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

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ABSTRACT

Do attitudes toward minorities affect Hispanic self-identification among people with Hispanic ancestry? 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 racial bias. A one standard deviation increase in bias decreases self-reported Hispanic identity by 5.8 and 10 percentage points for first and second-generation Hispanics, respectively. These effects are more prominent among second-generation immigrants whose mothers and fathers were born in a Spanish-speaking country than children of inter-ethnic parents.

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

JEL Classifications: I310, J15, J71

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I. Introduction

With the impending introduction of the 2020 Census, there is increasing interest in the counts of various groups defined by race, ethnicity, and gender. The recent Censuses allowed individuals to check off multiple categories regarding race and ethnicity, reflecting how the U.S. population has increasingly become multi-racial and multi-ethnic.[1] How individuals self-identify into various categories will have significant consequences on economic research focusing on earnings gaps using self-reported measures, representation, distribution of tax revenues, and transfers across groups and areas.

In this paper, I examine the determinants of self-identification as "Hispanic" among immigrants from Spanish-speaking countries, particularly the extent to which prejudice and bias in the community impact this decision. 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. Another example is the adoption of "oppositional" identities. Fryer and Torelli (2010) build a theory where black youths punish peers for striving for economic success, in other words, for "Acting White." On one hand, minority populations may underachieve to differentiate themselves from the majority group. Adoption of these identities then may have an economical cost. On the other hand, not formally adopting these identities may have a personal cost or social cost (such as losing friends in the above example).

Understanding the determinants of self-identification is vital for at least three reasons. First, as argued above, the rates of self-identification by the group will have significant consequences for political representation and the distribution of resources. Second, how individuals identify will impact measured changes in labor market outcomes among groups differentiated by race and ethnicity. Antman et al. (2016) show that among Mexican immi-

1. Sociologist discussed some implications of multiple ethnic and racial categories and the future of the multi-racial and multi-ethnic demography of the United States (Bratter, 2018; Alba, 2020).

grants, the least economically successful self-identify as being of Mexican origin, while the most successful do not, thereby understating why the rates of assimilation among Mexican immigrants could appear slower than other groups. Third, to the extent that individuals react to prejudice by not identifying with the group that the prejudice is targeted towards, we may not be able to document and get an accurate picture of the economic consequences of discrimination and prejudice.

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 the increase in the number of Hispanics in the United States questions on assimilation and mobility (Chetty et al., 2014, 2016, 2017; Abramitzky et al., 2020, 2014, 2016; Chetty 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]

My paper answers the following question: how do individual characteristics and social attitudes toward racial and ethnic minorities affect the self-reported identity of persons with Hispanic ancestry in the United States? I 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, to investigate how self-reported Hispanic identity is affected by attitudes toward racial and ethnic minorities. This paper addresses several strands of economic literature including studies of identity (Akerlof and Kranton, 2000; Kranton et al., 2020; Grossman and Helpman, 2021; Bonomi et al., 2021; Shayo, 2020; Antman and Duncan, 2015), immigrant assimilation (Smith, 2003; Antecol and Bedard, 2006; Abramitzky et al., 2016, 2014), and social attitudes (Charles and Guryan, 2008; Charles et al., 2018; Bertrand et al., 2021).

I motivate my analysis with a simple model in the vein of Akerlof and Kranton (2000). This framework implies that a person's sense of self, i.e., identity, contributes to utility.

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.

The payoffs from a person's identity are derived from a combination of the person's actions, others' actions, and the actions and behaviors associated, or proscribed, with the ethnic group to which they belong. People also receive payoffs from identity through the actions of others, and other parties can change identity payoffs. In other words, the actions of other members of an ethnic group could affect the identity payoffs of the person themselves by having actions and characteristics that align with the proscription. This framework allows for understanding the decision-making process that would lead people to self-destructive behavior, like starvation or self-mutilation. This model also introduces externality, where one person's identity choices affect and provoke responses in others. Consequently, the introduction of externality could explain why some men might feel threatened or behave in a toxic way if a woman worked in what is perceived to be a male-dominated field. The categories a person could belong to and the proscription could change with society. Hence, the choice a person makes to determine their self-image or identity affects their utility, thus, affecting their economic outcomes.

Furthermore, some persons might be able to choose their identity, while others might be forbidden from these same identity choices. The ethnic identity of a person exemplifies this concept well. A person could either live in a small town where their ethnicity is not accepted and thus hidden or in a big city, where it is easier for them to identify as their actual ethnicity. This person can receive personal payoffs from their authentic ethnic identity. The identity payoffs could be restricted, or even changed, by the other small-town residents. If the residents of the small town were prejudiced against people of particular ethnic identities, then the person would have negative payoffs from the actions of others.

Measuring identity choices outside of a lab is a challenging task because I must both observe and construct objective and self-reported measures of identity. To the extent of viewing identity choices as revealed preferences, most of the literature uses self-reported ethnicities. To take the insights of the Akerlof and Kranton (2000) framework to the data, I first need to construct objective and self-reported measures of ethnic identity. An objective and self-reported Hispanic identity would allow me to perceive the identity choices of an individual. I do this by using information from Hispanic immigrants. I use data from the place of birth of a person, the place of birth of a person's parents, and the person's ancestry and identification of their parents to construct an objective measure of identity. The self-reported measure of identity is whether a person answered yes or no to the question, "are you Latino/Hispanic?". I find these measures are 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. An objective measure of Hispanic identity could paint a complete picture of Hispanic assimilation and gaps between Hispanics and Whites.

I use data on 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 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 outcomes (Chetty et al., 2020; Glover et al., 2017), voting behavior (Friese et al., 2007), and health (Leitner et al., 2016). Additionally, Bursztyn et al. (2022) show that exposure to Arabs-Muslims at a county is predictive of lower county level Implicit Association Test (IAT) average.

Using the Implicit Association Test (IAT) of skin color bias in a state, I find that higher White implicit bias, or bias against people with darker skin, in a state is correlated with lower self-reported Hispanic identity among Hispanic immigrants. Specifically, a one standard deviation increase in bias is associated with a six percentage points decrease in the self-reported Hispanic identity among second-generation immigrants and 10 percentage points decrease in the self-reported Hispanic identity among third-generation immigrants. Additionally, a one standard deviation increase in bias is correlated with 15 percentage points decrease 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 12 percentage points decrtease in self-reported Hispanic identity. The results aligns with Akerlof and Kranton (2000); Kranton et al. (2020); Atkin et al. (2021) that social costs affects how a person identifies. I also find that bias is uncorrelated with migration decisions and is correlated with interethinc marriages. Additionally, these results align with the findings of Charles et al. (2018) that sexism at the place and time of birth (background sexism) and sexism where a woman currently lives (residential sexism) is correlated with lower wages and labor force participation.

This paper fits into three strands of the literature. First of which is the theoretical and empirical economic literature on racial and ethnic identities. Kranton et al. (2020) used a lab experimental design to deconstruct group biases. The experiment showed that people aligned with the Democratic Party showed strong in-group favoritism and bias toward other democrats. 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 not only a function of their own self-interest, but also 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' and their support for trade policies would hinge on the welfare of other members of the 'broad nation' and not their own self-interest. Consequently, this increased the support for protectionist policies. Bonomi et al. (2021) posit a model with class and cultural identities. They showed how a culturally 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 for "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 less Black employees, and in Giuliano et al. (2011) they found that employees of a certain race experience better outcomes when their manager shares the same race. Bagues et al. (2017) showed that having more women presence of hiring committees of academic jobs in Italy and Spain did not decrease the gender gap. Åslund et al. (2014) found that immigrant managers, compared to native managers, hired more immigrant employees. 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.

Researchers also investigated the effect of identity on police vehicle searches, arrests, court convictions, and court rulings. Donohue III and Levitt (2001) found as the number of White officers increases, the number of arrests of non-Whites increases with no effect on White arrests. They also found that the number of non-White police officers is associated with higher arrests of Whites with no effect on the number of arrests of non-Whites. Antonovics and Knight (2009) showed that there were evidence that police searches of minority motorists is statistical discrimination. They justified their conclusion given the fact that an officer is more likely to stop a motorist if the race of the officer and the race of the motorist are different. Shayo and Zussman (2011, 2017) found that a person is more likely to win a civil case in Israel if they were assigned a judge from the same ethnicity, while Anwar et al. (2012) showed that even the existence of just one Black jurist eliminates the White-Black Conviction gap. Luh (2022) found that highway troopers in Texas may have intentionally misreported the race of a motorist to avoid scrutiny. The same pattern of effect of racial and ethnic identities on outcomes does not change in developing countries (Franck and Rainer, 2012; Burgess et al., 2015; Kramon and Posner, 2016; Friedman, 2018; Hadah, 2022). More evidence on ethnic and racial biases toward in- and out-group members in the

National Basketball Association (NBA) (Price and Wolfers, 2010), Major League Baseball (MLB) umpires (Parsons et al., 2011), and soccer referees (Pope and Pope, 2015). When referees and umpires shared the same race or ethnicity of a player, the player is was likely to have had better outcomes.

The second strand of the literature to which this paper fits in is the economics of immigration and assimilation. This group researches how do immigrants fair in the United States upon and after arrival. Abramitzky et al. (2016) measured the speed at which immigrants from Europe, Asia, and Latin America. They construct a 'foreignness index' to estimate the probability that a given name is held by a non-native person, since names are signals of cultural identity. They found that the more time an immigrant spends in the United States, the less likely they give their child a foreign sounding name. Abramitzky et al. (2014) found that, on average, immigrants did not face a substantial occupational-based earnings penalty upon first arrival. They also found that immigrants advanced occupationally as fast as native workers. 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. Fouka (2020) studied the success of forced integration policies. The author found that people affected by the banning of the teaching of German language at school assimilated at slower rates. Abramitzky et al. (2019) found that children of immigrants, compared to native-born children, have higher rates of upward mobility. (Abramitzky et al., 2020) found that second-generation immigrants with foreign sounding names fared worse than comparable compatriots with a more 'assimilated' names, and thus, assimilated at lower rates. Abramitzky et al. (2020) also found that Jewish immigrants that left the ethnic enclaves were faster to assimilate into American society by earning 4 percent more than those that did not leave. Meng and Gregory (2005) studied the effect of intermarriage on assimilation and found that immigrants that intermarry earn significantly more than those that marry endogamously.

Other researchers studied the assimilation of Hispanic immigrants. (Antecol and Bedard, 2006) documented an interesting puzzle where non-native born Hispanics have better health outcomes than native born Hispanics, and (Trejo, 1997) showed that Mexican men earn substantially less than Whites.[3] 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 were able to 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 more healthy (Antman et al., 2016, 2020).

The third, and last, strand that 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) is 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. Taking into consideration the ethnic attrition that Antman et al. (2016) document, I investigate the determinants of

3. The Hispanic health paradox have 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).

what drive 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 and environmental determinants of identity. The empirical analysis in this paper documents how some observable, i.e. personal characteristics and societal attitude, 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 mold 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. Each group has associated set of behaviors, which I denote as $\boldsymbol{B}_{e_i}$.[4] Agent i's utility depends on their actions and the extent to which their actions affirm their identity I_i, a vector of their own actions $\boldsymbol{a_i}$, and a vector of other people's actions $\boldsymbol{a_{-i}}$:

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

Where $\boldsymbol{a_i}$ is the actions of person i, $\boldsymbol{a_{-i}}$ is the actions of others, and I_i is the identity function. A person's identity, I_i, is influenced by their own actions, the actions of others, and the behavior that is proscribed by their ethnicity. I write this as:

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

From this simple model, a person chooses action a_i that maximizes their utility function

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

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

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

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

When will such a person change their identity? Ethnicity effects optimization through $\frac{dI_i}{da_i}$. A person will change ethnic identity through: (1) choosing actions that will effect B_{e_i}; (2) the actions of others a_{-i}; (3) the size of the cost c.

The first order condition, along with the model, guides the empirical estimation in this paper. Applying this model to my empirical analysis, a person can choose their actions to determine how they identify as Hispanic or non-Hispanic. Additionally, the actions of other, or bias and prejudice toward Hispanics, will affect the decision of a person to identify as Hispanic or non-Hispanic. Therefore, this model guides how the bias affect I_i, and thus, determine the self-reported Hispanic identity e_i of Hispanic immigrants in the United States.

Actions that affect utility U_i through identity e_i can either be negative or positive. A loss in identity as a result of someone's own actions will be negative. Someone's actions might affirm their identities, and thus, their utility would experience a gain in identity. On the one hand, a person might experience large payoffs from self-identifying as non-Hispanic, $\tilde{U_i}^\star$, and small payoffs from keeping their Hispanic identity, $U_i^\star$, to which changing identities would be worth the cost, i.e. $\tilde{U_i}^\star \geq U_i^\star + c$. This is the case where first-generation and second-generation Hispanics would receive large payoffs in the labor and marriage market that it becomes the logical economic decision to change identities. The two groups would experience large losses when their peers do not accept them. On the other hand, a third-generation Hispanic has a low c. Additionally, given that they are third-generation Hispanics, it is more probable that they already fit in among their peers. Consequently, their choices to identify, or not identify, as Hispanic are less restricted.

Moreover, the proscribed behavior B_{e_i} and other people's actions a_{-i} could change over time in a way that changes the identity choices of i. For example, discrimination against Hispanics could decrease, and the proscribed behavior B_{e_i} could change. These changes could lead a person to choose the Hispanic identity over the Non-Hispanic identity or *vice versa*.

III. Data

I use several datasets for this paper. In this section, I will go over how I identify the different generations of Hispanic immigrants, the Current Population Survey, and the prejudice measure.

III.A. Current Population Survey and Identifying Hispanic Immigrant Generations

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 U.S. households to measure unemployment. 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 the first-, second-, and third-generations. This will consequently allow me to build an objective measure of the Hispanic identity of minors under 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 (endogamous), 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.[5] I restrict the sample to Whites and Hispanic, 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).

TABLE 1
CPS SUMMARY STATISTICS WITH SKIN IAT SCORES

	Overall	**By Generation**		
Characteristic	**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	11.5	8.3	7.9
	(5.1)	(4.3)	(5.0)	(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	39,882	31,927	36,726	53,000
(1999 dollars)	(48,692)	(38,804)	(45,353)	(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 county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third generation Hispanic immigrant children with native born parents and at least one grand parent born in a Spanish speaking country.
[2] Data source is the 2004-2020 Current Population Survey.

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-

5. I restrict first-generation immigrants to those with both parents born in a Spanish country to avoid including naturally born U.S. citizens that were born abroad to U.S. parents.

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.

Breaking down the CPS sample by the three generations of Hispanic immigrants, parents of third-generation Hispanics are better off than first and second-generation parents. The percentage of females is similar across the three generations, 48% for first-generation and 49% for second and third-generations. First-generation Hispanic youth are the eldest of the three. The average age of first-generation Hispanics is 11.5 years, 8.3 years for second-generation Hispanics, and 7.9 years for the third-generation immigrants. Parents of third-generation Hispanic immigrants were the most educated. 15% of parents of first-generation immigrants have a college degree, compared to 11% of parents of second-generation immigrants, and 23% of fathers and 22% of mothers of third-generation Hispanics. Third-generation families were also the wealthiest. The average total family income of a first-generation Hispanic child is $31,927, average total family income of a second-generation Hispanic child is $36,726, and average total family income of a third-generation Hispanic child is $53,000.

III.B. Identifying Hispanic Generation

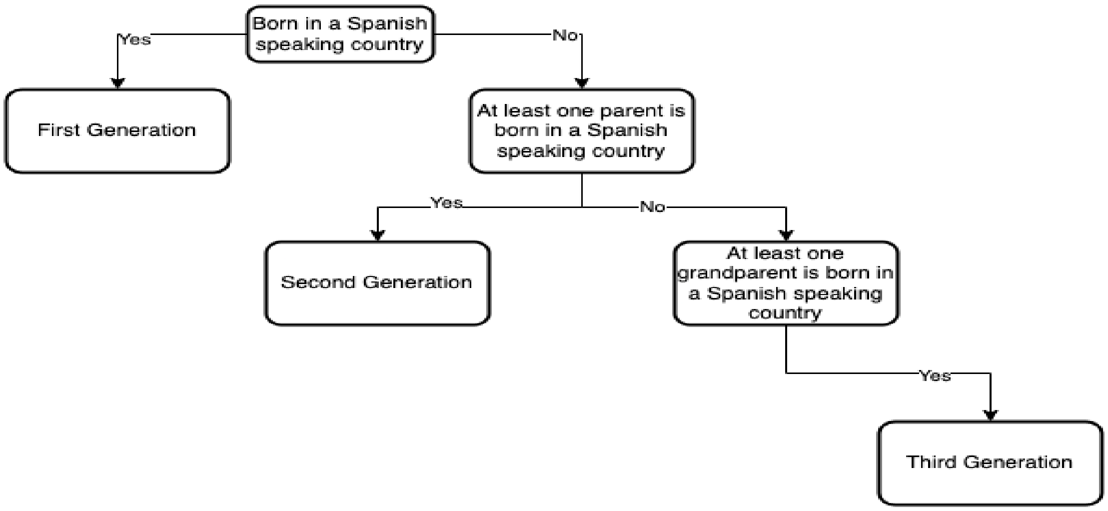
As previously stated, data on the objective Hispanic measure is not readily available. Consequently, it is hard to identify the different generations of Hispanics in the United States using public-use data. Therefore, much of the literature studying Hispanics relied on a self-reported—self-reported—measure of Hispanic identity. Consequently, a person is identified as Hispanic if they answered affirmatively whether they are Hispanic, Spanish, or Latino. Then, they are asked to which Hispanic sub-group they belong. 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.

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.[6] 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. Thus, I identify the different generations as follows: 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 U.S. 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 U.S., both parents are the U.S. born, and they have at least one grandparent that is born in a Spanish speaking ancestry, 4) a person is a fourth-generation Hispanic if they are born in the U.S., both parents are the U.S. born, and all grandparents are born in the U.S. and at least one parent that identified as Hispanic, and 5) a person is fourth-generation White if they are born in the U.S., both parents are the U.S. born, all grandparents are born in the U.S. and both parents identified as non-Hispanic White.

Moreover, using the place of birth of parents and grandparents, I can objectively identify their ethnic ancestry. Consequently, I can identify different type 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...

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

FIGURE 1
DIAGRAM OF THE THREE DIFFERENT GENERATIONS OF HISPANIC IMMIGRANTS



III.C. Hispanic Self-Identification and Attrition

Using the Current Population Survey (CPS), which provides information on the place of birth of a person and the place of births of their parents and grandparents, I can identify three generation of Hispanic immigrants. Figure (1) offers a visual representation of the algorithm I used to determine the different generations. A person would be a first-generation Hispanic immigrant if they were born in a Spanish-speaking country. A person is a second-generation Hispanic immigrant if they were born in the United States and at least one parent was born in a Spanish-speaking country. A person is a third-generation Hispanic immigrant if they were born in the United States and both parents were born in the United States and at least one parent identified as Hispanic or they have listed at least one Spanish-speaking ancestry.

Consistent with the literature on ethnic attrition among Hispanics, I find significant attrition among third-generation Hispanic immigrants.[7] 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.

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

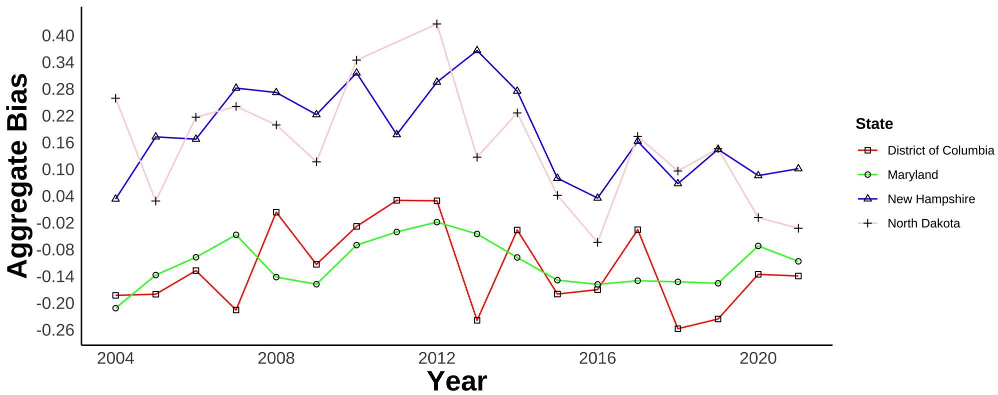
[1] The samples include children ages 17 and below who live in intact families. First-generation Hispanic immigrant children that were born in a Spanish speaking county. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country. Finally, native born third generation Hispanic immigrant children with native born parents and at least one grand parent born in a Spanish speaking country.
[2] Data source is the 2004-2020 Current Population Survey.

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

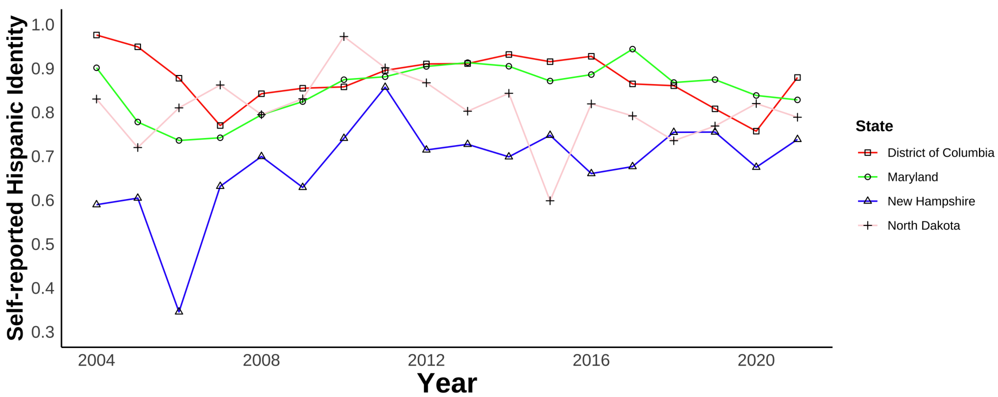
FIGURE 2

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. District of Colombia is the least biased geographical area and North Dakota is the most biased, and the bias units is in standard deviations. Self-reported Hispanic identity is among first, second, and third generation Hispanic immigrants aged 17 and younger that are still living in intact families.

Note. Bias data is from the 2004-2020 Harvard's Project Implicit Implicit Association Test scores. Identity data is from the 2004-2020 Current Population Survey (CPS).

III.D. Harvard's Project Implicit: Implicit Association Test

An implicit association test measures how people associate concepts—for example, Black and dark-skinned people—and evaluations—good, bad, or stereotypes. The test is designed to make it easier to respond to closely related items and to delve more deeply into the test details, a respondent is asked to quickly match words into categories shown on the screen (right and left). Thus, a respondent would sort a word into the category on the right by pressing the letter 'e' and on the left category by pressing the letter 'i'. I provide a few examples of what a test taker would see on a skin tone implicit association test by Harvard's Project Implicit. Therefore, the innovation of such a test lies in the fact that it could measure the attitudes and beliefs of people that they would be unwilling to report on a survey. For example, a person could believe that Black and White people are equally as likely to be good samaritans. However, their automatic association could show that Black people are associated with violence.

To this extent, I use skin tone implicit association test data to measure a state's prejudice. This data is from Harvard's Project Implicit, which measures the implicit biases of participants in their tests (Greenwald et al., 1998). The implicit bias toward minorities, as measured by the Implicit Association Test (IAT), is widely used by psychologists. Previous work has shown that IAT test scores are hard to manipulate (Egloff and Schmukle, 2002). Additionally, IAT scores were shown to be correlated with outcomes like 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 time series of the aggregate average implicit skin tone association between the state with the highest bias, North Dakota, and Washington DC the place with the lowest bias in figure (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.

Participating in the IAT, an online test, is voluntary. Therefore, the samples are not random and might suffer from selection bias of who decides to take the exam. However, as shown by Chetty et al. (2020), bias reflected by Implicit Association Test (IAT) scores could be a rough proxy for prejudiced attitudes in an area. 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 woman and 62% are Whites, or 56% non-Hispanic Whites. The test takers have high level of education. Only 11% of the sample are high school dropouts, and 9.5% have a high school diploma. Majority of the test takers, 29%, have some college experience, 7.1% have an associate's degree, and 18% have a bachelor's degree. The rest have post-undergraduate degrees with 6.2% have a some graduate experience, 13% have a master's degree, and 5.4% have a professional degree—i.e. Ph.D, MD, or JD.

I also present the demographics of a the representative Current Population Survey (CPS) sample over the same period in table (3). The average age in the Current Population Survey (CPS) is 38 year and 51% of the sample is female. Non-Hispanic Whites in the Current Population Survey (CPS) constitute 68% of the sample and 13% for Hispanics. As for education, 14% have a bachelor's degree, 33% are high school dropouts, and 23% received a high school diploma. 5.7% of the sample have a master's degree and 2.2% professional degree.

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

Characteristic	IAT N = 1,519,309	CPS 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 Implicit Association Test scores and 2004-2020 Current Population Survey (CPS).

IV. EMPIRICAL STRATEGY

IV.A. The Determinants of Hispanic Identity

Let H^g be the self-reported Hispanic identity variable for a person from the g^{th} generation, where $g \in \{1,2,3\}$. Also, let X be a vector controls.

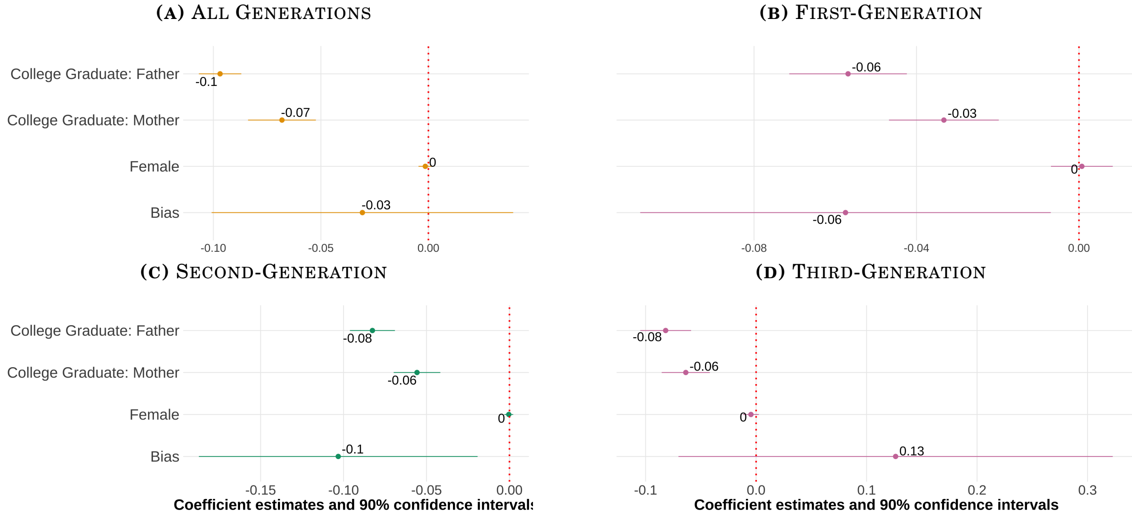
Using data from the Current Population Survey (CPS) and Harvard's Project Implicit Association Test (IAT), I can determine whether social attitudes toward racial and ethnic minorities affect a person's identity.

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

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

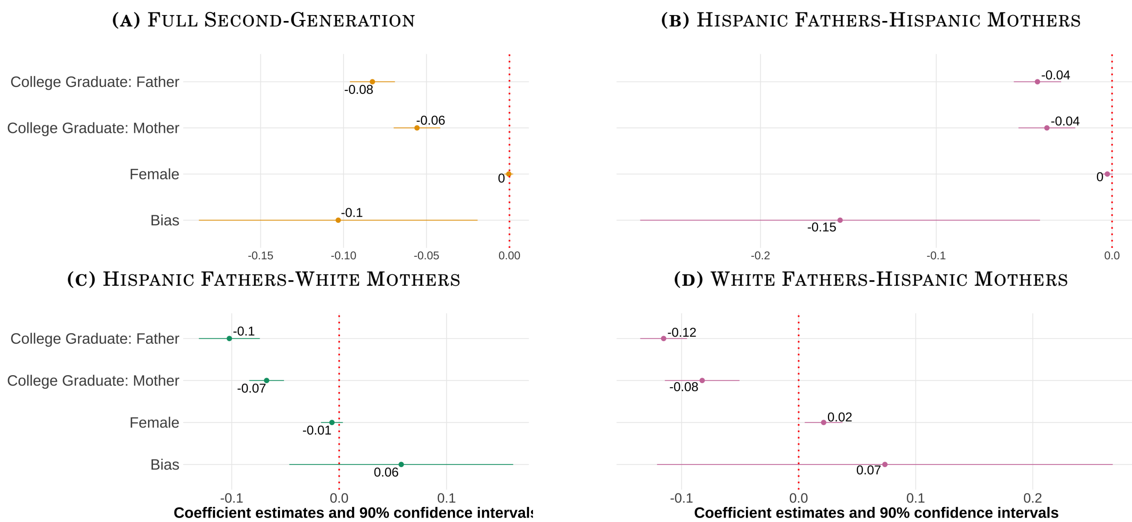
The coefficient of interest in equation (4) is β^g_1. This coefficient estimates the effects of bias in a state at a certain time on endogenous identity. In other words, when including region × year, the fixed effects controls for trends and chocks in a region. Consequently, β^g_1 estimates the effect of bias on self-reported Hispanic identity between states with-in a region. If $\beta^g_1 > 0$, then an increase in the bias in a state would increase the chance of Hispanic immigrants to identify as Hispanic. If $\beta^g_1 < 0$, then an increase in the bias in a state would decrease the chance of Hispanic immigrants identifying as Hispanic.

FIGURE 3
SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY GENERATION



Note. I show four panels of estimating equation (4). I include region × year fixed effects with controls for sex, quartic age, and parental education. 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 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.

FIGURE 4
SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY PARENTAL TYPES



Note. I show four panels of estimating equation (4). I include region × year fixed effects with controls for sex, quartic age, and parental education. Each panel is the results from the same regression but on different samples that are 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.

I also present other variations of equation (4). For example, I could run the regression on the sample of second-generation immigrants by parental type, where parental types depend on parental place of birth. This will produce three combinations of parent types: 1) father born in a Spanish Speaking country and mother born in a Spanish speaking country, or Hispanic-Hispanic (HH), 2) father born in a Spanish Speaking country and mother born in the U.S., or Hispanic-White (HW), 3) father born in the U.S. and mother born in a Spanish speaking country, or White-Hispanic (WH).

Moreover, I can estimate the effect of attitudes on identity by running the following equation.

$$\begin{aligned} H^2_{ist} = {} & \beta^2_0 + \beta^2_1 Bias_{st} + \sum_{n=1}^{2} \delta^2_n I_{\{ParentType_{ist}=n\}} \\ & + \sum_{m=1}^{2} \alpha^2_m Bias_{st} \times I_{\{ParentType_{ist}=m\}} \\ & + \beta^2_3 ParentalEducation_{ist} + \beta^2_4 Woman_{ist} \\ & + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \end{aligned} \tag{5}$$

$$\begin{aligned} H^3_{ist} = {} & \beta^3_0 + \beta^3_1 Bias_{st} + \sum_{n=1}^{14} \delta^3_n I_{\{GrandParentType_{ist}=n\}} \\ & + \sum_{m=1}^{14} \alpha^3_m Bias_{st} \times I_{\{GrandParentType_{ist}=m\}} \\ & + \beta^3_3 ParentalEducation_{ist} + \beta^3_4 Woman_{ist} \\ & + X^3_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \end{aligned} \tag{6}$$

Where H^2_{ist} and H^3_{ist} are the self-reported identity of second and third-generation person i that lives in state s at time t. Regressions (5) and (6) includes the state-year average bias, categorical 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 it is the omitted group, 2) father born in a Spanish Speaking country and mother born in the U.S., or Hispanic-White (HW), 3) father born in the U.S. and mother born in a Spanish speaking country, or White-Hispanic (WH). 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 it is the omitted group, 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 U.S. (HHHW), 3) paternal grandfather born in a Spanish speaking country, paternal grandmother born in a Spanish speaking country, maternal grandfather born in in the U.S., and maternal grandmother born in the U.S. (HHWW), etc.

The interaction term between the different types of parents and grandparents within a generation allows for comparing similar types of people and the effect of bias on their identity. For example, in regression (5), I am comparing the kids of inter-racial couples to those that are not, all of which are second-generation immigrants. The coefficient α_m would capture the effect of bias on self-reported identity of a particular group compared to the ommitted group—children of Hispanic fathers-Hispanic mothers (HH) or children of Hispanic grandparents (HHHH).

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

In this section, I introduce the estimation strategy of the effect of bias on the probability of having an interethnic marriage and migration. Estimating the effect of bias on interethnic marriages will take the following form:

$$HH^2_{ist} = \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist}$$
$$HW^2_{ist} = \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{7}$$
$$WH^2_{ist} = \beta^2_1 Bias_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist}$$

Where HH^2_{ist}, HW^2_{ist}, and WH^2_{ist} are variables representing the type of parents of a second generation Hispanic immigrant i in state s at time period t. HH^2_{ist} represents Hispanic-husband-Hispanic-wife couples, HW^2_{ist} represents Hispanic-husband-White-wife couples, and WH^2_{ist} represents White-husband-Hispanic-wife couples. $Bias_{st}$ is the average bias in state s at time t, and X^2_{ist} is a vector of partner specific controls that would affect a marriage match that include 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) separately using a linear probability model. Another way is by running the system of equation using an ordered multinational 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 a interethnic Hispanic-husband-White-wife marriage; (3) two corresponding to a interethnic White-husband-Hispanic-wife marriage. The coefficient of interest from (7) is β_1, which captures the effect of bias on the probability of forming an interethnic marriage.

The estimation strategy will take the following form to estimate the effect of bias on migration.

$$Migration^2_{ist} = \beta^2_1 Bias_{st} + \beta^2_2 X_{ist} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{8}$$

$$Migration^2_{ism} = \beta^2_1 Bias_{sm} + \beta^2_2 X_{ism} + X^2_{ism}\pi + \gamma_{rm} + \varepsilon_{ism} \tag{9}$$

$$BirthPlaceMigration^2_{ist} = \beta^2_1 Bias_{st} + \beta^2_2 X_{ist} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{10}$$

$$BirthPlaceMigration^2_{ilb} = \beta^2_1 Bias_{lb} + \beta^2_2 X_{ilb} + X^2_{ilb}\pi + \gamma_{lb} + \varepsilon_{ilb} \tag{11}$$

Where $Migration^2_{ist}$ is an indicator variable that is equal to one if person i in state s at time of the interview t migrated from somewhere else within the last year. $Migration^2_{ism}$ is an indicator variable that is equal to one if person i in state s one year before the time of the interview $m = t-1$ migrated from somewhere else. $BirthPlaceMigration^2_{ist}$ is an indicator variable that is equal to one if person i in state s at time of the interview t lives in a place that is different from their place of birth. $BirthPlaceMigration^2_{ilb}$ is an indicator variable that is equal to one if person i in birth state l does not currently live in the same place they lived in at the year of birth b. The analysis of equations (8), (9), (10), and (11) is restricted to second generation Hispanic immigrants. The coefficient of interest from the regressions is β_1, 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 specification to the bias variable. First specification from equation (8), I study the effect of the average bias in state s at time of the interview t on $Migration^2_{ist}$. Second specification from equation (9), I study the effect of the average bias in state s one year before the date of the interview $m = t-1$ on $Migration^2_{ism}$. Third specification from equation (10), I study the effect of the average bias in state s at time of the interview t on $BirthPlaceMigration^2_{ist}$. The fourth specification from equation (11), I study the effect of the average bias in state of birth l at year of birth b on $BirthPlaceMigration^2_{ilb}$.

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 parental education and income?

V.A. *Attitudes and its Effect on Identity*

In this section, I find that endogenous identity is determined by parental education, the presence of inter-ethnic parents, and the attitudes toward minorities. I find consistent evidence that having more educated parents is negatively associated with self-reported Hispanic identity. I additionally find that bias affects how Hispanic immigrants identify, and more bias in a state is associated with a lower likelihood of Hispanic immigrants identifying as Hispanic.

Moreover, by using Current Population Survey (CPS) data that was merged with Skin Tone Implicit Bias Test, I was able to estimate equations (4), (5), and (6). I present the results to these regressions in tables (11) and (34). Table (11) includes the results to the pooled estimation of equation (4), which estimates the effect of bias on the self-reported Hispanic identity of Hispanic immigrants. All columns include controls for sex, parental education, ethnically endogamous parents, and generation to which they belong. Each column has the estimation results with a different set of fixed effects. Identifying the bias effect on identity using an across-state estimation within region variation—with region fixed effects only—provides negative and statistically significant results. Therefore, the variation within state in bias is negatively correlated with a 7 percentage points reduction in Hispanic identification. After including non-parametric region × year fixed effects, which controls for differential trends within a region and regional shocks, show that the self-reported Hispanic identity in states with higher bias compared to those with lower bias decreases by seven percentage points but the results are statistically insignificant. The insignificant results could be the result of the heterogeneous effect of bias on different groups.

Estimating heterogeneous effect of bias on self-reported Hispanic identity by generation, I find that bias is correlated with a significant decrease in identity among first and second-generation Hispanic immigrants. In table (4), I provide the results estimating equation (4) separately for each generation with non-parametric $region \times year$ fixed effects. Column (1) includes the results estimating equation (4) on all generations. I find that skin tone bias is correlated with a statistically insignificant seven percentage point decrease in self-reported Hispanic identity. When estimating the equation for first-generation immigrants, I find that a one-unit increase in bias is associated with a 14 percentage point decrease in self-reported Hispanic identity, and the results are statistically significant. When estimating the equation for second-generation immigrants, I find that a one standard deviation increase in bias is associated with a six percentage point decrease in Hispanic identity, and the results are statistically significant. When estimating the equation for third-generation immigrants, I find that a one standard deviation increase in bias is associated with a 10 percentage points increase in Hispanic identity, but the results are statistically insignificant. These results indicate that endogenous identity is especially affected by attitudes in a society among first and second-generation immigrants. In contrast, attitudes do not affect 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 themselves into their new community, while third-generation immigrants are already assimilated. This is 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.

I estimate another set of heterogeneous effect of bias on self-reported Hispanic identity of second-generation Hispanics by parents types, I find a significant negative correlation between bias and endogenous Hispanic identity among second-generation Hispanic immigrants children of endogamously Hispanic parents—both the father and mother were born in Spanish speaking country. In table (5), I provide the results estimating equation (4) separately for each parent type—Spanish speaking country born father-Spanish speaking country born mother (HH), native born father-Spanish speaking country born mother (WH),

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	−0.06	−0.06*	−0.10**	0.13
	(0.04)	(0.03)	(0.05)	(0.12)
Female	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	−0.05***	−0.03***	−0.06***	−0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.06***	−0.06***	−0.08***	−0.08***
	(0.01)	(0.01)	(0.01)	(0.01)
N	844 481	85 390	560 100	198 991
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, 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 2004-2020 Current Population Survey.

and Spanish speaking country born father-native born mother (HW)—with region × year fixed effects. 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 six percentage points increase 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

7 percentage points increase 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.

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)	(2)	(3)	(4)
	H^2	H^2	H^2	H^2
Bias	−0.10**	−0.15**	0.06	0.07
	(0.05)	(0.07)	(0.06)	(0.12)
Female	0.00	0.00	−0.01	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)
College Graduate: Mother	−0.06***	−0.04***	−0.07***	−0.08***
	(0.01)	(0.01)	(0.01)	(0.02)
College Graduate: Father	−0.08***	−0.04***	−0.10***	−0.12***
	(0.01)	(0.01)	(0.02)	(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, 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.

TABLE 6
SELF-REPORTED HISPANIC IDENTITY AND BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS: BOTH PARENTS BORN IN A SPANISH SPEAKING COUNTRY

	(1) H^2	(2) H^2	(3) H^2	(4) H^2	(5) H^2	(6) H^2
Bias	−0.01	−0.02	−0.03	−0.04	−0.02	−0.15**
	(0.03)	(0.06)	(0.02)	(0.03)	(0.02)	(0.07)
Female	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	−0.05***	−0.05***	−0.03***	−0.03***	−0.03***	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.05***	−0.05***	−0.04***	−0.04***	−0.04***	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	405116	405116	405116	405116	405116	405116
Linear Trend	No	No	No	No	Yes	No
Mean	0.96	0.96	0.96	0.96	0.96	0.96
Year FE		X		X		
State FE			X	X		
Year × Region FE						X

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

[1] Each column is an estimation of a heterogeneous effect of regression (4) on second generation children of parents born in a Spanish speaking country (HH) with different specifications. 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 2004-2020 Current Population Survey.

Furthermore, I divide the results of estimating 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, if a person has two grandparents that were born in a Spanish speaking country, then they have two 'Hispanic' grandparents. The result of estimating the effect of bias on people with one objectively Hispanic grandparent is in table (7) column (1), with two objectively Hispanic grandparents is in table (7) column (2), with three objectively Hispanic grandparents is in table (7) column (3), and with four objectively Hispanic grandparents is in table (7) column (4). I find statistically significant effect of bias on self-reported Hispanic identity among third-generation Hispanic immigrants that have four objectively Hispanic grandparents. A one standard deviation increase in bias is associated with 12 percentage points decrease in the likelihood 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 7
SELF-REPORTED HISPANIC IDENTITY AND BIAS AMONG THIRD GENERATION HISPANIC IMMIGRANTS: BY GRANDPARENTAL TYPE (STATE)

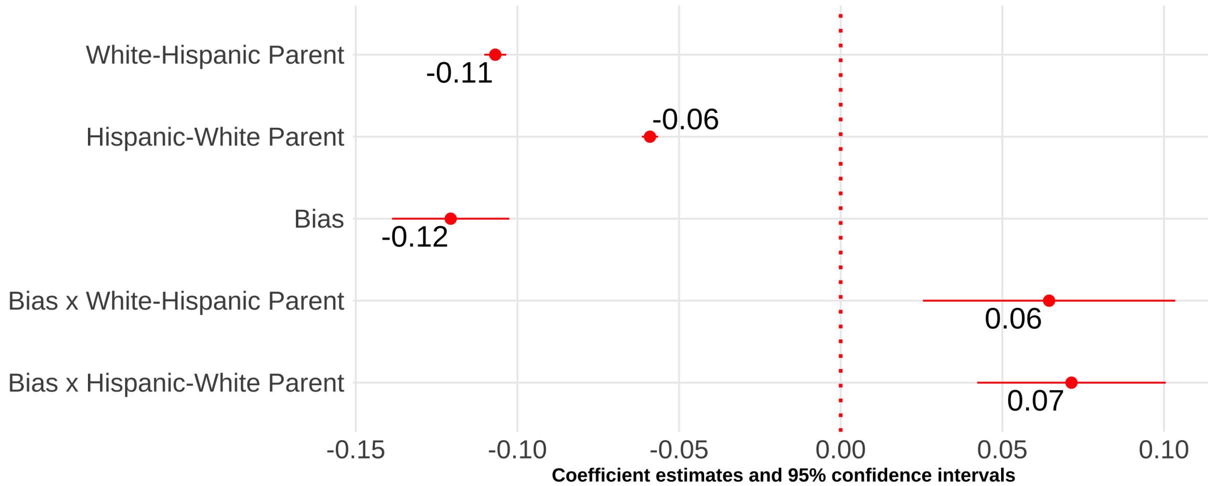
	Numer of Hispanic Grandparents			
	(1) One	(2) Two	(3) Three	(4) Four
Bias	0.16	0.18	0.21	−0.12*
	(0.22)	(0.15)	(0.27)	(0.07)
Female	−0.01	0.00	−0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Mother	−0.11***	−0.07***	0.02	−0.02
	(0.03)	(0.02)	(0.02)	(0.01)
College Graduate: Father	−0.12***	−0.08***	0.02	−0.03*
	(0.03)	(0.01)	(0.01)	(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
[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 5

EFFECT OF BIAS ON IDENTITY ON SECOND-GENERATION HISPANICS: INTERACTION (STATE)

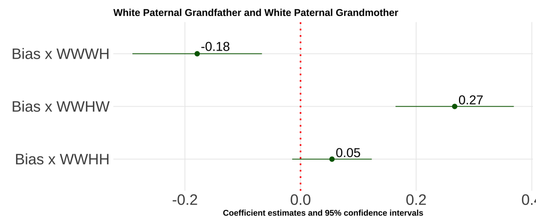


Note. I show four panels of estimating equation (5). I include region × year fixed effects with controls for sex, quartic age, and parental education. Each panel is the results from the same regression but of different combinations of grandparents types. Robust standard errors are reported. The samples 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.

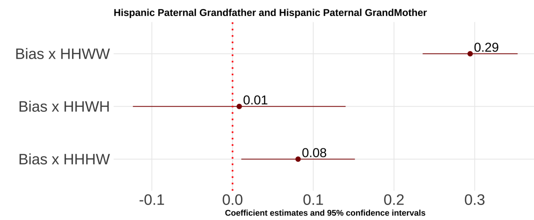
FIGURE 6

EFFECT OF BIAS ON IDENTITY ON THIRD-GENERATION HISPANICS: INTERACTION (STATE)

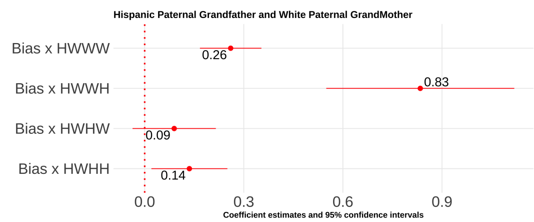
(A) WHITE PATERNAL GRAND FATHER AND WHITE PATERNAL GRAND MOTHER COMBINATIONS



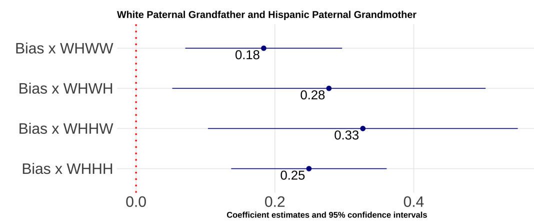
(B) HISPANIC PATERNAL GRAND FATHER AND HISPANIC PATERNAL GRAND MOTHER COMBINATIONS



(C) HISPANIC PATERNAL GRAND FATHER AND WHITE PATERNAL GRAND MOTHER COMBINATIONS



(D) WHITE PATERNAL GRAND FATHER AND HISPANIC PATERNAL GRAND MOTHER COMBINATIONS



Note. I show four panels of estimating equation (6). I include region × year fixed effects with controls for sex, quartic age, and parental education. Each panel is the results from the same regression but of different combinations 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 grand parent born in a Spanish speaking country.

Moreover, I find a statistically significant positive heterogeneous effect between bias and parents and grandparents types. In table (34) and figures (5), and (6), I provide the results estimating equations (5) (columns 1 and 2, and figure 5) and (6) (columns 3 and 4, and figure 6). I find that the effect of a one standard deviation increase in bias is correlated with a seven percentage points increase in Hispanic identity in children with an objectively Hispanic Father-White Mother (HW) compared to children of the objectively Hispanic father-Hispanic mother (table (34) column 1). I find that the effect of a one standard deviation increase in bias is correlated with a six percentage points increase in self-reported Hispanic identity in children with objectively White Father-Hispanic Mother (WH) compared to children of an objectively Hispanic father-Hispanic mother (table 34 column 1). I further look into the heterogeneous effect of bias on the different types of children based on the type of their grandparents (table (34) column 3). 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.[8]

To simplify, I will discuss the results in four groups by holding constant the origin of the paternal grandparents with the combination of the maternal grandparents. Among third generation immigrants with objectively White paternal grandfather-White paternal grandfather: (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 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 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: (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 grandmother are as likely as children with HHHH grandparents to self-identify as Hispanic; (3) those with objectively White maternal grandfather and White 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-White paternal grandfather: (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 White grandmother are as likely as children with HHHH grandparents to self-identify as Hispanic; (3) those

8. 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.

with objectively White maternal grandfather and Hispanic 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 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 grandfather: (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 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 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 grandmother are 18 percentage points more likely than children with HHHH grandparents to self-identify as Hispanic.

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

In this section, I will discuss the results of estimating the effect of bias on on intermarriages (equation 7) and on migration (equations 8, 9, 10, and 11). I find that bias is not correlated with the migration choices of that parents of second-generation immigrants. I also find that an increase in bias is associated with decrease in the likelihood interethnic marriage formation (37).

I find that bias does not affect the migration decisions that parents of second-generation Hispanic children make. I show the results of estimating regressions 8, 9, 10, and 11 in table (8). The results of estimating regression 8 is in column (1), where the dependent variable is an indicator variable that is equal to 1 if a person migrated from another state during the year before the survey and $Bias_{st}$ is the average bias in state the interviewee is currently living s during the year of the survey t. The results of estimating regression 9 is in column

(2), where the dependent variable is an indicator variable that is equal to 1 if a person migrated from another state during the year before the survey and $Bias_{sm}$ is the average bias in state the interviewee is currently living s one year prior to the survey $m = t - 1$. The results of estimating regression 10 is in column (3), where the dependent variable is an indicator variable that is equal to 1 if a person migrated from the state they were born in and $Bias_{st}$ is the average bias in state the interviewee is currently living s during the year of the survey t. The results of estimating regression 11 is in column (4), where the dependent variable is an indicator variable that is equal to 1 if a person migrated from the state they were born in and $Bias_{lb}$ is the average bias in 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 the second-generation Hispanic immigrants.

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: (1) zero is having a Hispanic father-Hispanic mother, (2) one is having a Hispanic father-White mother, and (3) three is having a White father-Hispanic mother. In table (37) I present the results of the regression exponetiated and at the margin since the results of a logit regression are 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 8
EFFECT OF BIAS ON MIGRATION PATTERNS

	(1) Migrated	(2) Migrated	(3) Migrated from Birth Place	(4) Migrated from Birth Place
$Bias_{st}$	−0.01		−0.15	
	(0.01)		(0.14)	
$Bias_{sm}$		−0.01		
		(0.01)		
$Bias_{lb}$				−0.18
				(0.26)
Female	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	0.01***	0.01***	0.03***	0.03***
	(0.00)	(0.00)	(0.01)	(0.01)
College Graduate: Father	0.01***	0.01***	0.03***	0.04***
	(0.00)	(0.00)	(0.01)	(0.01)
N	568416	568416	568416	307427
Year (t)× Region FE	X		X	
Birthyear (b)× Birth Region FE				X
($m = t - 1$)× 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), (10) in column (3) , and (11) in column (4).
[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 another state last year, and the right hand side variable is bias the year of the 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 another state last year, and the right hand side variable is bias the year before the survey year. Column (3) 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 (4) 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. I include controls for sex, quartic age, parental education, and region × year fixed effects. Standard errors are clustered on the state level.
[3] The samples include children ages 17 and below who live in intact families. Native born second-generation Hispanic immigrant children with at least one parent born in a Spanish speaking country.
[4] Data source is the 2004-2020 Census Data.

TABLE 9
EFFECT OF BIAS ON INTERETHNIC MARRIAGES: MARGINAL EFFECT OF AN ORDINAL MULTILOGIT AND PROBIT REGRESSIONS

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

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

[1] This is the result to estimating (7) as a multinomial ordered probit and logit regression.
[2] The results are of regressions where the left hand side variable is 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 affects the self-reported Hispanic identity of Hispanic immigrants. In this paper, my aim is not to establish ha causal effect of bias on self-reported Hispanic identity. My aim is 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 depend on self-reported identity might be overestimating or underestimating the effect of discrimination.

A few questions could arise on 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 the true identity of a child. I view the identity that is reported by a parent or a caregiver to be consistent with the true identity of the child since parents are important in shaping the identity of their children. Also, for my analysis, I compared states with high bias and states with low bias. 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 true 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 (10) and the results to estimating estimation of equation (4) in table (**??**) on all the generation divided by the the household/ proxy respondent. 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.[9] The estimation of equation (4) by proxy respondent, table (**??**), yields negative effect of bias on self-reported Hispanic identity for all types of proxy respondents. The effect 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 effect of bias 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 them-

9. 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 person respondent is between the ages of 15 to 17.

selves is the proxy respondent, but 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 10
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 could be the fact that the Implicit Association Test (IAT) are voluntary and are not representative of the population. While I do not claim that the Implicit Association Test (IAT) as a proxy for bias will be representative of 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 higher presence of Arab-Muslims is 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 overtime, and thus, are not the same. I address this concern by including non-parametric region × year fixed effects that would control for 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 does not vary across states with-in a region.

Moreover, as a robustness check, I use different specification and prejudice measures. 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 that most of the questions used to construct the prejudice measure in Charles and Guryan (2008) were discontinued after 1996. Consequently, making it 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, but these results are only significant among second-generation Hispanic immigrants children of native born fathers and Spanish speaking country born mothers, third-generation Hispanic immigrants immigrants, and third-generation Hispanic immigrants immigrants with two grandparents that were born in a Spanish speaking country (see tables 13, 14, and 15.) These results suggests that 'residual' prejudice mostly effect interethnic children.

Reverse causality between having more Hispanic people in a state and implicit bias is another concern I would like to address. It could be the case that the number of Hispanic people in a state affect the implicit bias on the residence of that state. In other words, having more Hispanics in Florida could affect the implicit bias of the residence of Florida. To show that this is not the case, I provide figures (8), and (16) as evidence. Figure (8) plot the percent of self-reported Hispanics in a state at a certain year on the average implicit bias in the same state during that year. Figure (16) plot 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 population in the United States grows becomes more multi-racial and multi-ethnic, the interest in the counts of groups defined by race, ethnicity, and gender grows in importance. The self-reported identity of the different groups of people will have important consequences on representation, distributional politics, and government transfers. Determining what affects endogenous identity is particularity important to researchers estimating earnings gaps using self-reported racial and ethnic measures. This paper investigates how do individual characteristics and social attitudes toward racial and ethnic minorities affect the self-reported identity of persons with Hispanics ancestry in the United States. I find that state-level bias significantly decreases the self-reported Hispanic identity of a person. These effects are more prominent among first- and second-generation immigrants where a one standard deviation increase in bias respectively decreases self-reported Hispanic identity by six and 10 percentage points. Also, among second-generation immigrants, the children of Hispanic Fathers-Hispanic Mothers are affected more by state-level bias.

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	0.10	−0.05**	0.04	−0.06
	(0.03)	(0.07)	(0.02)	(0.03)	(0.04)
Female	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	−0.06***	−0.06***	−0.04***	−0.05***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.07***	−0.07***	−0.06***	−0.06***	−0.06***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
First Gen	−1.31***	0.12***	0.37***	0.04***	0.26***
	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Second Gen	−1.33***	0.11***	0.35***	0.02***	0.24***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
N	844 481	844 481	844 481	844 481	844 481
State FE			X	X	
Year FE		X		X	
Mean	0.91	0.91	0.91	0.91	0.91
Year × Region FE					X

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

[1] Each column is an estimation of a regression the following regression (4) with different set of fixed effects. I include controls for sex, quartic age, parental education, and generational, parents' and grandparents' type dummy variables. Standard errors are clustered on the state level

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

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

TABLE 12

PARENTS' TYPE AND BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS (STATE)

	(1) HH	(2) HW	(3) WH
Bias	−0.05*	−0.02	0.06**
	(0.03)	(0.02)	(0.03)
College Graduate: Wife	−0.05***	0.02***	0.03***
	(0.01)	(0.00)	(0.01)
College Graduate: Husband	−0.08***	0.02***	0.06***
	(0.01)	(0.00)	(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	−0.02	−0.01	−0.13**
	(0.03)	(0.02)	(0.02)	(0.06)
Female	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	−0.05***	−0.04***	−0.08***	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.07***	−0.04***	−0.10***	−0.10***
	(0.01)	(0.01)	(0.01)	(0.02)
N	906106	111960	605316	188830
Mean	0.89	0.96	0.92	0.76
Year × Region FE	X	X	X	X

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

[1] Each column is an estimation of equation (4) by parents' type with region × year fixed effects with Charles and Guryan (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 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	−0.01	−0.15**
	(0.02)	(0.02)	(0.08)	(0.07)
Female	0.00	0.00	−0.01	0.02
	(0.00)	(0.00)	(0.01)	(0.01)
College Graduate: Mother	−0.08***	−0.04***	−0.10***	−0.11***
	(0.01)	(0.01)	(0.01)	(0.02)
College Graduate: Father	−0.10***	−0.04***	−0.15***	−0.15***
	(0.01)	(0.01)	(0.02)	(0.01)
N	605 316	433 135	97 699	74 482
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	−0.19***	−0.13	−0.02
	(0.10)	(0.07)	(0.19)	(0.03)
Female	0.00	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.00)
College Graduate: Mother	−0.10***	−0.08***	0.02	−0.04***
	(0.02)	(0.02)	(0.01)	(0.02)
College Graduate: Father	−0.13***	−0.09***	0.00	−0.01
	(0.03)	(0.02)	(0.02)	(0.02)
N	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.

TABLE 16
EFFECT OF HISPANIC ON BIAS: BY GENERATION

	(1) All Gens $Bias_{st}$	(2) First Gen $Bias_{st}$	(3) Second Gen $Bias_{st}$	(4) Third Gen $Bias_{st}$
Hispanic	0.00	0.00**	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.00*	0.00	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	0.00	0.01**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Father	0.00	0.00*	0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
N	844481	85390	560100	198991
Mean	0.91	0.96	0.94	0.82
Year × Region FE	X	X	X	X

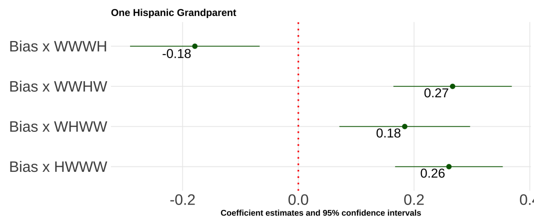
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[1] 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.
[2] Data source is the 2004-2020 Current Population Survey.

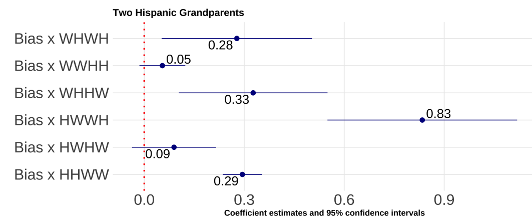
FIGURE 7

EFFECT OF BIAS ON IDENTITY ON THIRD-GENERATION HISPANICS: INTERACTION (STATE)

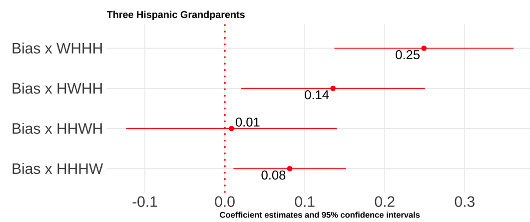
(A) GRANDPARENTS COMBINATIONS WITH ONE OBJECTIVELY HISPANIC GRANDPARENT



(B) GRANDPARENTS COMBINATIONS WITH TWO OBJECTIVELY HISPANIC GRANDPARENT



(C) GRANDPARENTS COMBINATIONS WITH THREE OBJECTIVELY HISPANIC GRANDPARENT

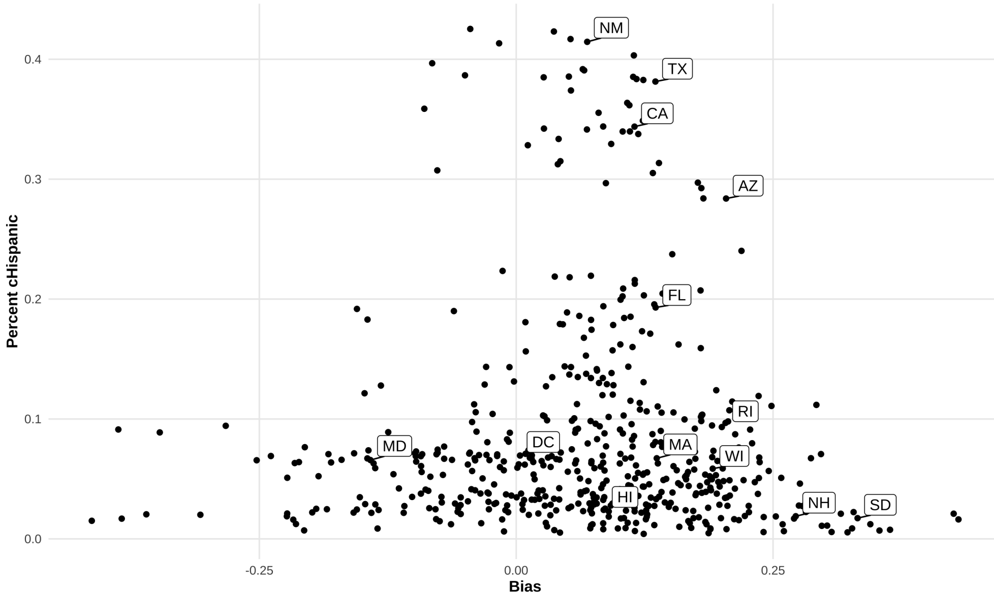


Note. I show four panels of estimating equation (6). I include region × year fixed effects with controls for sex, quartic age, and parental education. Each panel is the results from the same regression but of different combinations of grandparents types. Robust standard errors are reported. The samples 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 grand parent born in a Spanish speaking country.

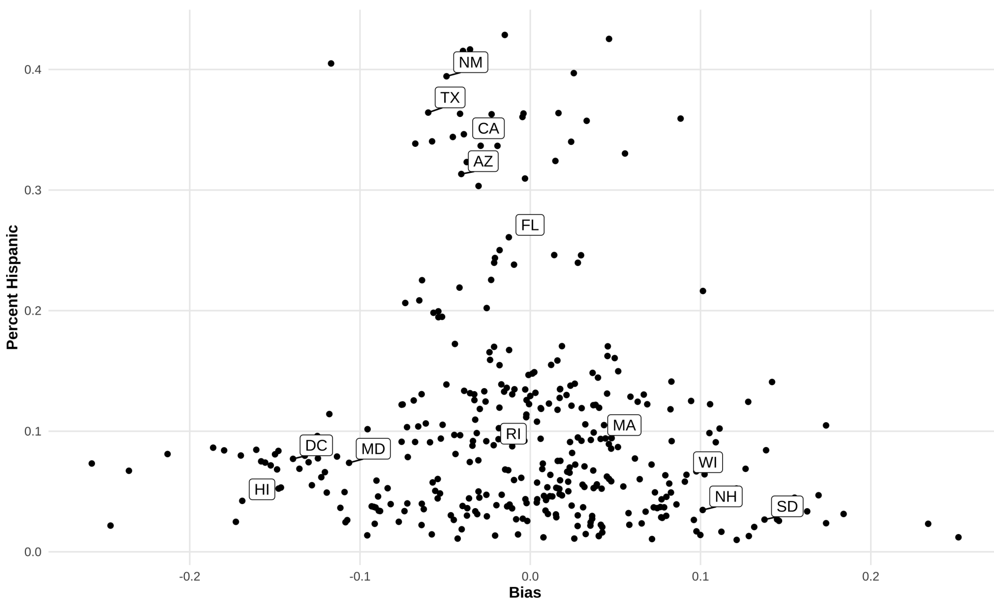
FIGURE 8

SCATTER PLOT OF PROPORTION SUBJECTIVELY HISPANIC ON BIAS

(A) YEAR < 2015



(B) YEAR ≥ 2015



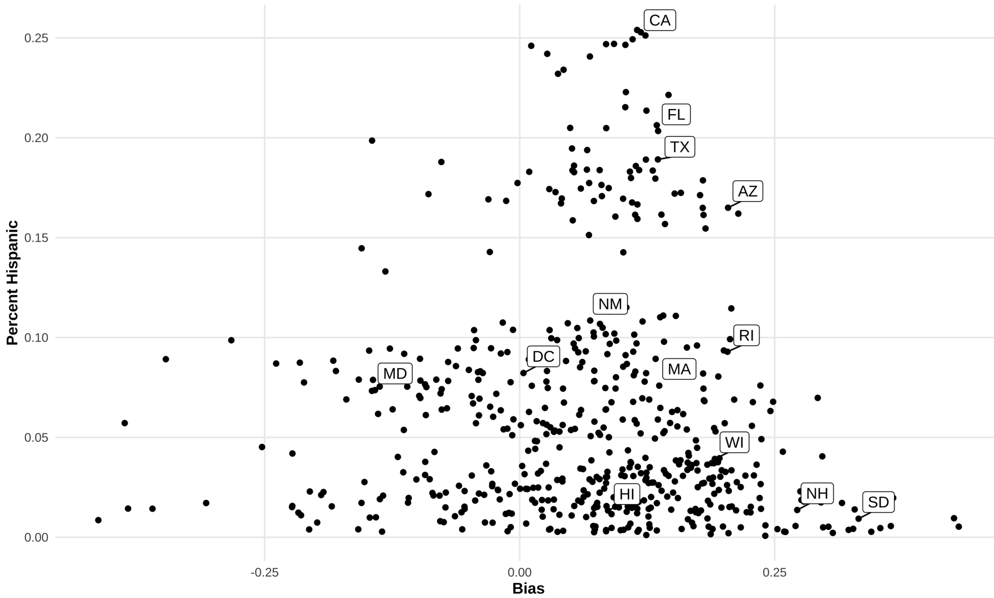
Note. Here are two scatter plots of bias on subjective Hispanic population in a state. Each dot represent a state at a certain year. Percent subjectively Hispanic = $\frac{\#\text{Hispanics}}{\text{Population}}$.

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

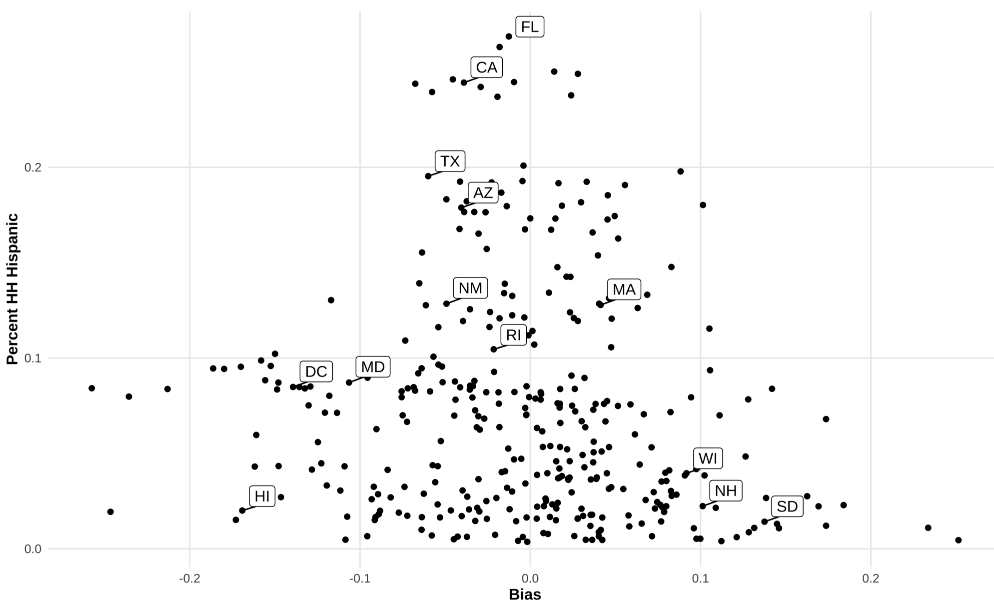
FIGURE 9

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

(A) YEAR < 2015



(B) YEAR ≥ 2015



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

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.

TABLE 17

SELF-REPORTED HISPANIC IDENTITY AND BIAS AMONG SECOND GENERATION HISPANIC IMMIGRANTS: BOTH PARENTS BORN IN A SPANISH SPEAKING COUNTRY

	(1) H^2	(2) H^2	(3) H^2	(4) H^2	(5) H^2	(6) H^2
Bias	−0.01	−0.02	−0.03	−0.04	−0.02	−0.15**
	(0.03)	(0.06)	(0.02)	(0.03)	(0.02)	(0.07)
Female	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	−0.05***	−0.05***	−0.03***	−0.03***	−0.03***	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.05***	−0.05***	−0.04***	−0.04***	−0.04***	−0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	405116	405116	405116	405116	405116	405116
Linear Trend	No	No	No	No	Yes	No
Mean	0.96	0.96	0.96	0.96	0.96	0.96
Year FE		X		X		
State FE			X	X		
Year × Region FE						X

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

[1] Each column is an estimation of a heterogeneous effect of regression (4) on second generation children of parents born in a Spanish speaking country (HH) with different specifications. 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 2004-2020 Current Population Survey.

TABLE 18

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	−0.10*	−0.03	−0.09*	−0.26**
	(0.05)	(0.02)	(0.05)	(0.12)
Female	0.00	−0.01	0.01	−0.03**
	(0.00)	(0.01)	(0.00)	(0.01)
College Graduate: Mother	−0.10***	−0.05**	−0.14***	−0.12***
	(0.02)	(0.02)	(0.02)	(0.03)
College Graduate: Father	−0.13***	−0.04	−0.17***	−0.22***
	(0.03)	(0.03)	(0.02)	(0.06)
N	157424	21888	105064	30472
Mean	0.83	0.96	0.87	0.58
R squared	0.384	0.018	0.223	0.249

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

[1] Each column is an estimation of equation (4) by parents' type 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 merge the GSS index in 1996 with CPS 1995-1999 years. 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 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 19

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	−0.09*	−0.05	−0.14	−0.21**
	(0.05)	(0.04)	(0.09)	(0.10)
Female	0.01	0.01*	0.00	0.01
	(0.00)	(0.00)	(0.02)	(0.02)
College Graduate: Mother	−0.14***	−0.06***	−0.22***	−0.15***
	(0.02)	(0.01)	(0.03)	(0.04)
College Graduate: Father	−0.17***	−0.05***	−0.25***	−0.25***
	(0.02)	(0.01)	(0.04)	(0.03)
N	105064	71440	18961	14663
R squared	0.223	0.018	0.108	0.115
Mean	0.87	0.96	0.7	0.66

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

[1] Each column is an estimation of equation (4) by parents' type 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 merge the GSS index in 1996 with CPS 1995-1999 years. 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 20

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	−0.22*	−0.34**	−0.57**	0.16
	(0.11)	(0.13)	(0.21)	(0.10)
Female	−0.04***	−0.05**	0.04	0.00
	(0.01)	(0.02)	(0.04)	(0.02)
College Graduate: Mother	−0.10**	−0.10	−0.04	−0.19***
	(0.04)	(0.07)	(0.23)	(0.06)
College Graduate: Father	−0.14***	−0.15***	−0.08	−0.06
	(0.02)	(0.04)	(0.16)	(0.08)
N	14931	10126	1848	3567
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 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 merge the GSS index in 1996 with CPS 1995-1999 years. 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.

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APPENDIX A: TABLES

TABLE 21

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 22

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 23

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 24

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 25

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 26

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

	HH				HW				WH				
1	NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		All
Hispanic Mother	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	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 27

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

	HH				HW				WH				
1	NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		NonHispanic Child		Hispanic Child		All
Hispanic Father	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	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 28
SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS

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	0.07***	−0.03	0.08***	−0.03
	(0.01)	(0.04)	(0.02)	(0.04)
Bias x White-Hispanic Parent	0.06***	−0.01	0.07***	−0.01
	(0.02)	(0.05)	(0.02)	(0.05)
Implicit Skin Tone Bias	−0.12***	−0.15***	−0.12***	−0.15***
	(0.01)	(0.03)	(0.01)	(0.03)
Hispanic-White Parent	−0.06***	−0.05***	−0.06***	−0.05***
	(0.00)	(0.00)	(0.00)	(0.00)
White-Hispanic Parent	−0.11***	−0.10***	−0.11***	−0.10***
	(0.00)	(0.00)	(0.00)	(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 29
SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS

Sample	All Sample	March Sup.	non-March Sup.	March Sup. with Income
	(1)	(2)	(3)	(4)
	H^3	H^3	H^3	H^3
Bias x HHHW	0.08**	0.06	0.08**	0.07
	(0.04)	(0.13)	(0.04)	(0.13)
Bias x HHWH	0.01	−0.11	0.02	−0.10
	(0.07)	(0.20)	(0.07)	(0.20)
Bias x HHWW	0.29***	0.26***	0.30***	0.25***
	(0.03)	(0.08)	(0.03)	(0.08)
Bias x HWHH	0.14**	0.00	0.14**	−0.01
	(0.06)	(0.18)	(0.06)	(0.18)
Bias x HWHW	0.09	−0.26	0.11*	−0.26
	(0.06)	(0.19)	(0.07)	(0.19)
Bias x HWWH	0.83***	0.36	0.85***	0.36
	(0.15)	(0.54)	(0.15)	(0.54)
Bias x HWWW	0.26***	0.24*	0.27***	0.23*
	(0.05)	(0.13)	(0.05)	(0.13)
Bias x WHHH	0.25***	0.16	0.25***	0.16
	(0.06)	(0.22)	(0.06)	(0.22)
Bias x WHHW	0.33***	0.50**	0.31**	0.51**
	(0.11)	(0.25)	(0.12)	(0.25)
Bias x WHWH	0.28**	−0.25	0.32***	−0.26
	(0.12)	(0.33)	(0.12)	(0.32)
Bias x WHWW	0.18***	−0.06	0.20***	−0.06

TABLE 29
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	0.05	0.05	0.05
	(0.04)	(0.10)	(0.04)	(0.10)
Bias x WWHW	0.27***	0.19	0.27***	0.19
	(0.05)	(0.14)	(0.06)	(0.14)
Bias x WWWH	−0.18***	−0.08	−0.19***	−0.09
	(0.06)	(0.16)	(0.06)	(0.16)
Implicit Skin Tone Bias	0.00	0.06	−0.01	0.07
	(0.02)	(0.06)	(0.02)	(0.06)
N	198 991	28 346	170 645	28 346
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 30

SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS AMONG ADULT 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	All	HH	HW	WH
	(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
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*
	(0.18)	(0.12)	(0.35)	(0.43)	(0.23)	(0.16)	(0.49)	(0.54)	(0.18)	(0.12)	(0.34)	(0.43)	(0.23)	(0.16)	(0.49)	(0.54)
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***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
Log Total Family Income													0.00	0.00	0.00	0.00
													(0.00)	(0.00)	(0.01)	(0.01)
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 31

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	0.29*	0.03	0.29*
	(0.06)	(0.18)	(0.06)	(0.18)
Bias x White-Hispanic Parent	−0.02	0.09	−0.03	0.09
	(0.07)	(0.23)	(0.07)	(0.23)
Implicit Skin Tone Bias	0.33***	0.38***	0.32***	0.38***
	(0.04)	(0.14)	(0.04)	(0.14)
Hispanic-White Parent	−0.11***	−0.18***	−0.11***	−0.18***
	(0.02)	(0.05)	(0.02)	(0.05)
White-Hispanic Parent	−0.13***	−0.16**	−0.13***	−0.16**
	(0.02)	(0.07)	(0.02)	(0.07)
Log Total Family Income				0.00
				(0.00)
N	237 595	33 458	204 137	33 458
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 32

SUBJECTIVE HISPANIC IDENTITY AND SKIN TONE IMPLICIT 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	Inter Ethnic	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
Implicit Skin Tone Bias	−0.10**	−0.15**	0.06	−0.15***	−0.16**	−0.09	−0.10*	−0.15**	0.07	−0.15***	−0.16**	−0.09
	(0.05)	(0.07)	(0.07)	(0.05)	(0.06)	(0.12)	(0.05)	(0.07)	(0.06)	(0.05)	(0.06)	(0.12)
Female	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
College Graduate: Mother	−0.06***	−0.04***	−0.07***	−0.05***	−0.03**	−0.07***	−0.06***	−0.04***	−0.07***	−0.05***	−0.03**	−0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
College Graduate: Father	−0.08***	−0.04***	−0.12***	−0.09***	−0.05***	−0.11***	−0.08***	−0.04***	−0.12***	−0.08***	−0.05***	−0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Log Total Family Income										0.00***	0.00	−0.01***
										(0.00)	(0.00)	(0.00)
Mean	0.94	0.96	0.9	0.94	0.97	0.9	0.94	0.96	0.89	0.94	0.97	0.9
N	560100	405116	154984	82428	59950	22478	477672	345166	132506	82428	59950	22478
Year-Region FE	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 33

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	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	H^2	H^2	H^2	H^2	H^2	H^2
Explicit Bias	−0.05	−0.09	0.08	0.04	0.02	−0.06	0.49***	−0.12	−0.05	−0.10	0.05	0.05	0.02	−0.06	0.49***	−0.12
	(0.06)	(0.08)	(0.11)	(0.19)	(0.05)	(0.07)	(0.11)	(0.21)	(0.06)	(0.08)	(0.11)	(0.20)	(0.05)	(0.07)	(0.11)	(0.21)
Female	0.00	0.00	−0.02	0.02	0.00	0.00	−0.01	0.02	0.00	0.00	−0.02	0.02	0.00	0.00	−0.01	0.02
	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.02)	(0.02)
College Graduate: Mother	−0.06***	−0.03	−0.04**	−0.12***	−0.05**	−0.02	−0.01	−0.16***	−0.06***	−0.03	−0.04**	−0.12***	−0.05**	−0.02	0.00	−0.16***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
College Graduate: Father	−0.08***	−0.04***	−0.17***	−0.07**	−0.09***	−0.05***	−0.16***	−0.07**	−0.08***	−0.04***	−0.17***	−0.06**	−0.09***	−0.05***	−0.15***	−0.07**
	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)	(0.05)	(0.03)	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.01)	(0.05)	(0.03)
Log Total Family Income													0.00***	0.00***	−0.01	−0.01**
													(0.00)	(0.00)	(0.00)	(0.00)
Mean	0.94	0.96	0.9	0.83	0.94	0.97	0.9	0.85	0.94	0.96	0.89	0.83	0.94	0.97	0.9	0.85
N	167005	122157	25648	19200	24844	18157	3846	2841	142161	104000	21802	16359	24844	18157	3846	2841
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, parental education.

[2] Standard errors are clustered on the state level

TABLE 34
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***	0.07***		
	(0.01)	(0.01)		
Bias x White-Hispanic Parent	0.06***	0.06***		
	(0.02)	(0.02)		
Bias x HHHW			0.08**	0.10***
			(0.04)	(0.03)
Bias x HHWH			0.01	0.01
			(0.07)	(0.07)
Bias x HHWW			0.29***	0.27***
			(0.03)	(0.03)
Bias x HWHH			0.14**	0.18***
			(0.06)	(0.06)
Bias x HWHW			0.09	0.16**
			(0.06)	(0.06)
Bias x HWWH			0.83***	0.82***
			(0.15)	(0.15)
Bias x HWWW			0.26***	0.23***
			(0.05)	(0.05)
Bias x WHHH			0.25***	0.31***
			(0.06)	(0.06)
Bias x WHHW			0.33***	0.36***
			(0.11)	(0.11)

TABLE 34
SELF-REPORTED HISPANIC IDENTITY AND BIAS: BY PARENTAL TYPE *(continued)*

	(1)	(2)	(3)	(4)
	H^2	H^2	H^3	H^3
Bias x WHWH			0.28**	0.39***
			(0.12)	(0.11)
Bias x WHWW			0.18***	0.19***
			(0.06)	(0.06)
Bias x WWHH			0.05	0.03
			(0.04)	(0.03)
Bias x WWHW			0.27***	0.25***
			(0.05)	(0.05)
Bias x WWWH			−0.18***	−0.17***
			(0.06)	(0.06)
Bias	−0.12***	−0.07***	0.00	0.08***
	(0.01)	(0.01)	(0.02)	(0.02)
Hispanic-White Parent	−0.06***	−0.06***		
	(0.00)	(0.00)		
White-Hispanic Parent	−0.11***	−0.11***		
	(0.00)	(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 34

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 35
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***	0.16***		
	(0.01)	(0.01)		
Bias x White-Hispanic Parent	0.18***	0.17***		
	(0.02)	(0.02)		
Bias x HHHW			0.16***	0.15***
			(0.04)	(0.04)
Bias x HHWH			0.11**	0.13***
			(0.05)	(0.05)
Bias x HHWW			0.28***	0.28***
			(0.02)	(0.02)
Bias x HWHH			0.06	0.07
			(0.07)	(0.07)
Bias x HWHW			−0.01	0.01
			(0.07)	(0.07)
Bias x HWWH			0.64***	0.62***
			(0.13)	(0.14)
Bias x HWWW			0.13***	0.11**
			(0.04)	(0.04)
Bias x WHHH			0.06	0.06
			(0.06)	(0.06)
Bias x WHHW			0.27**	0.31***
			(0.12)	(0.11)

TABLE 35
HISPANIC IDENTITY AND SKIN TONE IMPLICIT BIAS *(continued)*

	(1) Dad H^2	(2) Dad H^2	(3) Dad H^3	(4) Dad H^3
Bias x WHWH			0.86***	0.88***
			(0.14)	(0.14)
Bias x WHWW			−0.10*	−0.10*
			(0.06)	(0.06)
Bias x WWHH			0.37***	0.36***
			(0.04)	(0.04)
Bias x WWHW			0.38***	0.37***
			(0.04)	(0.04)
Bias x WWWH			0.00	0.01
			(0.05)	(0.05)
Implicit Skin Tone Bias	−0.04***	−0.03***	−0.11***	−0.06***
	(0.01)	(0.01)	(0.02)	(0.02)
Hispanic-White Parent	−0.05***	−0.05***		
	(0.00)	(0.00)		
White-Hispanic Parent	−0.32***	−0.32***		
	(0.00)	(0.00)		
N	560 100	560 100	198 991	198 991
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 35

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 36
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***	0.19***		
	(0.02)	(0.02)		
Bias x White-Hispanic Parent	0.02	0.02		
	(0.02)	(0.02)		
Bias x HHHW			−0.02	0.03
			(0.05)	(0.04)
Bias x HHWH			−0.16***	−0.16***
			(0.05)	(0.05)
Bias x HHWW			0.31***	0.30***
			(0.03)	(0.03)
Bias x HWHH			−0.16***	−0.13**
			(0.06)	(0.06)
Bias x HWHW			−0.04	−0.03
			(0.06)	(0.06)
Bias x HWWH			0.52***	0.53***
			(0.13)	(0.13)
Bias x HWWW			0.28***	0.28***
			(0.05)	(0.05)
Bias x WHHH			−0.03	0.03
			(0.05)	(0.05)
Bias x WHHW			−0.72***	−0.64***
			(0.13)	(0.12)

TABLE 36

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 WHWH			1.16***	1.27***
			(0.15)	(0.15)
Bias x WHWW			−0.12***	−0.09**
			(0.05)	(0.05)
Bias x WWHH			−0.11***	−0.11***
			(0.03)	(0.03)
Bias x WWHW			−0.19***	−0.18***
			(0.05)	(0.05)
Bias x WWWH			−0.04	−0.05
			(0.05)	(0.05)
Implicit Skin Tone Bias	−0.03***	−0.02**	0.08***	0.05***
	(0.01)	(0.01)	(0.02)	(0.02)
Hispanic-White Parent	−0.26***	−0.26***		
	(0.00)	(0.00)		
White-Hispanic Parent	−0.05***	−0.05***		
	(0.00)	(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 36

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

TABLE 37

EFFECT OF BIAS ON INTERETHNIC MARRIAGES: MARGINAL EFFECT OF AN ORDINAL MULTILOGIT AND PROBIT REGRESSIONS

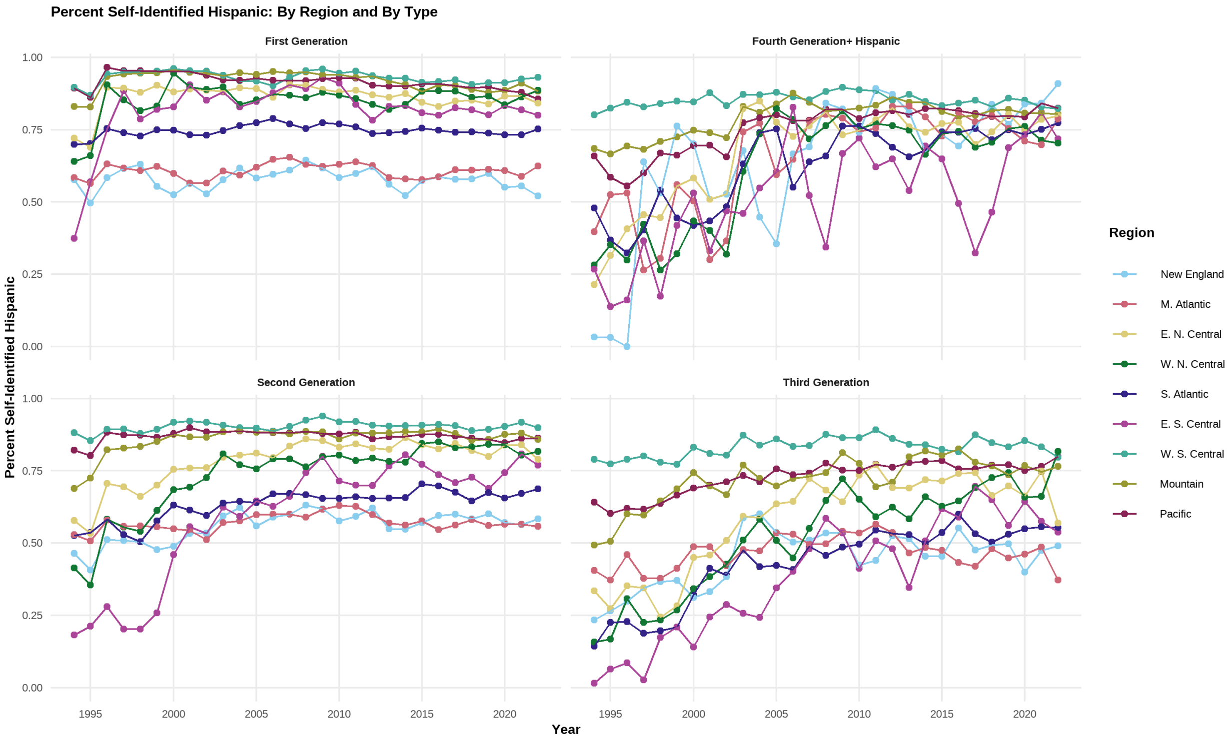
	(1) Probit Marginal Effect at Mean	(2) Logistic Marginal Effect at Mean
Bias	−0.04***	−0.02***
	(0.00)	(0.00)
College Indicator: Wife	−0.05***	−0.03***
	(0.00)	(0.00)
College Indicator: Husband	−0.07***	−0.05***
	(0.00)	(0.00)
Wife's Age	0.00***	0.00***
	(0.00)	(0.00)
Husband's Age	0.00	0.00
	(0.00)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

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

[1] This is the result to estimating (7) as a multinomial ordered probit and logit regression.
[2] The results are of regressions where the left hand side variable is 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.

Appendix B: Figures

Figure 10
Hispanic Identification Among Hispanic Immigrants: By Generation



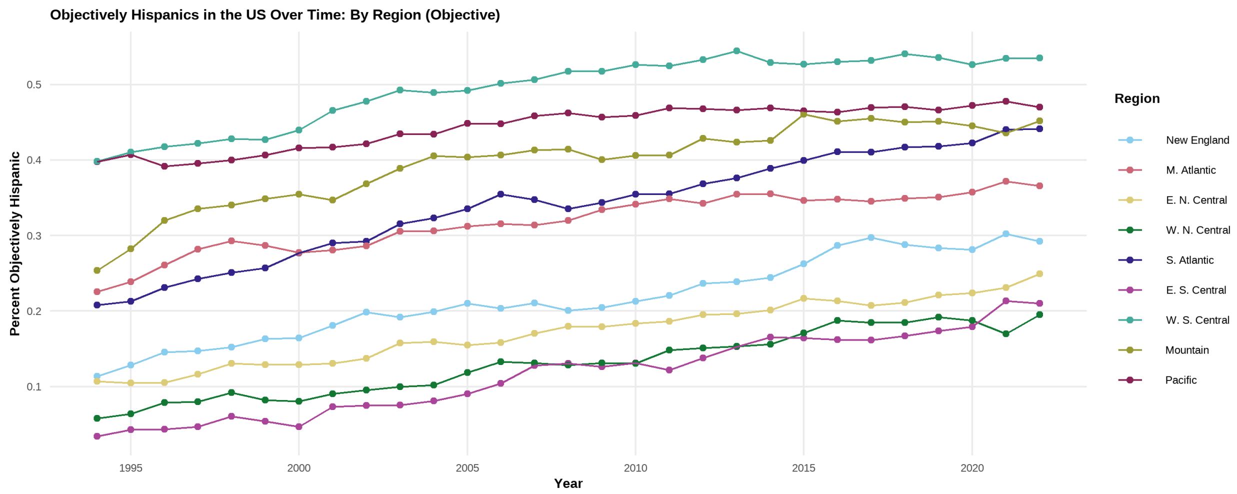

Objectively Hispanics in the US Over Time: By Region (Objective)
Percent Objectively Hispanic
0.5
0.4
0.3
0.2
0.1
1995
2000
2005
2010
2015
2020
Year
Region
New England
M. Atlantic
E. N. Central
W. N. Central
S. Atlantic
E. S. Central
W. S. Central
Mountain
Pacific

FIGURE 11
CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: IAT EXPLICIT BIAS QUESTION

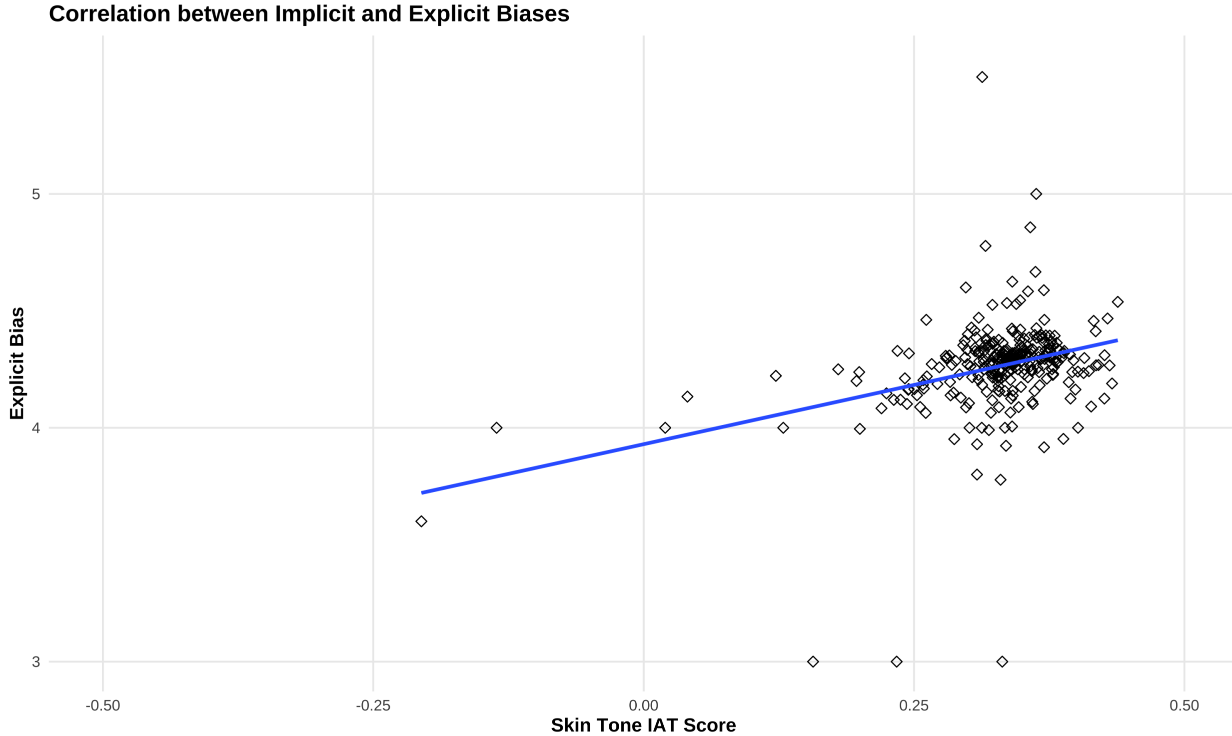


FIGURE 12

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

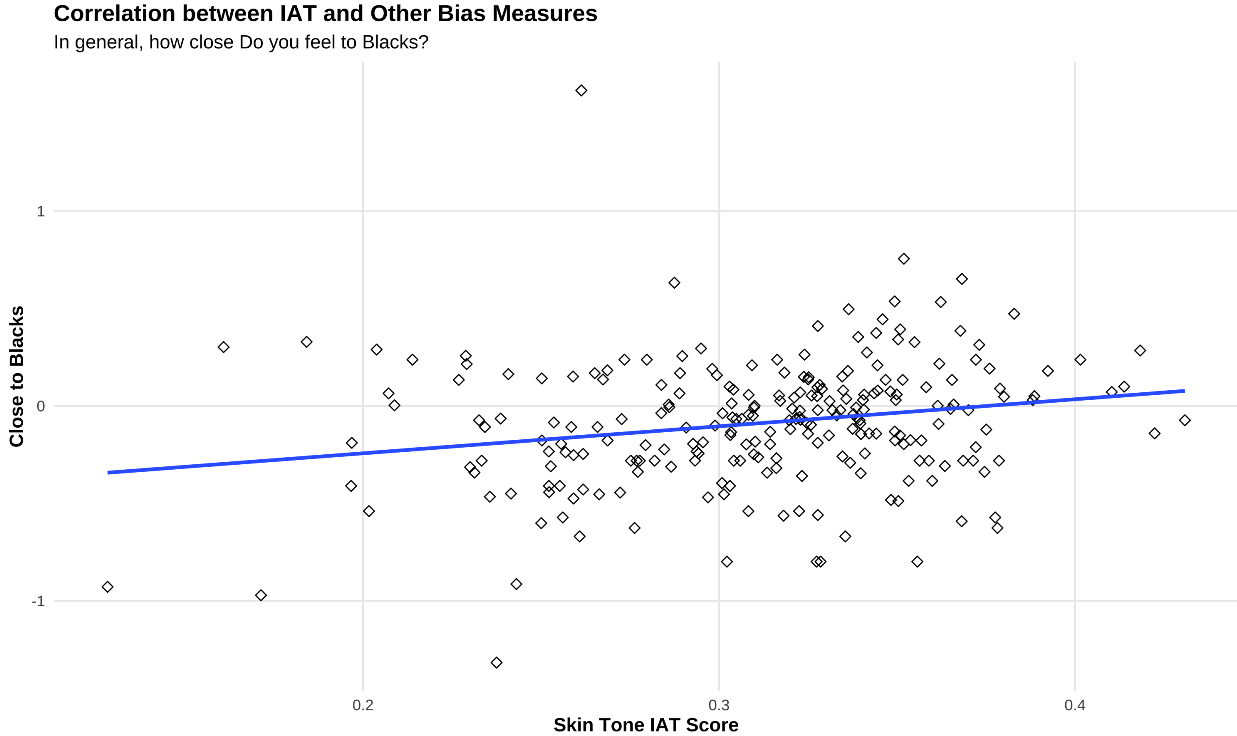
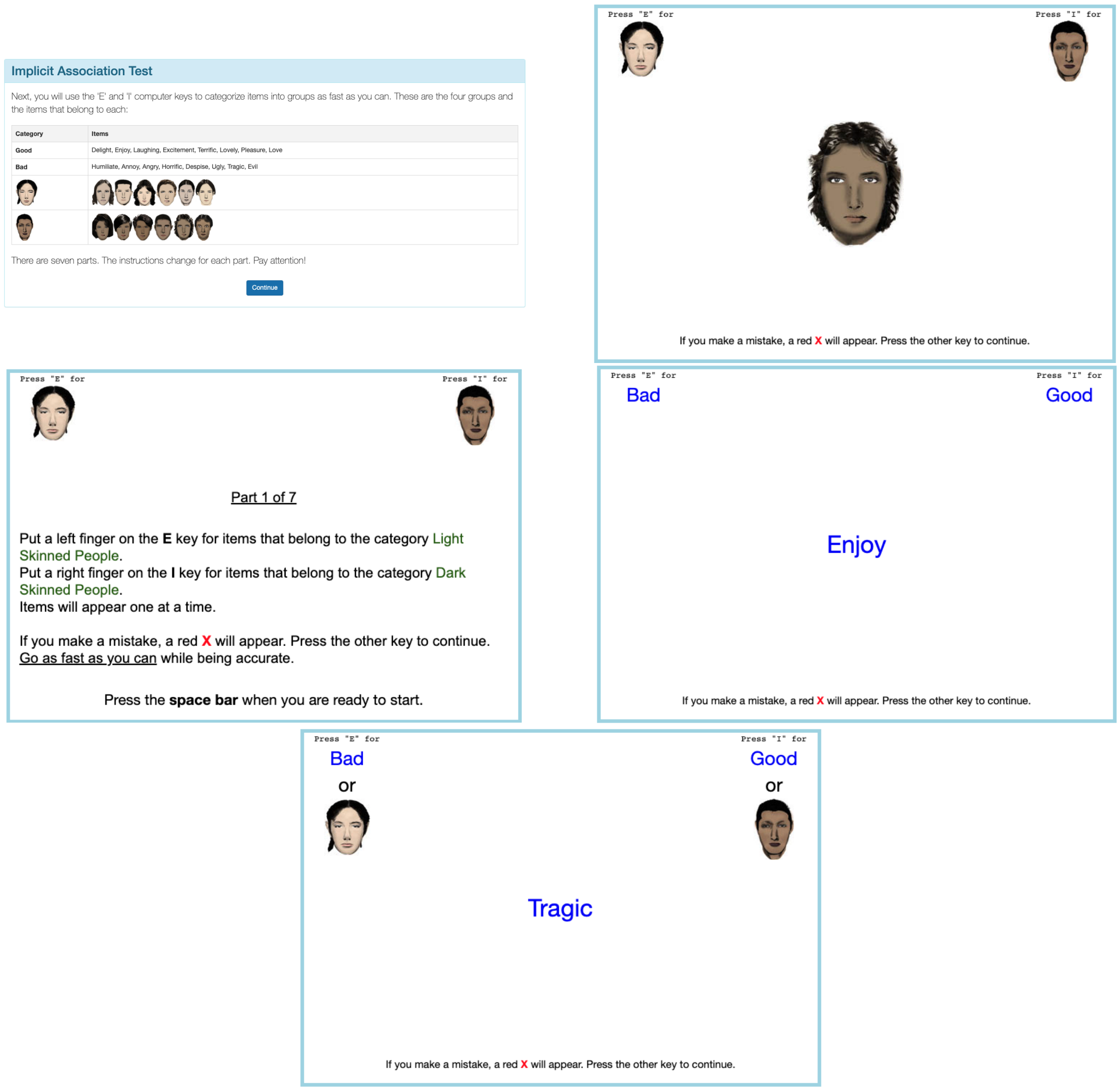


FIGURE 13
CORRELATION BETWEEN IMPLICIT AND EXPLICIT BIASES: GSS VOTE FOR A BLACK PRESIDENT QUESTION

Appendix C: Data

Figure 14
Examples of an Implicit Association Test

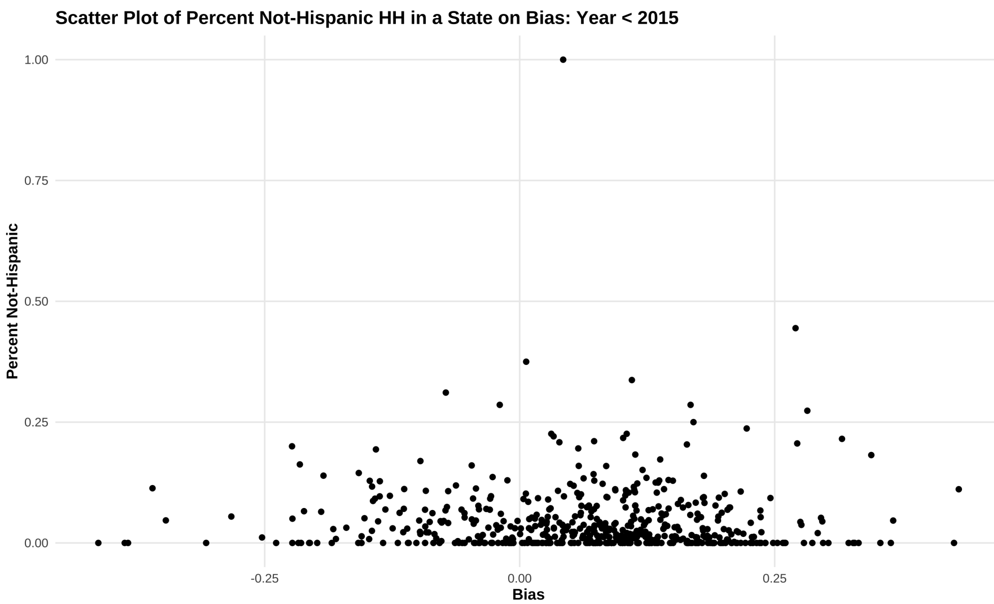


Note. Here are a few examples of what a respondent would see on an implicit association test.

FIGURE 15

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

(A) YEAR < 2015



(B) YEAR ≥ 2015

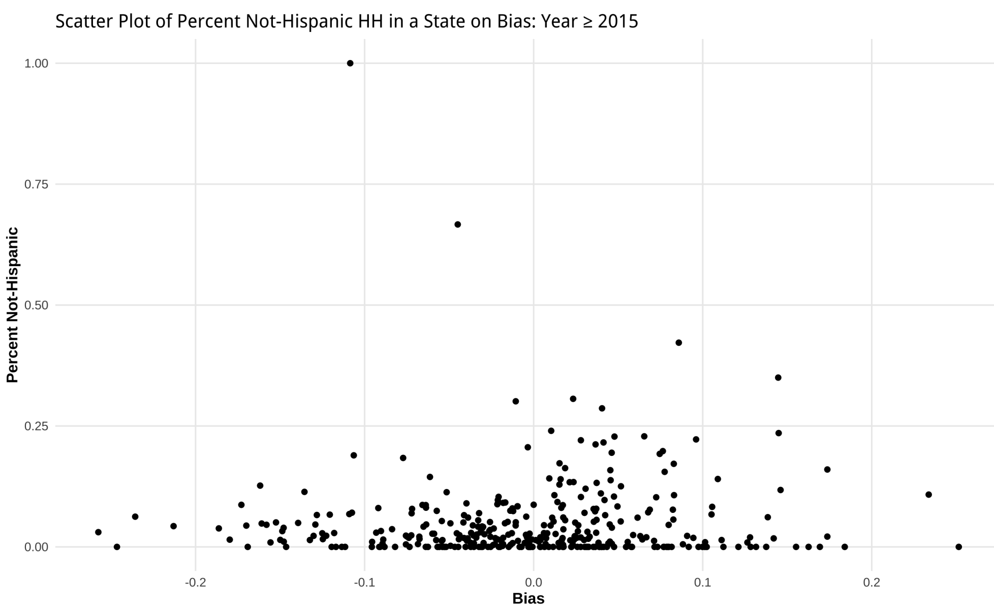
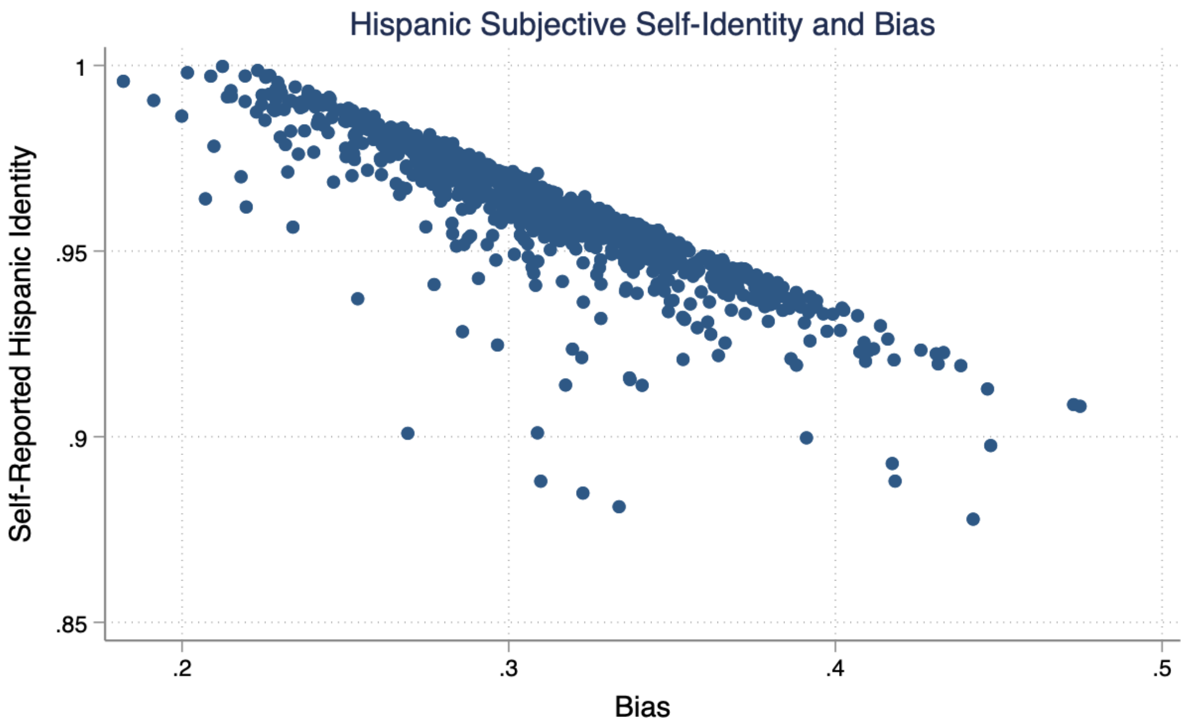


FIGURE 16

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

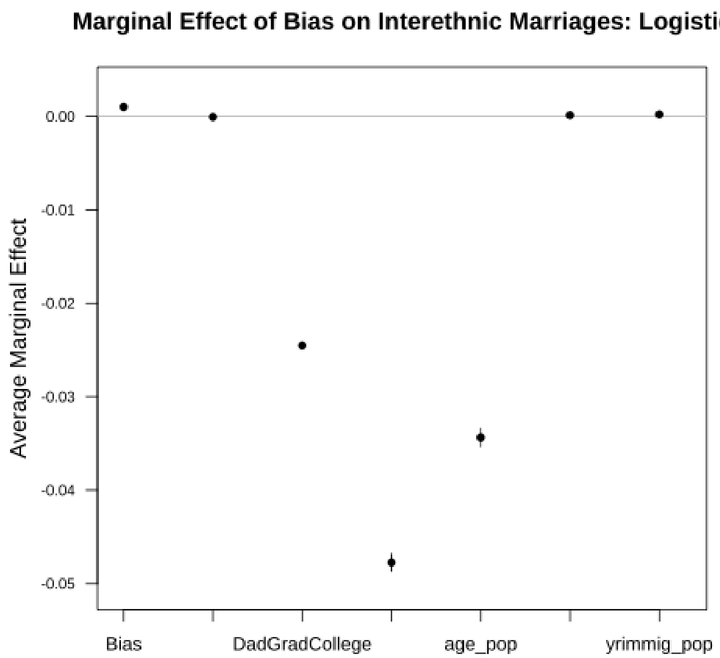


I include controls for sex, age, parental education, and state x egion fixed effects.

FIGURE 17

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

(A) LOGISTIC REGRESSION: COEFFICIENT INTERPRETED AS MARGINAL EFFECT



(B) PROBIT REGRESSION: COEFFICIENT INTERPRETED AS MARGINAL EFFECT