

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

HUSSAIN HADAH*

NOVEMBER 12, 2022

[CLICK HERE TO GET THE MOST UPDATED VERSION](#)

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 among children of inter-ethnic parents.

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

JEL Classifications: I310, J15, J71

*Department of Economics, University of Houston, Science Building 3581 Cullen Boulevard Suite 230, Houston, TX 77204-5019, United States (e-mail: hhadah@uh.edu).

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-year-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 place of birth 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 mobility Chetty 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 outcomes like economic (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 second-generation immigrants. Additionally, a one standard deviation increase in bias is associated with 13 percentage points decrease in the self-reported Hispanic identity among third-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 of objectively Hispanic parents. Among third-generation Hispanic children of objectively Hispanic grandparents, a one standard deviation increase in bias is associated with 14 percentage points decrease in self-reported Hispanic identity. I also find that state-level bias is uncorrelated with migration decisions and is correlated with a lower probability of interethnic marriage formations. 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.

This paper contributes to different literatures. 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 self-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 ex-

perience 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 Be-dard \(2006\)](#) 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. [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 more time 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 :

$$U_i = U_i(\mathbf{a}_i, \mathbf{a}_{-i}, I_i) \quad (1)$$

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:

$$I_i = I_i(\mathbf{a}_i, \mathbf{a}_{-i}; \mathbf{B}_{e_i}) \quad (2)$$

Where \mathbf{a}_i is the actions of person i , \mathbf{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 \mathbf{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 \mathbf{B}_{e_i} , and the actions of others \mathbf{a}_{-i} . This implies the following first-order condition (F.O.C.):

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

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

That is i will change identities when the benefits of doing so $\tilde{U}_i^* - U_i^*$ 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 (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 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 place of birth of their parents beginning in 1994, I could 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 place of birth of the respondent, 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. Consequently, a person is identified as

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.

Hispanic if they 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)
Fathers with College	0.14	0.15	0.11	0.23
Mothers with College	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)

¹ %; Mean (SD)

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 country. 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 2004-2020 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:

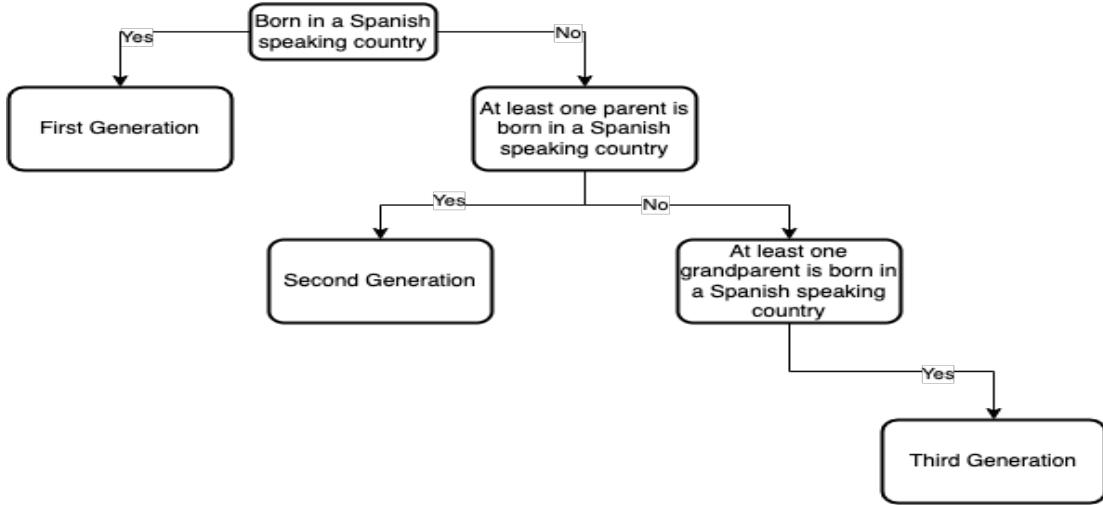
1. A person is a first-generation if they are born in a Spanish-speaking country with non-US-born parents
2. A person is a second-generation Hispanic if they are born in the US and at least one parent is born in a Spanish speaking country
3. A person is a third-generation Hispanic if they are born in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

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



Furthermore, since my analysis depends on a sub sample of the US population, I show in table (2) that I have enough observations in each generation. Moreover, 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.

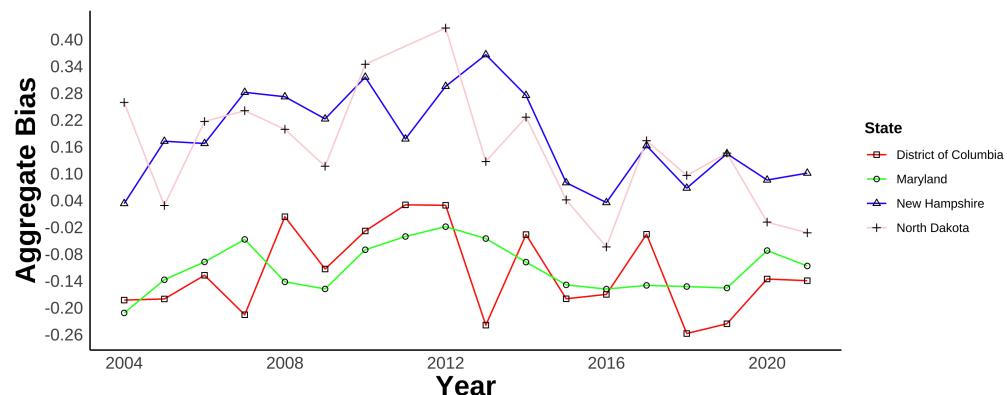
TABLE 2
HISPANIC SELF-IDENTIFICATION BY GENERATION

	Self-identify as Hispanic	Does Not Self-identify as 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
Both Sides	55401	2245	0.96	0.04
One Side	52879	17371	0.75	0.25

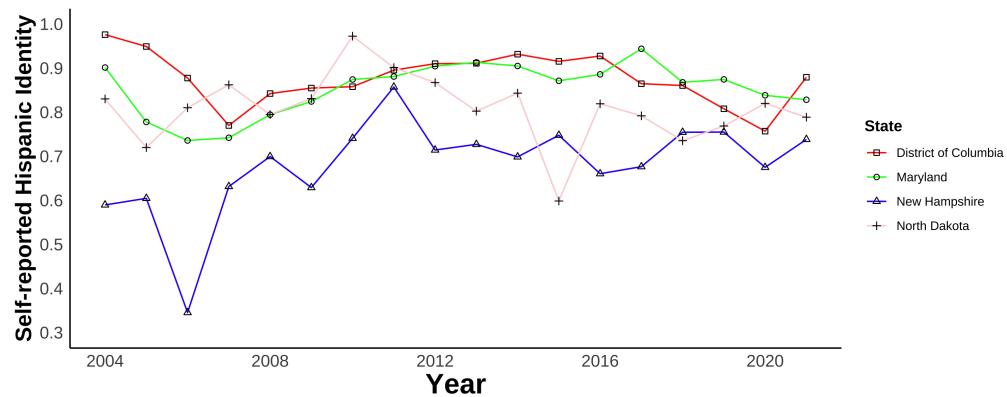
¹The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking country. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third generation Hispanic immigrant children with native born parents and at least one grand parent born in a Spanish speaking country.

²Data source is the 2004-2020 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



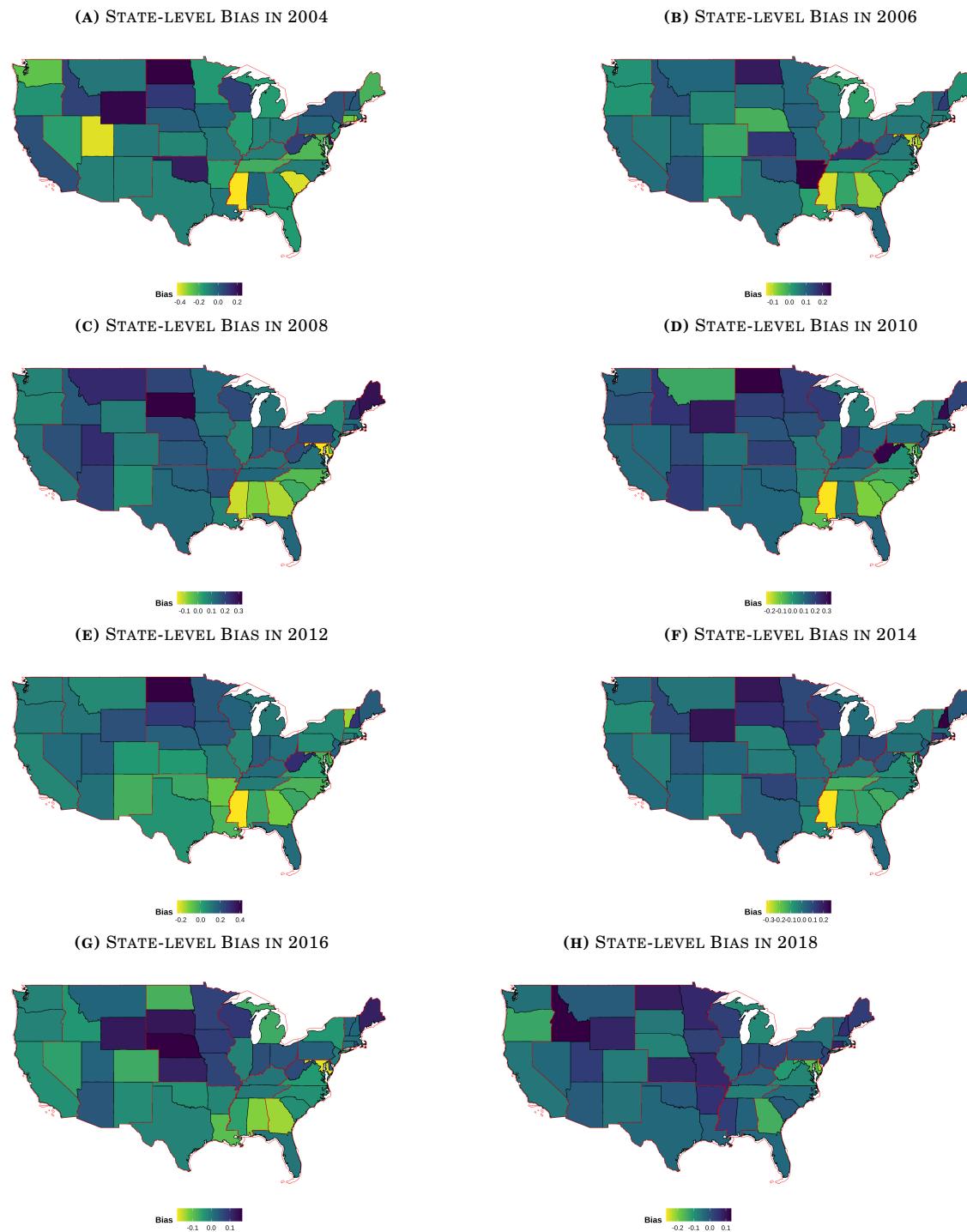
(B) SELF-REPORTED HISPANIC IDENTITY OVER TIME



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.

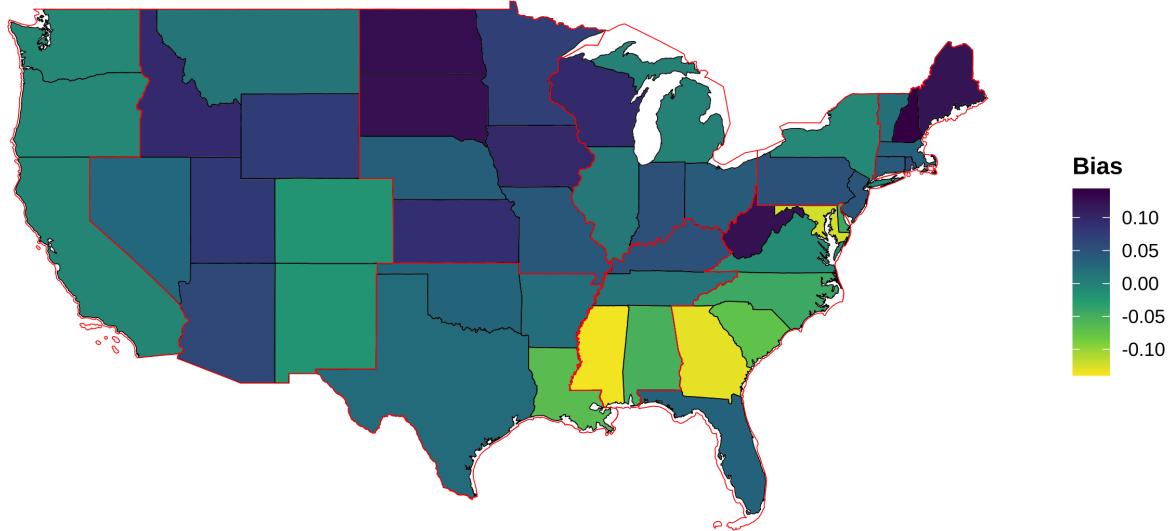
Note. Bias data is from the 2004-2021 Harvard's Project Implicit Association Test scores. Identity data is from the 2004-2021 Current Population Survey (CPS).

FIGURE 3
 MAPS OF STATE-LEVEL IMPLICIT ASSOCIATION TEST BIAS OVER TIME MEASURE BY STATE WITH CENSUS DIVISION REGIONAL BOUNDARIES



Note. In this figure, I show the state-level implicit bias by state in different years in the sample. Each panel presents state-level bias during a certain year. The boundaries in red represents 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 BY STATE WITH CENSUS DIVISION REGIONAL BOUNDARIES



Note. In this figure, I show the state-level implicit bias by state in the sample of IAT tests from 2004 to 2021. The boundaries in red represents 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 (16).

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 and with higher levels of education.

TABLE 3

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

Characteristic	IAT	CPS
	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)	

¹ Mean (SD); %

^a Data source is the 2004-2020 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 g . The regression I will estimate is as follows:

$$H_{ist}^g = \beta_1^g Bias_{st} + \beta_2^g DadCollegeGrad_{ist} + \beta_3^g MomCollegeGrad_{ist} + \beta_4^g Woman_{ist} + X_{ist}^g \pi + \gamma_{rt} + \varepsilon_{ist}; \text{where } g \in \{1, 2, 3\} \quad (4)$$

Where H_{ist}^g 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 if parents of i are college graduates and zero otherwise, and $Woman_{ist}$ is dummy variable that is equal to one if person i is a woman. Additionally, γ_{rt} is region-time fixed effects that controls for region \times year specific shocks. The region \times year also contains 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_1^g , captures the relationship between state-level bias and self-reported Hispanic identity. If $\beta_1^g > 0$, then individuals living in a state with higher bias would be more likely to self-report Hispanic identity. The identification β_1^g 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 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 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:

$$\begin{aligned}
H_{ist}^2 = & \beta_1^2 Bias_{st} + \sum_n \delta_n^2 I_{\{ParentType_{ist}=n\}} \\
& + \sum_m \alpha_m^2 Bias_{st} \times I_{\{ParentType_{ist}=m\}} \\
& + \beta_3^2 DadCollegeGrad_{ist} + \beta_4^2 MomCollegeGrad_{ist} \\
& + \beta_5^2 Woman_{ist} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist}
\end{aligned} \tag{5}$$

$$\begin{aligned}
H_{ist}^3 = & \beta_1^3 Bias_{st} + \sum_n \delta_n^3 I_{\{GrandParentType_{ist}=n\}} \\
& + \sum_m \alpha_m^3 Bias_{st} \times I_{\{GrandParentType_{ist}=m\}} \\
& + \beta_3^2 DadCollegeGrad_{ist} + \beta_4^2 MomCollegeGrad_{ist} \\
& + \beta_5^2 Woman_{ist} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist}
\end{aligned} \tag{6}$$

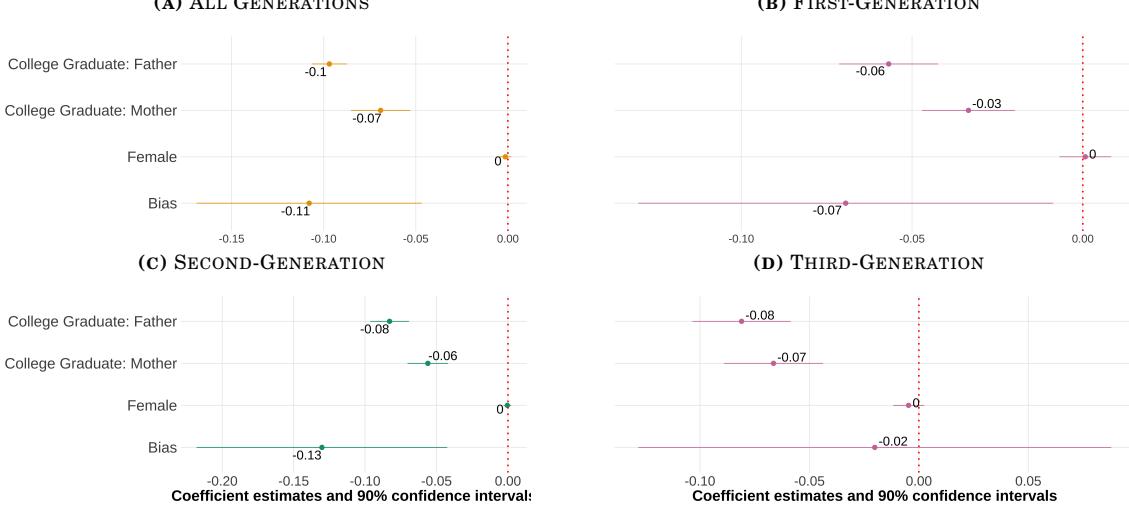
Where H_{ist}^2 and H_{ist}^3 are the self-reported identity of second and third-generation person i that lives in state s at time t . Regressions (5) and (6) include the state-year average bias, indicator variables $I_{\{ParentType_{ist}=n\}}$ and $I_{\{GrandParentType_{ist}=n\}}$, and the interaction 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 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 is the coefficient of the indicator variable $I_{\{ParentType_{ist}=\text{White-Hispanic(WH)}\}}$ and $\alpha_1^2 > 0$, 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, suppose α_1^3 is the coefficient of the indicator variable $I_{\{GrandParentType_{ist}=\text{Hispanic-Hispanic-White-White(HHWW)}\}}$ and $\alpha_1^3 > 0$. In that 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 \times 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 country. 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.

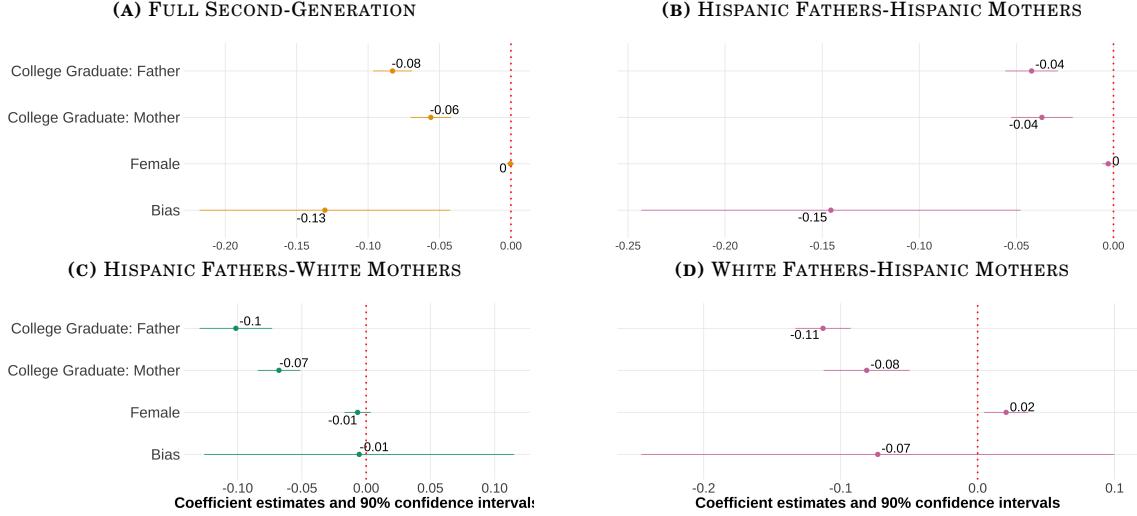
IV.B. The Effect of Bias on Interethnic Marriages and Migration

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

$$\begin{aligned}
 HH_{ist}^2 &= \beta_1^2 Bias_{st} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist} \\
 HW_{ist}^2 &= \beta_1^2 Bias_{st} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist} \\
 WH_{ist}^2 &= \beta_1^2 Bias_{st} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist}
 \end{aligned} \tag{7}$$

Where HH_{ist}^2 , HW_{ist}^2 , and WH_{ist}^2 are variables representing the type of parents of a second-generation Hispanic immigrant i in state s at time t . HH_{ist}^2 represents Hispanic-husband-Hispanic-wife couples, HW_{ist}^2 represents Hispanic-husband-White-wife couples, and WH_{ist}^2 represents White-husband-Hispanic-wife couples. $Bias_{st}$ is the average bias in state

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 \times 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.

s at time t , and X_{ist}^2 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:

$$BirthPlaceMigration_{ist}^2 = \beta_1^2 Bias_{st} + \beta_2^2 X_{ist} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist} \quad (8)$$

$$BirthPlaceMigration_{ilb}^2 = \beta_1^2 Bias_{lb} + \beta_2^2 X_{ilb} + X_{ilb}^2 \pi + \gamma_{lb} + \varepsilon_{ilb} \quad (9)$$

Where $BirthPlaceMigration_{ist}^2$ 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, $BirthPlaceMigration_{ilb}^2$ 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 . The analysis of equations (8) and (9) is restricted to second-generation Hispanic immigrants. The coefficient of interest from the regressions is β_1^2 , which captures the effect of bias on migration.

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

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:

$$Bias_{ist} - Bias_{ilb} = \beta_1^2 Hispanic_{ist} + X_{ist}^2 \pi + \varepsilon_{ist} \quad (10)$$

Where $Bias_{ist}$ 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 during the birth year b . The analysis is restricted to second-generation Hispanic immigrants 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 they 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, and region \times year fixed effect. Panel (A) of the figure (5) includes the results of estimating equation (4) on the overall 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 among first-generation immigrants. I find a negative relationship between state-level bias and

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

	(1) All Gens H_i	(2) First Gen H_i^1	(3) Second Gen H_i^2	(4) Third Gen H_i^3
Bias	-0.10** (0.04)	-0.07* (0.04)	-0.13** (0.05)	-0.02 (0.07)
Female	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
College Graduate: Mother	-0.05*** (0.01)	-0.03*** (0.01)	-0.06*** (0.01)	-0.07*** (0.01)
College Graduate: Father	-0.06*** (0.01)	-0.06*** (0.01)	-0.08*** (0.01)	-0.08*** (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. 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 grand parent born in a Spanish speaking country.

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

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
SELF-REPORTED HISPANIC IDENTITY AND BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS:
BY PARENTAL TYPE (STATE)

Parents Type	All	Both parents from Sp. Speaking country (HH)	Father from Sp. Speaking country (HW)	Mother from Sp. Speaking country (WH)
	(1) H^2	(2) H^2	(3) H^2	(4) H^2
Bias	-0.13** (0.05)	-0.15** (0.06)	-0.01 (0.07)	-0.07 (0.10)
Female	0.00 (0.00)	0.00 (0.00)	-0.01 (0.01)	0.02** (0.01)
College Graduate: Mother	-0.06*** (0.01)	-0.04*** (0.01)	-0.07*** (0.01)	-0.08*** (0.02)
College Graduate: Father	-0.08*** (0.01)	-0.04*** (0.01)	-0.10*** (0.02)	-0.11*** (0.01)
N	560100	405116	88421	66563
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), and 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 2004-2020 Current Population Survey.

In table (5), I provide the results 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.

In contrast, 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 bias effect on 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

SELF-REPORTED HISPANIC IDENTITY AND BIAS AMONG THIRD GENERATION HISPANIC IMMIGRANTS: BY GRANDPARENTAL TYPE (STATE)

	Number of Hispanic Grandparents			
	(1) One	(2) Two	(3) Three	(4) Four
Bias	-0.04 (0.11)	0.03 (0.09)	0.19 (0.26)	-0.14* (0.07)
Female	-0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)
College Graduate: Mother	-0.11*** (0.03)	-0.07*** (0.02)	0.02 (0.02)	-0.02 (0.01)
College Graduate: Father	-0.11*** (0.03)	-0.08*** (0.01)	0.02 (0.01)	-0.03* (0.01)
N	55 051	74 100	12 194	57 646
Year × Region FE	X	X	X	X

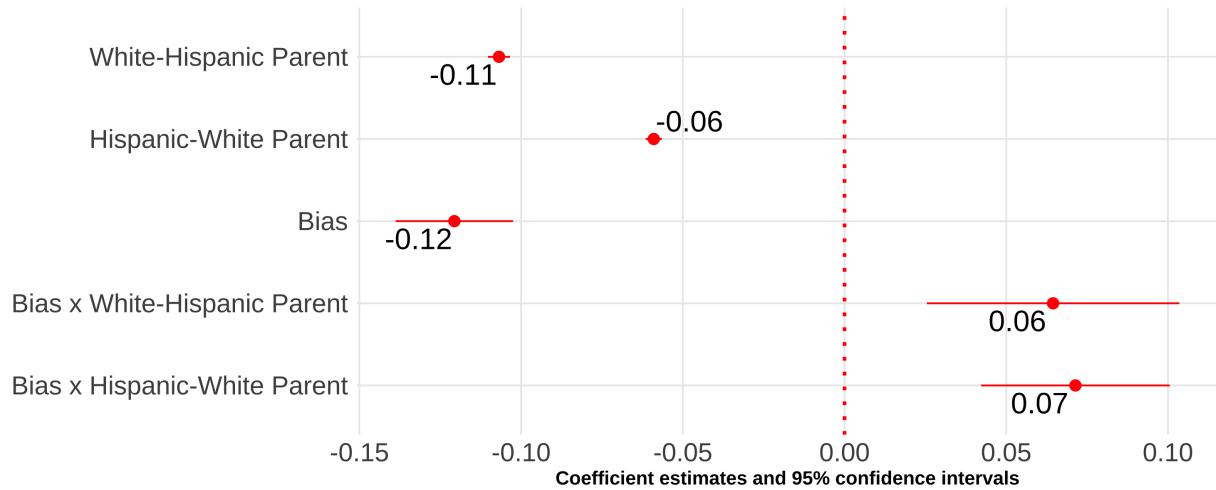
* p < 0.1, ** p < 0.05, *** p < 0.01

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.

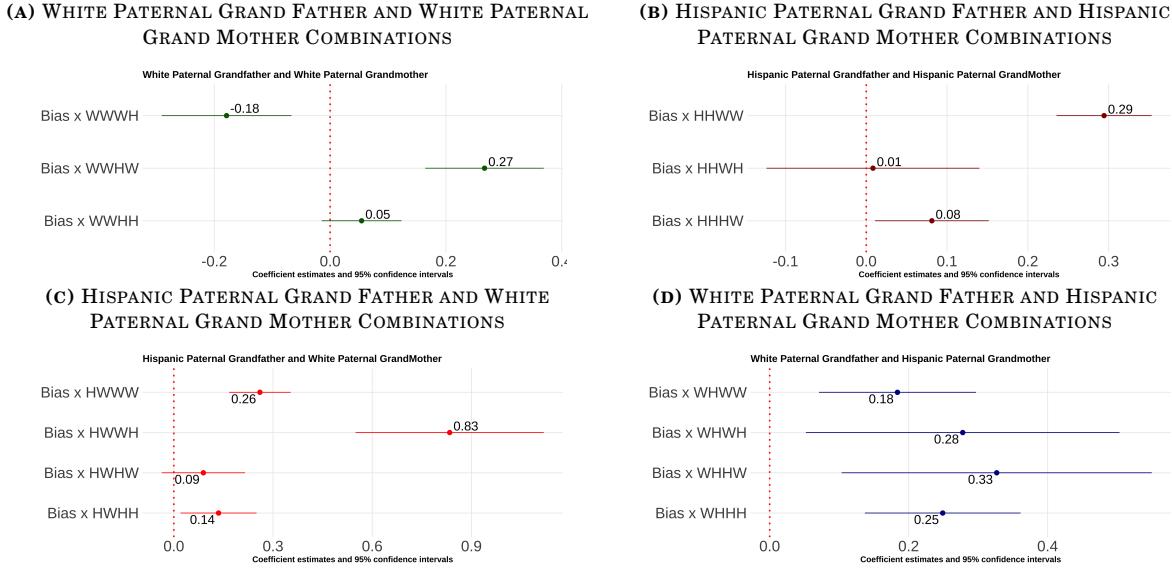
³ Data source is the 2004-2020 Current Population Survey.

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



Note. I show four panels of estimating equation (5). I include region \times year fixed effects with controls for sex, quartic age, 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 (STATE)**



Note. I show four panels of estimating equation (6). I include region \times year fixed effects with controls for sex, quartic age, and parental education. Each panel results from the same regression but is only 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 effect in 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 six 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 a six 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 effect of estimating 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 as likely as children with HHHH grandparents to self-identify as Hispanic; (2) those with objectively Hispanic maternal grandfather and White maternal grandmother are 27 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 eight 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 29 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic.

Among third-generation immigrants with objectively Hispanic paternal grandfather-

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.

White paternal grandmother (figure 8c): (1) those with objectively Hispanic maternal grandparents are 14 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic; (2) those with objectively Hispanic maternal grandfather and maternal White 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 83 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 26 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 25 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 33 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 28 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 18 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). 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 that bias does not affect the migration decisions 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, 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. $Bias_{ist} - Bias_{lb}$. Among second-generation Hispanic immigrant movers, those that self-report Hispanic identity live in states that are 0.01 standard deviations more biased than the state they were born.

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
EFFECT OF BIAS ON MIGRATION PATTERNS

	(1) Migrated from Birth Place	(2) Migrated from Birth Place	(3) $Bias_{st} - Bias_{lb}$
$Bias_{st}$	-0.15 (0.14)		
$Bias_{lb}$		-0.18 (0.26)	
Hispanic			0.01** (0.00)
Female	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
College Graduate: Mother	0.03*** (0.01)	0.03*** (0.01)	0.00 (0.00)
College Graduate: Father	0.03*** (0.01)	0.04*** (0.01)	-0.01* (0.00)
N	568416	307427	25704
Year (t) \times Region FE	X		
Birthyear (b) \times 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-repoited Hispanic identity into states with different levels of bias. I include controls for sex, quartic age, parental education, and region \times 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 at least one parent 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
EFFECT OF BIAS ON INTERETHNIC MARRIAGES: MARGINAL EFFECT OF AN ORDINAL MULTILOGIT AND PROBIT REGRESSIONS

	(1)	(2)
	Probit Marginal Effect at Mean	Logistic Marginal Effect at Mean
Bias	−0.04*** (0.00)	−0.02*** (0.00)
College Indicator: Wife	−0.05*** (0.00)	−0.03*** (0.00)
College Indicator: Husband	−0.07*** (0.00)	−0.05*** (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 a 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 2004-2020 Current Population Survey Data.

V.C. *Discussion*

The results 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 consistent with 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 areas. Even if these were not the case, I view my estimates to underestimate the actual effect of self-reported identity of a child once they are adults. 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 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), yields a negative effect of bias on self-reported Hispanic identity for all types of proxy respondents. The impact of bias on self-reported Hispanic identity is a reduction of ten percentage points when the objectively White mother is the proxy respondent, but the result is not statistically significant. The bias effect on self-reported Hispanic identity is a reduction of seven percentage points when the objectively Hispanic mother is the proxy respondent, but the result is not statistically significant. The effect of bias on self-reported Hispanic identity is a reduction of 23 percentage points when the objectively White father is the proxy respondent, but the result is not statistically significant. The effect of bias on self-reported Hispanic identity is a reduction of ten percentage points when the objectively Hispanic father is the proxy respondent, and the result is statistically significant. The effect of bias on self-reported Hispanic identity is a reduction of 12 percentage points when the person themselves is the proxy respondent, but

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.

the result is not statistically significant. The effect of bias on self-reported Hispanic identity is a reduction of 32 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. \(2016\)](#). Moreover, [Bursztyn et al. \(2022\)](#) show that geographical areas with a higher presence of Arab-Muslims are predictive of lower bias, measured by the Implicit Association Test (IAT), toward Arab-Muslims by non-Arab-Whites. 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 \times 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 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 13, 14, and 15.) These results suggest that ‘residual’ prejudice mainly affects interethnic children.

I want to address the 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. In other words, 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.

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 character-

istics 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 six and 10 percentage points decrease in self-reported Hispanic identity. Also, among second-generation immigrants, the children of Hispanic Fathers-Hispanic Mothers are affected more by state-level bias.

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 relied 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 most likely to be affected by bias are the most educated. In that 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.

TABLE 10
SUBJECTIVE HISPANIC IDENTITY AND SKIN IAT: BY PROXY RESPONDENT

Variable	White Mother Proxy	Hispanic Mother Proxy	White Father Proxy	Hispanic Father Proxy	Self	Other
	Hispanic	Hispanic	Hispanic	Hispanic	Hispanic	Hispanic
Prejudice Measure	-0.04 (0.11)	-0.03 (0.03)	-0.10 (0.10)	-0.04* (0.02)	-0.05 (0.05)	-0.14** (0.07)
Female	-0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00*** (0.00)	0.00 (0.01)	0.00 (0.00)
College Graduate: Mother	-0.02 (0.02)	-0.03*** (0.01)	-0.04*** (0.02)	-0.03*** (0.01)	-0.03* (0.02)	-0.03*** (0.01)
College Graduate: Father	-0.09*** (0.02)	-0.05*** (0.01)	0.00 (0.02)	-0.03*** (0.01)	-0.10*** (0.02)	-0.06*** (0.01)
First Gen	-0.10* (0.06)	0.07*** (0.01)	0.02 (0.05)	0.09*** (0.02)	0.13*** (0.02)	0.08*** (0.02)
Second Gen	0.05* (0.03)	0.04*** (0.01)	0.06*** (0.02)	0.05*** (0.01)	0.12*** (0.02)	0.06*** (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, 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 country. 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.

³ Data source is the 2004-2020 Current Population Survey.

TABLE 11
SELF-REPORTED HISPANIC IDENTITY AND BIAS

	(1) H_i	(2) H_i	(3) H_i	(4) H_i	(5) H_i
Bias	0.01 (0.03)	0.10 (0.07)	-0.05** (0.02)	0.04 (0.03)	-0.06 (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	-0.06*** (0.01)	-0.06*** (0.01)	-0.04*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)
College Graduate: Father	-0.07*** (0.01)	-0.07*** (0.00)	-0.06*** (0.01)	-0.06*** (0.01)	-0.06*** (0.01)
First Gen	-1.31*** (0.03)	0.12*** (0.01)	0.37*** (0.03)	0.04*** (0.01)	0.26*** (0.03)
Second Gen	-1.33*** (0.02)	0.11*** (0.01)	0.35*** (0.02)	0.02*** (0.01)	0.24*** (0.03)
N	844481	844481	844481	844481	844481
State FE			X	X	
Year FE		X		X	
Mean	0.91	0.91	0.91	0.91	0.91
Year \times 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, 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 country. 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
PARENTS' TYPE AND BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS (STATE)

	(1) <i>HH</i>	(2) <i>HW</i>	(3) <i>WH</i>
Bias	-0.05* (0.03)	-0.02 (0.02)	0.06** (0.03)
College Graduate: Wife	-0.05*** (0.01)	0.02*** (0.00)	0.03*** (0.01)
College Graduate: Husband	-0.08*** (0.01)	0.02*** (0.00)	0.06*** (0.01)
Wife's Age	0.00*** (0.00)	0.00*** (0.00)	0.00 (0.00)
Husband's Age	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Year Immigrated: Wife	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Year Immigrated: Husband	0.00*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
N	560 100	560 100	560 100
Year × Region FE	X	X	X

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

¹ This is the result to estimating (7) as a linear probability model.

² 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 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.

⁴ Data source is the 2004-2020 Current Population Survey.

TABLE 13

SELF-REPORTED HISPANIC IDENTITY AND CHARLES AND GURYAN (2012) PREJEDUICE MEASURE: BY GENERATION

	(1) All Gens H_i	(2) First Gen H_i^1	(3) Second Gen H_i^2	(4) Third Gen H_i^3
Bias	-0.03 (0.03)	-0.02 (0.02)	-0.01 (0.02)	-0.13** (0.06)
Female	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
College Graduate: Mother	-0.05*** (0.01)	-0.04*** (0.01)	-0.08*** (0.01)	-0.07*** (0.01)
College Graduate: Father	-0.07*** (0.01)	-0.04*** (0.01)	-0.10*** (0.01)	-0.10*** (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 (2012) Prejeduce measure. Charles and Guryan (2012) use the General Security Survey of the most common racial questions between 1970-2000 for their measure of prejeduce. To use Charles and Guryan (2012) prejeduce 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 prejeduce 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 grand parent born in a Spanish speaking country.

³ Data source is the 2004-2020 Current Population Survey.

TABLE 14

SELF-REPORTED HISPANIC IDENTITY AND CHARLES AND GURYAN (2012) PREJEDUICE MEASURE AMONG
SECOND GENERATION HISPANIC IMMIGRANTS: BY PARENTAL TYPE (STATE)

Parents Type	All	HH	HW	WH
	(1)	(2)	(3)	(4)
	H^2	H^2	H^2	H^2
Bias	-0.01 (0.02)	0.02 (0.02)	-0.01 (0.08)	-0.15** (0.07)
Female	0.00 (0.00)	0.00 (0.00)	-0.01 (0.01)	0.02 (0.01)
College Graduate: Mother	-0.08*** (0.01)	-0.04*** (0.01)	-0.10*** (0.01)	-0.11*** (0.02)
College Graduate: Father	-0.10*** (0.01)	-0.04*** (0.01)	-0.15*** (0.02)	-0.15*** (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 (2012) Prejeduice measure. Charles and Guryan (2012) use the General Security Survey of the most common racial questions between 1970-2000 for their measure of prejeduice. To use Charles and Guryan (2012) prejeduice 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 prejeduice 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 1994-2020 Current Population Survey.

TABLE 15
 SELF-REPORTED HISPANIC IDENTITY AND CHARLES AND GURYAN (2012) PREJEDUICE MEASURE AMONG
 THIRD GENERATION HISPANIC IMMIGRANTS: BY GRANDPARENTS TYPE (STATE)

	Numer of Hispanic Grandparents			
	(1) One	(2) Two	(3) Three	(4) Four
Bias	−0.14 (0.10)	−0.19*** (0.07)	−0.13 (0.19)	−0.02 (0.03)
Female	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.00)
College Graduate: Mother	−0.10*** (0.02)	−0.08*** (0.02)	0.02 (0.01)	−0.04*** (0.02)
College Graduate: Father	−0.13*** (0.03)	−0.09*** (0.02)	0.00 (0.02)	−0.01 (0.02)
N	62969	68431	12111	45319
Year × Region FE	X	X	X	X

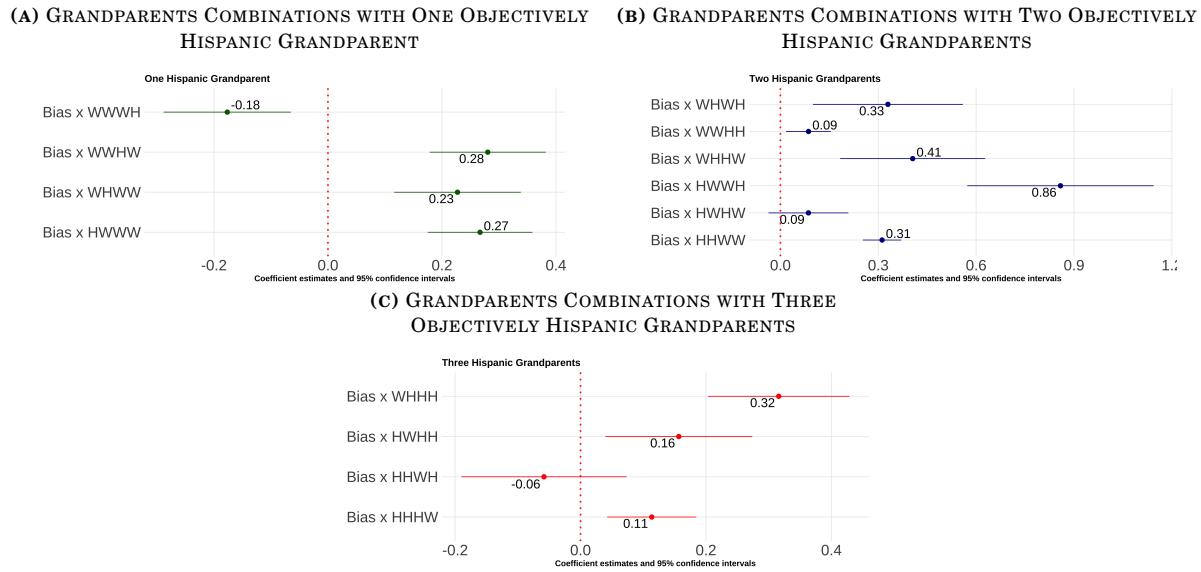
* p < 0.1, ** p < 0.05, *** p < 0.01

¹ Each column is an estimation of equation (4) by grandparents' type with region × year fixed effects with Charles and Guryan (2012) Prejeduice measure. Charles and Guryan (2012) use the General Security Survey of the most common racial questions between 1970-2000 for their measure of prejeduice. To use Charles and Guryan (2012) prejeduice 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 prejeduice 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.

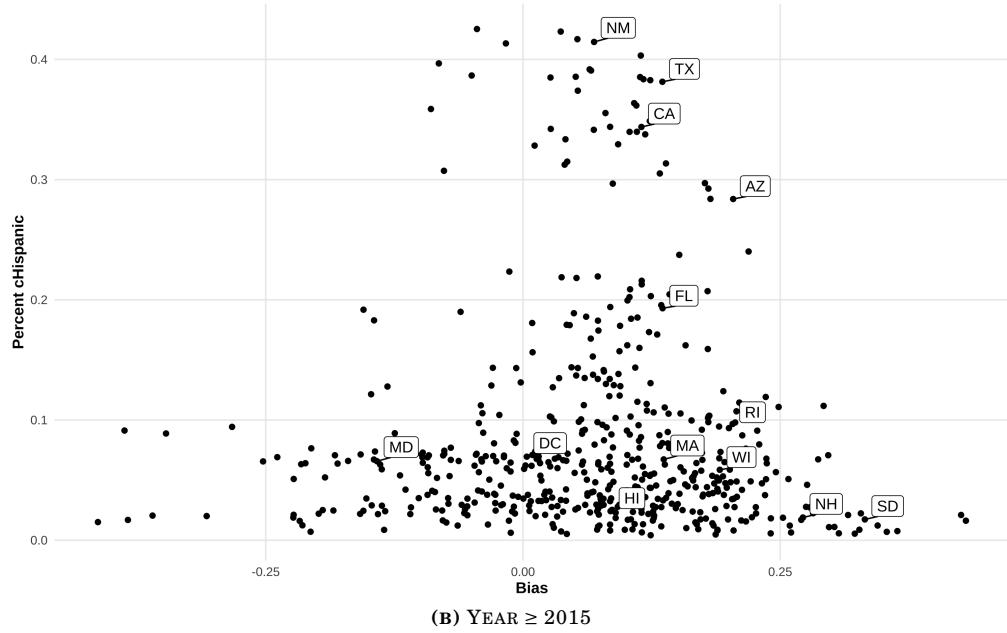
³ Data source is the 2004-2020 Current Population Survey.

FIGURE 9
**RELATIONSHIP BETWEEN BIAS AND SELF-REPORTED IDENTITY ON THIRD-GENERATION HISPANICS:
INTERACTION (STATE)**

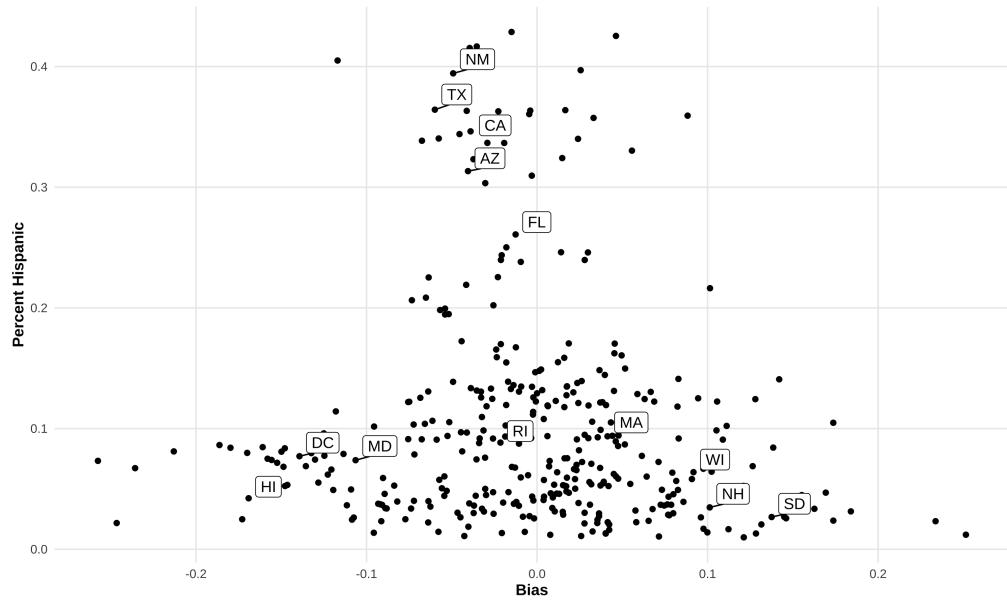


Note. I show four panels of estimating equation (6). I include region \times year fixed effects with controls for sex, quartic age, and parental education. Each panel results from the same regression but of a different combination of grandparents types. Robust standard errors are reported. The samples 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



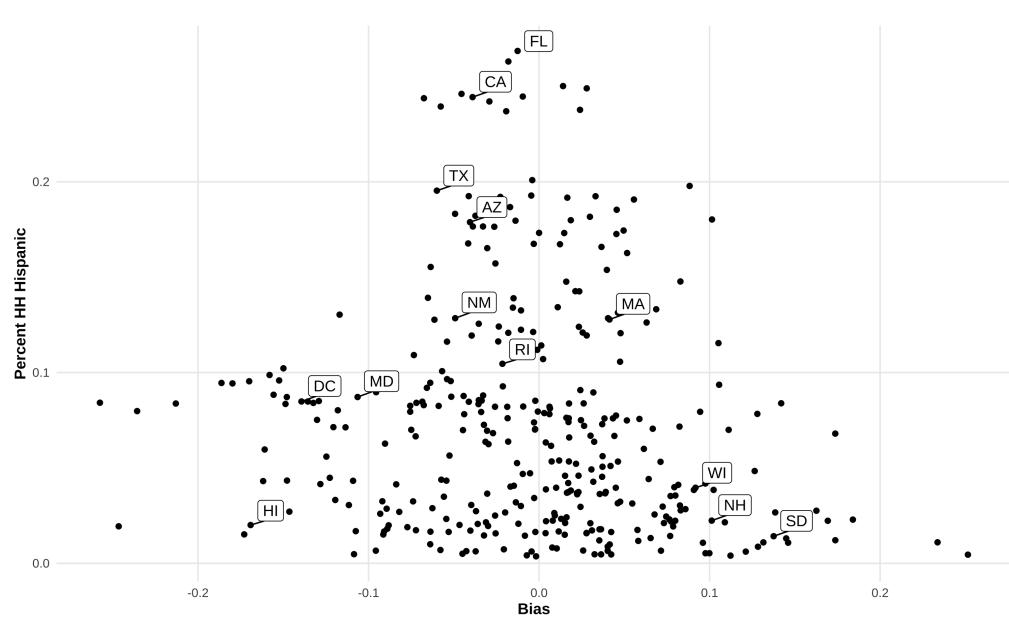
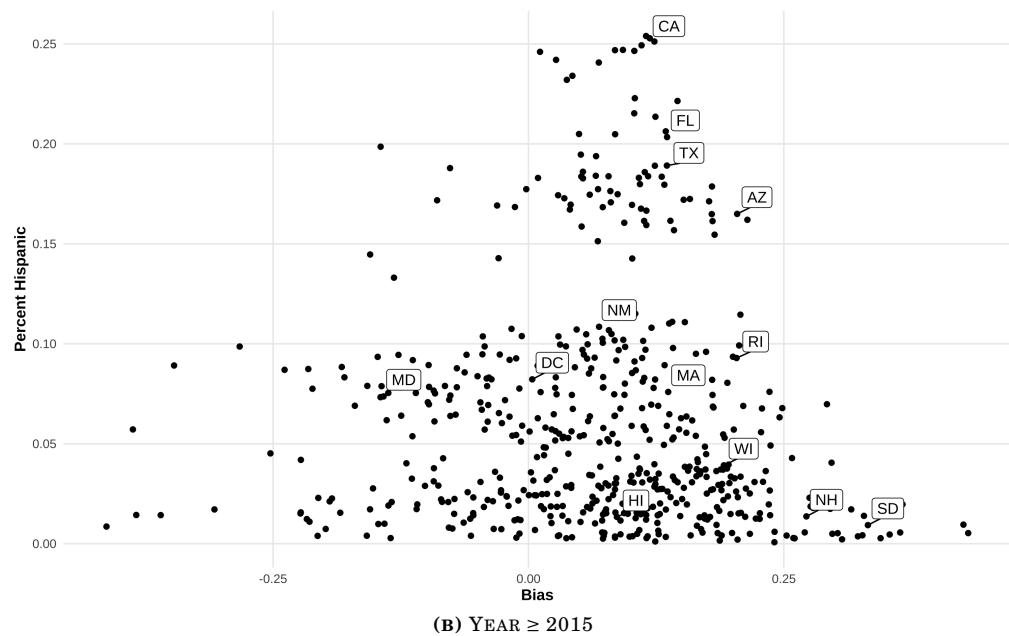
(B) YEAR \geq 2015



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



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.

REFERENCES

- Abramitzky, Ran, Leah Boustan, and Katherine Eriksson (2020). Do Immigrants Assimilate More Slowly Today Than in the Past? *American Economic Review: Insights*, 2(1), 125–141.
- Abramitzky, Ran, Leah Boustan, Katherine Eriksson, and Stephanie Hao (2020). Discrimination and the Returns to Cultural Assimilation in the Age of Mass Migration. *AEA Papers and Proceedings*, 110, 340–346.
- Abramitzky, Ran, Leah Platt Boustan, and Dylan Connor (2020). Leaving the Enclave: Historical Evidence on Immigrant Mobility from the Industrial Removal Office. Technical Report w27372, National Bureau of Economic Research, Cambridge, MA.
- Abramitzky, Ran, Leah Platt Boustan, and Katherine Eriksson (2014). A Nation of Immigrants: Assimilation and Economic Outcomes in the Age of Mass Migration. *Journal of Political Economy*, 122(3), 467–506.
- Abramitzky, Ran, Leah Platt Boustan, and Katherine Eriksson (2016). Cultural Assimilation during the Age of Mass Migration.
- Abramitzky, Ran, Leah Platt Boustan, Elisa Jácome, and Santiago Pérez (2019). Intergenerational Mobility of Immigrants in the US over Two Centuries. Technical Report w26408, National Bureau of Economic Research, Cambridge, MA.
- Akerlof, George A. and Rachel E. Kranton (2000). Economics and Identity. *Quarterly Journal of Economics*, 115(3), 715–753.
- Alba, Richard (2020). *The Great Demographic Illusion: Majority, Minority, and the Expanding American Mainstream*. Princeton University Press.
- Alesina, Alberto, Armando Miano, and Stefanie Stantcheva (2018). Immigration and Redistribution.
- Antecol, Heather and Kelly Bedard (2006). Unhealthy assimilation: Why do immigrants converge to American health status levels? *Demography*, 43(2), 337–360.
- Antman, Francisca and Brian Duncan (2015). Incentives to Identify: Racial Identity in the Age of Affirmative Action. *Review of Economics & Statistics*, 97(3), 710–713.
- Antman, Francisca and Brian Duncan (2021). American Indian Casinos and Native American Self-Identification.
- Antman, Francisca, Brian Duncan, and Stephen J. Trejo (2016). Ethnic Attrition and the Observed Health of Later-Generation Mexican Americans. *The American Economic Review*, 106(5), 467–471.
- Antman, Francisca M., Brian Duncan, and Stephen J. Trejo (2020). Ethnic attrition, assimilation, and the measured health outcomes of Mexican Americans. *Journal of Population Economics*, 33(4), 1499–1522.
- Åslund, Olof, Lena Hensvik, and Oskar Nordström Skans (2014). Seeking Similarity: How Immigrants and Natives Manage in the Labor Market. *Journal of Labor Economics*, 32(3), 405–441.

- Bagues, Manuel, Mauro Sylos-Labini, and Natalia Zinovyeva (2017). Does the Gender Composition of Scientific Committees Matter? *American Economic Review*, 107(4), 1207–1238.
- Bertrand, Marianne, Dolly Chugh, and Sendhil Mullainathan (2005). Implicit Discrimination. *American Economic Review*, 95(2), 94–98.
- Bertrand, Marianne and Sendhil Mullainathan (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. *American Economic Review*, 94(4), 991–1013.
- Bonomi, Giampaolo, Nicola Gennaioli, and Guido Tabellini (2021). Identity, Beliefs, and Political Conflict*. *The Quarterly Journal of Economics*, 136(4), 2371–2411.
- Bratter, Jenifer L. (2018). Multiracial Identification and Racial Gaps: A Work in Progress. *The Annals of the American Academy of Political and Social Science*, 677, 69–80.
- Bursztyn, Leonardo, Thomas Chaney, Tarek A. Hassan, and Aakash Rao (2022). The Immigrant Next Door: Long-Term Contact, Generosity, and Prejudice.
- Carlana, Michela (2019). Implicit Stereotypes: Evidence from Teachers' Gender Bias. *Quarterly Journal of Economics*, 134(3), 1163–1224.
- Charles, Kerwin Kofi and Jonathan Guryan (2008). Prejudice and Wages: An Empirical Assessment of Becker's The Economics of Discrimination. *Journal of Political Economy*, 116(5), 773–809.
- Charles, Kerwin Kofi, Jonathan Guryan, and Jessica Pan (2018). The Effects of Sexism on American Women: The Role of Norms vs. Discrimination.
- Chetty, Raj, David Grusky, Maximilian Hell, Nathaniel Hendren, Robert Manduca, and Jimmy Narang (2017). The fading American dream: Trends in absolute income mobility since 1940. *Science*, 356(6336), 398–406.
- Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter (2020). Race and Economic Opportunity in the United States: An Intergenerational Perspective*. *The Quarterly Journal of Economics*, 135(2), 711–783.
- Chetty, Raj, Nathaniel Hendren, and Lawrence F. Katz (2016). The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment. *American Economic Review*, 106(4), 855–902.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States *. *The Quarterly Journal of Economics*, 129(4), 1553–1623.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner (2014). Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *American Economic Review*, 104(5), 141–147.
- Dee, Thomas S. (2005). A Teacher Like Me: Does Race, Ethnicity, or Gender Matter? *The American Economic Review*, 95(2), 158–165.

- Duncan, Brian and Stephen J. Trejo (2005). Ethnic Identification, Intermarriage, and Unmeasured Progress by Mexican Americans. Working Paper 11423, National Bureau of Economic Research.
- Duncan, B. and S. J. Trejo (2011a). Intermarriage and the intergenerational transmission of ethnic identity and human Capital for Mexican Americans. *J Labor Econ*, 29.
- Duncan, B. and S. J. Trejo (2011b). Who remains Mexican? Selective ethnic attrition and the inter-generational Progress of Mexican Americans. In D. L. Leal and S. J. Trejo (Eds.), *Latinos and the Economy: Integration and Impact in Schools, Labor Markets, and Beyond*. New York: Springer.
- Duncan, Brian and Stephen J. Trejo (2017). The Complexity of Immigrant Generations: Implications for Assessing the Socioeconomic Integration of Hispanics and Asians. *ILR Review: The Journal of Work and Policy*, 70(5), 1146–1175.
- Duncan, Brian and Stephen J. Trejo (2018a). Identifying the Later-Generation Descendants of U.S. Immigrants: Issues Arising from Selective Ethnic Attrition. *The ANNALS of the American Academy of Political and Social Science*, 677(1), 131–138.
- Duncan, Brian and Stephen J. Trejo (2018b). Socioeconomic Integration of U.S. Immigrant Groups over the Long Term: The Second Generation and Beyond. Working Paper 24394, National Bureau of Economic Research.
- Egloff, Boris and Stefan C. Schmukle (2002). Predictive validity of an implicit association test for assessing anxiety. *Journal of Personality and Social Psychology*, 83, 1441–1455.
- Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry (2021). Integrated Public Use Microdata Series, Current Population Survey: Version 9.0.
- Fouka, Vasiliki, Soumyajit Mazumder, and Marco Tabellini (2022). From Immigrants to Americans: Race and Assimilation during the Great Migration. *The Review of Economic Studies*, 89(2), 811–842.
- Friese, Malte, Matthias Bluemke, and Michaela Wänke (2007). Predicting voting behavior with implicit attitude measures: The 2002 German parliamentary election. *Experimental Psychology*, 54(4), 247–255.
- Fryer, Roland G. and Steven D. Levitt (2004). The Causes and Consequences of Distinctively Black Names. *The Quarterly Journal of Economics*, 119(3), 767–805.
- Fryer, Roland G. and Paul Torelli (2010). An empirical analysis of ‘acting white’. *Journal of Public Economics*, 94(5), 380–396.
- Gershenson, Seth, Stephen B. Holt, and Nicholas W. Papageorge (2016). Who believes in me? The effect of student–teacher demographic match on teacher expectations. *Economics of Education Review*, 52, 209–224.
- Giuliano, Laura, David I. Levine, and Jonathan Leonard (2009). Manager Race and the Race of New Hires. *Journal of Labor Economics*, 27(4), 589–631.
- Giuliano, Laura, David I. Levine, and Jonathan Leonard (2011). Racial Bias in the Manager-Employee Relationship: An Analysis of Quits, Dismissals, and Promotions at a Large Retail Firm. *Journal of Human Resources*, 46(1), 26–52.

- Giuntella, O. (2016). Assimilation and health: Evidence from linked birth records of second- and third-generation Hispanics. *Demography*, 53.
- Giuntella, Osea (2017). Why does the health of Mexican immigrants deteriorate? New evidence from linked birth records. *Journal of Health Economics*, 54, 1–16.
- Giuntella, O., Z. L. Kone, I. Ruiz, and C. Vargas-Silva (2018). Reason for immigration and immigrants' health. *Public Health*, 158, 102–109.
- Giuntella, Osea and Luca Stella (2017). The Acceleration of Immigrant Unhealthy Assimilation. *Health Economics*, 26(4), 511–518.
- Glover, Dylan, Amanda Pallais, and William Pariente (2017). Discrimination as a Self-Fulfilling Prophecy: Evidence from French Grocery Stores. *Quarterly Journal of Economics*, 132(3), 1219–1260.
- Greenwald, Anthony G., Debbie E. McGhee, and Jordan L. K. Schwartz (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology*, 74(6), 1464–1480.
- Grossman, Gene M and Elhanan Helpman (2021). Identity Politics and Trade Policy. *The Review of Economic Studies*, 88(3), 1101–1126.
- Hadah, Hussain (2020). The Impact of Hispanic Last Names and Identity on Labor Market Outcomes.
- Jardina, Ashley (2019). *White Identity Politics*. Cambridge Studies in Public Opinion and Political Psychology. Cambridge: Cambridge University Press.
- Kranton, Rachel, Matthew Pease, Seth Sanders, and Scott Huettel (2020). Deconstructing bias in social preferences reveals groupy and not-groupy behavior. *Proceedings of the National Academy of Sciences*, 117(35), 21185–21193.
- Leitner, Jordan B., Eric Hehman, Ozlem Ayduk, and Rodolfo Mendoza-Denton (2016). Racial bias is associated with ingroup death rate for Blacks and Whites: Insights from Project Implicit. *Social Science & Medicine*, 170, 220–227.
- Meng, Xin and Robert G. Gregory (2005). Intermarriage and the Economic Assimilation of Immigrants. *Journal of Labor Economics*, 23(1), 135–174.
- Smith, James P. (2003). Assimilation across the Latino generations. *The American Economic Review*, 93(2), 315.
- Trejo, Stephen J. (1997). Why do Mexican Americans earn low wages? *Journal of Political Economy*, 105(6), 1235.

APPENDIX A: TABLES

TABLE 16

HISPANIC SELF-IDENTIFICATION BY GENERATION IN HIGH BIAS STATE (ABOVE 80TH PERCENTILE)

	Identify as Hispanic	Does Not Identify as Hispanic	% Identify as Hispanic
1st Gen.	25553	971	0.96
2nd Gen.	143979	10588	0.93
Hispanic on:			
Both Sides	103425	3739	0.97
One Side	40554	6849	0.86
3rd Gen.	40522	10362	0.8
Both Sides	10450	536	0.95
One Side	10256	3720	0.73

TABLE 17

HISPANIC SELF-IDENTIFICATION BY GENERATION IN LOW BIAS STATE (BELOW 20TH PERCENTILE)

	Identify as Hispanic	Does Not Identify as Hispanic	% Identify as Hispanic
1st Gen.	22066	967	0.96
2nd Gen.	141130	10234	0.93
Hispanic on:			
Both Sides	103760	3826	0.96
One Side	37370	6408	0.85
3rd Gen.	42973	9878	0.81
Both Sides	12004	386	0.97
One Side	11032	3885	0.74

TABLE 18

TABULATION OF HISPANIC-HISPANIC PARENTY BY SUBJECTIVE HISPANIC IDENTITY: FULL SAMPLE

Subjective Identity		N	Percent
Hispanic-Hispanic	Hispanic	516551	96.40
	Not Hispanic	19318	3.60

TABLE 19

TABULATION OF HISPANIC-HISPANIC PARENTY BY SUBJECTIVE HISPANIC IDENTITY: TOP 10 PERCENTILE BIAS

Subjective Identity		N	Percent
Hispanic-Hispanic	Hispanic	52534	95.48
	Not Hispanic	2486	4.52

TABLE 20

TABULATION OF HISPANIC-HISPANIC PARENTY BY SUBJECTIVE HISPANIC IDENTITY: BOTTOM 10 PERCENTILE BIAS

Subjective Identity		N	Percent
Hispanic-Hispanic	Hispanic	51549	95.82
	Not Hispanic	2251	4.18

TABLE 21
TABULATION OF IDENTITY BY PARENTS TYPE AND CHILD'S IDENTITY: MOTHER AS PROXY RESPONDENT

1	HH				HW				WH				All Percent
	NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		
Hispanic Mother	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	All Percent
NonHispanic Mom	5696	1.36	2244	0.53	7583	1.80	22289	5.30	4129	0.98	998	0.24	10.22
Hispanic Mom	4440	1.06	274034	65.21	980	0.23	56302	13.40	3147	0.75	38361	9.13	89.78
All	10136	2.41	276278	65.75	8563	2.04	78591	18.70	7276	1.73	39359	9.37	100.00

TABLE 22
TABULATION OF IDENTITY BY PARENTS TYPE AND CHILD'S IDENTITY: FATHER AS PROXY RESPONDENT

1	HH				HW				WH				All Percent
	NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		
Hispanic Father	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	All Percent
NonHispanic Dad	3743	1.72	2308	1.06	2244	1.03	1747	0.80	6183	2.83	9224	4.23	11.66
Hispanic Dad	2931	1.34	147103	67.42	1841	0.84	22794	10.45	485	0.22	17601	8.07	88.34
All	6674	3.06	149411	68.47	4085	1.87	24541	11.25	6668	3.06	26825	12.29	100.00

TABLE 23
SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS

Sample	All Sample	March Sup.	non-March Sup.	March Sup. with income
	(1)	(2)	(3)	
	H^2	H^2	H^2	
Bias x Hispanic-White Parent	0.07*** (0.01)	-0.03 (0.04)	0.08*** (0.02)	-0.03 (0.04)
Bias x White-Hispanic Parent	0.06*** (0.02)	-0.01 (0.05)	0.07*** (0.02)	-0.01 (0.05)
Implicit Skin Tone Bias	-0.12*** (0.01)	-0.15*** (0.03)	-0.12*** (0.01)	-0.15*** (0.03)
Hispanic-White Parent	-0.06*** (0.00)	-0.05*** (0.00)	-0.06*** (0.00)	-0.05*** (0.00)
White-Hispanic Parent	-0.11*** (0.00)	-0.10*** (0.00)	-0.11*** (0.00)	-0.10*** (0.00)
Log Total Family Income				0.00*** (0.00)
N	560100	82428	477672	82428
Mean	0.94	0.94	0.94	0.94
Year-Region FE	X	X	X	X

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

¹ I include controls for sex, quartic age, and parental education.

TABLE 24
SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS

Sample	All Sample	March Sup.	non-March Sup.	March Sup. with Income
	(1)	(2)	(3)	
	H^3	H^3	H^3	
Bias x HHHW	0.08** (0.04)	0.06 (0.13)	0.08** (0.04)	0.07 (0.13)
Bias x HHWH	0.01 (0.07)	-0.11 (0.20)	0.02 (0.07)	-0.10 (0.20)
Bias x HHWW	0.29*** (0.03)	0.26*** (0.08)	0.30*** (0.03)	0.25*** (0.08)
Bias x HWHH	0.14** (0.06)	0.00 (0.18)	0.14** (0.06)	-0.01 (0.18)
Bias x HWHW	0.09 (0.06)	-0.26 (0.19)	0.11* (0.07)	-0.26 (0.19)
Bias x HWWH	0.83*** (0.15)	0.36 (0.54)	0.85*** (0.15)	0.36 (0.54)
Bias x HWWW	0.26*** (0.05)	0.24* (0.13)	0.27*** (0.05)	0.23* (0.13)
Bias x WHHH	0.25*** (0.06)	0.16 (0.22)	0.25*** (0.06)	0.16 (0.22)
Bias x WHHW	0.33*** (0.11)	0.50** (0.25)	0.31** (0.12)	0.51** (0.25)
Bias x WHWH	0.28** (0.12)	-0.25 (0.33)	0.32*** (0.12)	-0.26 (0.32)
Bias x WHWW	0.18***	-0.06	0.20***	-0.06

TABLE 24
SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS (*continued*)

	(1)	(2)	(3)	(4)
	H^3	H^3	H^3	H^3
	(0.06)	(0.16)	(0.06)	(0.16)
Bias x WWHH	0.05 (0.04)	0.05 (0.10)	0.05 (0.04)	0.05 (0.10)
Bias x WWHW	0.27*** (0.05)	0.19 (0.14)	0.27*** (0.06)	0.19 (0.14)
Bias x WWWH	-0.18*** (0.06)	-0.08 (0.16)	-0.19*** (0.06)	-0.09 (0.16)
Implicit Skin Tone Bias	0.00 (0.02)	0.06 (0.06)	-0.01 (0.02)	0.07 (0.06)
N	198991	28346	170645	28346
Mean	0.82	0.83	0.82	0.83
Year-Region FE	X	X	X	X

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

¹ I include controls for sex, quartic age, and parental education.

TABLE 25
 SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS AMONG ADULT SECOND GENERATION HISPANIC IMMIGRANTS: BY PARENTAL TYPE (STATE)

Parents Type	Sample	All Sample						March Sup.						non-March Sup.						March Sup. and Control for Income									
		All		HH		WH		All		HH		HW		WH		All		HH		HW		All		HH		HW		WH	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	H^2	H^2	H^2	H^2	H^2	H^2	H^2	H^2	H^2	H^2		
Implicit Skin Tone Bias	0.34*	-0.01	0.42	0.64	0.46*	-0.05	0.60	1.03*	0.33*	-0.01	0.40	0.61	0.46*	-0.05	0.60	1.03*													
Female	0.00	0.00	-0.01	0.04***	0.01	0.00	-0.02	0.05***	0.00	0.00	-0.01	0.04***	0.00	0.00	-0.02	0.05***													
Log Total Family Income																													
N	237595	156819	46175	34601	33458	22350	6353	4755	204137	134469	39822	29846	33458	22350	6353	4755													
Mean	0.92	0.96	0.85	0.8	0.94	0.97	0.89	0.84	0.92	0.96	0.84	0.8	0.94	0.97	0.89	0.84													
Year-Region FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X													

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

¹ I include controls for sex, quartic age, education.

² This is a sample of second generation adults between the ages of 25 to 54. The sample is restricted to head of households and partners/spouses.

³ Standard errors are clustered on the state level

TABLE 26
 SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS: ADULT SECOND GENERATION
 IMMIGRANTS

Sample	All Sample	March Sup.	non-March Sup.	March Sup with income
	(1)	(2)	(3)	(4)
	H^2	H^2	H^2	H^2
Bias x Hispanic-White Parent	0.05 (0.06)	0.29* (0.18)	0.03 (0.06)	0.29* (0.18)
Bias x White-Hispanic Parent	-0.02 (0.07)	0.09 (0.23)	-0.03 (0.07)	0.09 (0.23)
Implicit Skin Tone Bias	0.33*** (0.04)	0.38*** (0.14)	0.32*** (0.04)	0.38*** (0.14)
Hispanic-White Parent	-0.11*** (0.02)	-0.18*** (0.05)	-0.11*** (0.02)	-0.18*** (0.05)
White-Hispanic Parent	-0.13*** (0.02)	-0.16** (0.07)	-0.13*** (0.02)	-0.16** (0.07)
Log Total Family Income				0.00 (0.00)
N	237595	33458	204137	33458
Mean	0.92	0.94	0.92	0.94
Year-Region FE	X	X	X	X

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

¹ I include controls for sex, quartic age, and parental education.

² This is a sample of second generation adults between the ages of 25 to 54. The sample is restricted to head of households and partners/spouses.

TABLE 27
 SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS: BY PARENTAL TYPE
 (STATE)

Parents Type	Sample		All Sample				March Sup.				non-March Sup.				March Sup. and Control for Income					
			All		HH		Inter Ethnic		All		HH		Inter Ethnic		All		HH		Inter Ethnic	
	(1) H^2	(2) H^2	(3) H^2	(4) H^2	(5) H^2	(6) H^2	(7) H^2	(8) H^2	(9) H^2	(10) H^2	(11) H^2	(12) H^2	(13) H^2	(14) H^2	(15) H^2	(16) H^2	(17) H^2	(18) H^2		
Implicit Skin Tone Bias	-0.10*** (0.05)	-0.15** (0.07)	0.06 (0.07)	-0.15*** (0.05)	-0.16** (0.06)	-0.09 (0.12)	-0.10* (0.05)	-0.15*** (0.05)	0.07 (0.07)	-0.15*** (0.05)	0.07 (0.06)	-0.16*** (0.05)	-0.15*** (0.05)	-0.16*** (0.05)	-0.09 (0.12)	-0.16*** (0.06)	-0.16*** (0.06)	-0.16*** (0.06)		
Female	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.01 (0.01)	0.00 (0.00)	0.00 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)		
College Graduate: Mother	-0.06*** (0.01)	-0.04*** (0.01)	-0.07*** (0.01)	-0.05*** (0.01)	-0.03** (0.01)	-0.07*** (0.01)	-0.03** (0.01)	-0.07*** (0.01)	-0.03** (0.01)	-0.07*** (0.01)	-0.04*** (0.01)	-0.06*** (0.01)	-0.04*** (0.01)	-0.04*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.03** (0.01)	-0.07*** (0.01)		
College Graduate: Father	-0.08*** (0.01)	-0.04*** (0.01)	-0.12*** (0.01)	-0.09*** (0.01)	-0.05*** (0.01)	-0.12*** (0.01)	-0.05*** (0.01)	-0.11*** (0.01)	-0.05*** (0.01)	-0.11*** (0.01)	-0.08*** (0.01)	-0.12*** (0.01)	-0.04*** (0.01)	-0.12*** (0.01)	-0.08*** (0.01)	-0.08*** (0.01)	-0.05*** (0.01)	-0.11*** (0.01)		
Log Total Family Income																				
Mean	0.94	0.96	0.9	0.94	0.97	0.9	0.94	0.96	0.89	0.94	0.94	0.89	0.94	0.94	0.97	0.97	0.9	0.9		
N	560,100	405,116	154,984	82,428	59,950	22,478	47,7672	345,166	132,506	82,428	59,950	22,478								
Year-Region FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		

¹ I include controls for sex, quartic age, parental education.

² Standard errors are clustered on the state level

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

TABLE 28
SUBJECTIVE HISPANIC IDENTITY AND EXPLICIT BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS: BY PARENTAL TYPE (STATE)

Sample		All Sample						March Sup.						non-March Sup.						March Sup. and Control for Income						
Parents Type		All	HH	HW	WH	All	HH	HW	WH	All	HH	HW	WH													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	H^2	H^2	H^2	H^2	H^2	H^2	H^2	H^2	H^2	
Explicit Bias	-0.05 (0.06)	-0.09 (0.08)	0.08 (0.11)	0.04 (0.19)	0.02 (0.05)	-0.06 (0.07)	0.49*** (0.11)	-0.12 (0.21)	-0.05 (0.06)	-0.10 (0.08)	0.05 (0.11)	0.05 (0.20)	0.02 (0.20)	0.05 (0.05)	0.02 (0.07)	-0.06 (0.11)	0.49*** (0.11)	-0.12 (0.21)	-0.06 (0.05)	0.02 (0.05)	0.05 (0.07)	0.02 (0.07)	0.05 (0.11)	0.02 (0.11)	-0.06 (0.11)	-0.12 (0.21)
Female	0.00 (0.00)	0.00 (0.00)	-0.02 (0.02)	0.02 (0.02)	0.00 (0.00)	-0.01 (0.00)	-0.01 (0.02)	0.02 (0.02)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.02 (0.02)	0.02 (0.02)	0.00 (0.00)	-0.02 (0.02)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)	
College Graduate: Mother	-0.06*** (0.02)	-0.03 (0.02)	-0.04** (0.02)	-0.12*** (0.02)	-0.05** (0.03)	-0.02 (0.02)	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.03)	-0.02 (0.03)	-0.02 (0.03)	-0.03 (0.02)	-0.03 (0.02)	-0.03 (0.02)	-0.04** (0.02)	-0.04** (0.02)	-0.04** (0.02)	-0.04** (0.02)	-0.05** (0.02)	-0.05** (0.02)	-0.05** (0.02)	-0.05** (0.02)	-0.05** (0.02)	-0.05** (0.02)	-0.05** (0.02)	
College Graduate: Father	-0.08*** (0.02)	-0.04*** (0.01)	-0.17*** (0.03)	-0.07*** (0.03)	-0.09*** (0.03)	-0.05*** (0.02)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)									
Log Total Family Income																										
Mean	0.94 N	0.96 167005	0.9 122157	0.83 25648	0.9 19200	0.94 24844	0.97 X	0.9 X	0.9 X	0.94 X	0.95 X	0.96 X	0.97 X	0.94 X	0.95 X	0.96 X	0.94 X	0.95 X	0.96 X	0.94 X	0.95 X	0.96 X	0.94 X	0.95 X		
Year × Region FE																										

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

¹ I include controls for sex, quartic age, parental education.

² Standard errors are clustered on the state level

TABLE 29
SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY PARENTAL TYPE

Sample:	Second Generation		Third Generation	
	(1)	(2)	(3)	(4)
	H^2	H^2	H^3	H^3
Bias x Hispanic-White Parent	0.07*** (0.01)	0.07*** (0.01)		
Bias x White-Hispanic Parent	0.06*** (0.02)	0.06*** (0.02)		
Bias x HHHW			0.08** (0.04)	0.10*** (0.03)
Bias x HHWH			0.01 (0.07)	0.01 (0.07)
Bias x HHWW			0.29*** (0.03)	0.27*** (0.03)
Bias x HWHH			0.14** (0.06)	0.18*** (0.06)
Bias x HWHW			0.09 (0.06)	0.16** (0.06)
Bias x HWWH			0.83*** (0.15)	0.82*** (0.15)
Bias x HWWW			0.26*** (0.05)	0.23*** (0.05)
Bias x WHHH			0.25*** (0.06)	0.31*** (0.06)
Bias x WHHW			0.33*** (0.11)	0.36*** (0.11)

TABLE 29
SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY PARENTAL TYPE (*continued*)

	(1)	(2)	(3)	(4)
	H^2	H^2	H^3	H^3
Bias x WWHH			0.28** (0.12)	0.39*** (0.11)
Bias x WHWW			0.18*** (0.06)	0.19*** (0.06)
Bias x WWHH			0.05 (0.04)	0.03 (0.03)
Bias x WWHW			0.27*** (0.05)	0.25*** (0.05)
Bias x WWWH			-0.18*** (0.06)	-0.17*** (0.06)
Bias	-0.12*** (0.01)	-0.07*** (0.01)	0.00 (0.02)	0.08*** (0.02)
Hispanic-White Parent	-0.06*** (0.00)	-0.06*** (0.00)		
White-Hispanic Parent	-0.11*** (0.00)	-0.11*** (0.00)		
N	560100	560100	198991	198991
Mean	0.94	0.94	0.82	0.82
Region FE		X		X
Year FE		X		X
Year × Region FE	X		X	

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

TABLE 29
 SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY PARENTAL TYPE (*continued*)

(1)	(2)	(3)	(4)
H^2	H^2	H^3	H^3

Note:

I include controls for sex, quartic age, parental education.

Robust standard errors are reported.

The samples include 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. Native born third generation Hispanic immigrant children with native born parents and at least one grand parent born in a Spanish speaking country.

Data source is the 2004-2020 Current Population Survey.

TABLE 30
HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS

Sample:	Second Generation		Third Generation	
	(1)	(2)	(3)	(4)
	Dad H^2	Dad H^2	Dad H^3	Dad H^3
Bias x Hispanic-White Parent	0.16*** (0.01)	0.16*** (0.01)		
Bias x White-Hispanic Parent	0.18*** (0.02)	0.17*** (0.02)		
Bias x HHHW			0.16*** (0.04)	0.15*** (0.04)
Bias x HHWH			0.11** (0.05)	0.13*** (0.05)
Bias x HHWW			0.28*** (0.02)	0.28*** (0.02)
Bias x HWHH			0.06 (0.07)	0.07 (0.07)
Bias x HWHW			-0.01 (0.07)	0.01 (0.07)
Bias x HWWH			0.64*** (0.13)	0.62*** (0.14)
Bias x HWWW			0.13*** (0.04)	0.11** (0.04)
Bias x WHHH			0.06 (0.06)	0.06 (0.06)
Bias x WHHW			0.27** (0.12)	0.31*** (0.11)

TABLE 30
HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS (*continued*)

	(1)	(2)	(3)	(4)
	Dad H^2	Dad H^2	Dad H^3	Dad H^3
Bias x WWHH			0.86*** (0.14)	0.88*** (0.14)
Bias x WHWW			-0.10* (0.06)	-0.10* (0.06)
Bias x WWHH			0.37*** (0.04)	0.36*** (0.04)
Bias x WWHW			0.38*** (0.04)	0.37*** (0.04)
Bias x WWWH			0.00 (0.05)	0.01 (0.05)
Implicit Skin Tone Bias	-0.04*** (0.01)	-0.03*** (0.01)	-0.11*** (0.02)	-0.06*** (0.02)
Hispanic-White Parent	-0.05*** (0.00)	-0.05*** (0.00)		
White-Hispanic Parent	-0.32*** (0.00)	-0.32*** (0.00)		
N	560100	560100	198991	198991
Mean	0.91	0.91	0.74	0.74
Region FE		X		X
Year FE		X		X
Year-Region FE	X		X	

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

TABLE 30
 HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS (*continued*)

	(1)	(2)	(3)	(4)
	Dad H^2	Dad H^2	Dad H^3	Dad H^3

¹ I include controls for sex, quartic age, parental education and total family income.

² Standard errors are clustered on the state level

TABLE 31
MOTHERS' SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS

Sample:	Second Generation		Third Generation	
	(1)	(2)	(3)	(4)
	Mom H^2	Mom H^2	Mom H^3	Mom H^3
Bias x Hispanic-White Parent	0.19*** (0.02)	0.19*** (0.02)		
Bias x White-Hispanic Parent	0.02 (0.02)	0.02 (0.02)		
Bias x HHHW			-0.02 (0.05)	0.03 (0.04)
Bias x HHWH			-0.16*** (0.05)	-0.16*** (0.05)
Bias x HHWW			0.31*** (0.03)	0.30*** (0.03)
Bias x HWHH			-0.16*** (0.06)	-0.13** (0.06)
Bias x HWHW			-0.04 (0.06)	-0.03 (0.06)
Bias x HWWH			0.52*** (0.13)	0.53*** (0.13)
Bias x HWWW			0.28*** (0.05)	0.28*** (0.05)
Bias x WHHH			-0.03 (0.05)	0.03 (0.05)
Bias x WHHW			-0.72*** (0.13)	-0.64*** (0.12)

TABLE 31
MOTHERS' SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS (*continued*)

	(1)	(2)	(3)	(4)
	Mom H^2	Mom H^2	Mom H^3	Mom H^3
Bias x WWHH			1.16*** (0.15)	1.27*** (0.15)
Bias x WHWW			-0.12*** (0.05)	-0.09** (0.05)
Bias x WWHH			-0.11*** (0.03)	-0.11*** (0.03)
Bias x WWHW			-0.19*** (0.05)	-0.18*** (0.05)
Bias x WWWH			-0.04 (0.05)	-0.05 (0.05)
Implicit Skin Tone Bias	-0.03*** (0.01)	-0.02** (0.01)	0.08*** (0.02)	0.05*** (0.02)
Hispanic-White Parent	-0.26*** (0.00)	-0.26*** (0.00)		
White-Hispanic Parent	-0.05*** (0.00)	-0.05*** (0.00)		
N	560100	560100	198991	198991
Mean	0.91	0.91	0.75	0.75
Region FE		X		X
Year FE		X		X
Year-Region FE	X		X	

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

TABLE 31
 MOTHERS' SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS (*continued*)

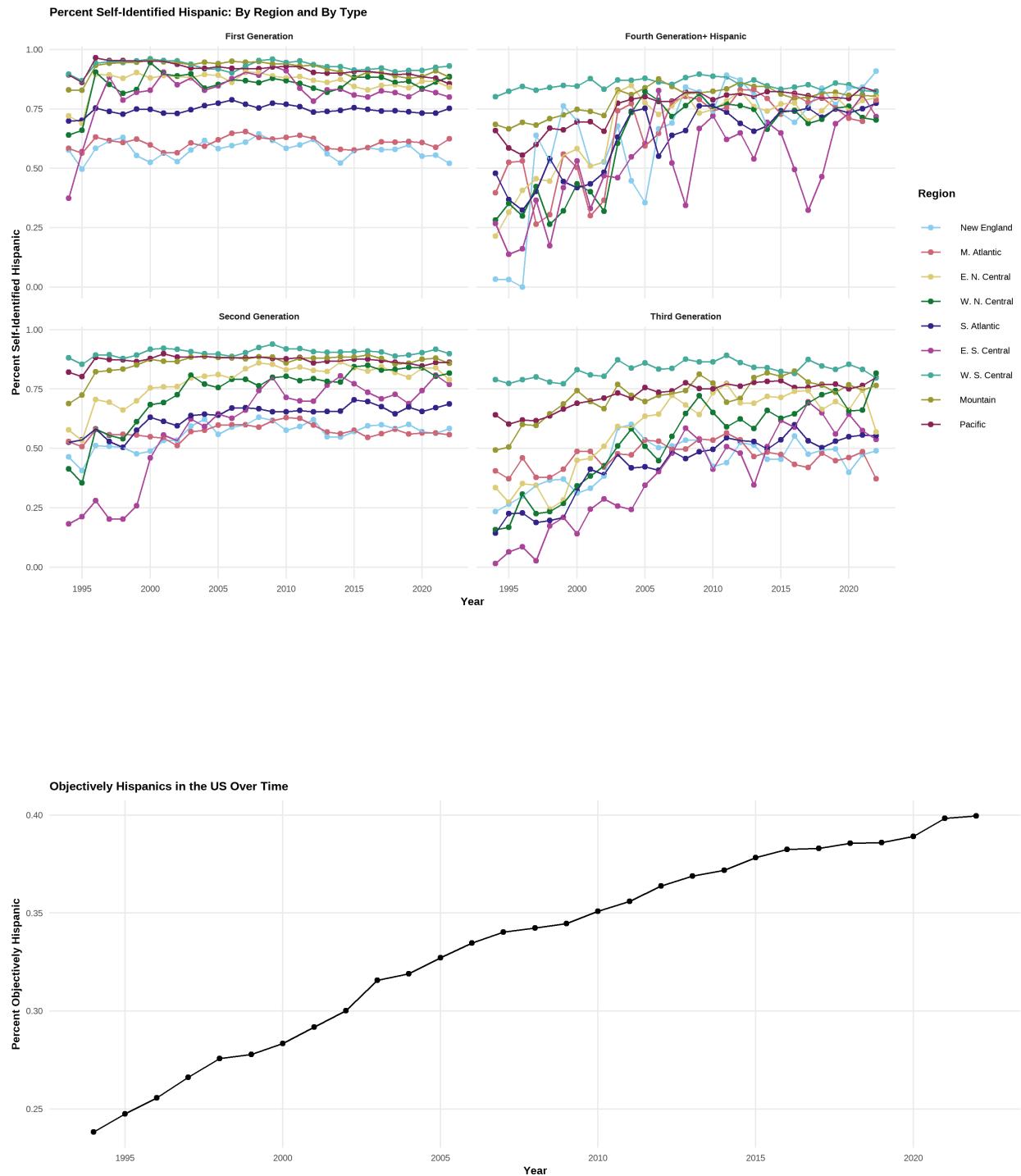
	(1)	(2)	(3)	(4)
	Mom H^2	Mom H^2	Mom H^3	Mom H^3

¹ I include controls for sex, quartic age, and parental education.

² Standard errors are clustered on the state level

APPENDIX B: FIGURES

FIGURE 12
HISPANIC IDENTIFICATION AMONG HISPANIC IMMIGRANTS: BY GENERATION



Objectively Hispanics in the US Over Time: By Region (Objective)

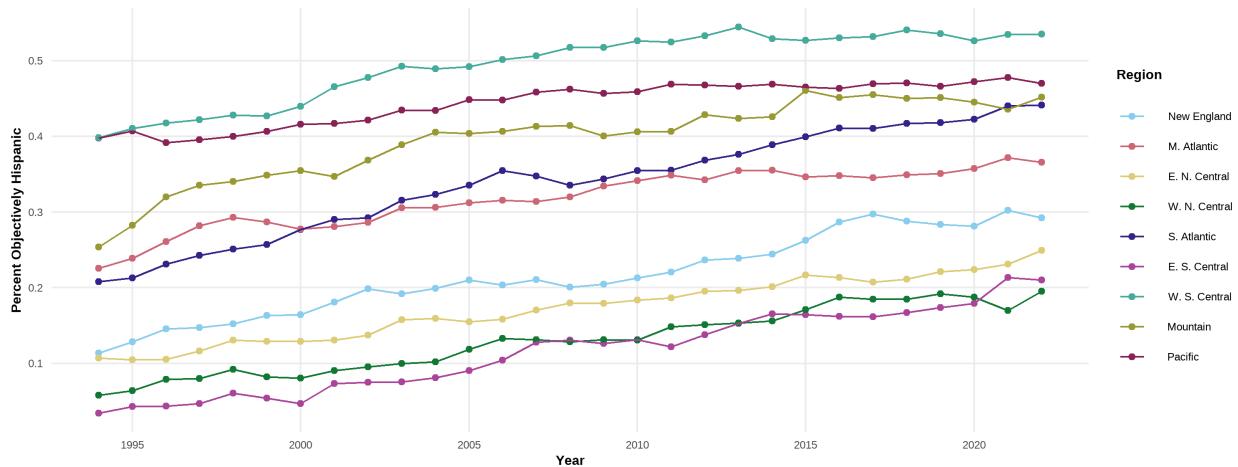


FIGURE 13
CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: IAT EXPLICIT BIAS QUESTION
Correlation between Implicit and Explicit Biases

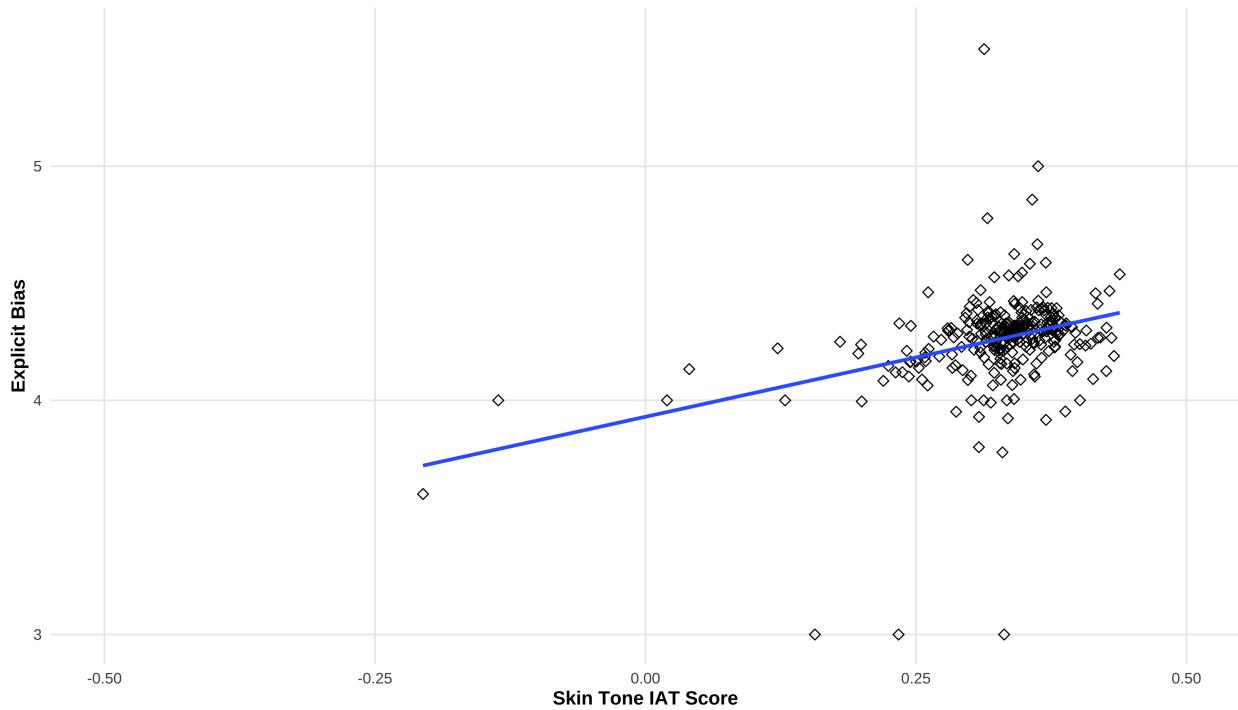


FIGURE 14

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

Correlation between IAT and Other Bias Measures

In general, how close Do you feel to Blacks?

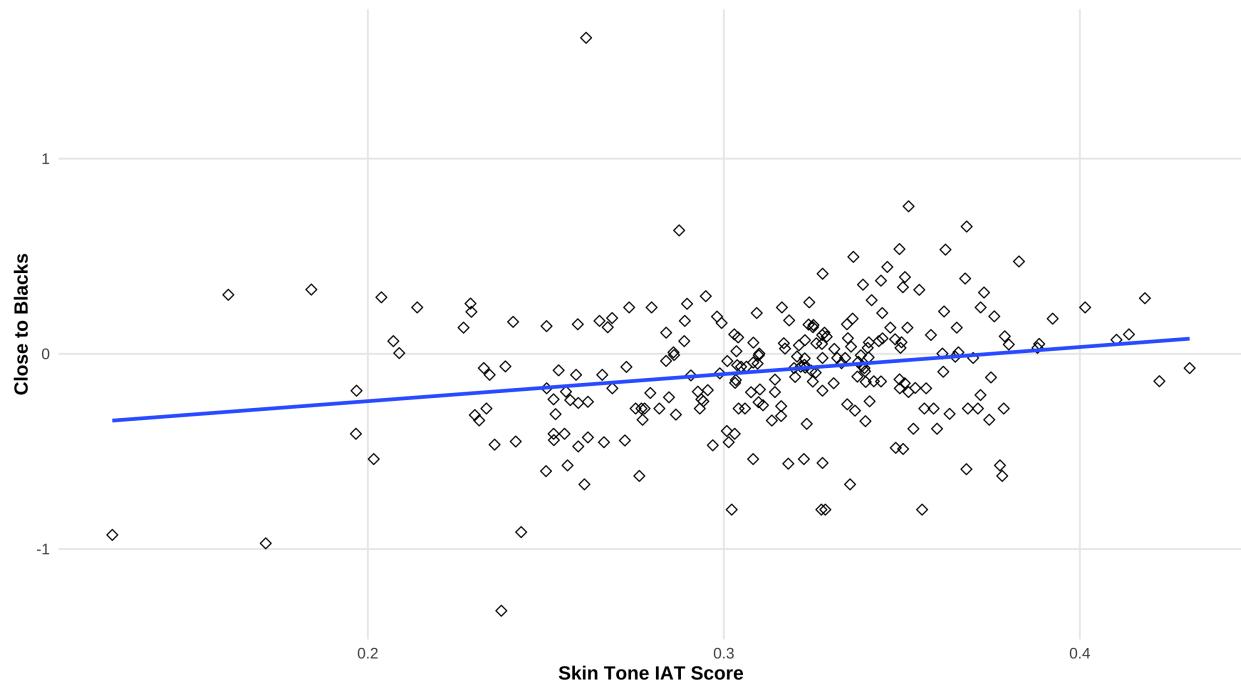
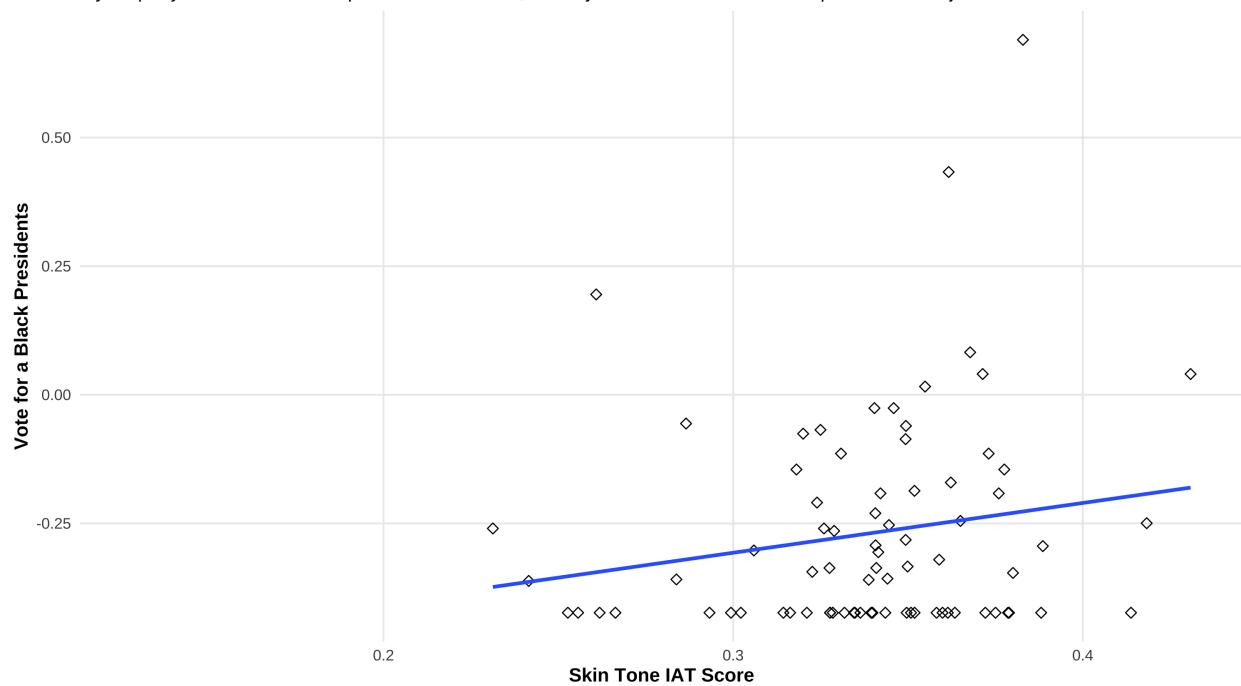


FIGURE 15
 CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: GSS VOTE FOR A BLACK PRESIDENT
 QUESTION

Correlation between IAT and Other Bias Measures

If your party nominated a Black person for President, would you vote for him if he were qualified for the job?



APPENDIX C: DATA

FIGURE 16
EXAMPLES OF AN IMPLICIT ASSOCIATION TEST

Implicit Association Test

Next, you will use the 'E' and 'I' computer keys to categorize items into groups as fast as you can. These are the four groups and the items that belong to each:

Category	Items
Good	Delight, Enjoy, Laughing, Excitement, Terrific, Lovely, Pleasure, Love
Bad	Humiliate, Annoy, Angry, Horrific, Despise, Ugly, Tragic, Evil
	 
	 

There are seven parts. The instructions change for each part. Pay attention!

[Continue](#)

Press "E" for 

Press "I" for 



If you make a mistake, a red X will appear. Press the other key to continue.

Press "E" for 

Press "I" for 

Part 1 of 7

Put a left finger on the E key for items that belong to the category Light Skinned People.
Put a right finger on the I key for items that belong to the category Dark Skinned People.
Items will appear one at a time.

If you make a mistake, a red X will appear. Press the other key to continue. Go as fast as you can while being accurate.

Press the **space bar** when you are ready to start.

Press "E" for **Bad**

Press "I" for **Good**

Enjoy

If you make a mistake, a red X will appear. Press the other key to continue.

Press "E" for **Bad**
or

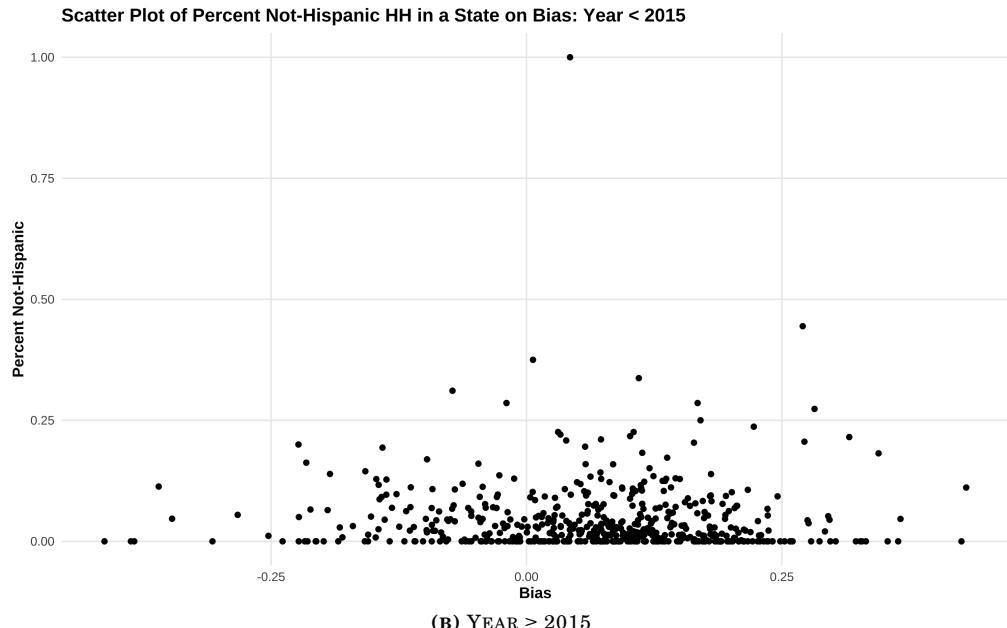

Press "I" for **Good**
or


Tragic

If you make a mistake, a red X will appear. Press the other key to continue.

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

FIGURE 17
SCATTER PLOT OF NON-HISPANIC SECOND-GENERATION HISPANIC-HISPANIC PARENTS ON BIAS
(A) YEAR < 2015



(B) YEAR \geq 2015

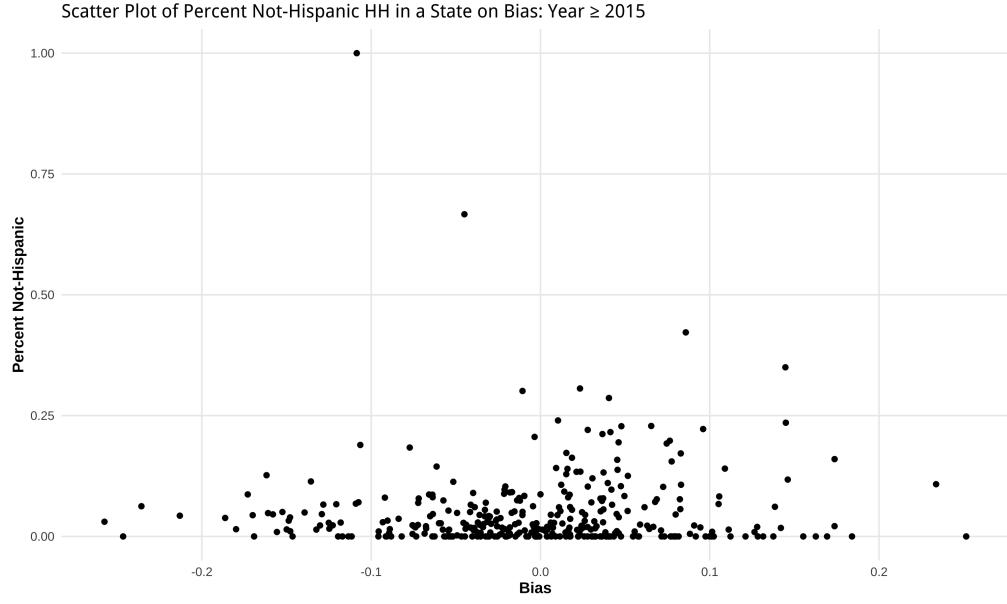
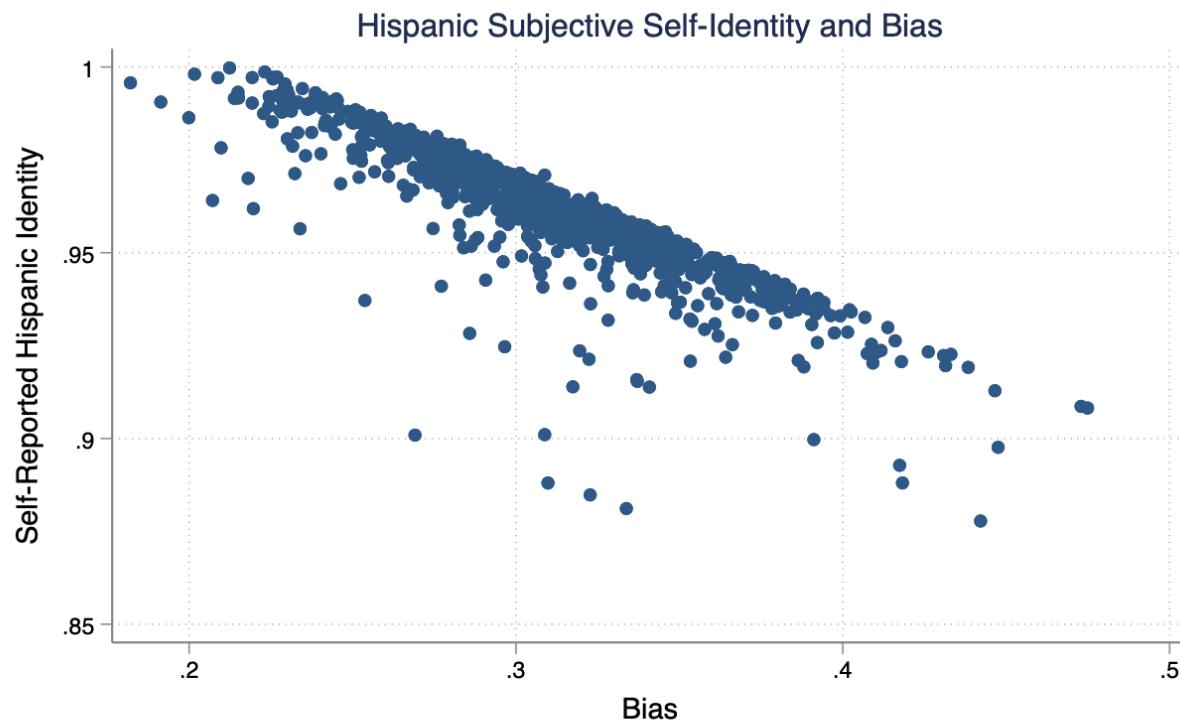


FIGURE 18
SCATTER PLOT OF HISPANIC SECOND-GENERATION HISPANIC-HISPANIC PARENTS ON BIAS WITH
YEAR-REGION FE



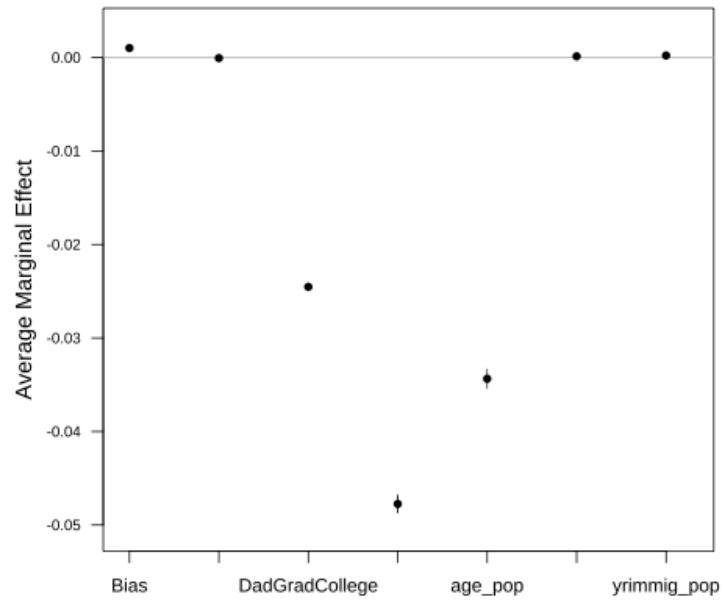
I include controls for sex, age, parental education, and state x region fixed effects.

FIGURE 19

LOGISTIC AND PROBIT REGRESSIONS OF THE EFFECT OF BIAS ON INTERETHNIC MARRIAGES

(A) LOGISTIC REGRESSION: COEFFICIENT INTERPRETED AS MARGINAL EFFECT

Marginal Effect of Bias on Interethnic Marriages: Logistic



(B) PROBIT REGRESSION: COEFFICIENT INTERPRETED AS MARGINAL EFFECT

Marginal Effect of Bias on Interethnic Marriages: Probit

