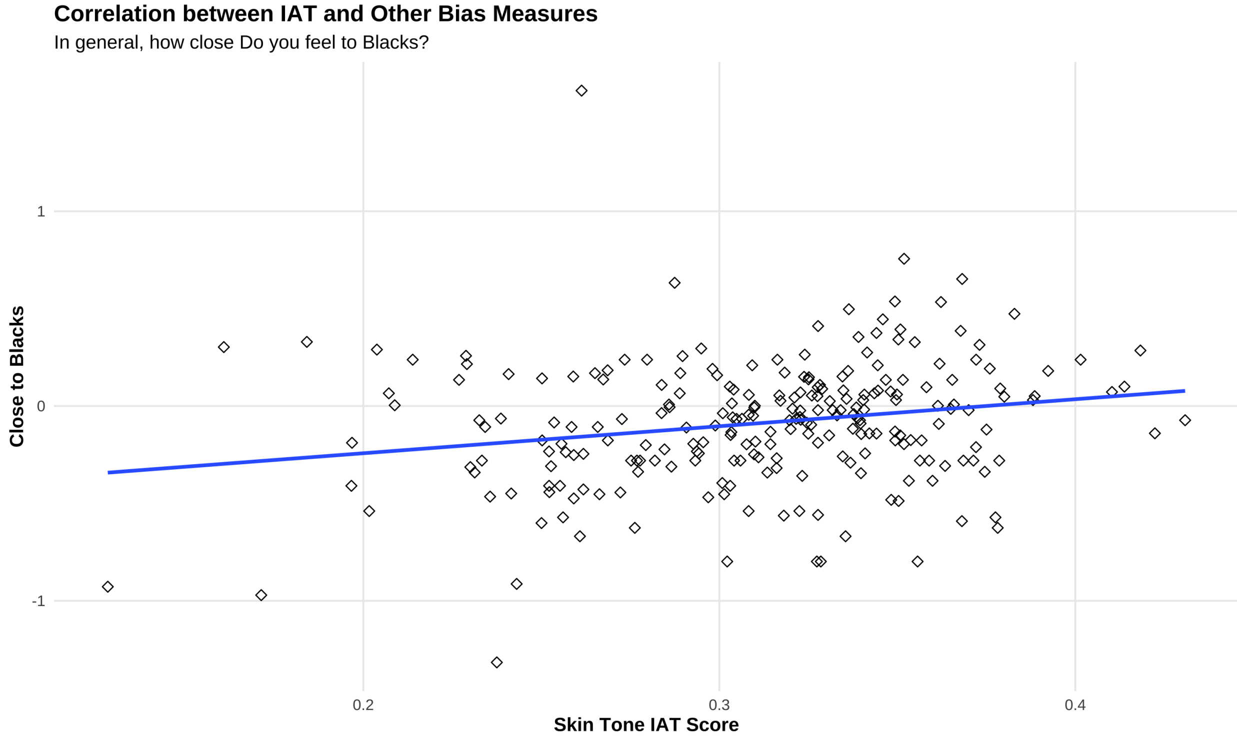


FIGURE 15

CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: GSS VOTE FOR A BLACK PRESIDENT QUESTION

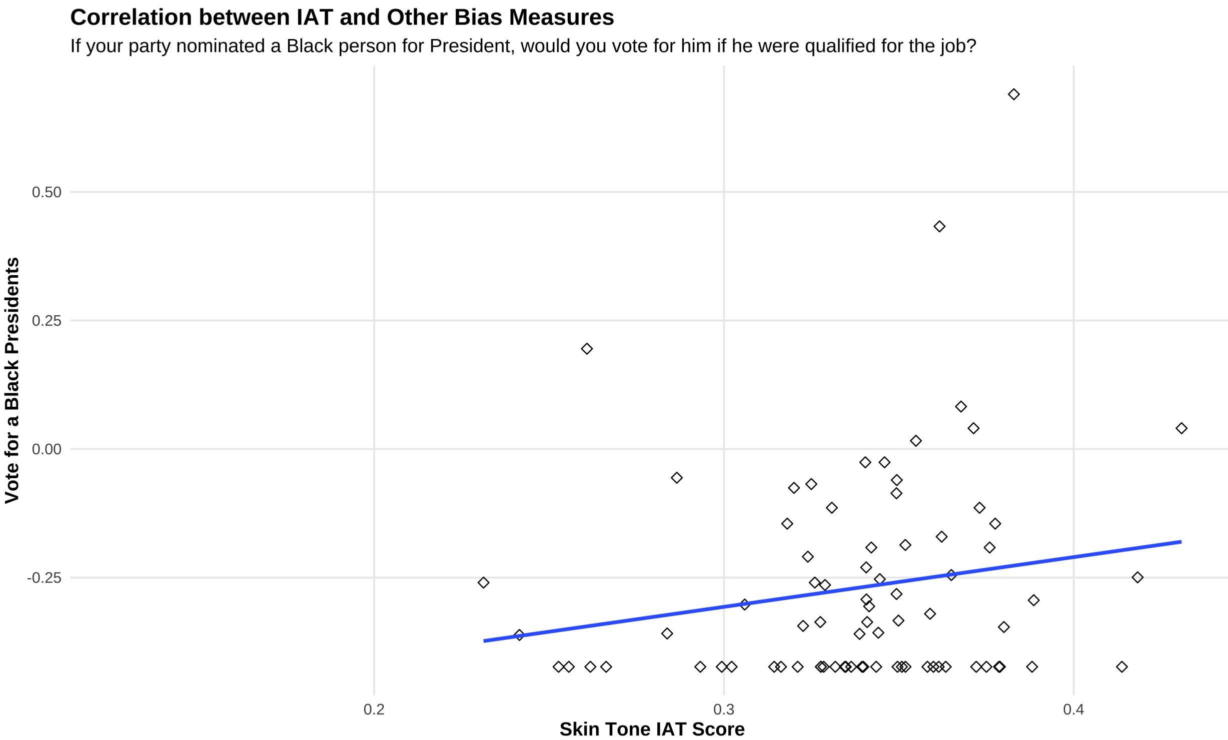
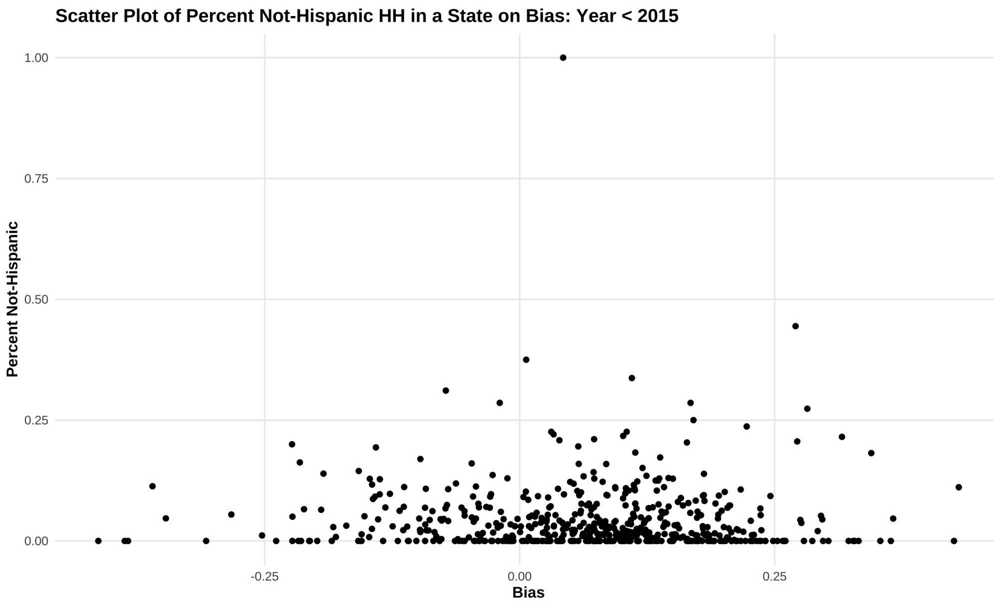


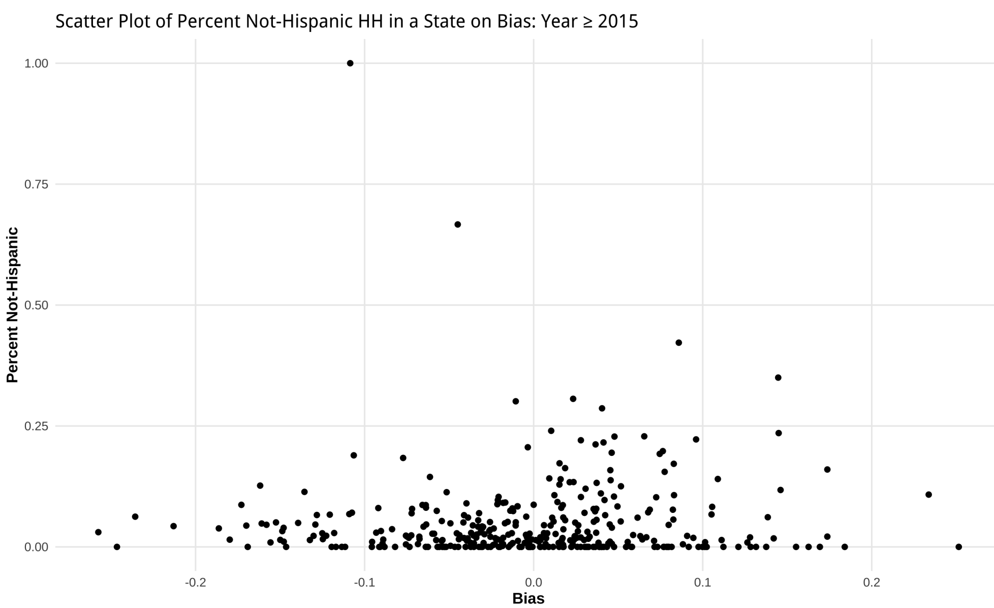
FIGURE 16

SCATTER PLOT OF NON-HISPANIC SECOND-GENERATION HISPANIC-HISPANIC PARENTS ON BIAS

(A) YEAR < 2015

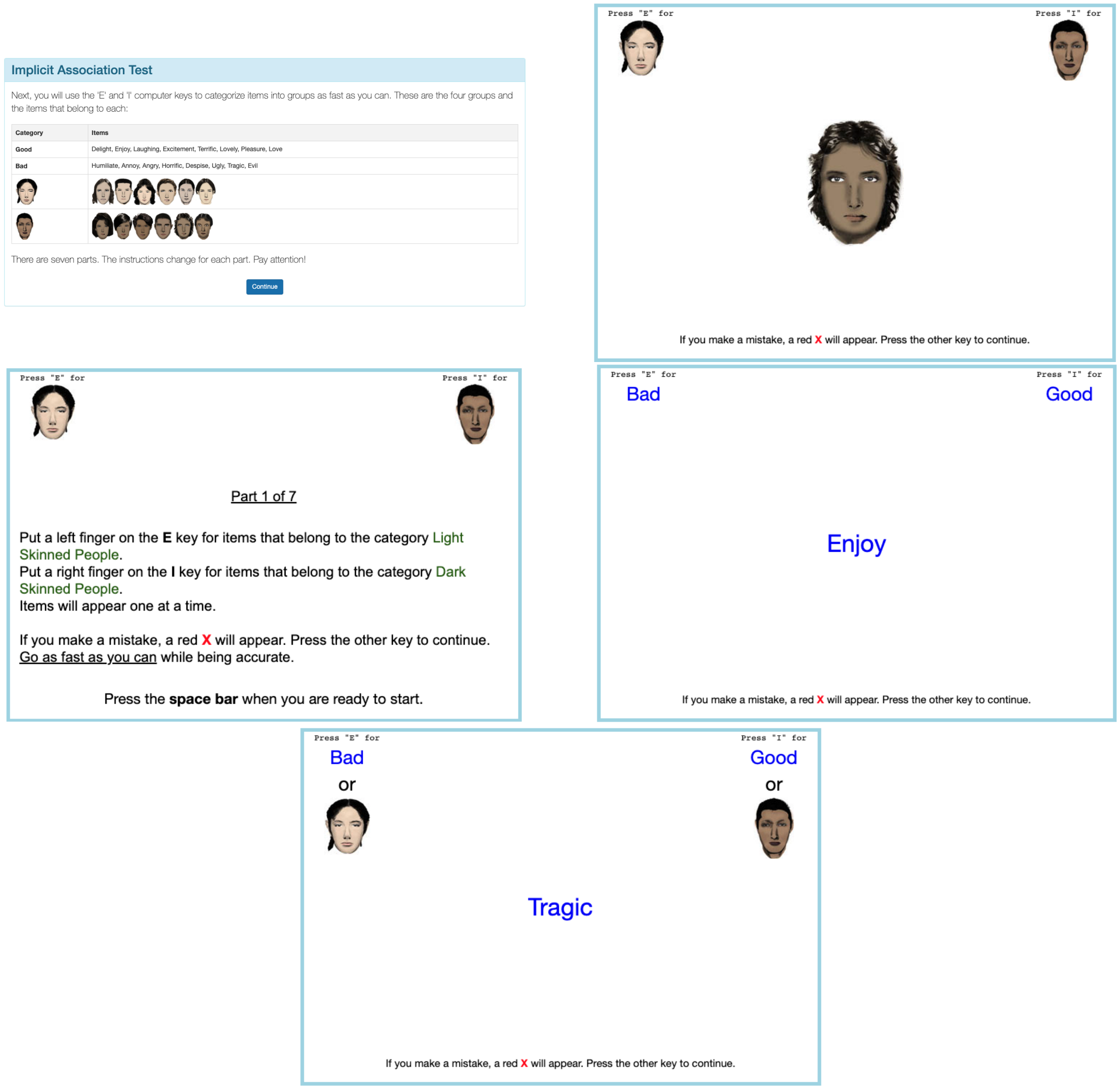


(B) YEAR ≥ 2015



Appendix C: Data

Figure 17
Examples of an Implicit Association Test



Note. Here are a few examples of what a respondent would see on an implicit association test.