The Effect of Racial and Ethnic Attitudes on Asian Identity in the U.S

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Abstract

In this paper, I study the determinants of the choice to identify as Asian among those whose parents, grandparents, or selves were born in an Asian country. Using a multiple proxy regression approach, I construct a bias measure based on the Implicit Association Test (IAT), the American National Election Studies (ANES), and hate crimes against Asians. I find that individuals with Asian ancestry are significantly less likely to self-identify as Asian if they live in states with high levels of bias: a one standard deviation increase in bias decreases self-reported Asian identity by 9 percentage points across all generations, with effects of 5 percentage points (statistically insignificant) for first-generation, 8 percentage points for second-generation, and 8 percentage points for third-generation Asian Americans. Children of mixed-race families are most influenced by racial bias, with bias decreasing Asian racial identity by 15 percentage points among children of Asian fathers and White mothers, and 10 percentage points among children of White fathers and Asian mothers. Multinomial logit results show that higher bias pushes Asian father-White mother adults toward "White only" identity and White father-Asian mother adults out of "Asian only" and toward multiracial identity; third-generation respondents with two Asian grandparents similarly shift away from "Asian only" toward both multiracial and White identities. Parental education and income have modest, composition-specific effects that are small relative to bias. These findings have implications for the interpretation of research on racial and ethnic gaps in economic outcomes and accurate population measurement. **JEL**: I310, J15, J71, Z13

Keywords: Economics of Minorities, Race, and Immigrants; Discrimination and Prejudice; Stratification Economics

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1 Introduction

Asian Americans represent the fastest-growing racial group in the United States, yet their experiences with discrimination and identity formation remain underexplored in economic research.[1] Unlike other minority groups, Asian Americans occupy a distinctive position in America's racial hierarchy—simultaneously experiencing discrimination and being labeled as "perpetual foreigners" while also being characterized through the 'model minority' stereotype (Fouka, Mazumder, and Tabellini 2022). This dual status creates complex incentives around racial identity choices that fundamentally differ from other groups' experiences. Understanding how both anti-Asian bias and socioeconomic status influence racial identity decisions is crucial, as the selection could systematically distort the true enumeration of Asian in the US, the empirical assessments of Asian American outcomes and the true extent of discrimination they face.

An extensive literature has documented Asian-White gaps in various outcomes (Arabsheibani and Wang 2010; Chiswick 1983; Duleep and Sanders 2012; Hilger 2016), yet the role of identity selection in shaping these disparities remains understudied. The challenge lies in defining and measuring racial identity, particularly when individuals possess agency in how they racially self-identify. If reporting Asian racial identity represents a strategic choice influenced by local discrimination, measured gaps may systematically vary across geographic contexts in ways that previous research has not fully explored.

Various contextual factors, including anti-Asian sentiment and stereotypes, can influence how individuals navigate their racial identity choices. The COVID-19 pandemic have brought renewed attention to how external hostility shapes Asian American experiences (Gover, Harper, and Langton 2020). In this paper, I examine the determinants of Asian racial identity reporting and analyze how Asian Americans strategically select between Asian and White racial identities. Specifically, I investigate how anti-Asian bias, education, and family income shape decisions to identify racially as Asian American. I also break down the analysis by generation and family structure (interracial versus endogamous parents) and examine what racial identities individuals with objective Asian ancestry report (Asian only, White only, multiracial, etc.).

This paper has important implications for public policy and economic research

[1] The 2020 Census counted more than 20 million Asian Americans—6.4 percent of the population—nearly double the number counted two decades earlier (Flood, King, et al., Integrated Public Use Microdata Series, Current Population Survey). The Asian American population numbers are based on the author's calculations from the Current Population Survey and US Census data.

for several reasons. First, if individuals respond to prejudice by avoiding Asian racial identification, conventional analyses of racial gaps may systematically underestimate disparities in the most prejudiced areas. This would lead to misunderstanding of both the extent and geographic distribution of discrimination against Asian Americans. Second, identity choices may influence measured labor market trajectories among racial groups, potentially making Asian American integration appear more successful than reality suggests, thereby reinforcing model minority stereotypes that obscure genuine barriers faced by Asian American communities. Third, strategic identity reporting affects the enumeration of Asian American populations, with implications for political representation, resource allocation, and the design of policies aimed at addressing racial inequities.

I explore how individual characteristics and societal attitudes toward Asian Americans influence racial identity reporting. I use identity and ancestry data from the Current Population Survey (CPS) combined with measures of anti-Asian bias derived from Harvard's Project Implicit Association Test (IAT), the American National Election Studies (ANES), and hate crimes targeting Asian Americans.[2] I ground my analysis in the theoretical framework of Akerlof and Kranton (2000), explicitly modeling how external prejudice creates differential utility from identity choices and establishing conditions under which individuals strategically modify their racial self-presentation. I also use Current Population Survey (CPS) data to study the effect of education (parental and individual) and family income on Asian racial identity reporting.

Measuring identity choices outside of lab settings is challenging, requiring both objective ancestry indicators and subjective identity measures. I leverage birthplace and ancestry data to construct objective Asian ancestry measures, then analyze deviations between objective ancestry and subjective racial identity. I find that racial identity reporting responds to both individual characteristics and environmental factors reflecting local discrimination levels.

I document that heightened anti-Asian bias correlates with reduced Asian racial identity reporting among individuals with Asian ancestry. Specifically, a one standard deviation increase in bias corresponds to a statistically significant 9 percentage point decrease in Asian racial identification among all generations combined. When examined by generation, the effects show a 5 percentage point decrease among first-generation immigrants (statistically insignificant), an 8 percentage

[2]The IAT data comes from Harvard's Project Implicit (Greenwald, McGhee, and Schwartz 1998). Implicit bias measures have gained prominence in economics, with IAT scores correlating with economic outcomes (Chetty et al. 2020; Glover, Pallais, and Pariente 2017), voting patterns (Friese, Bluemke, and Wänke 2007), and health disparities (Leitner et al. 2016).

point decrease among second-generation individuals, and an 8 percentage point decrease among third-generation Asian Americans.

When analyzing the heterogeneity results by family structure, I find that: bias effects are strongest among children from mixed-race families. A one standard deviation bias increase leads to a 15 percentage point decrease in Asian racial identity among children of Asian fathers and White mothers and a 10 percentage point decrease among children of White fathers and Asian mothers. Among adult samples, these patterns are even more pronounced, with second-generation adults from White father-Asian mother families showing 24 percentage point decreases in Asian racial identity in response to bias increases.

Notably, I find that more educated and wealthy Asian Americans are more likely to maintain their Asian racial identity, with college-educated parents and higher household incomes positively correlating with Asian racial identity. This selective retention of Asian identity among successful individuals creates a measurement bias: when researchers use self-reported racial identity to study Asian American outcomes, they inadvertently oversample high-achieving Asians while missing those who have strategically adopted non-Asian identities in response to bias. Consequently, studies may overestimate Asian American success and underestimate the speed of apparent assimilation, as successful Asians remain visible in the data while struggling Asians disappear into other racial categories.

Multinomial logit analyses reveal that anti-Asian bias fundamentally reshapes racial identity choices. Among adult Asian father-White mother respondents, a one standard deviation increase in bias shifts reporting toward "White only" (about +0.14) and away from multiracial identity (about –0.11); White father-Asian mother adults move out of "Asian only" (about –0.13) into multiracial (about +0.09) and slightly "White only" (about +0.05). Third-generation respondents with two Asian grandparents similarly shift away from "Asian only" (about –0.10) toward both alternatives ("White only" about +0.05; "Asian and White" about +0.06), while bias effects are small and imprecise when only one grandparent is Asian. Parental education exerts modest, composition-specific effects—e.g., maternal education boosts "Asian only" for some groups and paternal education can reduce "White only"—but these shifts are much smaller than the bias-driven movements. These patterns underscore that local prejudice, more than socioeconomic resources, drives strategic identity choices and can distort measured Asian-White gaps in highly prejudiced areas.

This research contributes to multiple bodies of scholarly literature in economics. First, it extends the economics of identity framework by examining how racial stereotypes—both positive and negative—influence identity choices (Akerlof and

Kranton 2000). Building on Charness and Chen (2020) and Atkin, Colson-Sihra, and Shayo (2021), I show that Asian Americans face a complex utility landscape where Asian identity can simultaneously signal competence (in educational contexts) and foreignness (in social settings). The analysis connects to stratification economics research examining how racial hierarchies shape economic outcomes (Darity 2022; Darity, Mason, and Stewart 2006). This framework extends to Asian American experiences, where model minority stereotypes create unique forms of racialization distinct from other groups' experiences (Diette et al. 2015; Goldsmith, Hamilton, and Darity 2007; Hamilton, Goldsmith, and Darity 2009).

While Akerlof and Kranton (2000) theoretical model that I use provides a logical framework for understanding how bias affects racial identity, the behavioral literature on racial identity and assimilation offers crucial empirical insights that complement this theoretical approach. Research in this tradition emphasizes how racial identity is not merely a cognitive construct but is actively performed, negotiated, and reconstructed through daily interactions and life experiences (Waters 1990). Telles and Ortiz (2008)'s study of Mexican Americans demonstrates how individuals strategically adapt their racial presentations across different social contexts while maintaining core identity elements across generations.

Similarly, behavioral studies have documented how discrimination experiences shape identity salience and group attachment, with individuals developing adaptive strategies that range from ethnic distancing to reactive ethnicity depending on situational factors (Zhou 1997). This behavioral perspective reveals that racial identity operates as both a response to external categorization and an active process of boundary maintenance (Cornell and Hartmann 2006). While this literature has primarily relied on qualitative observations and ethnographic methods to document identity flexibility, the present analysis advances this understanding by quantifying these strategic choices through systematic comparison of objective ancestry measures with subjective racial identification across varying environmental contexts.

My paper also contributes to research on discrimination in economic contexts. Bertrand and Mullainathan (2004) and Charles and Guryan (2008) demonstrate how prejudice affects labor market outcomes, while recent work by Bursztyn et al. (2022) explores how long-term exposure shapes attitudes. My analysis extends this literature by examining how discrimination influences the fundamental question of racial self-identification.

Within immigration and integration research, this work builds on studies examining how Asian Americans navigate assimilation processes (Abramitzky, Boustan, and Eriksson 2014, 2016). Unlike European immigrant groups, Asian Americans face persistent "perpetual foreigner" stereotypes that complicate integration patterns regardless of generational status (Fouka, Mazumder, and Tabellini 2022). The model minority myth creates additional complexity, as Asian racial identity may carry both benefits and costs depending on context (Meng and Gregory 2005).

This paper most closely relates to recent economic research on racial identity fluidity and strategic racial identity (Antman and Duncan 2015, 2021; Antman, Duncan, and Trejo 2016; Hadah 2024). However, while previous work focused primarily on Hispanic ethnic attrition, Asian American identity choices operate through different economic mechanisms due to distinct stereotypes, discrimination patterns, and socioeconomic profiles. The concept of "racial identity flexibility" among Asian Americans reflects both the economic advantages and constraints of model minority positioning.

Recent work in behavioral economics provides additional context for understanding these identity choices. Bordalo et al. (2016) demonstrate how stereotypes influence economic decision-making, while Bonomi, Gennaioli, and Tabellini (2021) show how identity affects political and economic preferences. My analysis contributes to this literature by showing how external discrimination shapes the fundamental choice of racial identity.

Recognizing the identity flexibility that characterizes Asian American experiences, I investigate the economic determinants driving racial self-identification decisions. I examine how personal and environmental factors influence the complexity of endogenous racial identity among Asian Americans, recognizing that the model minority stereotype creates unique economic incentive structures not present for other groups. The empirical analysis documents how observable characteristics—individual traits and societal attitudes—affect racial identity reporting among Asian Americans. These findings have important implications for measuring racial economic disparities and understanding how discrimination operates in modern labor markets.

2 Theoretical Framework

I develop a theoretical framework for understanding racial identity choice that extends Akerlof and Kranton (2000) to incorporate stereotype-specific costs and benefits. Unlike generic minority identification models, this framework recognizes that Asian Americans face unique utility trade-offs where racial identity can signal both positive attributes (academic achievement, work ethic) and negative characteristics (foreignness, social exclusion).

Formally, individual i belongs to racial group $r_i \in \{A, W\}$, where A represents Asian and W represents White. Agent i's utility depends on their actions and how those actions interact with their chosen racial identity I_i:

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

Individual identity I_i reflects personal actions, others' behaviors toward them, and societal expectations associated with their racial group:

$$I_i = I_i(\mathbf{a_i}, \mathbf{a_{-i}}; \mathbf{S}_{r_i}) \tag{2}$$

where $\mathbf{a_i}$ represents individual i's actions, $\mathbf{a_{-i}}$ captures others' actions affecting i's identity (including anti-Asian bias), and $\mathbf{S}_{r_i}$ denotes societal stereotypes and expectations associated with racial group membership.[3]

The key insight for Asian Americans is that $\mathbf{S}_A$ includes both positive stereotypes (academic excellence, economic success) and negative ones (perpetual foreigner status, social exclusion). This creates context-dependent utility from Asian identification—beneficial in some settings (academic achievement contexts) but costly in others (social acceptance, political inclusion).

Individual i selects actions $\mathbf{a_i}$ to maximize utility given their racial group r_i, associated stereotypes $\mathbf{S}_{r_i}$, and others' actions $\mathbf{a_{-i}}$. The first-order condition becomes:

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

The solution $a_i^\star$ yields utility $U_i^\star$. Now suppose individuals can strategically choose their racial identity at cost c. They will switch identities when $\tilde{U_i}^\star \geqslant U_i^\star + c$, where $\tilde{U_i}^\star$ represents utility under the alternative racial identity.

Identity switching occurs when benefits $\tilde{U_i}^\star - U_i^\star$ exceed costs c. These net benefits are non-zero only when $\frac{dI_i}{d\mathbf{a_i}} \neq 0$ and $\frac{\partial U_i}{\partial I_i} \neq 0$. This framework suggests empirical analysis should focus on: (1) individual characteristics affecting optimal actions under different racial identities, (2) contextual factors (anti-Asian bias) creating differential treatment by racial group, (3) populations with low switching costs c, and (4) groups whose utility significantly depends on racial identity.

In the empirical analysis, I investigate characteristics affecting individual actions under different identity choices from point (1). These characteristics include immigrant generation, mixed-race versus mono-racial family structure, etc.

[3]This extends Akerlof and Kranton (2000)'s prescription concept to encompass both negative stereotypes and positive model minority expectations.

I also examine how anti-Asian bias influences identity choices. Finally, restricting analysis to individuals with low identity switching costs c ensures the sample excludes populations unlikely to modify racial identification—for example, non-Asian Whites without Asian ancestry.

The model predicts that anti-Asian bias increases the utility differential between White and Asian racial identity, making identity switching more attractive. Mixed-race individuals face lower switching costs due to phenotypic ambiguity, while later-generation Asian Americans may find identity switching more feasible due to cultural assimilation.

3 Data Sources and Measurement Strategy

In this section, I describe the datasets I use in the analysis. To examine relationships between social attitudes and Asian racial identity reporting, I need both subjective and objective Asian identity measures for identifying appropriate Asian American subgroups. I use the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS) (Flood, King, et al., Integrated Public Use Microdata Series, Current Population Survey) with ancestry information through the places of birth of individuals, their parents, and grandparents to construct objective identity measures. I develop composite anti-Asian bias measures using Lubotsky and Wittenberg (2006)'s multiple proxy regression method to reduce attenuation bias.

3.1 Measuring Asian Racial Identity

I measure Asian racial identity using Current Population Survey (CPS) data from 2004–2021, enabling construction of objective Asian ancestry measures for minors living with parents. Following Antman, Duncan, and Trejo (2016) and Antman, Duncan, and Trejo (2020), I utilize birthplace information for individuals, parents, and grandparents to create objective Asian ancestry indicators.[4] The methodology allows for the identification of first-, second-, and third-generation Asian Americans (see Figure 1 for visual representation). This approach enables me to construct objective Asian ancestry measures for minors under age 17 living with parents. I also use another CPS sample of adults aged 18+ to examine whether their racial identity reporting patterns differ from minors. For the adult

[4]This approach parallels previous research but focuses on racial rather than ethnic categorization.

sample, I can only identify first- and second-generation.[5]

The objective ancestry measure—distinct from subjective racial identification where respondents select "Asian" as their race—depends on birthplaces across three generations.[6] The three identifiable generations include: 1) first-generation immigrants born in Asian countries with both parents also born in Asian countries, 2) second-generation individuals who are US-born citizens with at least one parent born in an Asian country, and 3) third-generation Asian Americans who are US-born citizens with two US-born parents and at least one grandparent born in an Asian country.

Note that while the ancestry measure provides an objective assessment of Asian heritage, it may not capture all nuances of racial identity. For instance, White individuals with Asian ancestry born to non-Asian parents in Asia, such as on American military bases, may be classified as Asian in the data. To avoid potential misclassification, I remove individuals who report that they were born abroad of American parents. The final sample includes Asian Americans, first-, second-, and third-generation immigrants aged 17 and younger living with parents between 2004 and 2021. I present the summary statistics in Table (1). The adult sample includes first- and second-generation Asian American immigrants aged 18 and older between 2004 and 2021. I show the summary statistics for the adult sample in Table (2).

While CPS relies on household respondents (parents or caregivers) to report children's racial identity, this proxy reporting likely reflects children's actual identity since parents significantly influence identity formation. Antman, Duncan, and Trejo (2020) supports this perspective, noting that parental reporting likely underestimates rather than overestimates ethnic attrition, as children may be more likely to drop ethnic identities once they establish separate households as adults. They also cite evidence that children's observed rates of Mexican identification do not vary systematically with which household member serves as respondent.

My data shows consistent Asian identity reporting regardless of whether mother (72%), father (72%), or child/other caregiver (87%) serves as respondent, as shown in Table 3.[7] Furthermore, ethnic attrition patterns among adults align with those

[5]Since adults still living with parents might not be representative of the overall adult population and is a rare occurrence, I do not link adults to their parents.

[6]For this analysis, Asian countries comprise East Asian and Southeast Asian nations, including China, Hong Kong, Taiwan, Japan, Korea, Mongolia, Cambodia, Indonesia, Laos, Malaysia, Philippines, Singapore, Thailand, and Vietnam, but exclude South Asian and Middle Eastern countries, consistent with standard demographic classifications.

[7]According to CPS guidelines, household respondents must be at least 15 years old with sufficient household knowledge. When the proxy is 'self,' the respondent ranges from 15 to 17 years old.

observed in children, as shown in Table (4) for children versus Table (5) for adults, suggesting that proxy reporting aligns with individuals' self-identification.

The overall sample comprises 49% females, with 65% self-reporting Asian racial identity—answering affirmatively to "what is your race." Average age is 8.4 years. Approximately 52% of mothers and 52% of fathers hold college degrees. Additional summary statistics for the overall sample and each generation appear in Table (1).

Using parental and grandparental birthplaces, I objectively identify ethnic ancestry and categorize different family types. For second-generation children, parental birthplaces create three objective categories:

1. Objectively Asian-father-Asian-mother (AA)
2. Objectively Asian-father-White-mother (AW)
3. Objectively White-father-Asian-mother (WA)

Similarly, grandparental birthplaces create 15 objective categories for third-generation children: (1) objectively Asian paternal grandfather-Asian paternal grandmother-Asian maternal grandfather-Asian maternal grandmother (AAAA); (2) objectively White paternal grandfather-Asian paternal grandmother-Asian maternal grandfather-Asian maternal grandmother (WAAA); (3) objectively Asian paternal grandfather-White paternal grandmother-Asian maternal grandfather-Asian maternal grandmother (AWAA), etc.

My analysis employs a subsample of the US population; Tables 4 and 2 demonstrate sufficient observations across generations for both adults and children. Consistent with literature on ethnic and racial identity fluidity among Asian and Hispanic Americans, I document significant attrition among third-generation Asian Americans.[8]

3.2 Measuring Anti-Asian Sentiment

I construct anti-Asian sentiment measures using implicit association tests, American National Election Studies, and hate crimes targeting Asian Americans from 2004–2021.

Since my analysis compares high and low bias states, estimates remain valid provided reporting patterns do not systematically differ between these contexts.

[8] Antman, Duncan, and Trejo (2016), Antman, Duncan, and Trejo (2020), and Duncan and Trejo (2018a, 2018b) document substantial identity attrition among various groups.

The implicit association test measures conceptual associations—for example, linking Asian Americans with negative stereotypes—and evaluative responses. Respondents rapidly categorize words into screen-displayed categories. Figure (A.1) shows examples from Harvard's Project Implicit skin tone test.

I employ Asian-focused implicit association test data to construct anti-Asian prejudice proxies (Greenwald, McGhee, and Schwartz 1998). This measure has extensive social science applications, particularly in psychology. Previous research demonstrates the difficulty of manipulating IAT scores (Egloff and Schmukle 2002). The IAT measures bias direction and magnitude while capturing unconscious biases individuals may be unwilling to report. A meta-analysis of over 122 IAT studies by Greenwald, McGhee, and Schwartz (1998) finds significantly higher predictive validity for IAT compared to self-report measures. Research correlates IAT tests with economic outcomes (Chetty et al. 2020; Glover, Pallais, and Pariente 2017), voting behavior (Friese, Bluemke, and Wänke 2007), and health (Leitner et al. 2016).[9]

However, some research questions IAT predictive validity claims. Implicit Association Tests may not reliably measure or predict implicit prejudice or biased behaviors. Research shows implicit biases experience minor, temporary intervention-induced changes. Additionally, implicit bias fails to predict dictator game contributions or social pressure susceptibility, highlighting distinctions between implicit bias and biased actions (Arkes and Tetlock 2004; Forscher et al. 2019; Lee 2018). Therefore, I supplement IAT with explicit bias measures from American National Election Studies (ANES) and hate crimes against Asian individuals to construct a composite bias measure.

Using the ANES survey, I develop another racial animus proxy using ANES surveys measuring discrimination against racial groups (American National Election Studies 2021). ANES, conducted since 1948, is widely used in political science research. The survey examines attitudes toward different racial groups, voting intentions, and political questions. I employ several 2004–2020 ANES questions measuring racial animus. The racial animus index averages responses across multiple animus-measuring questions.[10] While the ANES racial animus questions primarily focus on attitudes toward Black Americans, research demonstrates that

[9] IAT participation is voluntary, potentially creating selection bias. However, IAT-reflected bias serves as a proxy for prejudiced attitudes (Chetty et al. 2020).

[10] Questions parallel those used by Charles and Guryan (2008): (1) "Conditions Make it Difficult for Blacks to Succeed", (2) "Blacks Should Not Have Special Favors to Succeed", (3) "Blacks Must Try Harder to Succeed", (4) "Blacks Gotten Less than They Deserve Over the Past Few Years", and (5) "Feeling Thermometer Toward Asians."

racial prejudices are highly correlated across different minority groups, with individuals who express bias toward one racial minority typically holding similar attitudes toward others (Almasalkhi 2023; Mora and Paschel 2020). These measures therefore capture broader patterns of racial animus that extend beyond anti-Black sentiment specifically. When combined with the Asian-focused IAT measures and hate crimes against Asian Americans in my composite index, this multi-proxy approach weights the bias measure more heavily toward Asian-specific prejudice while still capturing the general racial climate.

Finally, I incorporate Uniform Crime Reports (UCR) data quantifying hate crimes against Asian Americans (Bureau of Justice Statistics 2023). Hate crime data provides tangible measures of racially-motivated aggression and discrimination. Combined with implicit and explicit bias measures, this enables a comprehensive understanding of prejudice across states. This multidimensional approach—implicit bias, explicit bias, and hate crime statistics—offers a fuller understanding of the racial prejudice landscape.

To reduce attenuation bias and measurement error, I follow Lubotsky and Wittenberg (2006) in constructing composite bias measures using IAT, ANES racial animus measures, and hate crimes against Asian Americans.[11] Figure (2a) graphically represents bias measures over time in the most and least biased locations. Figure (2b) shows Asian racial identity reporting in the two most and least biased locations. Lower scores indicate less bias; higher scores indicate greater racial animus. One standard deviation bias increase is equivalent to moving from Washington, DC, or Vermont to North Dakota in 2020. State-level average bias over time appears in Figure (3), with overall 2004–2021 averages in Figure (4).

4 From the Data: Asian Racial Identity and Attrition

Table (4) displays racial attrition patterns across generations. Among first-generation Asian Americans, 96% self-report Asian racial identity. This drops to 73% among second-generation and 31% among third-generation Asian Americans. Attrition is driven primarily by children from interracial families. Among second-generation children, those with two Asian parents report 97% Asian racial identity, while those with one Asian and one White parent report only 33%. Similarly, among third-generation children, 94% of those with four Asian grandparents report Asian racial identity compared to 25% overall. Adult samples show similar patterns (Table 5). Among second-generation adults, those with two Asian par-

[11] Additional methodological details appear in the Data Online Appendix, Section 7.

ents report 95% Asian racial identity, while those with one Asian and one White parent report 37%.

Figures 5–8 display racial identity choices among objectively Asian children by generation and family structure.[12] Among all objectively Asian children (Figure 5), 63% report Asian only identity, 15% White only, and 15% Asian and White/Pacific Islander. First-generation children overwhelmingly report Asian only identity (94%, Figure 6). Family structure strongly predicts second-generation identity choices (Figure 7). Children with two Asian parents overwhelmingly report Asian only identity (96%), while those from interracial families show substantially lower rates: 36% for Asian father-White mother families and 29% for White father-Asian mother families.

Third-generation patterns reveal increasing identity fluidity (Figure 8). White only identity becomes most common overall (35%), followed by Asian only (29%), Asian and White/Pacific Islander (29%), and other multiracial identities (7%). The number of Asian grandparents strongly predicts choices: those with one Asian grandparent report 54% White only, while those with four Asian grandparents report 92% Asian only.

These patterns demonstrate that racial identity becomes increasingly fluid across generations, with endogamous Asian families maintaining high rates of Asian racial identity while interracial family structures significantly increase non-Asian identity choices. These findings highlight the importance of distinguishing between ancestral background and self-reported racial identity when analyzing Asian American outcomes.

5 Empirical Approach and Findings

To understand associations between Asian racial self-identification and anti-Asian bias, I estimate regressions of the following form for each generation g:

$$\begin{aligned} A_{ist}^{g} &= \beta_1^{g} AntiAsianBias_{st} + \beta_2^{g} DadCollegeGrad_{ist} + \beta_3^{g} MomCollegeGrad_{ist} \\ &+ \beta_4^{g} Women_{ist} + X_{ist}^{g}\pi + \gamma_{rt} + \varepsilon_{ist}; \text{where } g \in \{1, 2, 3\} \end{aligned} \tag{4}$$

where A_{ist}^{g} represents self-reported Asian racial identity of person i in state s at interview time t, $AntiAsianBias_{st}$ represents average anti-Asian bias in state

[12] Beginning in 2003, the CPS allowed respondents to report multiple racial identities. I categorize responses into six classifications: (1) Asian only, (2) White only, (3) Asian and White/Pacific Islander, (4) other non-Asian multiracial combinations, (5) Asian combined with other races, and (6) Asian/Pacific Islander.

s at time t, $DadCollegeGrad_{ist}$ and $MomCollegeGrad_{ist}$ are indicator variables equaling one if father or mother graduated college, $Women_{ist}$ indicates sex, and X_{ist} represents a control vector.[13] Additionally, γ_{rt} represents region-time fixed effects controlling for region $\times$ year specific shocks.[14] Region $\times$ year controls also account for systematic regional differences in overall Asian American populations and anti-Asian bias, even with temporal variation. Throughout the analysis, I cluster standard errors at the state level, accounting for correlation of the error term ε_{ist} within states over time.

Since specifications include region $\times$ year fixed effects γ_{rt}, the β_1^g coefficient summarizes individual i's responsiveness to anti-Asian bias changes in their state of residence. In other words, β_1^g captures associations between Asian racial identity reporting and anti-Asian bias across states within Census division regions. Additionally, γ_{rt} fixed effects account for regional and national bias trends over time. Consequently, β_1^g provides correlations between Asian racial identity reporting and anti-Asian bias beyond national and regional bias trends. If individuals in states within the same region responded similarly to bias changes, then β_1^g would equal zero.

Moreover, to further understand how explanatory variables affect Asian racial identity reporting, I estimate a multinomial logit model replacing the depMoreover, to further understand how explanatory variables affect Asian racial identity reporting, I estimate a multinomial logit model replacing the dependent variable A_{ist}^g with categorical racial identity choices: (1) Asian only, (2) White only, (3) Asian and White/Pacific Islander. The equation is as follows:

$$\log\left(\frac{P(Y_{ist}^g = j)}{P(Y_{ist}^g = \text{Asian only})}\right) = \beta_{1j}^g AntiAsianBias_{st} + \beta_{2j}^g DadCollegeGrad_{ist} + \beta_{3j}^g MomCollegeGrad_{ist} + \beta_{4j}^g Female_{ist} + X_{ist}^g \pi_j + \gamma_{rtj} + \varepsilon_{istj}; \quad j \in \{\text{White only, Asian and White}\} \tag{5}$$

where Y_{ist} represents the categorical racial identity of person i in state s at interview time t, j indexes the identity categories, with "Asian only" as the reference category, $P(Y_{ist}^g = j)$ denotes the probability of person i in state s at time t choosing identity j, $\mathbf{X}_{ist}^g$ represents the vector of controls that include quartic age, Asian

[13] Controls include quartic age, Asian population fraction in state s, parent types (WA, AW, or AA), grandparent types (AAAA, AAAW, etc.), and generation dummy variables.

[14] I exclude state fixed effects due to insufficient within-state bias variation.

population fraction, parent types, grandparent types, and generation dummies, $\boldsymbol{\beta}_j^g$ denotes the coefficient vector for outcome j and generation g, and J indexes the three identity categories. Finally, γ_{rtj} represents region-time fixed effects that would control for region $\times$ year specific shocks affecting identity choice j, and ε_{istj} is the error term.

The model specification allows the effects of anti-Asian bias and other covariates to vary across identity choices. For instance, $\beta^g_{1,\text{White only}}$ captures how anti-Asian bias affects the log-odds of choosing "White only" versus "Asian only" identity, while $\beta^g_{1,\text{Asian and White}}$ measures the bias effect on choosing "Asian and White" versus "Asian only." This framework enables analysis of how bias, sex, and parental education differentially influence various identity strategies available to individuals with Asian ancestry.

The coefficients of interest are β^g_{1j}, β^g_{2j}, β^g_{3j}, and β^g_{4j}, which capture how anti-Asian bias, parental education, and sex influence the likelihood of selecting each identity category relative to "Asian only." I estimate separate models for each generation $g \in \{1, 2, 3\}$ to assess whether these relationships differ across generational status.

The multinomial specification proves particularly appropriate for analyzing Asian American identity choices because it accounts for the distinct utility individuals may derive from different identity options. Unlike binary choice models, the multinomial framework recognizes that choosing "White only" identity represents a fundamentally different strategy than selecting "Asian and White" multiracial identity, even though both are alternatives to "Asian only" that may respond to anti-Asian bias. This distinction is particularly important for mixed-ancestry individuals, who may strategically choose between complete ethnic distancing (reporting "White only") and maintaining partial ethnic connection through multiracial identity ("Asian and White").

Since log odds coefficients from multinomial logit models are difficult to interpret directly, I compute the predicted probabilities of each identity choice at different anti-Asian bias levels, holding other covariates constant and summarizing results with the median across 1,000 bootstrap resamples (with percentile-based 95% confidence intervals). This approach provides more intuitive insights into how bias influences the likelihood of selecting each identity category and is easier to understand.

5.1 Results

5.1.1 Dichotomous Asian Racial Identity Reporting and Anti-Asian Bias

Anti-Asian bias negatively correlates with Asian racial identity reporting, with the strongest effects among mixed-race individuals and later-generation Asian Americans.

I report main results from estimating equation (4) in Figure (9), showing results for all generations (panel A) and separately by generation (panels B-D). A one standard deviation increase in anti-Asian bias correlates with a 9 percentage point decrease in Asian racial identity reporting across all generations. By generation, the effects are 5 percentage points for first-generation (statistically insignificant), 8 percentage points for second-generation, and 8 percentage points for third-generation Asian Americans. College-educated parents increase Asian racial identity reporting by approximately 1 percentage point among all objectively Asian individuals.[15] Gender shows minimal effects on Asian identity reporting across most specifications, while parental education effects vary by generation, with stronger positive associations among second-generation immigrants.

Adult samples show similar patterns (Figure 10).[16] A one standard deviation increase in anti-Asian bias correlates with a 5 percentage point decrease in Asian racial identity reporting across all adults, with a 2 percentage point decrease among first-generation adults (statistically insignificant) and a 13 percentage point decrease among second-generation adults. Higher household income and years of education both positively correlate with Asian identity reporting, with each additional year of education associated with approximately 1–2 percentage point increases.

Results by family structure (Figure 11) reveal stronger bias effects among children from interracial families. Among second-generation children, a one standard deviation increase in anti-Asian bias correlates with statistically insignificant 5 percentage point decrease for those with endogamous Asian parents (panel B), but significant 15 percentage point decrease for Asian father-White mother children (panel C) and 10 percentage point decrease for White father-Asian mother children (panel D). Maternal college education consistently shows positive effects on Asian identity reporting in endogamous families and Asian father-White

[15] Results using county-level and MSA-level anti-Asian bias measures show similar patterns (Figures A.2, A.3, A.4, and A.5). Marginal effects from logit and probit models closely align with linear probability model coefficients across all generations (Tables A.1–A.4).

[16] For adults with Asian ancestry, I can only observe birthplaces of the person and their parents, not grandparents, limiting analysis to first- and second-generation individuals.

mother families, with particularly strong associations (approximately 11 percentage points) in the latter group.

Adult second-generation results show even larger heterogeneity by family structure (Figure 12). A one standard deviation increase in anti-Asian bias correlates with a 13 percentage point decrease across all second-generation adults, with the largest effect among White father-Asian mother adults (24 percentage points, panel D). Notably, higher education positively correlates with Asian identity reporting among mixed-race adults but shows no effect in endogamous families, suggesting that more educated individuals with Asian ancestry are more likely to maintain their Asian racial identity. This selective retention implies that studies using self-reported racial identity may overestimate Asian American success and underestimate assimilation speed, as successful Asians remain visible in the data while less successful Asians attrit to other racial categories.

Third-generation results by number of Asian grandparents (Table 6) show mostly statistically insignificant bias effects, except among children with three Asian grandparents, where a one standard deviation increase in anti-Asian bias correlates with a 69 percentage point decrease in Asian racial identity reporting. Parental education effects are strongest among those with two Asian grandparents, where maternal college education increases Asian identity reporting by 7 percentage points.[17]

5.1.2 Multinomial Logit Results: Racial Identity Choices and Anti-Asian Bias

This section presents results from the multinomial logit analysis, revealing how anti-Asian bias differentially affects the probability of choosing "Asian only," "White only," or "Asian and White" racial identity. The effects prove particularly pronounced among mixed-race Asian Americans, on whom I focus the discussion. Because multinomial logit models express coefficients in log-odds form, I present average marginal effects showing how each explanatory variable affects the probability of choosing each racial identity, as displayed in Figures 13–15.[18]

Second-Generation Subsample by Parental Composition. Parental compo-

[17] Interaction models examining how bias effects vary by individual characteristics within mixed-race families reveal some heterogeneity (Figures A.6 and A.7). Among Asian father-White mother adults, negative effects of above-average state bias are more pronounced for those with college-educated mothers, while effects are more uniform among White father-Asian mother adults. Among third-generation individuals, interaction effects are generally small and statistically insignificant, except among those with three Asian grandparents where maternal education shows stronger moderating effects.

[18] I present the predicted probabilities from the multinomial logit regressions in the online appendix in Figures A.8–A.13.

sition reveals substantial differences between Asian father-White mother (AW) and White father-Asian mother (WA) families (Figure 13). Among AW families, an increase of one standard deviation in anti-Asian bias from the mean increases the probability of reporting "Asian only" identity by 13 percentage points and decreases the probability of reporting "White only" identity by 20 percentage points. Among WA families, a one standard deviation increase in bias decreases the probability of reporting "Asian only" by 12 percentage points and increases the probability of reporting "White only" identity by 10 percentage points.

Gender exerts minimal effects in both family types. Parental education operates differently by family structure. Among AW families, maternal college education increases the probability of reporting "Asian only" and decreases the probability of reporting "White only." Paternal college education increases the probability of reporting "Asian and White" and decreases the probability of reporting "Asian only." Among WA families, maternal education produces virtually no change across identity categories, while paternal college education increases the probability of reporting "Asian and White" identity and decreases the probability of reporting "White only" identity.

Adult second-generation marginal effects (Figure 14) show similar directional patterns but with wide confidence intervals. Among AW adults, higher anti-Asian bias pushes identity toward "White only" (about +0.14) and away from "Asian and White" (about –0.11), with a small, imprecise decline for "Asian only." Years of education increase the probability of reporting "Asian only" (roughly +0.02) and reduce "White only" reporting (about –0.02), while household income shows near-zero effects across categories. Gender effects remain modest: females tilt slightly toward "Asian and White" with offsetting small declines in the other categories.

Among WA adults, anti-Asian bias markedly reduces "Asian only" identification (about –0.13) and shifts probability toward multiracial (about +0.09) and, to a lesser extent, "White only" (about +0.05), though estimates are imprecise. Education again nudges responses toward "Asian only" (about +0.02) and away from "White only" (about –0.02), with negligible change in multiracial reporting. Household income reduces "Asian only" (about –0.02) and modestly raises "Asian and White" identity (about +0.02). Gender effects are small and statistically indistinguishable from zero.

Third-Generation Subsample by Grandparent Composition. Third-generation identity choices vary systematically with the number of Asian grandparents (Figure 15). Anti-Asian bias has small, imprecise effects for those with one Asian grandparent, tilting probability modestly toward multiracial identity (about +0.04) and away from both “Asian only” and “White only” (about –0.02 each). With two Asian grandparents, higher bias more clearly pulls respondents away from “Asian only” (about –0.10) toward both “White only” (+0.05) and “Asian and White” (+0.06).

Parental education matters differently by grandparent composition. Among those with one Asian grandparent, maternal college completion shifts identity toward “Asian and White” (about +0.09) and away from “White only” (about –0.10), with little effect on “Asian only.” Paternal college shows the same pattern but slightly smaller magnitudes (“Asian and White” about +0.07; “White only” about –0.03; “Asian only” about –0.03). Among those with two Asian grandparents, maternal college markedly raises “Asian only” (about +0.07) and lowers “Asian and White” (about –0.07), with negligible change in “White only.” Paternal college reduces “White only” (about –0.11) and increases multiracial reporting (about +0.12), leaving “Asian only” unchanged. Gender effects remain small in both groups.

Taken together, the multinomial results show that anti-Asian bias moves identity away from “Asian only” toward “White only” or multiracial options, especially among mixed-ancestry adults and third-generation respondents with two Asian grandparents. Education and income partially offset this drift for some groups (e.g., AW adults, WA adults, and third-generation individuals with two Asian grandparents), while parental education often shifts mixed-ancestry respondents toward maintaining at least partial Asian identification. This selective retention underscores that studies relying on self-reported racial identity may overstate Asian American socioeconomic success and understate assimilation speed, as individuals with more resources and education are more likely to keep Asian identification visible in the data.

6 Robustness Checks and Alternative Explanations

This section explores empirical relationships between anti-Asian bias and interracial marriage and migration patterns among second-generation Asian Americans as robustness checks for the main analysis and to address proxy response effects. I examine how anti-Asian bias affects interracial marriage likelihood and Asian American migration decisions within the United States.

I investigate relationships between anti-Asian bias and interracial marriages using the following regression specification:

$$\mathtt{interracial}^2_{ist} = \beta^2_1 \mathtt{AntiAsianBias}_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{6}$$

where $\mathtt{interracial}^2_{ist}$ indicates interracial couples, i.e., Asian husband-White wife or White husband-Asian wife, $\mathtt{AntiAsianBias}_{st}$ represents average anti-Asian bias in state s at time t, and X^2_{ist} represents partner-specific controls affecting marriage matching, including wife's and husband's education, age, and years since US immigration.

I present estimation results for equation (6) in Table (8). A one standard deviation increase in anti-Asian bias raises interracial parent probabilities by 4 percentage points. Breaking down by couple ethnicity: a one standard deviation increase in anti-Asian bias associates with a 1 percentage point decrease in Asian husband-White wife marriage likelihood and a 3 percentage point increase in Asian wife-White husband marriage likelihood. The positive correlation between anti-Asian bias and interracial marriage may result from Asian Americans in high-bias states aiming to reduce the likelihood that their children signal Asian ethnicity. For example, Asian American women in high-bias states might marry non-Asian White husbands, providing children non-Asian surnames.

I also investigate relationships between anti-Asian bias and migration. Since CPS does not report birth states, I use 2004–2021 Censuses to construct second-generation Asian American samples (Flood, Ronald, et al., Integrated Public Use Microdata Series, USA). I construct mover variables indicating whether second-generation Asian Americans moved from birth states to other states. I use the following models to estimate relationships between anti-Asian bias and migration:

$$\mathtt{BirthPlaceMigration}^2_{ist} = \beta^2_1 \mathtt{AntiAsianBias}_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{7}$$

$$\mathtt{BirthPlaceMigration}^2_{ilb} = \beta^2_1 \mathtt{AntiAsianBias}_{lb} + X^2_{ilb}\pi + \gamma_{lb} + \varepsilon_{ilb} \tag{8}$$

where $\mathtt{BirthPlaceMigration}^2_{ist}$ indicates whether person i in state s at interview time t lives in a state different from their birth state, and $\mathtt{BirthPlaceMigration}^2_{ilb}$ indicates whether person i born in state l in year b currently lives in a different state. The analysis, restricted to second-generation Asian Americans with both Asian-born parents, uses equations (7) and (8).

I employ two approaches to define bias variables when studying relationships between bias and migration. The first specification from equation (7) estimates relationships between average bias at interview time t in state s and $\mathtt{BirthPlaceMigration}^2_{ist}$.

The second specification from equation (8) estimates relationships between average bias in birth state l at birth year b and $\mathrm{BirthPlaceMigration}^2_{ilb}$.

I also estimate whether Asian-identifying individuals tend to move from high-bias to low-bias states using:

$$Y_{ist} = \beta_0 + \beta_1^2 \mathrm{Asian}_{ist} + X^2_{ist}\pi + \varepsilon_{ist} \tag{9}$$

where $Y_{ist} \equiv \mathrm{AntiAsianBias}_{ist} - \mathrm{AntiAsianBias}_{ilb}$, $\mathrm{AntiAsianBias}_{ist}$ represents person i's anti-Asian bias in state s at interview time t, and $\mathrm{AntiAsianBias}_{ilb}$ represents person i's anti-Asian bias in birth state l at birth year b. The analysis restricts to second-generation Asian Americans with both Asian-born parents who migrated from birth state l to another state s.

I show the results of estimating Equations (7), (8), and (9) in Table (7) columns (1), (2), and (3), respectively. Among second-generation immigrants, no significant correlations exist between anti-Asian bias and migration decisions. Among second-generation Asian American movers, those self-reporting Asian racial identity live in states with 0.06 standard deviations greater bias than their birth states. While this result shows selection into more biased states among Asian-identifying second-generation immigrants, it does not affect the main results showing correlations between anti-Asian bias and Asian racial identity reporting. Since Asian-identifying individuals are moving to higher-bias states, my assessment of the relationship between bias and Asian racial identity reporting might underestimate bias effects.

Several concerns merit discussion. First, CPS self-reported identity comes from household respondents—parents or adult caregivers. I view parent- or caregiver-reported identity as an accurate representation of children's identity since parents essentially shape children's self-concepts. Moreover, since my analysis compares high- and low-bias states, estimates remain valid provided reporting patterns do not systematically differ between these contexts.

Moreover, Duncan and Trejo (2011) show that reported Hispanic racial identity does not vary with household respondent identity. Consistent with this, Table (3) shows that Asian racial identity reporting equals 72 percentage points when mothers or fathers serve as proxies and 87 percentage points when children or other caregivers serve as household respondents.[19] To further address this concern, I examine adult Asian American samples where individuals self-report racial

[19] According to CPS guidelines, household respondents must be at least 15 years old with sufficient household knowledge. When the proxy is 'self,' respondents range from 15 to 17 years old.

identity. I find similar patterns of ethnic attrition and bias effects among adults (Table 5 and Figures 10–12).

Another concern involves reverse causality between larger Asian American or Black populations in states and bias levels. Greater Asian American populations might affect resident bias levels. To demonstrate this is not occurring, Figure (A.14) plots self-reported Asian American state percentages against average anti-Asian bias in those states. I find no correlations between anti-Asian bias and Asian American state populations, making reverse causality unlikely.

Finally, bias and Asian racial identity reporting relationship estimates could be biased if non-Asian-identifying individuals migrate to more prejudiced states. I have shown above this is not occurring (Table 7). I find no evidence of relationships between migration decisions and anti-Asian bias. Additionally, those reporting Asian racial identity moved from less biased birthplaces and lived in more biased states at survey times. Thus, my results might underestimate relationships between anti-Asian bias and Asian racial identity reporting.

7 Conclusion

As American society becomes increasingly multiracial, racial identity choices will significantly influence political representation, resource allocation, and social cohesion. Understanding the determinants of identity is particularly important for researchers studying discrimination's role in racial economic gaps. This paper demonstrates how individual characteristics and anti-Asian sentiment influence racial identity reporting among Asian Americans.

I find that individuals with Asian ancestry are significantly less likely to racially identify as Asian in states with heightened anti-Asian bias. Across all generations, a one standard deviation increase in bias correlates with a statistically significant 9 percentage point decrease in Asian racial identity reporting. When examined by generation, the relationships show a one standard deviation increase in bias correlating with a 5 percentage point decrease among first-generation immigrants (statistically insignificant), an 8 percentage point decrease among second-generation immigrants, and an 8 percentage point decrease among third-generation Asian Americans.

Anti-Asian bias produces substantially larger effects among individuals with greater identity flexibility. Among second-generation immigrant children from mixed-race families, a one standard deviation increase in anti-Asian bias correlates with a 15 percentage point decrease in Asian racial identity reporting among children of Asian fathers and White mothers, and a 10 percentage point decrease among children of White fathers and Asian mothers. Adult samples reveal even more pronounced patterns, with second-generation adults from White father-Asian mother families showing 24 percentage point decreases in response to bias increases.

Using multinomial logit analysis, I show that anti-Asian bias fundamentally reshapes racial identity. A one standard deviation increase in bias nudges adult Asian father-White mother respondents toward "White only" identity (about +0.14) and away from multiracial identity (about –0.11), while White father-Asian mother adults exit "Asian only" (about –0.13) toward multiracial (about +0.09) and, to a lesser extent, "White only" (about +0.05). Among third-generation respondents with two Asian grandparents, higher bias shifts reporting away from "Asian only" (about –0.10) toward both "White only" (+0.05) and "Asian and White" (+0.06), with much smaller, imprecise changes when only one grandparent is Asian. These strategic identity adjustments highlight that bias pressures are most pronounced for mixed-ancestry families and later-generation individuals with greater identity flexibility.

These results have important consequences for Asian American enumeration, assimilation patterns, and social mobility. Since anti-Asian bias negatively correlates with Asian racial identity reporting, most race and ethnicity research relying on self-reported identity measures may systematically misestimate racial gaps. If individuals whose identities are most affected by bias are also the most educated, racial gaps will be overestimated in the most biased states. Furthermore, identity decisions likely profoundly affect people's choices, investments, and well-being.

This study encourages further research into relationships between bias and self-reported identities for other groups. Similar analysis could examine bias effects on sexual minority identities and other ethnic and racial minorities such as Black, Native American, and Arab American populations in the United States. Researchers could also explore outcome differences between ethnic and racial minorities who self-report versus those who do not using restricted administrative data.

The research opens several avenues for future investigation. First, scholars could examine how recent anti-Asian violence following the COVID-19 pandemic has influenced identity patterns, providing natural experiments in bias effects. Second, researchers might explore identity choices in specific institutional contexts like college admissions or workplace advancement, where model minority stereotypes create complex incentive structures. Third, analysis could extend to other Asian American subgroups, recognizing that Chinese, Korean, Vietnamese, and other communities face distinct stereotypes and discrimination patterns. Fourth, more granular geographic analysis at the county or zip-code level could provide more precise measures of local bias, though data limitations prevent this in the current analysis.

Understanding strategic racial identification among Asian Americans is essential for designing effective anti-discrimination policies and accurately measuring racial equity progress. As debates over affirmative action, immigration, and racial justice continue to evolve, recognizing how Asian Americans navigate identity choices becomes increasingly critical for promoting inclusive and equitable outcomes.

References

Abramitzky, Ran, Leah Platt Boustan, and Katherine Eriksson. 2014. "A Nation of Immigrants: Assimilation and Economic Outcomes in the Age of Mass Migration." *Journal of Political Economy* 122, no. 3 (June): 467–506. https://doi.org/10.1086/675805.

———. 2016. "Cultural Assimilation during the Age of Mass Migration." Prepublished, July. Working Paper. https://doi.org/10.3386/w22381. National Bureau of Economic Research: 22381.

Akerlof, George A., and Rachel E. Kranton. 2000. "Economics and Identity." *Quarterly Journal of Economics* 115, no. 3 (August): 715–753. https://doi.org/10.1162/003355300554881.

Almasalkhi, Nadia. 2023. "Links between Anti-Immigrant Bias and Racial Prejudice in California."

American National Election Studies. 2021. *ANES 2020 Time Series Study Full Release [Dataset and Documentation].* https://www.electionstudies.org.

Antman, Francisca, and Brian Duncan. 2015. "Incentives to Identify: Racial Identity in the Age of Affirmative Action." *Review of Economics & Statistics* 97, no. 3 (July): 710–713. https://doi.org/10.1162/REST_a_00527.

———. 2021. "American Indian Casinos and Native American Self-Identification" (August 29, 2021).

Antman, Francisca, Brian Duncan, and Stephen J. Trejo. 2016. "Ethnic Attrition and the Observed Health of Later-Generation Mexican Americans." *The American Economic Review* 106 (5): 467–471. http://www.jstor.org/stable/43861065.

Antman, Francisca M., Brian Duncan, and Stephen J. Trejo. 2020. "Ethnic Attrition, Assimilation, and the Measured Health Outcomes of Mexican Americans." *Journal of Population Economics* (Heidelberg, Netherlands) 33, no. 4 (October): 1499–1522. https://doi.org/https://doi-org.ezproxy.lib.uh.edu/10.1007/s00148-020-00772-8.

Arabsheibani, G Reza, and Jie Wang. 2010. "Asian-white male wage differentials in the United States." *Applied Economics Letters* 17 (1): 37–43.

Arkes, Hal R., and Philip E. Tetlock. 2004. "Attributions of Implicit Prejudice, or "Would Jesse Jackson 'Fail' the Implicit Association Test?"" *Psychological Inquiry* (US) 15 (4): 257–278. https://doi.org/10.1207/s15327965pli1504_01.

Atkin, David, Eve Colson-Sihra, and Moses Shayo. 2021. "How Do We Choose Our Identity? A Revealed Preference Approach Using Food Consumption." *Journal of Political Economy* 129, no. 4 (April): 1193–1251. https://doi.org/10.1086/712761.

Bertrand, Marianne, and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review* 94, no. 4 (September): 991–1013. https://doi.org/10.1257/0002828042002561.

Bonomi, Giampaolo, Nicola Gennaioli, and Guido Tabellini. 2021. "Identity, Beliefs, and Political Conflict*." *The Quarterly Journal of Economics* 136, no. 4 (November 1, 2021): 2371–2411. https://doi.org/10.1093/qje/qjab034.

Bordalo, Pedro, Katherine Coffman, Nicola Gennaioli, and Andrei Shleifer. 2016. "Stereotypes*." *The Quarterly Journal of Economics* 131, no. 4 (November 1, 2016): 1753–1794. https://doi.org/10.1093/qje/qjw029.

Bureau of Justice Statistics. 2023. *Uniform Crime Reporting Program Data Series [Dataset].* https://catalog.data.gov/dataset/uniform-crime-reporting-program-data-series-16edb.

Bursztyn, Leonardo, Thomas Chaney, Tarek A. Hassan, and Aakash Rao. 2022. "The Immigrant Next Door: Long-Term Contact, Generosity, and Prejudice." Pre-published, March 31, 2022. SSRN Scholarly Paper. https://doi.org/10.2139/ssrn.3781974.

Charles, Kerwin Kofi, and Jonathan Guryan. 2008. "Prejudice and Wages: An Empirical Assessment of Becker's The Economics of Discrimination." *Journal of Political Economy* 116, no. 5 (October): 773–809. https://doi.org/10.1086/593073.

Charness, Gary, and Yan Chen. 2020. "Social Identity, Group Behavior, and Teams." *Annual Review of Economics* 12 (1): 691–713. https://doi.org/10.1146/annurev-economics-091619-032800.

Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter. 2020. "Race and Economic Opportunity in the United States: An Intergenerational Perspective*." *The Quarterly Journal of Economics* 135, no. 2 (May 1, 2020): 711–783. https://doi.org/10.1093/qje/qjz042.

Chiswick, Barry R. 1983. "An analysis of the earnings and employment of Asian-American men." *Journal of Labor Economics* 1 (2): 197–214.

Cornell, Stephen, and Douglas Hartmann. 2006. *Ethnicity and race: Making identities in a changing world.* Sage Publications.

Darity, William A. 2022. "Position and Possessions: Stratification Economics and Intergroup Inequality." *Journal of Economic Literature* 60, no. 2 (June 1, 2022): 400–426. https://doi.org/10.1257/jel.20211690.

Darity, William A., Patrick L. Mason, and James B. Stewart. 2006. "The Economics of Identity: The Origin and Persistence of Racial Identity Norms." *Journal of Economic Behavior & Organization* 60, no. 3 (July 1, 2006): 283–305. https://doi.org/10.1016/j.jebo.2004.09.005.

Diette, Timothy M., Arthur H. Goldsmith, Darrick Hamilton, and William Darity. 2015. "Skin Shade Stratification and the Psychological Cost of Unemployment: Is There a Gradient for Black Females?" *The Review of Black Political Economy* 42, nos. 1-2 (January 1, 2015): 155–177. https://doi.org/10.1007/s12114-014-9192-z.

Duleep, Harriet Orcutt, and Seth G Sanders. 2012. "The economic status of Asian Americans before and after the Civil Rights Act."

Duncan, B., and S. J. Trejo. 2011. "Intermarriage and the Intergenerational Transmission of Ethnic Identity and Human Capital for Mexican Americans." *J Labor Econ* 29.

Duncan, Brian, and Stephen J. Trejo. 2018a. "Identifying the Later-Generation Descendants of U.S. Immigrants: Issues Arising from Selective Ethnic Attrition." *The ANNALS of the American Academy of Political and Social Science* 677, no. 1 (May 1, 2018): 131–138. https://doi.org/10.1177/0002716218763293.

———. 2018b. *Socioeconomic Integration of U.S. Immigrant Groups over the Long Term: The Second Generation and Beyond.* Working Paper, Working Paper Series 24394. National Bureau of Economic Research, March. https://doi.org/10.3386/w24394.

Egloff, Boris, and Stefan C. Schmukle. 2002. "Predictive Validity of an Implicit Association Test for Assessing Anxiety." *Journal of Personality and Social Psychology* (US) 83:1441–1455. https://doi.org/10.1037/0022-3514.83.6.1441.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2021. (Integrated Public Use Microdata Series, Current Population Survey: Version 9.0. V. 9.0). https://doi.org/10.18128/D030.V9.0.

Flood, Sarah, Goeken Ronald, Schouweiler Megan, and Sobek Matthew. 2021. (Integrated Public Use Microdata Series, USA: Version 12.0. V. 9.0). https://doi.org/10.18128/D030.V9.0.

Forscher, Patrick S., Calvin K. Lai, Jordan R. Axt, Charles R. Ebersole, Michelle Herman, Patricia G. Devine, and Brian A. Nosek. 2019. "A Meta-Analysis of Procedures to Change Implicit Measures." *Journal of Personality and Social Psychology* (US) 117 (3): 522–559. https://doi.org/10.1037/pspa0000160.

Fouka, Vasiliki, Soumyajit Mazumder, and Marco Tabellini. 2022. "From Immigrants to Americans: Race and Assimilation during the Great Migration." *The Review of Economic Studies* 89, no. 2 (March 1, 2022): 811–842. https://doi.org/10.1093/restud/rdab038.

Friese, Malte, Matthias Bluemke, and Michaela Wänke. 2007. "Predicting Voting Behavior with Implicit Attitude Measures: The 2002 German Parliamentary Election." *Experimental Psychology* (Germany) 54 (4): 247–255. https://doi.org/10.1027/1618-3169.54.4.247.

Glover, Dylan, Amanda Pallais, and William Pariente. 2017. "Discrimination as a Self-Fulfilling Prophecy: Evidence from French Grocery Stores." *Quarterly Journal of Economics* 132, no. 3 (August): 1219–1260. https://doi.org/10.1093/qje/qjx006.

Goldsmith, Arthur H., Darrick Hamilton, and William Darity. 2007. "From Dark to Light: Skin Color and Wages among African-Americans." *The Journal of Human Resources* 42 (4): 701–738. https://www.jstor.org/stable/40057327.

Gover, Angela R., Shannon B. Harper, and Lynn Langton. 2020. "Anti-Asian Hate Crime During the COVID-19 Pandemic: Exploring the Reproduction of Inequality." *American Journal of Criminal Justice* 45 (4): 647–667.

Greenwald, Anthony G., Debbie E. McGhee, and Jordan L. K. Schwartz. 1998. "Measuring Individual Differences in Implicit Cognition: The Implicit Association Test." *Journal of Personality and Social Psychology* (US) 74 (6): 1464–1480. https://doi.org/10.1037/0022-3514.74.6.1464.

Hadah, Hussain. 2024. "The effect of racial and ethnic attitudes on Hispanic identity in the United States." *Southern Economic Journal.*

Hamilton, Darrick, Arthur H. Goldsmith, and William Darity. 2009. "Shedding "Light" on Marriage: The Influence of Skin Shade on Marriage for Black Females." *Journal of Economic Behavior & Organization* 72, no. 1 (October 1, 2009): 30–50. https://doi.org/10.1016/j.jebo.2009.05.024.

Hilger, Nathaniel. 2016. *Upward mobility and discrimination: The case of Asian Americans.* Technical report. National Bureau of Economic Research.

Lee, Daniel J. 2018. “Does Implicit Bias Predict Dictator Giving?” *Games* 9, no. 4 (4): 73. https://doi.org/10.3390/g9040073.

Leitner, Jordan B., Eric Hehman, Ozlem Ayduk, and Rodolfo Mendoza-Denton. 2016. “Racial Bias Is Associated with Ingroup Death Rate for Blacks and Whites: Insights from Project Implicit.” *Social Science & Medicine* 170 (December 1, 2016): 220–227. https://doi.org/10.1016/j.socscimed.2016.10.007.

Lubotsky, Darren, and Martin Wittenberg. 2006. “Interpretation of Regressions with Multiple Proxies.” *The Review of Economics and Statistics* 88, no. 3 (August 1, 2006): 549–562. https://doi.org/10.1162/rest.88.3.549.

Meng, Xin, and Robert G. Gregory. 2005. “Intermarriage and the Economic Assimilation of Immigrants.” *Journal of Labor Economics* 23, no. 1 (January): 135–174. https://doi.org/10.1086/425436.

Mora, G Cristina, and Tianna S Paschel. 2020. “Antiblackness as a logic for anti-immigrant resentment: Evidence from California.” In *Sociological Forum,* 35:918–940. Wiley Online Library.

Telles, Edward E, and Vilma Ortiz. 2008. *Generations of exclusion: Mexican-Americans, assimilation, and race.* Russell Sage Foundation.

Waters, Mary C. 1990. “Ethnic Options: Choosing Identities in America.” (Berkeley).

Zhou, Min. 1997. “Segmented assimilation: Issues, controversies, and recent research on the new second generation.” *International migration review* 31 (4): 975–1008.

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Table 1: CPS Summary Statistics

Characteristic	Overall	By Generation		
	All Sample N = 318,404	**First** N=40,033	**Second** N=199,294	**Third** N=79,077
Female	0.49	0.53	0.49	0.49
Asian	0.65	0.96	0.73	0.31
Age	8.4 (5.1)	10.9 (4.5)	8.3 (5.1)	7.7 (5.0)
College Graduate: Father	0.52	0.59	0.52	0.50
College Graduate: Mother	0.52	0.56	0.51	0.52
Total Family Income (1999 dollars)	87,031 (84,797)	75,815 (74,489)	88,295 (88,411)	89,436 (80,051)

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

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

Table 2: Current Population Survey (CPS) Summary Statistics

Characteristic	Overall	By Generation	
	All Sample N = 48,153	**First** N=35,728	**Second** N=12,425
Female	0.56	0.58	0.50
Asian	0.90	0.96	0.73
Age	46 (17)	49 (16)	38 (17)
Years of Education	14.0 (3.5)	13.9 (3.8)	14.5 (2.5)
Total Family Income (1999 dollars)	68,121 (71,266)	66,093 (70,444)	73,950 (73,269)

[1] The samples include people of Asian ancestry ages 18 and above. First-generation Asian immigrants were born in a Asian country. Native-born second-generation Asian immigrants have at least one parent born in a Asian country.

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

Table 3: Main Effect of Proxy on Second-Generation's Asian Self-identification

Parents Type	All	Asian-Asian	Asian-White	White-Asian
Proxy:				
Mother	0.72	0.97	0.37	0.3
Father	0.72	0.97	0.39	0.29
Self	0.87	0.97	0.23	0.31
Others	0.88	0.96	0.6	0.54

[1] The samples include children ages 17 and below who live in intact families. A proxy is the person that answered the Current Population Survey questionnaire.

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

Table 4: Asian Self-identification by Generation

	Self-identify as Asian	Self-identify as non-Asian	% Self-identify as Asian	% Self-identify as non-Asian
1st Gen.	14,811	688	0.96	0.04
2nd Gen.	58,756	21,381	0.73	0.27
Asian on:				
Both Sides	49,118	1,717	0.97	0.03
One Side	9,638	19,664	0.33	0.67
3rd Gen.	10,394	23,048	0.31	0.69
Asian on:				
Both Sides	5,428	316	0.94	0.06
One Side	3,030	9,213	0.25	0.75

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

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

Table 5: Asian Self-identification by Generation

	Self-identify as Asian	Self-identify as non-Asian	% Self-identify as Asian	% Self-identify as non-Asian
1st Gen.	275,516	11,037	0.96	0.04
2nd Gen.	74,345	28,027	0.73	0.27
Asian on:				
Both Sides	59,880	2,935	0.95	0.05
One Side	14,465	25,092	0.37	0.63

[1] The samples include people of Asian ancestry ages 18 and above. First-generation Asian immigrants were born in a Asian country. Native-born second-generation Asian immigrants have at least one parent born in a Asian country.

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

Table 6: Relationship Between Bias and Self-Reported Asian identity Among Third-Generation Asian Immigrants: By Grandparental Type

	Number of Asian Grandparents			
	(1) One	(2) Two	(3) Three	(4) Four
Bias	-0.01	-0.09	-0.69**	-0.11
	(0.04)	(0.08)	(0.32)	(0.06)
Female	-0.01	-0.01	-0.04	-0.03**
	(0.01)	(0.02)	(0.06)	(0.01)
College Graduate: Mother	0.01	0.07**	0.08	0.00
	(0.01)	(0.03)	(0.09)	(0.03)
College Graduate: Father	-0.04***	0.00	-0.07	0.00
	(0.01)	(0.04)	(0.08)	(0.01)
Observations	14,453	12,678	567	5,744
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 Asian immigrants by number of Asian grandparents with region × year fixed effects. I include controls for sex, quartic age, fraction of Asians in a state, and parental education. Standard errors are clustered on the state level.

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

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

Table 7: Relationship Between Bias and Migration

	(1) Migrated from Birth Place	(2) Migrated from Birth Place	(3) $\text{Bias}_{ist} - \text{Bias}_{ilb}$
Bias_{st}	0.13*		
	(0.07)		
Bias_{lb}		-0.03	
		(0.17)	
Asian			0.02
			(0.04)
Female	0.00	-0.01	0.00
	(0.00)	(0.00)	(0.02)
College Graduate: Mother	0.01***	0.00	-0.01
	(0.00)	(0.01)	(0.03)
College Graduate: Father	-0.03***	-0.03***	0.03
	(0.01)	(0.01)	(0.02)
Observations	73,563	41,641	2,075
Mean	0.15	0.15	-0.1
Year $\times$ Region FE	X		
Birthyear $\times$ Birth Region FE		X	

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

[1] Each column is an estimation of equations (7) in column (1), (8) in column (2), and (9) in column (3).

[2] Column (1) is a regression where the left hand side variable is a dummy variable that is equal to one if a person migrated from the state were born in and the right hand side variable is bias the year of survey. Column (2) is a regression where the left hand side variable is a dummy variable that is equal to one if a person migrated from the state were born in and the right hand side variable is bias the year of birth in the state of birth. Column (3) is a regression where the left hand side variable is the difference between state-level bias during the year of the survey in the current state the respondent is living in, and state-level bias during the year of birth in the state of birth and the right hand side variable is self-reported Asian identity. This regression captures the selection of those that self-reported Asian identity into states with different levels of bias. I include controls for sex, quartic age, parental education, fraction of Asians in a state, and region × year fixed effects. Standard errors are clustered on the state level.

[3] The samples include children ages 17 and below who live in intact families. Native-born second-generation Asian immigrant children with both parents born in a Asian country. The sample in the column (3) regression is further restricted to only those that migrated from their birth state.

[4] Data source is the 2004-2021 Census Data.

Table 8: Relationship Between Bias and Interracial Marriages

		Asian Men	Asian Women
	(1) Interracial	(2) Interracial	(3) Interracial
Bias	0.04***	−0.01	0.03**
	(0.01)	(0.01)	(0.01)
College Graduate: Wife	0.04***	0.04***	0.05***
	(0.00)	(0.01)	(0.00)
College Graduate: Husband	−0.01*	−0.01	−0.02***
	(0.00)	(0.01)	(0.00)
Observations	69,800	52,103	60,214
Year × Region FE	X	X	X

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

[1] This is the result to estimating (6) 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 household level.

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

Figure 1: Diagram of the Three Different Generations of Asian Immigrants.

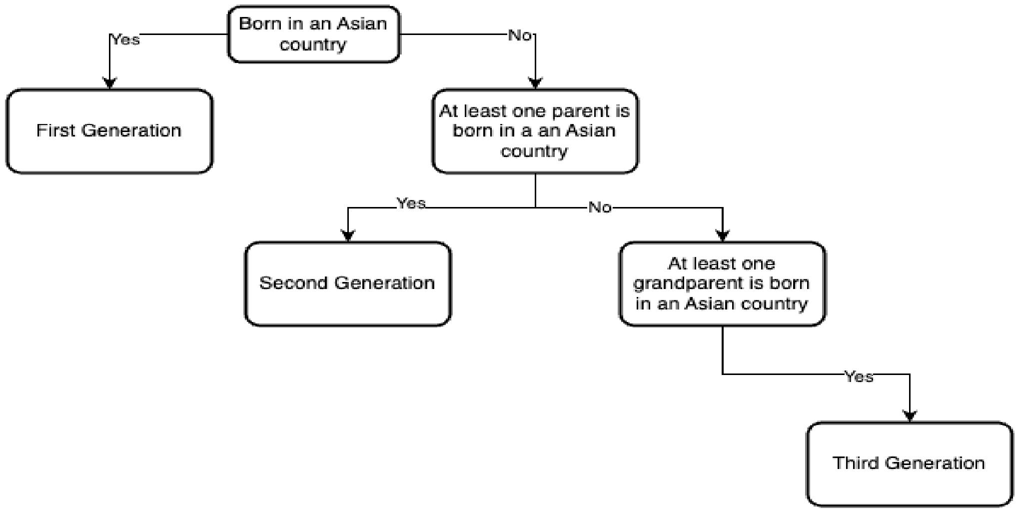
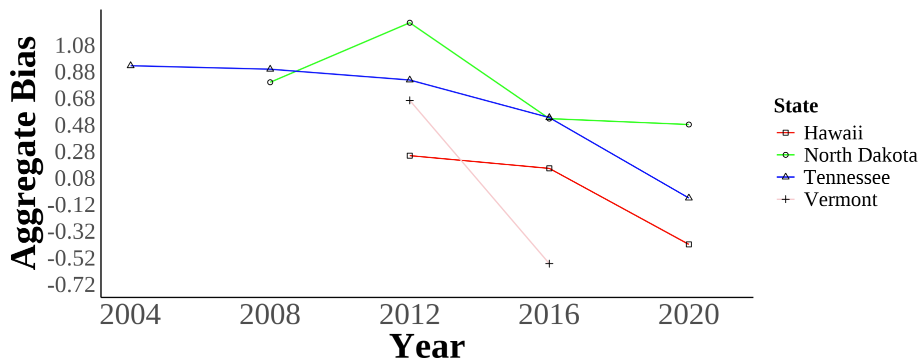
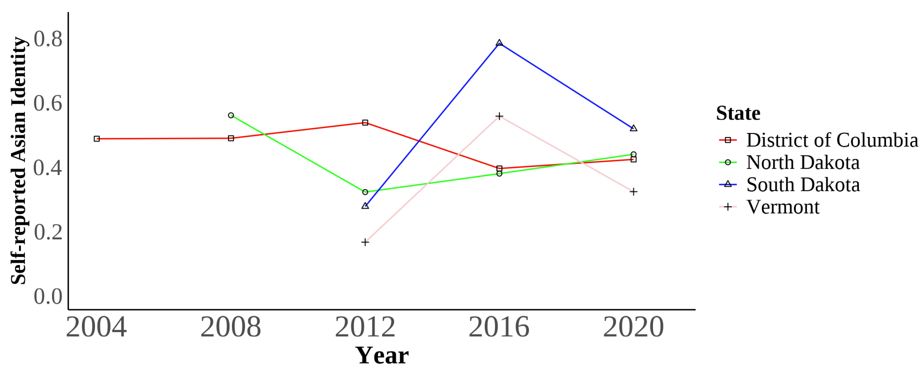


Figure 2: Bias and Self-reported Asian Identity in the Least and Most Biased Places

(a) Bias Over Time



(b) Self-reported Asian Identity Over Time

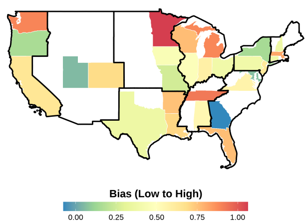


These two panels show the trends in bias (panel a) and self-reported Asian identity among Asian immigrants (panel b) of the least and most biased places in the data. The District of Colombia is the least biased geographical area, and North Dakota is the most biased. The bias units are in standard deviations.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

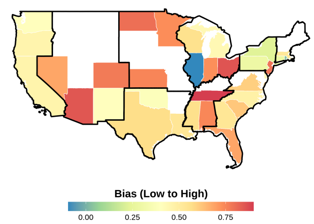
Bias data is from the 2004–2021 Harvard's Project Implicit Association Test scores, American National Election Studies (ANES), and state-level hate crimes against Asians. Identity data is from the 2004–2021 Current Population Survey (CPS).

Figure 3: Maps of State-level Association Test Bias Over Time Measure with Census Division Regional Boundaries

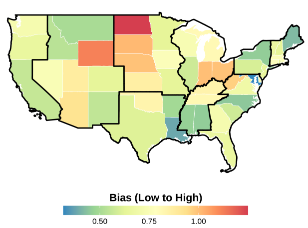
(a) State-level Bias in 2004



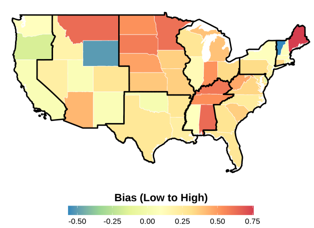
(b) State-level Bias in 2008



(c) State-level Bias in 2012

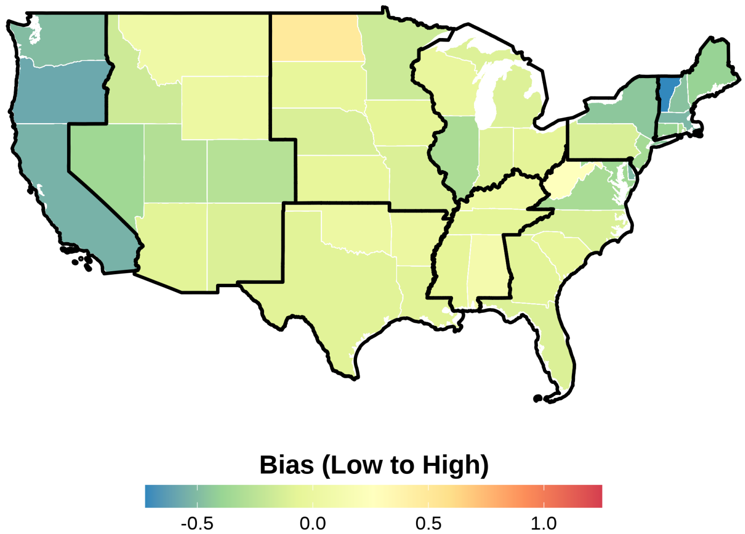


(d) State-level Bias in 2016



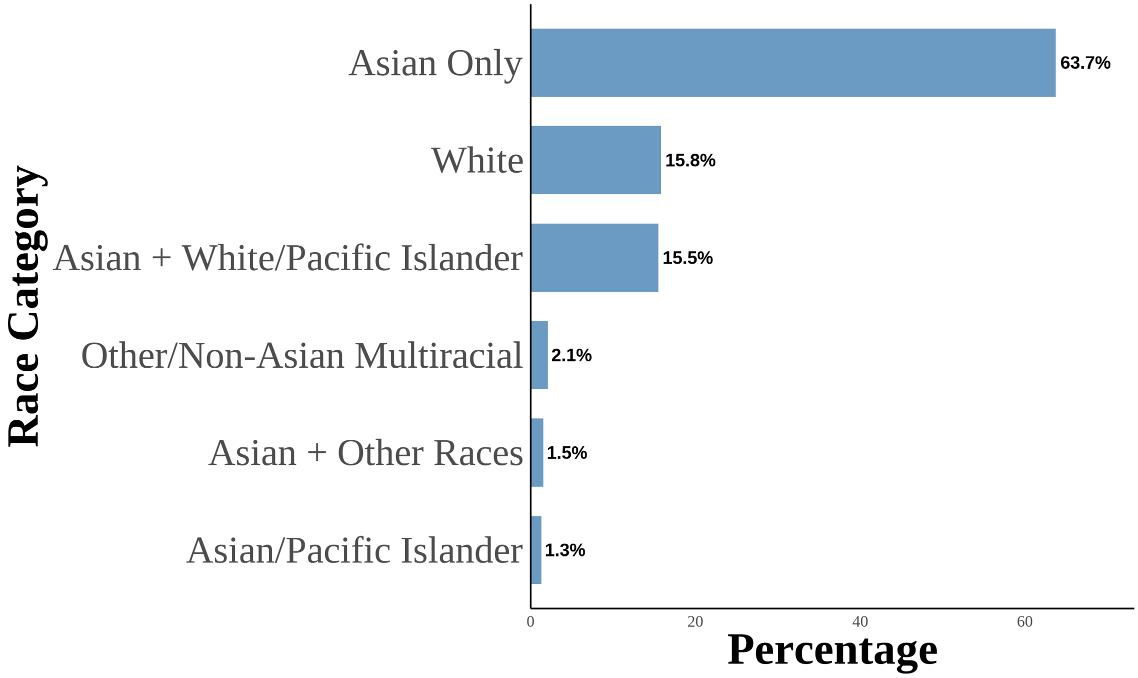
This figure shows the state-level bias index in different years in the sample. The bias units are in standard deviations and ranges from low to high bias. Bias index is constructed following Lubotsky and Wittenberg (2006). The data is from the 2004–2021 Harvard's Project Implicit Association Test scores, American National Election Studies (ANES), and state-level hate crimes against Asians. Each panel presents state-level bias during a certain year. The boundaries in black represent the different Census divisions in the United States. Notice how there is a variation across states within a region.

Figure 4: Maps of State-level Bias 2004–2021 Measure with Census Division Regional Boundaries



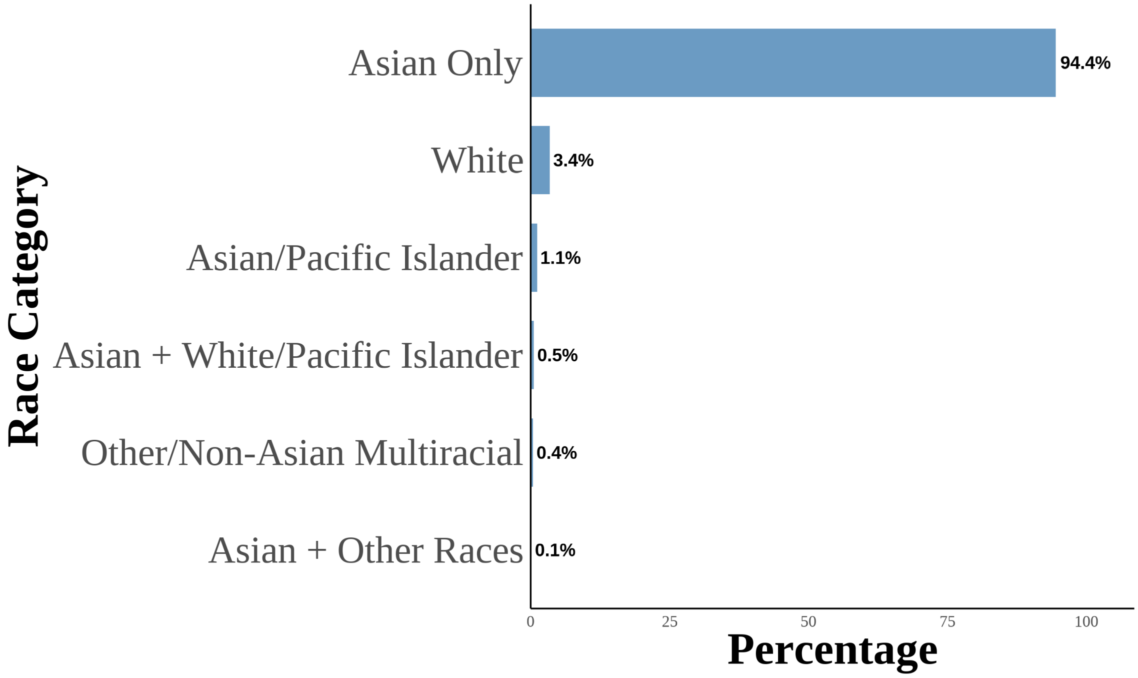
This figure shows the state-level bias index in the sample from 2004 to 2021. The bias units are in standard deviations and ranges from low to high bias. Bias index is constructed following Lubotsky and Wittenberg (2006). The data is from the 2004–2021 Harvard's Project Implicit Association Test scores, American National Election Studies (ANES), and state-level hate crimes against Asians. The boundaries in black represent the different Census divisions in the United States. Notice how there is a variation across states within a region.

Figure 5: Asian Racial Identity



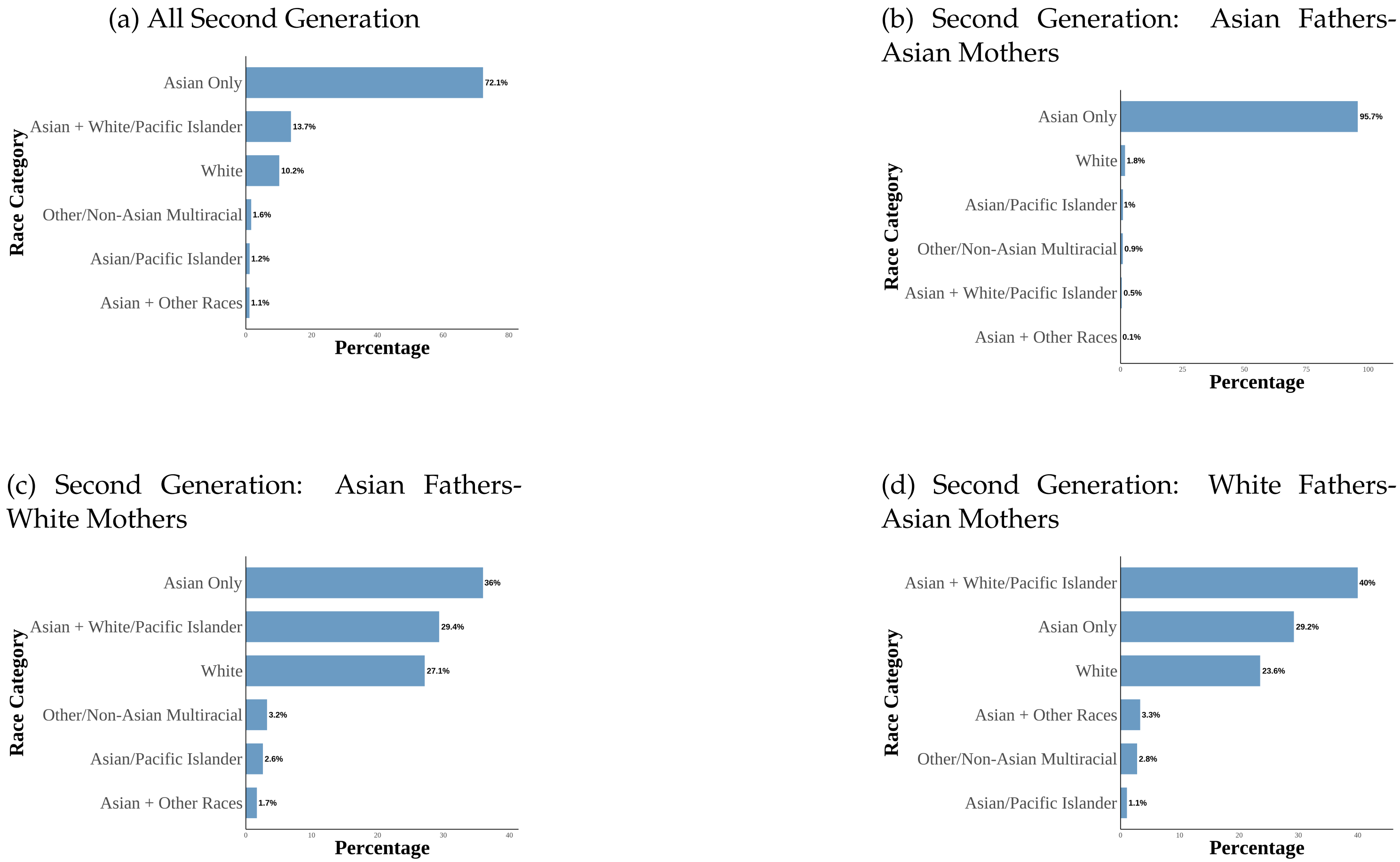
This figure shows the distribution of Asian racial identity among respondents. The data is aggregated from the 2004–2021 Current Population Survey (CPS). The sample includes first-, second-, and third-generation objectively Asian Americans. Following Antman, Duncan, and Trejo (2016) and Antman, Duncan, and Trejo (2020), I utilize birthplace information for individuals, parents, and grandparents to create objective Asian ancestry indicators.

Figure 6: Asian Racial Identity: First Generation



This figure shows the distribution of Asian racial identity among respondents. The data is aggregated from the 2004–2021 Current Population Survey (CPS). The sample includes first-generation objectively Asian Americans. Following Antman, Duncan, and Trejo (2016) and Antman, Duncan, and Trejo (2020), I utilize birthplace information for individuals, parents, and grandparents to create objective Asian ancestry indicators. A first-generation Asian American is defined as an individual born in an Asian country and is not a US citizen born to US citizen parents abroad.

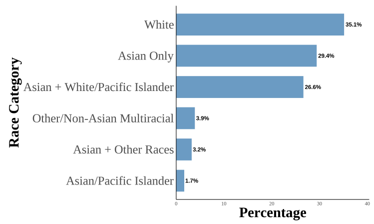
Figure 7: Asian Racial Identity: Second Generation



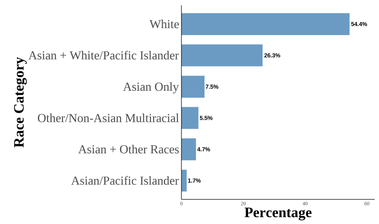
This figure shows the distribution of Asian racial identity among respondents. The data is aggregated from the 2004–2021 Current Population Survey (CPS). The sample includes second-generation objectively Asian Americans. Following Antman, Duncan, and Trejo (2016) and Antman, Duncan, and Trejo (2020), I utilize birthplace information for individuals, parents, and grandparents to create objective Asian ancestry indicators. A second-generation Asian American is defined as a native-born individual with at least one parent born in an Asian country. The first panel is for second-generation Asian Americans. The second panel is for second-generation Asian Americans with both parents born in an Asian country. The third panel is for second-generation Asian Americans with an Asian father and a White mother. The fourth panel is for second-generation Asian Americans with a White father and an Asian mother.

Figure 8: Asian Racial Identity: Third Generation

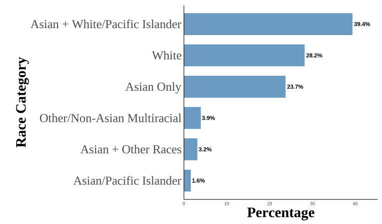
(a) All Third Generation



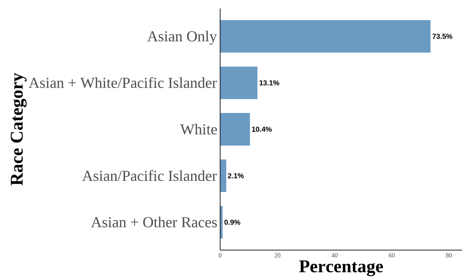
(b) Third Generation: One Asian Grandparent



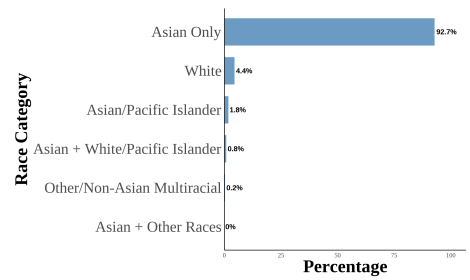
(c) Third Generation: Two Asian Grandparents



(d) Third Generation: Three Asian Grandparents

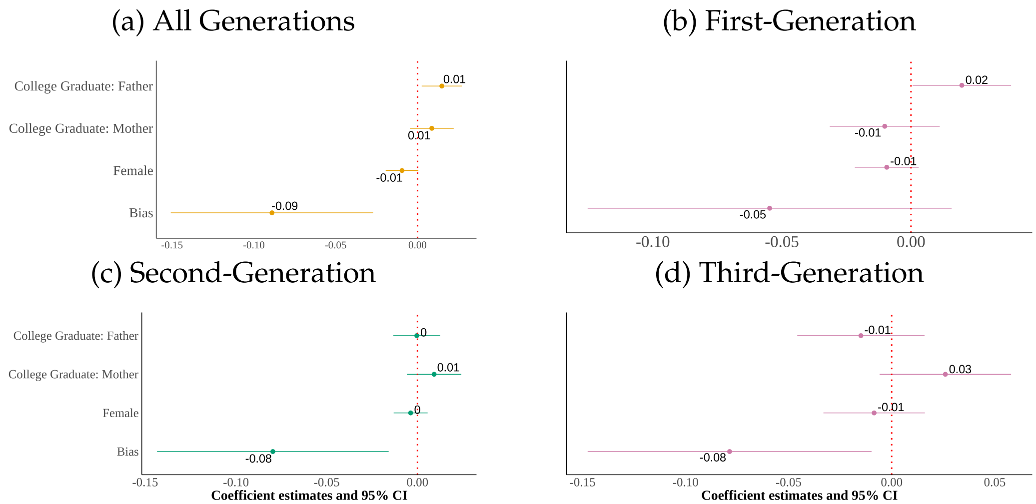


(e) Third Generation: Four Asian Grandparents



This figure shows the distribution of Asian racial identity among respondents. The data is aggregated from the 2004–2021 Current Population Survey (CPS). The sample includes second-generation objectively Asian Americans. Following Antman, Duncan, and Trejo (2016) and Antman, Duncan, and Trejo (2020), I utilize birthplace information for individuals, parents, and grandparents to create objective Asian ancestry indicators. A third-generation Asian American is defined as a native-born individual with native-born parents and at least one grandparent born in an Asian country. The first panel is for third-generation Asian Americans. The second panel is for third-generation Asian Americans with one grandparent born in an Asian country. The third panel is for third-generation Asian Americans with two grandparents born in an Asian country. The fourth panel is for third-generation Asian Americans with three grandparents born in an Asian country. The fifth panel is for third-generation Asian Americans with four grandparents born in an Asian country.

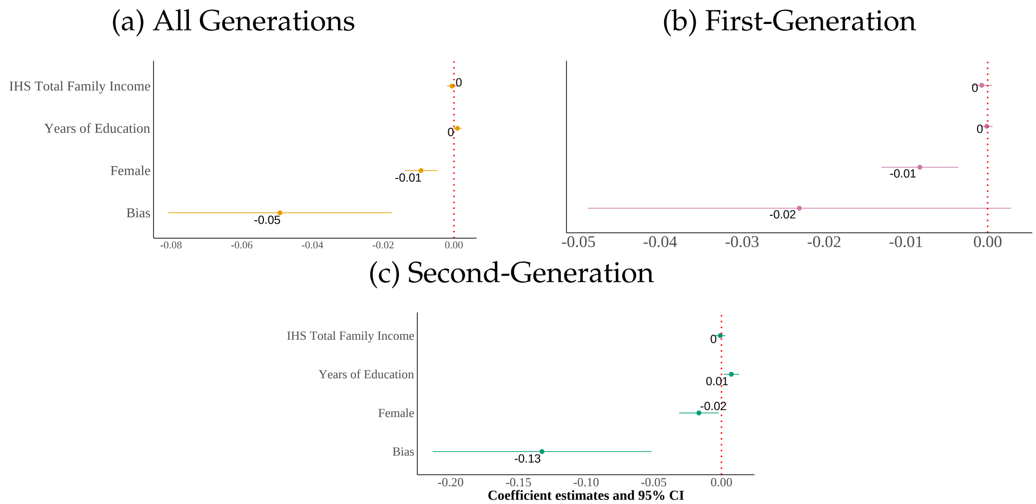
Figure 9: Relationship Between Self-Reported Asian Identity and Bias: By Generation



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

Figure 10: Relationship Between Self-Reported Asian Identity and Bias: By Generation Among Adults

(a) All Generations (b) First-Generation (c) Second-Generation

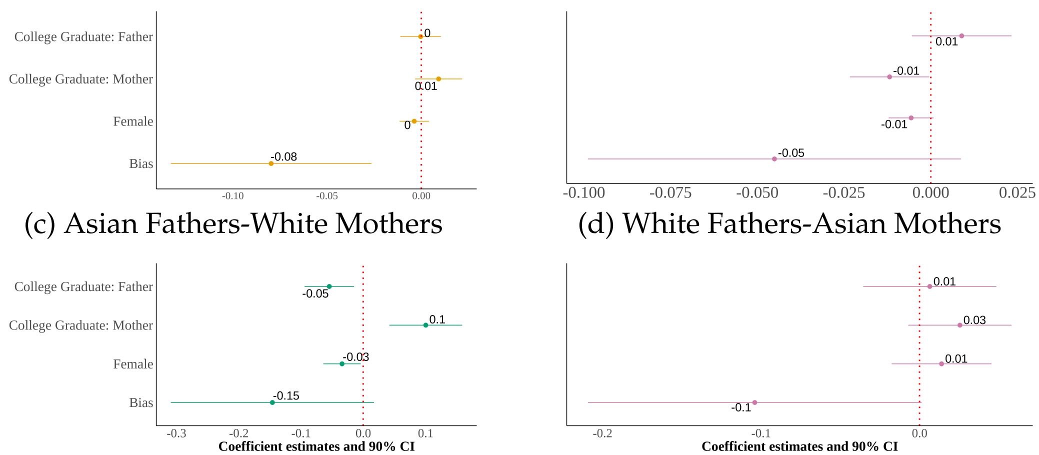


I show three panels of estimating equation (4) on a sample of adults. I include region × year fixed effects with controls for sex, quartic age, years of education, and inverse hyperbolic sine of income. The dependent variable is self-reported Asian identity and the independent variable is state-level bias. Each panel is the results from the same regression but on different samples that are divided by generation. Standard errors are clustered on the state level. The samples include first- and second-generation Asian adults ages 18 and above. First-generation Asian immigrants are individuals that were born in a Asian country. Native-born second-generation Asian immigrants are individuals with at least one parent born in a Asian country.

Figure 11: Relationship Between Self-Reported Asian Identity and Bias: By Parental Types

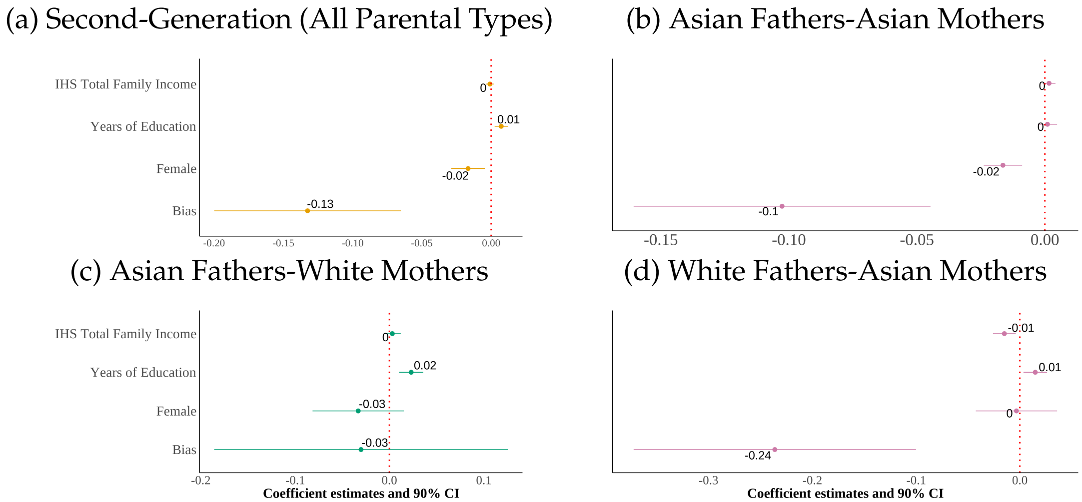
(a) Second-Generation (All Parental Types) (b) Asian Fathers-Asian Mothers

(c) Asian Fathers-White Mothers (d) White Fathers-Asian Mothers



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

Figure 12: Relationship Between Self-Reported Asian Identity and Bias: By Parental Types Among Adults

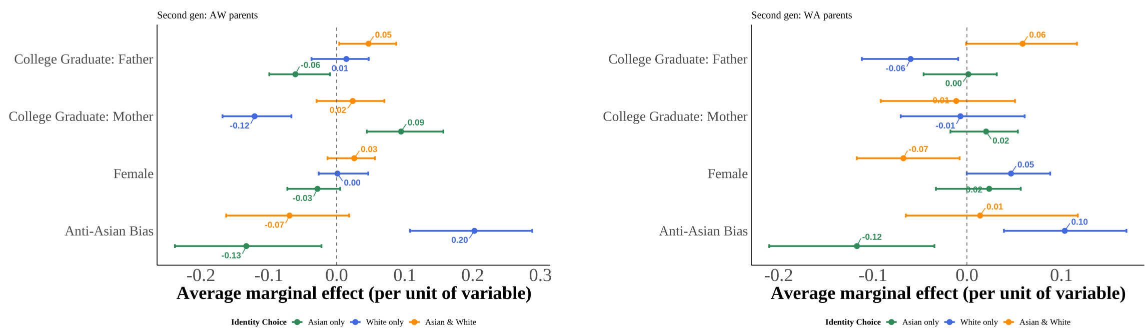


I show four panels of estimating equation (4) on a sample of adults. I include region × year fixed effects with controls for sex, quartic age, years of education, and the inverse hyperbolic sine of income. The dependent variable is self-reported Asian identity and the independent variable is state-level bias. Each panel results from the same regression but on different samples divided by parental types. Standard errors are clustered on the state level. The samples include second-generation Asian individuals ages 18 and above. Native-born second-generation Asian immigrant individuals with at least one parent born in an Asian country.

Figure 13: Marginal Effects of Key Covariates on Racial Identity Choice by Parental Ancestry (Second-Generation Asian Americans)

(a) Asian Father-White Mother (AW)

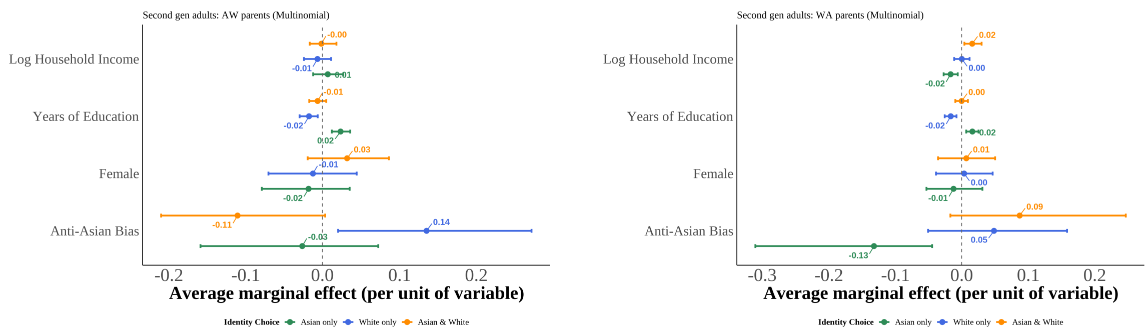
(b) White Father-Asian Mother (WA)



This figure displays the marginal effects of key covariates on the probability of each racial identification outcome, estimated from equation (5) using multinomial logit models for second-generation Asian Americans by parental ancestry configuration. Marginal effects represent the change in predicted probability for a one-unit increase in the covariate (or discrete change from 0 to 1 for binary variables), holding other variables at their sample means. I include region $\times$ year fixed effects with controls for quartic age and local Asian population share. Each point corresponds to the median marginal effect across 1,000 bootstrap resamples, with 95% percentile confidence intervals. Second-generation Asian Americans are native-born individuals with at least one Asian-born parent.

Figure 14: Marginal Effects of Key Covariates on Racial Identity Choice by Parental Ancestry (Adult Second-Generation Asian Americans)

(a) Asian Father-White Mother (AW) (b) White Father-Asian Mother (WA)

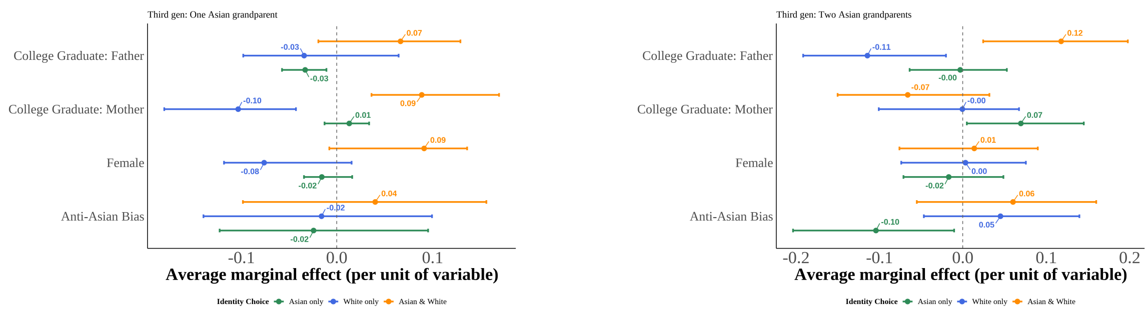


This figure displays the marginal effects of key covariates on the probability of each racial identification outcome, estimated from equation (5) using multinomial logit models for second-generation adults with Asian father/White mother (AW) and White father/Asian mother (WA). Marginal effects represent the change in predicted probability for a one-unit increase in the covariate (or discrete change from 0 to 1 for binary variables), holding other variables at their sample means. I include region $\times$ year fixed effects with controls for quartic age and local Asian population share. Each point corresponds to the median marginal effect across 1,000 bootstrap resamples, with 95% percentile confidence intervals. Second-generation Asian Americans are native-born individuals with at least one Asian-born parent.

Figure 15: Marginal Effects of Key Covariates on Racial Identity Choice by Number of Asian Grandparents (Third-Generation Asian Americans)

(a) One Asian Grandparent

(b) Two Asian Grandparents



This figure displays the marginal effects of key covariates on the probability of each racial identification outcome, estimated from equation (5) using multinomial logit models for third-generation Asian Americans by number of Asian grandparents. Marginal effects represent the change in predicted probability for a one-unit increase in the covariate (or discrete change from 0 to 1 for binary variables), holding other variables at their sample means. I include region × year fixed effects with controls for quartic age and local Asian population share. Each estimate is the median across 1,000 bootstrap resamples, and 95% percentile confidence intervals accompany every point.

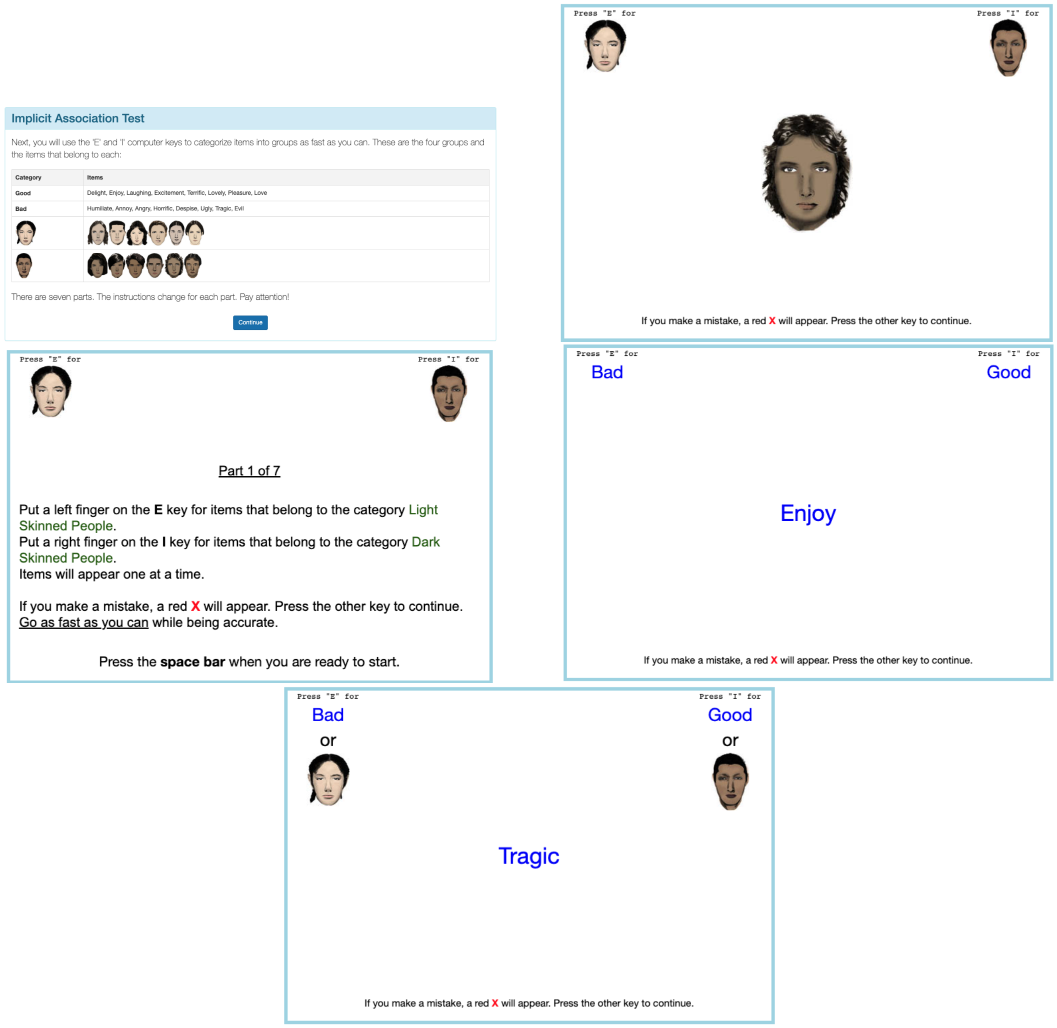
ONLINE APPENDIX

The Effect of Racial and Ethnic Attitudes on Asian Identity in the U.S

Hussain Hadah

Data

Figure A.1: Examples of an Implicit Association Test



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

Tables

Table A.1: Asian Identity Models - All Generations (with Marginal Effects)

	LPM	Logit (ME)	Probit (ME)
Bias	-0.0890***	-0.0896***	-0.1046***
	(0.0308)	(0.2704)	(0.2704)
Female	-0.0095*	-0.0103**	-0.0121**
	(0.0050)	(0.0422)	(0.0422)
College Graduate: Mother	0.0087	0.0097	0.0114
	(0.0067)	(0.0571)	(0.0571)
College Graduate: Father	0.0148**	0.0153***	0.0178***
	(0.0061)	(0.0486)	(0.0486)
Mean	0.65	0.65	0.65
Observations	129,078	129,078	129,078

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

[1] Linear Probability Model (LPM) shows coefficients. Logit and Probit show marginal effects.
[2] All models include region × year fixed effects.
[3] Standard errors clustered at state level.
[4] ME = Marginal Effects calculated at sample means.

Table A.2: Asian Identity Models - First Generation (with Marginal Effects)

Model Type	LPM	Logit (ME)	Probit (ME)
	LPM	Logit (ME)	Probit (ME)
Bias	-0.0548	-0.0394	-0.0157
	(0.0351)	(0.7894)	(0.7894)
Female	-0.0094	-0.0112	-0.0045
	(0.0062)	(0.1666)	(0.1666)
College Graduate: Mother	-0.0102	-0.0125	-0.0050
	(0.0106)	(0.2610)	(0.2610)
College Graduate: Father	0.0197**	0.0217**	0.0087**
	(0.0095)	(0.2446)	(0.2446)
Mean	0.96	0.96	0.96
Observations	15,499	13,855	13,855

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

[1] First generation Asian immigrants only.
[2] Linear Probability Model (LPM) shows coefficients. Logit and Probit show marginal effects.
[3] Standard errors clustered at state level.
[4] ME = Marginal Effects calculated at sample means.

Table A.3: Asian Identity Models - Second Generation (with Marginal Effects)

Model Type	LPM	Logit (ME)	Probit (ME)
	LPM	Logit (ME)	Probit (ME)
Bias	-0.0797**	-0.0766**	-0.0851**
	(0.0318)	(0.3400)	(0.3400)
Female	-0.0037	-0.0044	-0.0049
	(0.0047)	(0.0492)	(0.0492)
College Graduate: Mother	0.0092	0.0090	0.0100
	(0.0075)	(0.0693)	(0.0693)
College Graduate: Father	-0.0004	0.0002	0.0002
	(0.0064)	(0.0647)	(0.0647)
Mean	0.73	0.73	0.73
Observations	80,137	80,137	80,137

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

[1] Second generation Asian immigrants only.

[2] Linear Probability Model (LPM) shows coefficients. Logit and Probit show marginal effects.

[3] Standard errors clustered at state level.

[4] ME = Marginal Effects calculated at sample means.

Table A.4: Asian Identity Models - Third Generation (with Marginal Effects)

Model Type	LPM	Logit (ME)	Probit (ME)
	LPM	Logit (ME)	Probit (ME)
Bias	-0.0786**	-0.0859**	-0.0807**
	(0.0343)	(0.3497)	(0.3497)
Female	-0.0085	-0.0078	-0.0073
	(0.0123)	(0.1189)	(0.1189)
College Graduate: Mother	0.0260	0.0278*	0.0261*
	(0.0159)	(0.1293)	(0.1293)
College Graduate: Father	-0.0149	-0.0128	-0.0120
	(0.0154)	(0.1231)	(0.1231)
Mean	0.31	0.31	0.31
Observations	33,442	33,405	33,405

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

[1] Third generation Asian immigrants only.

[2] Linear Probability Model (LPM) shows coefficients. Logit and Probit show marginal effects.

[3] Standard errors clustered at state level.

[4] ME = Marginal Effects calculated at sample means.

Table A.5: Subjective Asian Identity and Asian Bias

	(1) A_i	(2) A_i	(3) A_i	(4) A_i	(5) A_i	(6) A_i	(7) A_i	(8) A_i
Bias	−0.04***	−0.14***	−0.02***	−0.02	−0.03***	−0.07**	−0.10***	−0.04
	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.03)	(0.03)	(0.03)
Female	−0.01**	−0.01**	−0.01**	−0.01*	−0.01**	−0.01*	−0.01*	−0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
College Graduate: Mother	0.01	0.01	0.01	0.01	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	0.01**	0.01*	0.01**	0.01**	0.01**	0.01**	0.01**	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Both parents Asian	0.63***	0.63***	0.62***	0.62***	0.63***	0.63***	0.63***	0.62***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
First Gen	0.01	0.02	0.02*	0.02**	0.02*	0.02**	0.02*	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Second Gen	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	129078	129078	129078	129078	129078	129078	129078	129078
Region FE					X	X		
Year FE		X		X		X		
State FE			X	X				X
Year-Region FE							X	X

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

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

[2] Standard errors are clustered on the state level.

Table A.6: Relationship Between Bias and Self-Reported Asian Identity: By Generation

	(1) A_i	(2) A_i^1	(3) A_i^2	(4) A_i^3
Bias	-0.09***	-0.05	-0.08**	-0.08**
	(0.03)	(0.04)	(0.03)	(0.03)
Female	-0.01*	-0.01	0.00	-0.01
	(0.00)	(0.01)	(0.00)	(0.01)
College Graduate: Mother	0.01	-0.01	0.01	0.03
	(0.01)	(0.01)	(0.01)	(0.02)
College Graduate: Father	0.01**	0.02**	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)
Observations	129,078	15,499	80,137	33,442
Mean	0.65	0.44	0.22	0.66
Year × Region FE	X	X	X	X

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

[1] Each column is an estimation of a heterogeneous effect of regression (4) by generation with region × year fixed effects. I include controls for sex, quartic age, fraction of Asians in a state, and parental education. I also added parents' (AA, AW, and WA) and grandparents' (AAAA, AAAW, AAWA, etc.) type dummy variables to the regression on second and third generation immigrants, where A is objectively Asian (born in a Asian country) and W is objectively White (native-born). Standard errors are clustered on the state level.

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

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

Table A.7: Relationship Between Bias and Self-Reported Asian identity Among Second-Generation Asian Immigrants: By Parental Type

Parents Type	All	Both Parents from Asian Country (AA)	Father from Asian Country (AW)	Mother from Asian Country (WA)
	(1)	(2)	(3)	(4)
	A^2	A^2	A^2	A^2
Bias	-0.08**	-0.05	-0.15	-0.10
	(0.03)	(0.03)	(0.10)	(0.06)
Female	0.00	-0.01	-0.03*	0.01
	(0.00)	(0.00)	(0.02)	(0.02)
College Graduate: Mother	0.01	-0.01*	0.10***	0.03
	(0.01)	(0.01)	(0.03)	(0.02)
College Graduate: Father	0.00	0.01	-0.05**	0.01
	(0.01)	(0.01)	(0.02)	(0.03)
Observations	80,137	50,835	9,055	20,247
Year × Region FE	X	X	X	X
Mean	0.73	0.97	0.39	0.3

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

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

[2] The samples include second-generation Asian children ages 17 and below who live in intact families. Native-born second-generation Asian immigrant children with at least one parent born in a Asian 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 Asian country (AA), column (3) includes the results to regression (4) on second-generation immigrants that who has a father that was born in a Asian country and a native-born mother (AW), 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 Asian country (WA).

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

Table A.8: Logistic Regression Analysis of Bias and Interracial Marriages

		Asian Men	Asian Women
	(1) Interethnic	(2) Interethnic	(3) Interethnic
Bias	0.38***	−0.19	0.33**
	(0.11)	(0.16)	(0.14)
College Graduate: Wife	0.35***	0.44***	0.56***
	(0.04)	(0.06)	(0.05)
College Graduate: Husband	−0.06	−0.03	−0.15***
	(0.04)	(0.06)	(0.05)
Observations	69,800	52,032	60,171
Year × Region FE	X	X	X

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

[1] This is the result to estimating (6) as a logistic regression. The coefficients are exponentiated, thus should be interpreted as odds ratios.

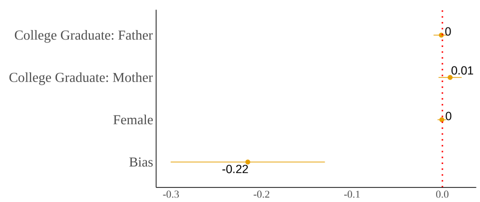
[2] I include controls for partners' sex, age, education, and years since immigrating to the United States. Standard errors are clustered on the household level.

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

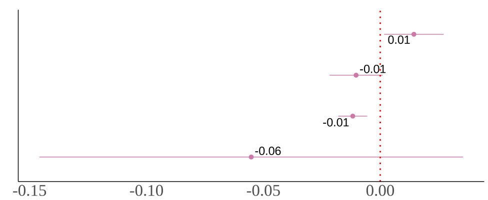
Figures

Figure A.2: Relationship Between Self-Reported Asian Identity and Bias: By Generation at the County Level

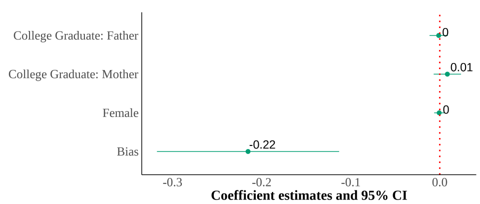
(a) All Generations



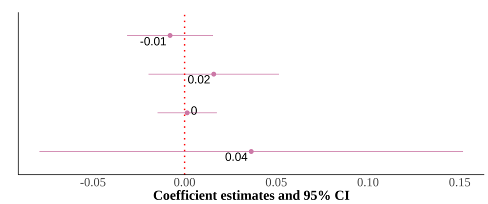
(b) First-Generation



(c) Second-Generation



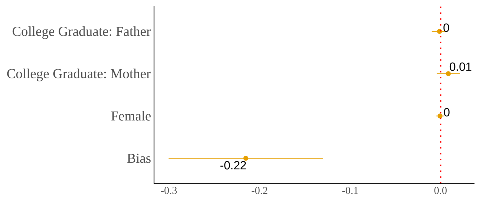
(d) Third-Generation



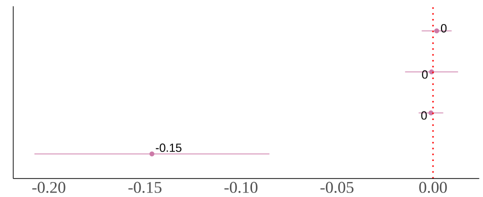
I show four panels of estimating the effect of county-level anti-Asian implicit bias. I include state and year fixed effects with controls for sex, quartic age, and parental education. The dependent variable is self-reported Asian identity and the independent variable is county-level bias. Each panel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

Figure A.3: Relationship Between Self-Reported Asian Identity and Bias: By Parental Types at the County Level

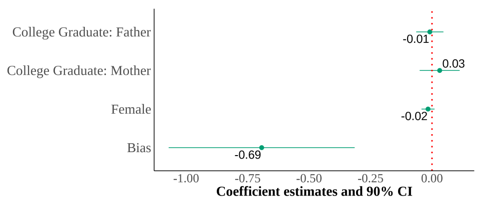
(a) Second-Generation (All Parental Types)



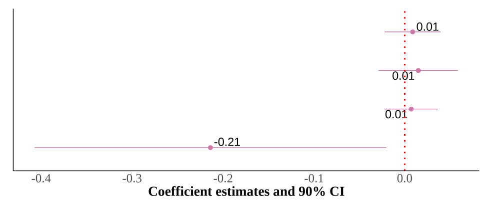
(b) Asian Fathers-Asian Mothers



(c) Asian Fathers-White Mothers

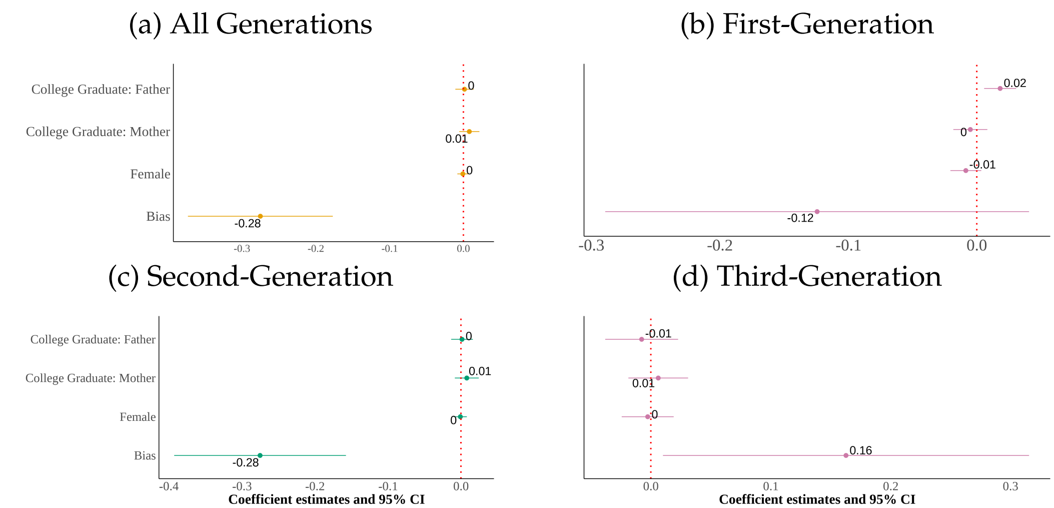


(d) White Fathers-Asian Mothers



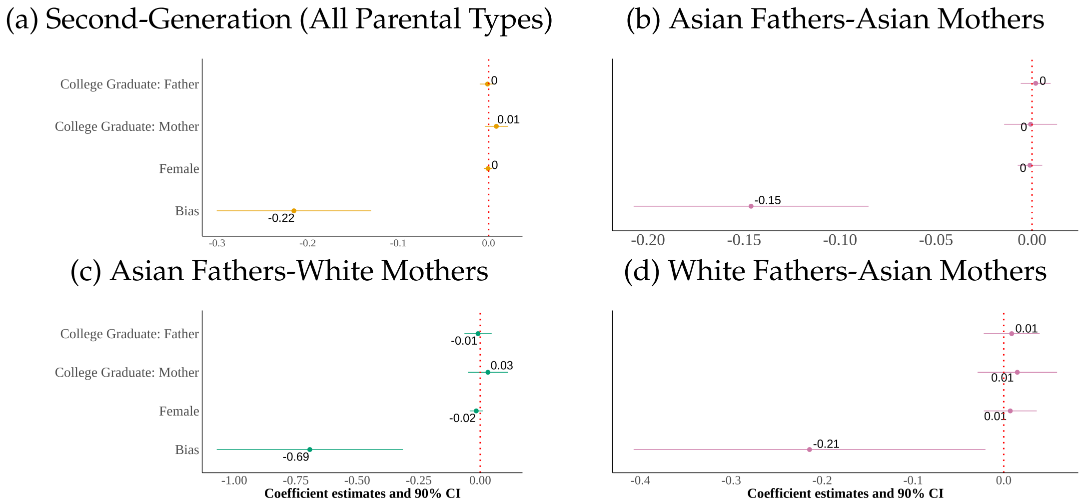
I show four panels of estimating the effect of county-level anti-Asian implicit bias—using the implicit association test (IAT) scores. I include state and year fixed effects with controls for sex, quartic age, and parental education. The dependent variable is self-reported Asian identity and the independent variable is county-level bias. Each panel results from the same regression but on different samples divided by parental types. Standard errors are clustered on the state level. The samples include second-generation Asian children ages 17 and below who live in intact families. Native-born second-generation Asian immigrant children with at least one parent born in an Asian country.

Figure A.4: Relationship Between Self-Reported Asian Identity and Bias: By Generation at the MSA Level



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

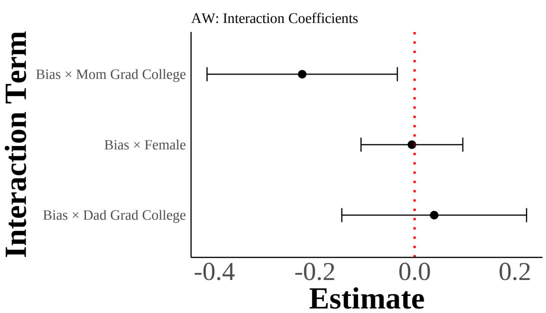
Figure A.5: Relationship Between Self-Reported Asian Identity and Bias: By Parental Types at the MSA Level



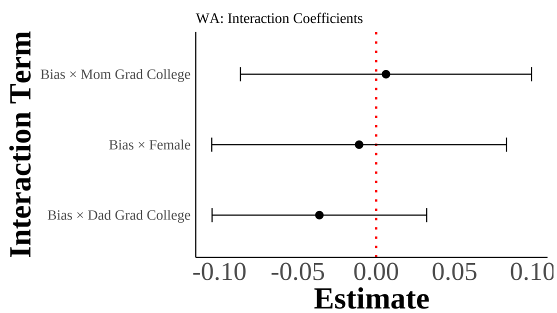
I show four panels of estimating the effect of county-level anti-Asian implicit bias—using the implicit association test (IAT) scores. I include state and year fixed effects with controls for sex, quartic age, and parental education. The dependent variable is self-reported Asian identity and the independent variable is county-level bias. Each panel results from the same regression but on different samples divided by parental types. Standard errors are clustered on the state level. The samples include second-generation Asian children ages 17 and below who live in intact families. Native-born second-generation Asian immigrant children with at least one parent born in an Asian country.

Figure A.6: Interaction Effects of Anti-Asian Bias with Gender and Parental Education: By Mixed Parental Types Among Adults

(a) Asian Fathers-White Mothers



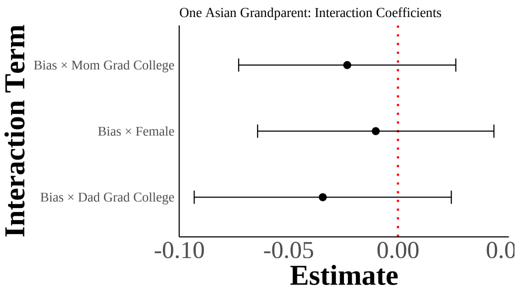
(b) White Fathers-Asian Mothers



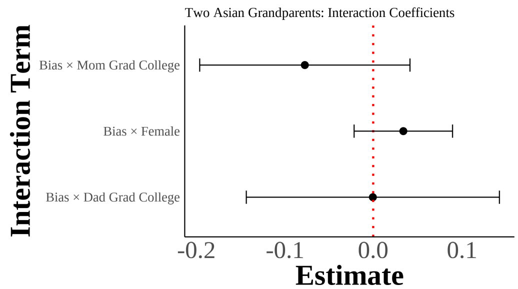
I show interaction coefficients from estimating equation (4) with interaction terms for gender and parental education. I include region $\times$ year fixed effects with controls for sex, quartic age, years of education, and the inverse hyperbolic sine of income. The dependent variable is self-reported Asian identity and the independent variables include demeaned state-level bias interacted with gender and parental education indicators. Each panel results from separate regressions on different samples divided by mixed parental types. Standard errors are clustered on the state level. The samples include second-generation Asian individuals ages 18 and above with mixed-race parentage. Native-born second-generation Asian immigrant individuals with one parent born in an Asian country and one parent born outside of Asia.

Figure A.7: Interaction Effects of Anti-Asian Bias with Gender and Parental Education: By Asian Grandparent Count Among Third Generation

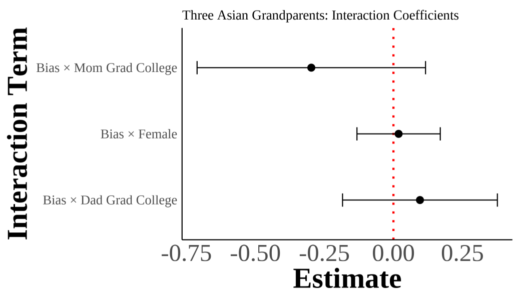
(a) One Asian Grandparent



(b) Two Asian Grandparents



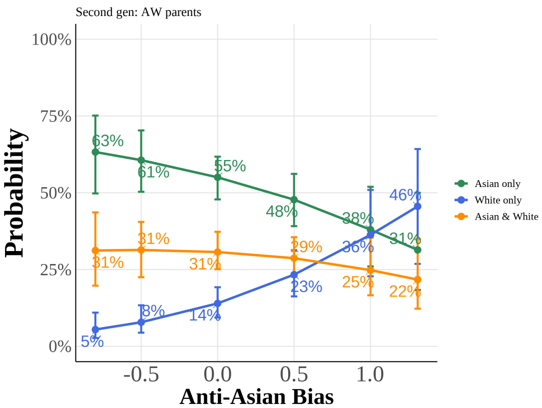
(c) Three Asian Grandparents



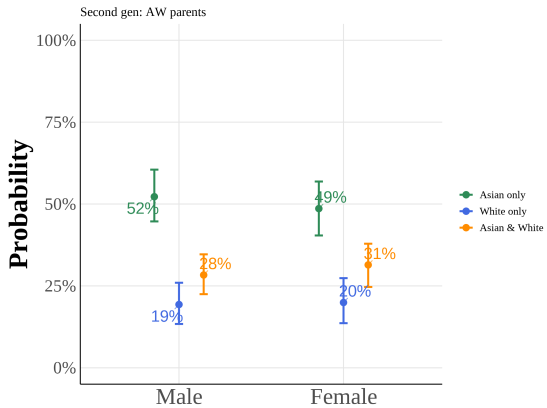
I show interaction coefficients from estimating equation (4) with interaction terms for gender and parental education on third-generation samples. I include region $\times$ year fixed effects with controls for sex, quartic age, years of education, and the inverse hyperbolic sine of income. The dependent variable is self-reported Asian identity and the independent variables include demeaned state-level bias interacted with gender and parental education indicators. Each panel results from separate regressions on different samples divided by the number of Asian grandparents. Standard errors are clustered on the state level. The samples include third-generation Asian individuals with varying degrees of Asian ancestry through grandparents. Native-born third-generation individuals with at least one grandparent born in an Asian country.

Figure A.8: Multinomial Logit Model: Predicted Probabilities of Racial Identity Choice by Key Covariates (Second-Generation Asian Americans with Asian Fathers and White Mothers)

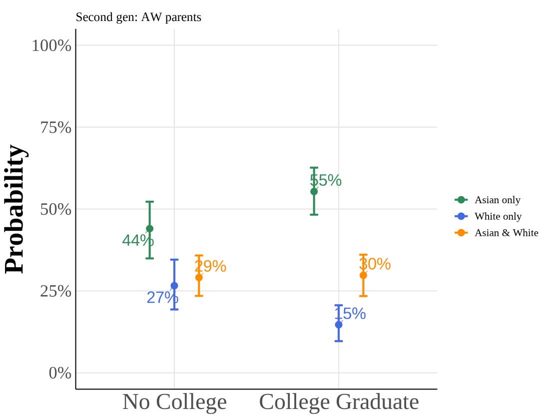
(a) Anti-Asian Bias



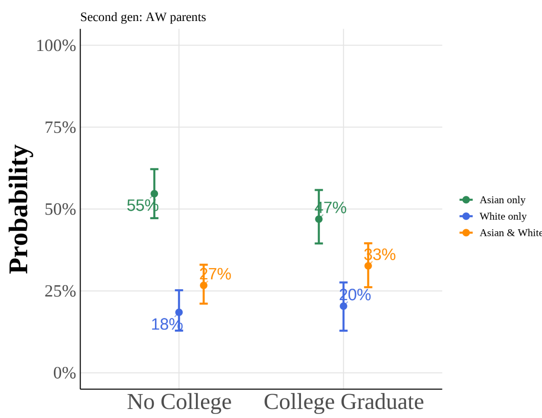
(b) Female



(c) College Graduate: Mother

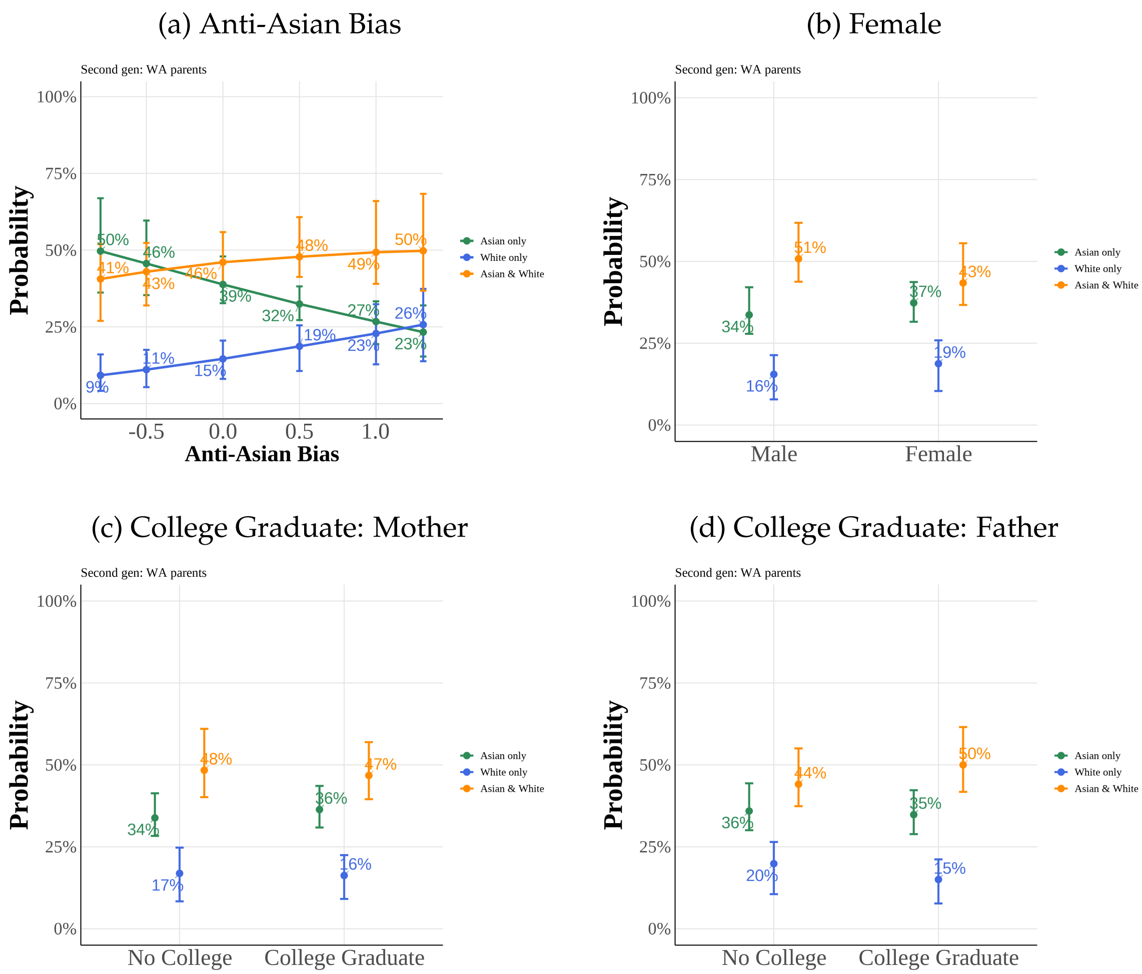


(d) College Graduate: Father



This figure shows predicted probabilities from estimating equation (5) using a multinomial logit model for the subsample of second-generation Asian Americans with Asian fathers and White mothers. The model estimates the probability of choosing "Asian only", "White only", or "Asian and White" racial identification as a function of anti-Asian bias, gender, and parental education. I include region × year fixed effects with controls for quartic age and local Asian population share. All other variables are held at their sample means. Reported curves depict the median predicted probability across 1,000 bootstrap resamples, and 95% confidence intervals follow the corresponding bootstrap percentile limits.

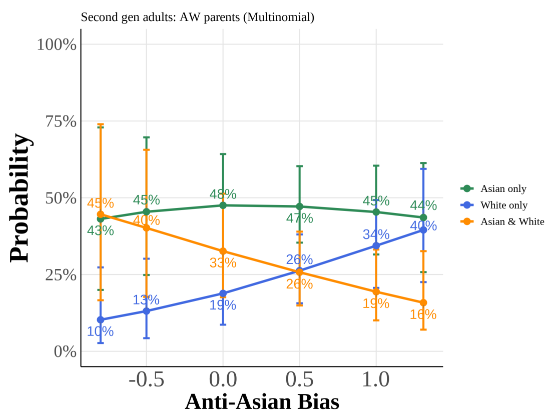
Figure A.9: Multinomial Logit Model: Predicted Probabilities of Racial Identity Choice by Key Covariates (Second-Generation Asian Americans with White Fathers and Asian Mothers)



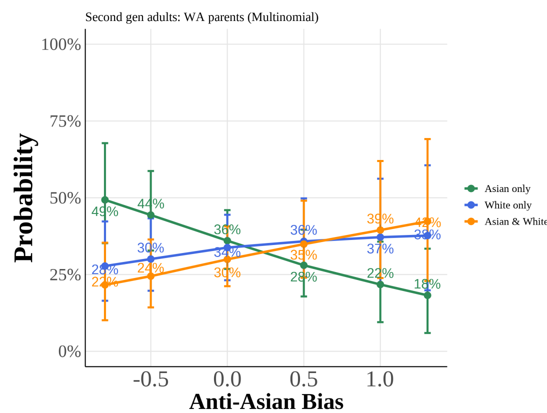
This figure shows predicted probabilities from estimating equation (5) using a multinomial logit model for the subsample of second-generation Asian Americans with White fathers and Asian mothers. The model estimates the probability of choosing "Asian only", "White only", or "Asian and White" racial identification as a function of anti-Asian bias, gender, and parental education. I include region $\times$ year fixed effects with controls for quartic age and local Asian population share. All other variables are held at their sample means. Reported curves depict the median predicted probability across 1,000 bootstrap resamples, and 95% confidence intervals follow the corresponding bootstrap percentile limits.

Figure A.10: Multinomial Logit Model: Predicted Probabilities of Racial Identity Choice by Anti-Asian Bias and Gender (Second Generation Adults, AW/WA)

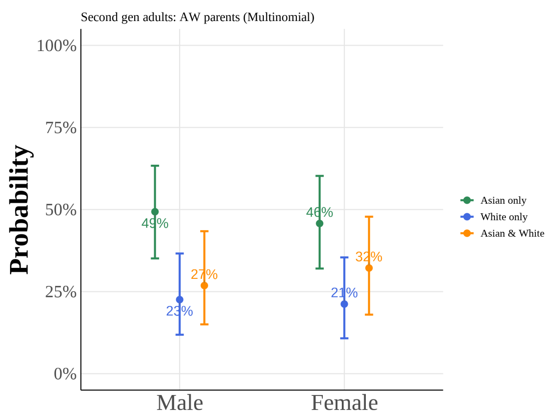
(a) Anti-Asian Bias (AW)



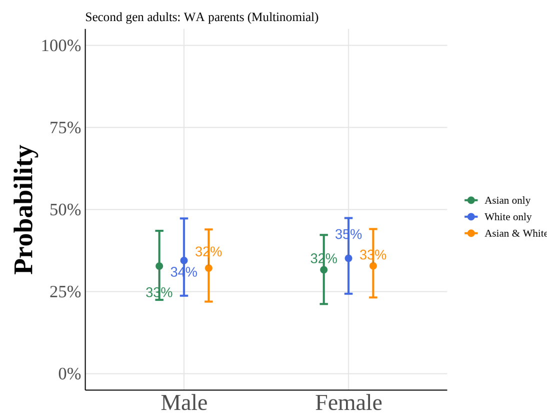
(b) Anti-Asian Bias (WA)



(c) Female (AW)



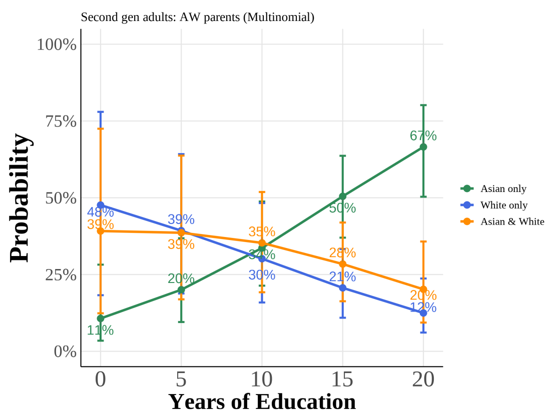
(d) Female (WA)



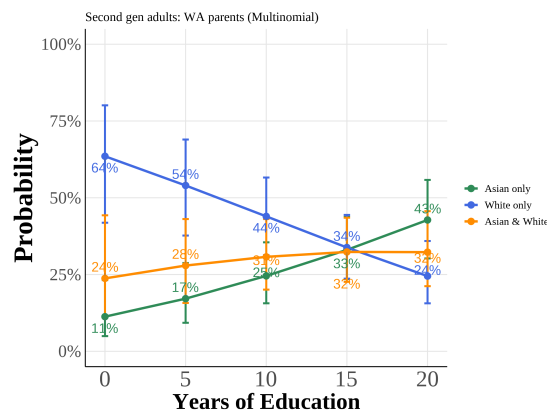
Predicted probabilities from multinomial logit models for second-generation adults with Asian father/White mother (AW) and White father/Asian mother (WA). Each panel shows the probability of choosing each racial identity as a function of anti-Asian bias or gender, holding other covariates at their means. Curves plot the median predicted probability across 1,000 bootstrap resamples, with 95% confidence intervals given by the bootstrap percentile bounds.

Figure A.11: Multinomial Logit Model: Predicted Probabilities of Racial Identity Choice by Years of Education and Income (Second Generation Adults, AW/WA)

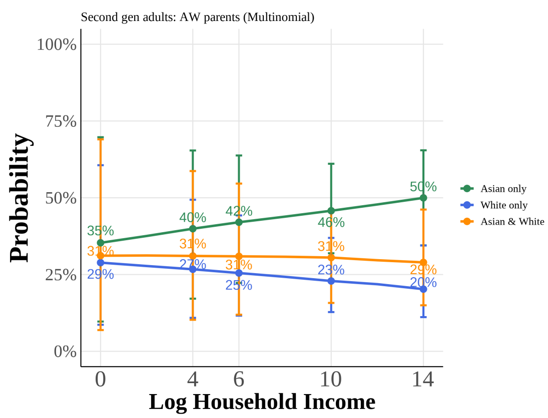
(a) Years of Education (AW)



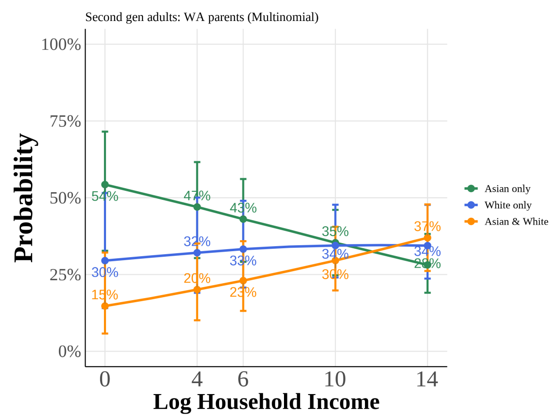
(b) Years of Education (WA)



(c) Log Family Income (AW)



(d) Log Family Income (WA)



Predicted probabilities from multinomial logit models for second-generation adults with Asian father/White mother (AW) and White father/Asian mother (WA). Each panel shows the probability of choosing each racial identity as a function of total years of education or log family income, holding other covariates at their means. Curves plot the median predicted probability across 1,000 bootstrap resamples, with 95% confidence intervals given by the bootstrap percentile bounds.

Figure A.14: Scatter Plot of Proportion Subjectively Asian on Bias

(a) Year < 2015

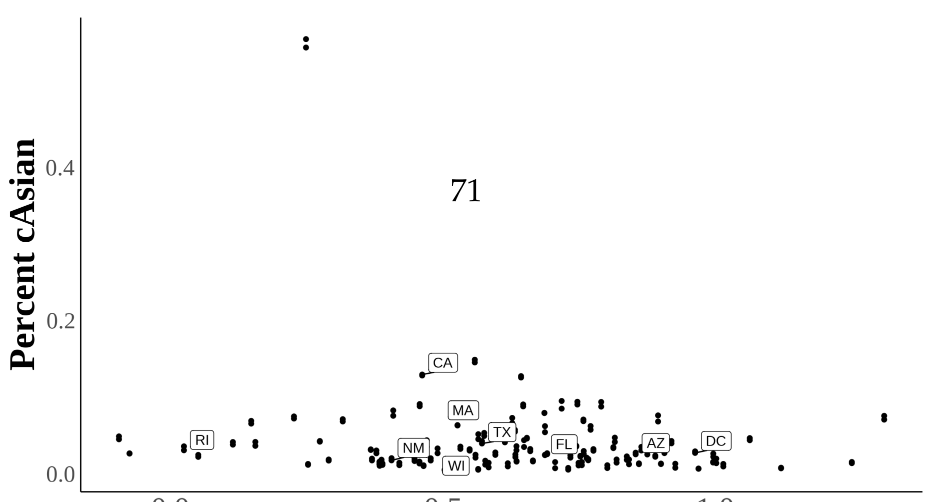
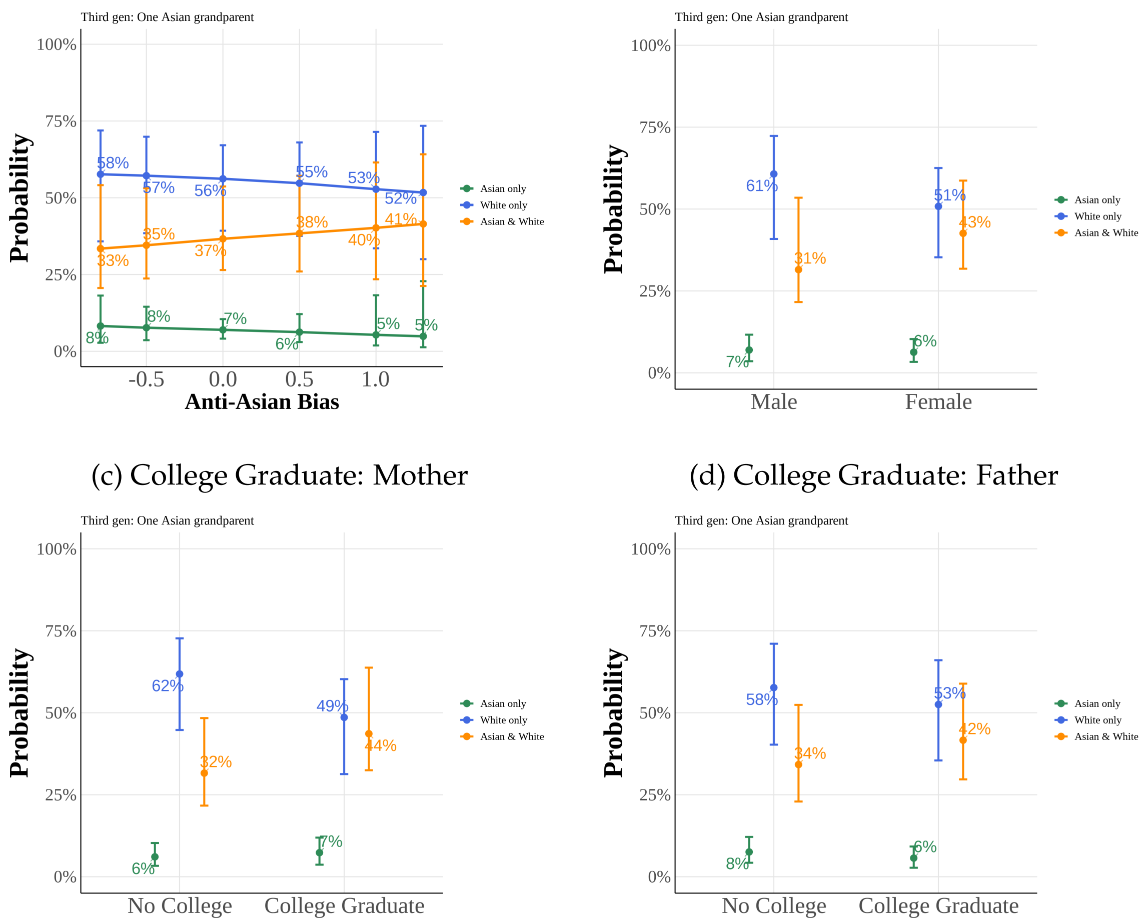


Figure A.12: Multinomial Logit Model: Predicted Probabilities of Racial Identity Choice by Key Covariates (Third-Generation Asian Americans with One Asian Grandparent)



(a) Anti-Asian Bias

(b) Female

(c) College Graduate: Mother

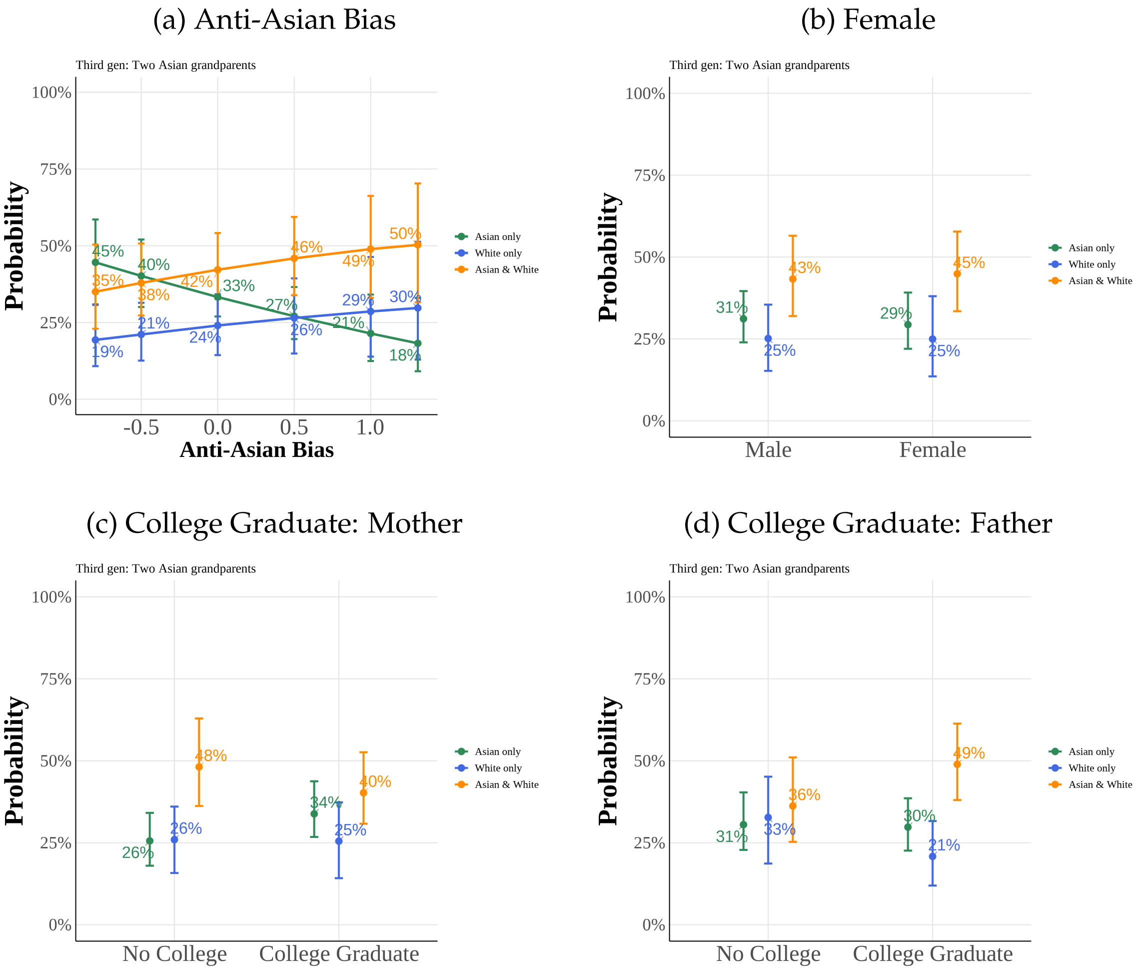
(d) College Graduate: Father

This figure shows predicted probabilities from estimating equation (5) using a multinomial logit model for the subsample of third-generation Asian Americans with one Asian grandparent. The model estimates the probability of choosing "Asian only", "White only", or "Asian and White" racial identification as a function of anti-Asian bias, gender, and parental education. I include region $\times$ year fixed effects with controls for quartic age and local Asian population share. All other variables are held at their sample means. Reported curves depict the median predicted probability across 1,000 bootstrap resamples, with 95% percentile confidence intervals from the same draws.

Using Lubotsky and Wittenberg (2006) to Construct Bias Index

In Lubotsky and Wittenberg (2006), the authors propose a method to reduce measurement error in proxies by constructing a composite index. The Lubotsky-

Figure A.13: Multinomial Logit Model: Predicted Probabilities of Racial Identity Choice by Key Covariates (Third-Generation Asian Americans with Two Asian Grandparents)



This figure shows predicted probabilities from estimating equation (5) using a multinomial logit model for the subsample of third-generation Asian Americans with two Asian grandparents. The model estimates the probability of choosing "Asian only", "White only", or "Asian and White" racial identification as a function of anti-Asian bias, gender, and parental education. I include region × year fixed effects with controls for quartic age and local Asian population share. All other variables are held at their sample means. Reported curves depict the median predicted probability across 1,000 bootstrap resamples, with 95% percentile confidence intervals from the same draws.

Wittenberg (henceforth LW) consider a model where a covariate is unobserved. Therefore, they use two proxies in its place, which will have measurement error.

Thus, the LW method allows researchers to use two proxies that are error-ridden.

LW consider a setup with the following model:

$$y = \alpha + \beta x^* + \epsilon$$
$$x_1 = x^* + \mu_1$$
$$x_2 = x^* + \mu_2$$

Where x_i^* is the unobserved covariate, x_{1i} and x_{2i} are the proxies, and the measurement errors μ_1 and μ_2 are assumed to be classical and allowed to covary. The covariance matrix of the errors is given by:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix}$$

Replacing the unobserved x^* with x_1 or x_2 yields the following expectations of the OLS estimates:

$$\mathbb{E}\left[\hat{\beta}_1\right] = \beta \frac{\sigma_{x^*}^2}{\sigma_{x^*}^2 + \sigma_1^2} \quad ; \quad \mathbb{E}\left[\hat{\beta}_2\right] = \beta \frac{\sigma_{x^*}^2}{\sigma_{x^*}^2 + \sigma_2^2}$$

Both estimates are biased; the one with the smaller variance of the measurement error being less biased.

LW then propose defining a new proxy x_3 as a weighted average of x_1 and x_2:

$$x_3 = \lambda x_1 + (1 - \lambda) x_2$$

To minimize the attenuation bias in the OLS estimate of β, they solve for the optimal value of λ:

$$\lambda^* = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}$$

This optimal value of λ is not directly useful because the variances of the measurement errors and their covariance are unobserved. However, if you estimate a bivariate regression using OLS (i.e., regress y on x_1 and x_2), then the expectation of the sum of the two coefficient estimates is identical to the expectation of the OLS coefficient estimate on x_3 in a univariate regression using the optimal choice of λ:

$$\mathbb{E}\left[\hat{\beta}_1 + \hat{\beta}_2\right] = \mathbb{E}\left[\hat{\beta}_{x_3}\right]$$

Thus, OLS produces an estimate of β with the least bias by optimally combining the information in x_1 and x_2.