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TITLE AND AUTHORS

TITLE AND RUNNING HEAD

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

Running Head: **Bias and Asian Identity**

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Data Availability Statement

The data that support the findings of this study will be openly available to all researchers after the review process. For immediate information regarding the data and/or computer programs used for this study, please contact Hussain Hadah at hhadah@tulane.edu.

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ABSTRACT

I study the determinants of the choice to identify as Asian among those who could—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 for all immigrants. A one standard deviation increase in bias decreases self-reported Asian identity by 8 and 9 percentage points for second- and third-generation Asians respectively. These findings have implications for the interpretation of research on racial and ethnic gaps in economic outcomes and the correct counting of the population. **JEL:** I310, J15, J71, Z13

KEYWORDS

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 while being characterized through the “model minority” stereotype. This dual status creates complex incentives around racial identity choices that fundamentally differ from other groups' experiences, as Asian identification can signal both academic excellence and perpetual foreignness.

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. To the extent that 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.

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.

Various contextual factors, including anti-Asian sentiment and stereotype threat, can influence how individuals navigate their racial identity choices. Recent events have brought renewed attention to how external hostility shapes Asian American experiences. 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 shapes decisions to racially identify, or not, as Asian American.

This paper has important implications for several reasons. First, if individuals respond to prejudice by avoiding Asian racial identification, conventional analyses of racial gaps may systematically overestimate 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 utilize 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 a 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.

Measuring identity choices outside of lab settings presents 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 identification. The analysis reveals that racial identity reporting negatively correlates with individual characteristics like parental education, and with environmental factors reflecting local discrimination levels.

Among individuals with Asian ancestry, I document that heightened anti-Asian bias correlates with reduced Asian racial identity reporting. Specifically, a one standard deviation increase in bias corresponds to a statistically significant 9 percentage point decrease in Asian racial identification among first-generation immigrants, a statistically insignificant 5 percentage point decrease among second-generation individuals, and a statistically significant 8 percentage point decrease among third-generation Asian Americans. The analysis by family structure reveals additional heterogeneity: bias effects prove strongest among children from mixed-race families, with a one standard deviation bias increase correlating with

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).

a 15 percentage point decrease in Asian identification among children of Asian fathers and White mothers, and a 10 percentage point decrease among children of White fathers and Asian mothers. These patterns suggest that economically successful Asian Americans—those with higher education and wealth—may strategically avoid Asian racial identification, leading research using subjective measures to underestimate Asian-White gaps in highly prejudiced areas.

This research contributes to multiple scholarly literatures 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 my formal theoretical model 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) study of Mexican Americans demonstrates how individuals strategically adapting 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.

The 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, Bous-

tan, 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 identification 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 ethnic identification (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.

Taking into consideration the identity flexibility that characterizes Asian American experiences, I investigate the economic determinants driving racial self-identification decisions. Hadah (2024) finds that bias and self-reported Hispanic identity are negatively associated among objectively Hispanic immigrants. I aim to exam-

ine how certain 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:

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

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:

$$\frac{\partial U_i}{\partial \mathbf{a}_i} + \frac{\partial U_i}{\partial I_i} \cdot \frac{dI_i}{d\mathbf{a}_i} = 0 \quad (3)$$

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

Identity switching occurs when benefits $\tilde{U}_i^* - U_i^*$ exceed costs c . These net

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

benefits are non-zero only when $\frac{dI_i}{da_i} \neq 0$ 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.

From 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. 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 identification, 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

This section describes the datasets employed in the analysis. To examine relationships between social attitudes and Asian racial identity reporting, I require both subjective and objective Asian identity measures for selecting appropriate

Asian American subgroups. I utilize 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 to construct objective identity measures. I develop composite anti-Asian bias measures using Lubotsky and Wittenberg (2006)’s methodology 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 perfect identification of first-, second-, and third-generation Asian Americans (see Figure 2 for visual representation). This approach enables construction of objective Asian ancestry measures for minors under age 17 living with parents.

The objective ancestry measure—distinct from subjective racial identification where respondents select “Asian” as their race—depends on birthplaces across three generations. 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

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

parent born in an Asian country, 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. It is important to 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 not 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 sample includes Asian Americans, first-, second-, and third-generation immigrants aged 17 and younger living with parents between 2004 and 2021. Summary statistics appear in Table (1).

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. Duncan and Trejo (2011) support this perspective, demonstrating no variation in Asian identification based on household respondent type. The data confirms consistent Asian identity reporting regardless of whether mother (72%), father (72%), or child/other caregiver (87%) serves as respondent, as shown in Table 6.⁵ Since my analysis compares high and low bias states, estimates remain valid provided reporting patterns don't systematically differ between these contexts.

The overall sample comprises 49% females, with 65% self-reporting Asian racial

5. 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.

identity—answering affirmatively to “what is your race.” Average age equals 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 US population subsample; Table (2) demonstrates sufficient observations across generations. Consistent with literature on racial identity fluidity among Asian Americans, I document significant attrition among third-generation Asian Americans.⁶ Table (2) displays these patterns: most first- and

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

second-generation Asian Americans racially self-identify as Asian. Among first-generation Asian Americans, 96% self-report Asian racial identity. Among second-generation Asian Americans, 73% self-identify as Asian, while 31% of third-generation Asian Americans choose Asian racial identification. Attrition among second- and third-generation Asian Americans primarily occurs among children from interracial families.

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. 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 IAT score manipulation difficulty (Egloff and Schmukle 2002).

The IAT measures bias direction and magnitude while capturing unconscious biases individuals may be unwilling to report. 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. However, some research

questions IAT predictive validity claims.⁷ 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) to construct composite bias measures.

I develop another racial animus proxy using ANES surveys ([American National Election Studies 2021](#)) measuring discrimination against racial groups. ANES, conducted since 1948, enjoys widespread political science usage. 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.⁸ While the ANES racial animus questions primarily focus on attitudes toward Black Americans, research demonstrates that 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

7. Research correlates IAT tests with economic outcomes (Chetty et al. 2020; Glover, Pallais, and Pariente 2017), voting behavior (Frieze, Bluemke, and Wänke 2007), and health (Leitner et al. 2016). IAT participation is voluntary, potentially creating selection bias. However, IAT-reflected bias serves as a prejudiced attitude proxy (Chetty et al. 2020).

8. 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.”

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 racially-motivated aggression and discrimination measures. Combined with implicit and explicit bias measures, this enables comprehensive prejudice understanding across states. This multidimensional approach—implicit bias, explicit bias, and hate crime statistics—offers fuller racial prejudice landscape understanding.

To reduce attenuation bias and measurement error, I follow Lubotsky and Wittenberg (2006) constructing composite bias measures using IAT, ANES racial animus measures, and hate crimes against Asian Americans.⁹ Figure (1a) graphically represents bias measures over time in most and least biased locations. Figure (1b) 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 increases equivalent to moving from Washington, DC, or Vermont to North Dakota in 2020. State-level average bias over time appears in Figure (3) maps, with overall 2004-2021 averages in Figure (4).

9. Additional methodological details appear in the Data Online Appendix, Section C.1.

4 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 :

$$A_{ist}^g = \beta_1^g \text{AntiAsianBias}_{st} + \beta_2^g \text{DadCollegeGrad}_{ist} + \beta_3^g \text{MomCollegeGrad}_{ist} + \beta_4^g \text{Women}_{ist} + X_{ist}^g \pi + \gamma_{rt} + \varepsilon_{ist}; \text{ where } g \in \{1, 2, 3\} \quad (4)$$

Where A_{ist}^g represents self-reported Asian racial identity of person i in state s at interview time t , $\text{AntiAsianBias}_{st}$ represents average anti-Asian bias in state s at time t , $\text{DadCollegeGrad}_{ist}$ and $\text{MomCollegeGrad}_{ist}$ are indicator variables equaling one if father or mother graduated college, Women_{ist} indicates sex, and X_{ist} represents a control vector.¹⁰ Additionally, γ_{rt} represents region-time fixed effects controlling for region \times year specific shocks.¹¹ 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 state level accounting for error term ε_{ist} correlation within states over time.

Since specifications include region \times year γ_{rt} , the β_1^g coefficient summarizes individual i responsiveness to anti-Asian bias changes in their residence state. In other words, β_1^g captures associations between Asian racial identity reporting

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

11. I exclude state fixed effects due to insufficient within-state bias variation.

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 regional states responded similarly to bias changes, then β_1^g equals zero.

5 Results

The empirical analysis provides consistent evidence that anti-Asian bias negatively correlates with Asian racial identity reporting. These relationships are strongest among individuals with greatest identity flexibility—mixed-race individuals and later-generation Asian Americans.

I report main results from estimating equation (4) in Figure (5). I present results estimating the main specification for all generations in panel (A) and for first-, second-, and third-generation subsamples in panels (B), (C), and (D), respectively. Anti-Asian bias and Asian racial identity reporting exhibit negative associations. One standard deviation anti-Asian bias increases correlate with 9 percentage point decreases in Asian racial identity reporting. Among first- and second-generation Asian Americans, one standard deviation anti-Asian bias increases associate with 5 and 8 percentage point decreases in Asian racial identity reporting. The first-generation coefficient lacks statistical significance, but confidence intervals remain predominantly negative. Among third-generation Asian Americans, one standard deviation anti-Asian bias increases associate with 8 percentage point

decreases in Asian racial identity reporting. Moreover, I find that—among all objectively Asian individuals—having a college-educated father or mother increases Asian racial identity reporting by 1 percentage point.

I report identical regression results for second-generation immigrant subsamples by parent type—interracial versus endogamous parents—in Figure (6). I present main specification results for second-generation immigrants in panel (A) and for AA, AW, and WA children subsamples in panels (B), (C), and (D), respectively. Children from interracial families show greater bias influence. One standard deviation anti-Asian bias increases associate with 5 percentage point decreases in Asian racial identity reporting among endogamous parent children—estimates are statistically insignificant. However, one standard deviation anti-Asian bias increases associate with 15 percentage point decreases in Asian racial identity reporting among Asian father-White mother children, and 10 percentage point decreases among White father-Asian mother children.

I also report regression results for third-generation immigrant subsamples by Asian grandparent numbers in Table (3). Overall anti-Asian bias effects on different Asian American children types are negative but mostly statistically insignificant. One standard deviation anti-Asian bias increases associate with 69 percentage point decreases in Asian racial identity reporting among Asian American children with three Asian-born grandparents.

6 Robustness Checks and Alternative Explanations

This section explores empirical relationships between anti-Asian bias and interracial marriages, plus migration patterns among second-generation Asian Americans as robustness checks for main analysis and proxy response effects. I examine anti-Asian bias impacts on interracial marriage likelihood, focusing on interracial couples, and Asian American migration decisions within the United States.

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

$$\text{interracial}_{ist}^2 = \beta_1^2 \text{AntiAsianBias}_{st} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist} \quad (5)$$

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

I present equation (5) estimation results in Table (4). One standard deviation anti-Asian bias increases raise interracial parent probabilities by 4 percentage points. Breaking down analysis by couple ethnicity: one standard deviation anti-Asian bias increases associate with 1 percentage point decreases in Asian husband-White wife marriage chances. One standard deviation anti-Asian bias increases associate with 3 percentage point increases in Asian wife-White hus-

band chances. Anti-Asian bias and interracial marriage positive correlations may result from Asian Americans in high-bias states aiming to reduce children's Asian ethnicity signal likelihood. 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 doesn't report birth states, I use 2004-2021 Censuses constructing 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 estimating relationships between anti-Asian bias and migration:

$$\text{BirthPlaceMigration}_{ist}^2 = \beta_1^2 \text{AntiAsianBias}_{st} + X_{ist}^2 \pi + \gamma_{rt} + \varepsilon_{ist} \quad (6)$$

$$\text{BirthPlaceMigration}_{ilb}^2 = \beta_1^2 \text{AntiAsianBias}_{lb} + X_{ilb}^2 \pi + \gamma_{lb} + \varepsilon_{ilb} \quad (7)$$

Where $\text{BirthPlaceMigration}_{ist}^2$ indicates whether person i in state s at interview t lives in states different from birth states. $\text{BirthPlaceMigration}_{ilb}^2$ indicates whether person i in birthplace l doesn't currently live in the same state as birth year b . Analysis, restricted to second-generation Asian Americans with both Asian-born parents, uses equations (6) and (7).

I employ two approaches defining bias variables studying relationships between bias and migration variables. First specification from equation (6) estimates

relationships between average bias at interview time t in state s and $\text{BirthPlaceMigration}_{ist}^2$. Second specification from equation (7) estimates relationships between average bias in birth state l at birth year b and $\text{BirthPlaceMigration}_{ilb}^2$.

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

$$Y_{ist} = \beta_0 + \beta_1^2 \text{Asian}_{ist} + X_{ist}^2 \pi + \varepsilon_{ist} \quad (8)$$

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

I show the results of estimating Equations (6), (7), and (8) in Table (5) 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 birth states. While this result shows selection into more biased states among second-generation immigrants, it doesn't affect main results showing correlations between anti-Asian bias and Asian racial identity reporting. Since Asian-identifying individuals are movers, my bias and Asian racial identity reporting relationship assessments might underestimate bias effects.

These findings indicate negative correlations between anti-Asian bias and Asian racial identity reporting among Asian Americans. While I don't aim establishing causal anti-Asian bias effects on Asian racial identity reporting, I illustrate correlations between bias and racial identification. These correlations suggest that depending on state bias levels, racial gaps relying on self-reported identity might overestimate or underestimate discrimination effects.

Several analysis concerns exist. First, Current Population Survey (CPS) self-reported identity comes from household respondents—parents or adult caregivers. Thus, 'self-reported' racial identity might not reflect children's true identity. I view parent- or caregiver-reported identity as accurate child identity representation since parents essentially shape children's self-concepts. Also, I compare high- and low-bias states for analysis. Estimates remain unchanged if self-reporting likelihood doesn't differ between these states.

Moreover, Duncan and Trejo (2011) show reported Hispanic identification doesn't vary with household respondent identity. Additionally, I present main Asian racial identity reporting effects by household respondent in Table (6). Main reported Asian racial identity effects equal 72 percentage points when mothers serve as proxies, 72 percentage points when fathers serve as proxies, and 87 percentage points when children or other caregivers serve as household respondents.¹²

A second concern involves IAT voluntary participation and non-representative population sampling. While I don't claim IAT anti-Asian bias proxies represent

12. According to Current Population Survey (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.

populations, Egloff and Schmukle (2002) demonstrate manipulation difficulty. Several studies correlate IAT with economic outcomes (Chetty et al. 2020; Glover, Pallais, and Pariente 2017), voting behavior (Frieze, Bluemke, and Wänke 2007), decision-making (Bertrand, Chugh, and Mullainathan 2005; Carlana 2019), and health (Leitner et al. 2016). Another concern involves IAT test-taker characteristic changes over time, creating non-identical samples. I address this concern including non-parametric region \times year fixed effects controlling systematic test-taker characteristic differences between regions. These changes remain controlled provided test-taker characteristic differences don't vary across states within regions. Most importantly, I use ANES racial animus measures and hate crimes against Asian Americans constructing composite bias measures reducing measurement error using Lubotsky and Wittenberg (2006).

Another concern involves reverse causality between greater Asian American or Black populations in states and bias levels. Greater Asian American populations in states might affect resident bias levels. For example, more Asian Americans in California or Black Americans in Louisiana could affect California and Louisiana resident bias. To demonstrate this isn't occurring, I provide Figure (A.2) evidence. Figure (A.2) plots self-reported Asian American state percentages at specific years against average anti-Asian bias in identical states during those years. I find no correlations between anti-Asian bias and Asian American state populations, making reverse causality unlikely.

Finally, bias (prejudice) and Asian racial identity reporting relationship estimators could be biased if non-Asian-identifying individuals migrate to more prej-

duced states. I've shown above this isn't occurring (Table 5). I find no evidence of relationships between migration decisions and anti-Asian bias. Additionally, I find 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 identity determinants are 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 increases anti-Asian bias. The relationships between Asian racial identity reporting and anti-Asian bias among first-generation immigrants show one standard deviation bias increases correlating with 9 percentage point decreases in Asian racial identity reporting; results are statistical significance. Relationships between Asian racial identity reporting and anti-Asian bias are more prominent among second-generation immigrants, where one standard deviation bias increases correlate with 5 percentage point decreases in Asian racial identity reporting. Among third-generation Asian Americans, one standard

deviation anti-Asian bias increases correlate with 8 percentage point decreases in Asian racial identity reporting.

Additionally, anti-Asian bias produces more substantial effects among second-generation immigrant children from mixed-race families. One standard deviation anti-Asian bias increases correlate with 15 percentage point decreases in Asian racial identity reporting among second-generation Asian American children of Asian fathers and White mothers, and 10 percentage point decreases among children of White fathers and Asian mothers. I also find anti-Asian bias positively correlates with interracial marriage and shows no correlation with migration decisions.

These results are important due to consequences for correct Asian American and minority enumeration, integration patterns, and social mobility. They indicate anti-Asian bias could significantly affect how economists estimate racial gaps. Most race and ethnicity research relies on self-reported racial and ethnic identity measures. Since anti-Asian bias negatively correlates with Asian racial identity reporting, characteristics of those avoiding Asian racial identification could produce important consequences. For example, if individuals whose identities are most likely affected by bias represent the most educated, then racial gaps will be overestimated in the most biased states. Furthermore, identity decisions likely profoundly affect people's choices, investments, and well-being.

Moreover, this study could encourage further research into relationships between bias and self-reported identities for other groups. Analysis of bias effects on self-reported identity could apply to other groups. For example, researchers could

estimate 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 don't using restricted administrative data.

The research opens several avenues for future investigation. First, scholars could examine how recent anti-Asian violence following COVID-19 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 units, such as counties, city, or zip-code level, could provide a more precise measure of local bias. However, data limitations prevent the use of these finer geographic levels in the current analysis. Future research could explore this question using more detailed geographic identifiers if such data becomes available, allowing for a deeper understanding of how local contexts shape racial identity.

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 evolving, recognizing how Asian Americans navigate identity

choices becomes increasingly critical for promoting inclusive and equitable outcomes.

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Table 1: CPS Summary Statistics

Characteristic	Overall	By Generation		
	All Sample	First	Second	Third
	N = 318,404	N=40,033	N=199,294	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: Asian Self-identification by Generation

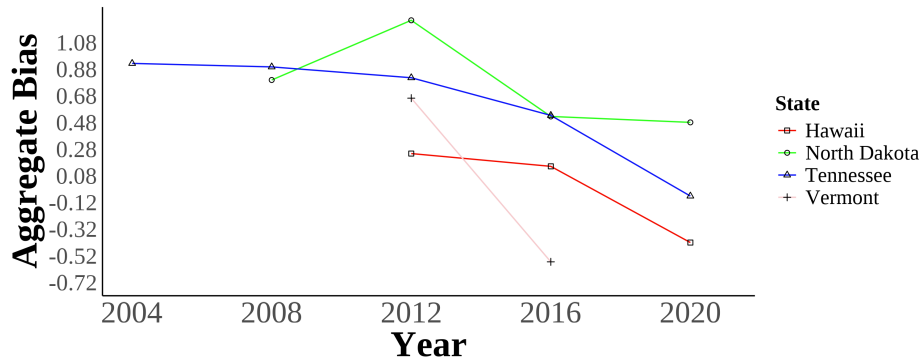
	Self-identify as Asian	Self-identify as non-Asian	% Self-identify as Asian	% Self-identify as non-Asian
1st Gen.	14,811	688	0.96	0.04
2nd Gen.	58,756	21,381	0.73	0.27
Asian on:				
Both Sides	49,118	1,717	0.97	0.03
One Side	9,638	19,664	0.33	0.67
3rd Gen.	10,394	23,048	0.31	0.69
Asian on:				
Both Sides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

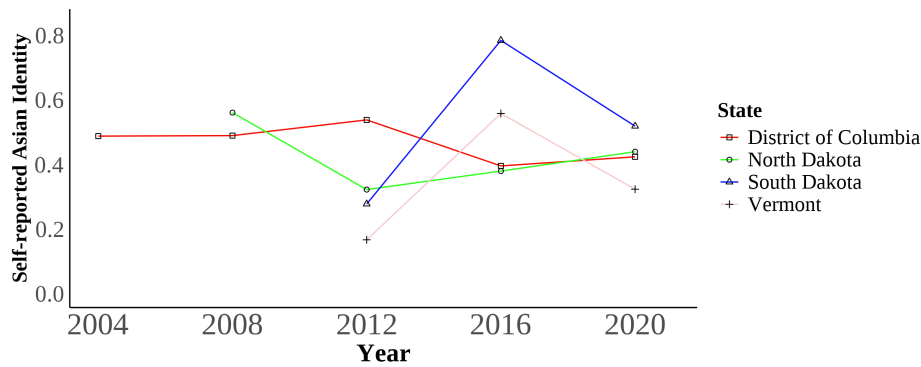
² Data source is the 2004-2021 Current Population Survey.

Figure 1: 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 Columbia 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 2: Diagram of the Three Different Generations of Asian Immigrants.

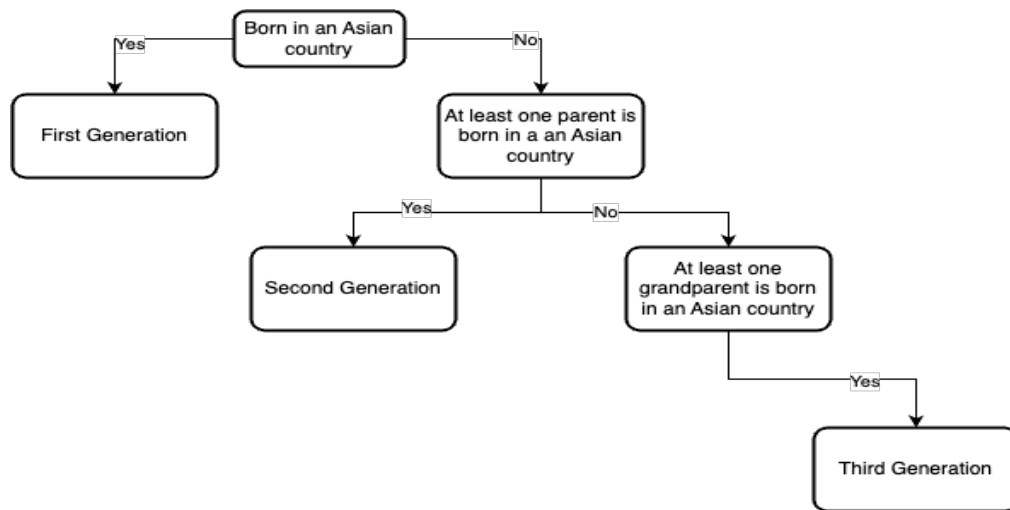
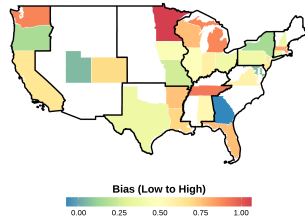
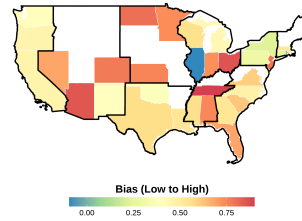


Figure 3: Maps of State-level Association Test Bias Over Time Measure with Census Division Regional Boundaries

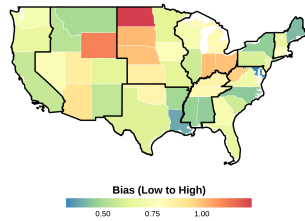
(a) State-level Bias in 2004



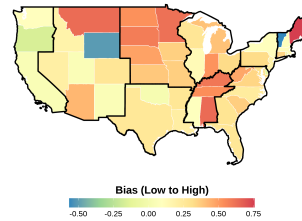
(b) State-level Bias in 2008



(c) State-level Bias in 2012

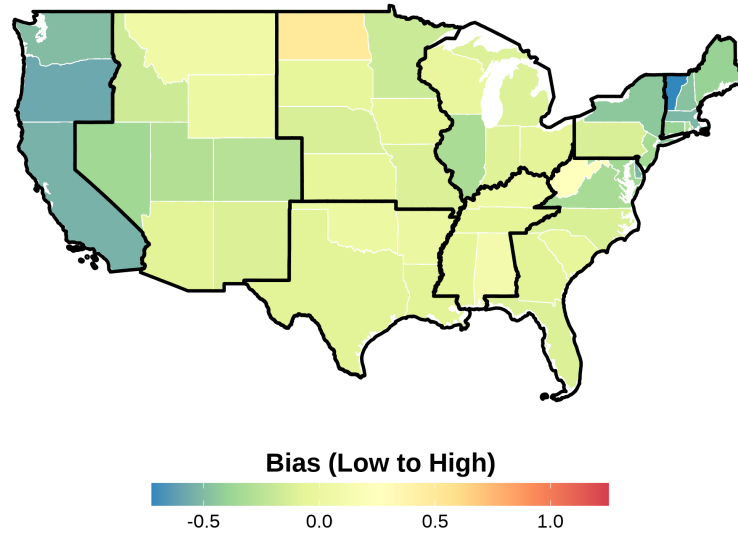


(d) State-level Bias in 2016



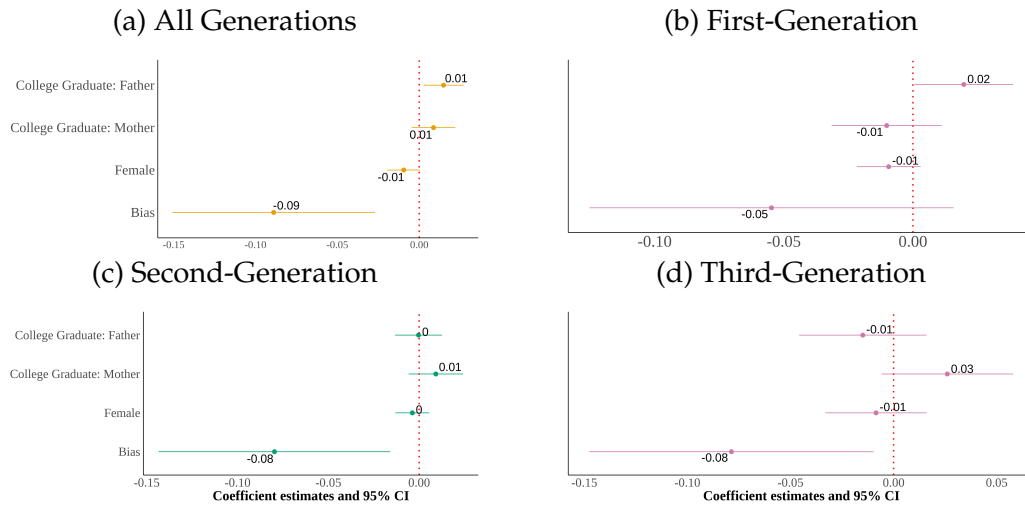
This figure shows the state-level bias index in different years in the sample. The bias units are in standard deviations and ranges from low to high bias. Bias index is constructed following Lubotsky and Wittenberg (2006). The data is from the 2004-2021 Harvard's Project Implicit Association Test scores, 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



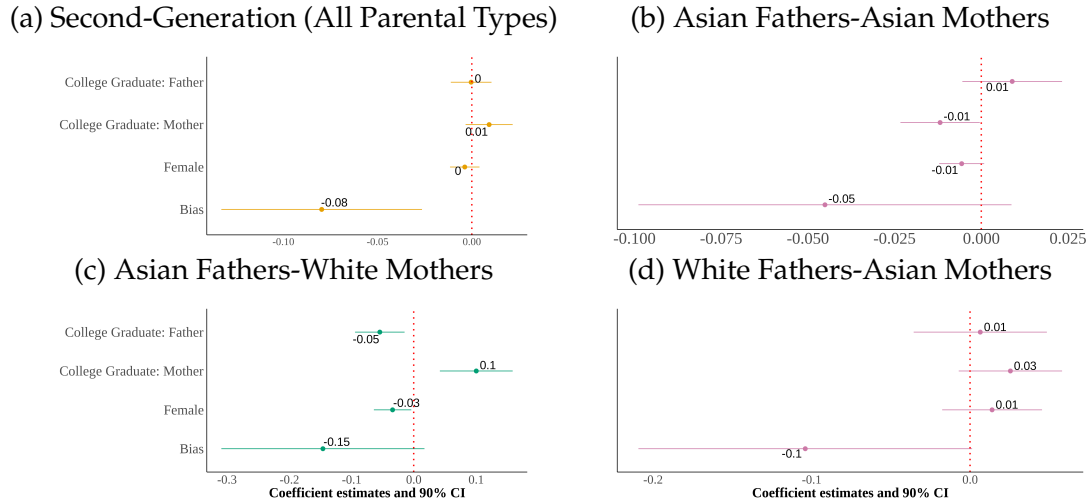
This figure shows the state-level bias index in the sample from 2004 to 2021. The bias units are in standard deviations and ranges from low to high bias. Bias index is constructed following Lubotsky and Wittenberg (2006). The data is from the 2004-2021 Harvard's Project Implicit Association Test scores, 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: Relationship Between Self-Reported Asian Identity and Bias: By Generation



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



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.

Table 3: Relationship Between Bias and Self-Reported Asian identity Among Third-Generation Asian Immigrants: By Grandparental Type

	Number of Asian Grandparents			
	(1)	(2)	(3)	(4)
	One	Two	Three	Four
Bias	-0.01 (0.04)	-0.09 (0.08)	-0.69** (0.32)	-0.11 (0.06)
Female	-0.01 (0.01)	-0.01 (0.02)	-0.04 (0.06)	-0.03** (0.01)
College Graduate: Mother	0.01 (0.01)	0.07** (0.03)	0.08 (0.09)	0.00 (0.03)
College Graduate: Father	-0.04*** (0.01)	0.00 (0.04)	-0.07 (0.08)	0.00 (0.01)
Observations	14,453	12,678	567	5,744
Year \times 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 \times 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 4: Relationship Between Bias and Interracial Marriages

		Asian Men	Asian Women
	(1)	(2)	(3)
	Interracial	Interracial	Interracial
Bias	0.04*** (0.01)	−0.01 (0.01)	0.03** (0.01)
College Graduate: Wife	0.04*** (0.00)	0.04*** (0.01)	0.05*** (0.00)
College Graduate: Husband	−0.01* (0.00)	−0.01 (0.01)	−0.02*** (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 (5) 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.

Table 5: Relationship Between Bias and Migration

	(1) Migrated from Birth Place	(2) Migrated from Birth Place	(3) $Bias_{ist} - Bias_{ilb}$
$Bias_{st}$	0.13* (0.07)		
$Bias_{lb}$		-0.03 (0.17)	
Asian			0.02 (0.04)
Female	0.00 (0.00)	-0.01 (0.00)	0.00 (0.02)
College Graduate: Mother	0.01*** (0.00)	0.00 (0.01)	-0.01 (0.03)
College Graduate: Father	-0.03*** (0.01)	-0.03*** (0.01)	0.03 (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 (6) in column (1), (7) in column (2), and (8) 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 \times year fixed effects. Standard errors are clustered on the state level.

³ The samples include children ages 17 and below who live in intact families. Native-born second-generation 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 6: 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.

A Responses to Editors and Referee

I would like to thank the editors and the anonymous referees for their insightful comments, suggestions, and effort and time in reviewing this paper. I have addressed all the comments and suggestions in the revised manuscript. Below, I provide a summary of the changes made to the manuscript in response to the comments and suggestions.

B Responses to Referee One

I would like to thank referee one for the insightful comments and suggestions.

Below is a detailed response to the comments and suggestions.

R1: 1. Beginning with the paper’s theoretical account of racial bias and its potential impact on racial identity, I appreciate the author’s use of formal theory to present a logical and rational model explaining why bias may affect racial identity. However, I feel the author misses an important literature on racial identity and assimilation that focuses on the behavioral aspects of race and racial identity. While they do briefly touch on some of this literature, I suggest that revisions have a greater focus on the behavioral literature on racial identity and assimilation in addition to the formal model. A good work that I could suggest on this topic is Telles and Ortiz’s *Generations of Exclusion*.

Response: I thank the referee for this suggestion. I have added a paragraph in the introduction discussing Telles and Ortiz’s *Generations of Exclusion* and other related works on racial identity and assimilation. Specifically, I add the following paragraph in the introduction: “While my formal theoretical model 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) study of Mexican Americans demonstrates how individuals strategically adapting 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 strate-

gies 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.”

R1: 2. As for the methods, I have a few concerns that I hope the author can address in future drafts. One concern that looms over the paper for me is that the ‘objective’ measure of Asian background may not be as objective as it seems. For instance, it is unclear that, say, the children or grandchildren of people who were born to non-asian parents in Asia, for example, on an American military base, would be classified as Asian. I don’t think this is a huge concern for the analysis, but it needs to at least be addressed.

Response: I appreciate the referee’s attention to this issue. It is a point I address in the paper’s data section in the following footnote “I restrict first-generation cases to those whose parents were born in Asian countries to exclude US citizens born abroad to American parents”. Following the comment, I am going to add a few sentences to clarify this point. Specifically, I will add the following sentences in the data section: “It is important to 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 not be classified as Asian in the data. To avoid potential misclassification, I remove individuals who report that they were born abroad of American parents.”

R1: 3. Second, I am concerned that using the state as the unit of analysis for regional bias may be problematic. Perhaps the bias of the community that one grows up in would be better measured at the city or zip-code level. For instance, those who live in Austin, Texas may have a very different experience with bias than those who live in rural west Texas. If the authors could provide even a supplemental analysis in which they analyze this at local level, this would help significantly to alleviate these concerns.

Response: I thank the referee for this suggestion. I agree that using more granular geographic units would provide a more precise measure of local bias. However, there are major data limitations that prevent me from doing so. First, the CPS does not provide geographic identifiers below the county level and only for 45% of the sample and only for counties with larger populations. Therefore, if used at the county level, I would lose more than half of the sample and potentially introduce bias. Second, even if I had access to more granular geographic identifiers in the CPS, to my knowledge, there are no measures of racial bias at more granular geographic levels. The General Social Survey (GSS), which I use as one of my measures of racial bias, is only representative at the the state level. The American National Election Studies (ANES) is only available at the state level. The Uniform Crime Reports (UCR), which I use to calculate anti-Asian hate crimes, is recom-

mended to not be used at the county level and is not available at lower levels. The Implicit Association Test (IAT) data is the only dataset that available at the county level, however, many social scientists have raised concerns about using the IAT on it's own. Therefore, while I agree with the referee that using more granular geographic units would be ideal, I am limited by data availability. I will add a paragraph to the conclusion discussing this limitation and suggesting that future research could explore this question using more granular geographic units if data becomes available. Specifically, I will add the following paragraph to the conclusion: "More granular geographic units, such as counties, city, or zip-code level, could provide a more precise measure of local bias. However, data limitations prevent the use of these finer geographic levels in the current analysis. Future research could explore this question using more detailed geographic identifiers if such data becomes available, allowing for a deeper understanding of how local contexts shape racial identity."

R1: 4. Additionally, while I understand why children are of particular interest, I would also like to see what the results look like for Asian adults. Is this phenomenon of calculating one's identity concentrated among children? Do they come to identify more with their Asian roots as they reach adolescence and adulthood? Are the same calculations being made by adults? These are important questions that including the sample of adults could be useful to help answer.

Response:

R1: 5. Lastly and importantly, it is also unclear to me why the

author uses measures of animus towards African Americans from the ANES in their bias index, especially when measures of animus towards Asian Americans are available on the very same study. Here I think the author either needs to make a case for the bias they are interested in being more broad than just bias toward Asian-Americans or they need to reestimate their measures of bias.

Thank you for this important methodological observation. You raise a valid point about the conceptual alignment between my bias measures and outcomes. Let me clarify my approach: The ANES racial animus questions do primarily focus on attitudes toward Black Americans, I also use measures of animus toward Asian Americans. Research consistently shows that racial prejudices are highly correlated across different minority groups—individuals who express bias toward one racial minority typically hold similar attitudes toward others (Almasalkhi [2023](#); Mora and Paschel [2020](#)). These measures therefore capture general patterns of racial animus rather than group-specific bias alone. Crucially, my composite bias index combines three distinct components: (1) Asian-focused IAT measures, (2) ANES racial animus questions, and (3) hate crimes specifically targeting Asian Americans. This multi-proxy approach effectively weights the overall bias measure toward Asian-specific prejudice (two of three components directly measure anti-Asian sentiment) while incorporating information about the broader racial climate through the ANES measures. This methodological choice serves two purposes: it reduces measurement error through the composite approach while capturing both specific anti-Asian bias and the general environment of racial prejudice that affects all minority groups.

C Responses to Referee Two

I would like to thank referee two for the insightful and constructive comments and suggestions. Below is a detailed response to the comments and suggestions.

R2: 1.

R2: 2.

R2: 3.

R2: 4.

R2: 5.

R2: 6.

ONLINE APPENDIX

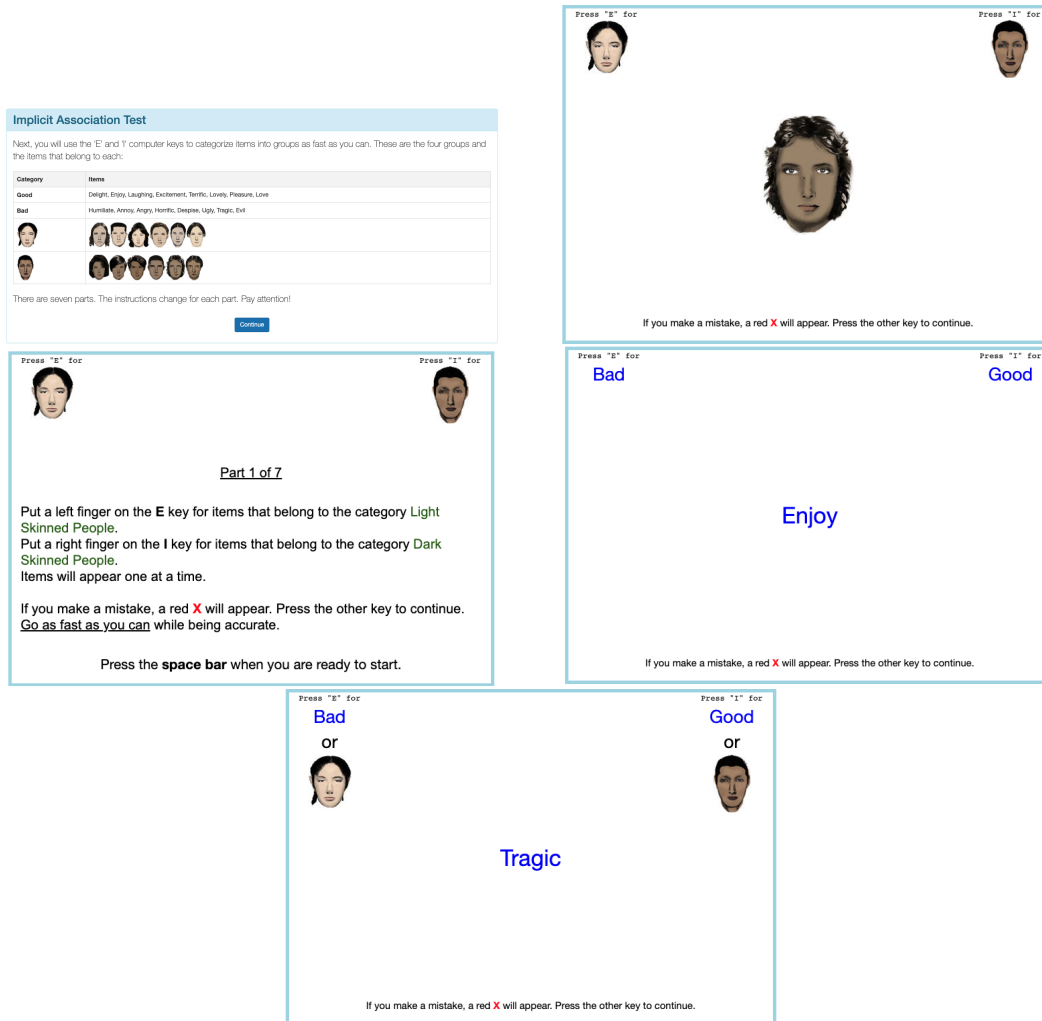
The Effect of Racial and Ethnic Attitudes on Asian Identity in the U.S

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A 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.

B Tables

Table A.1: Subjective Asian Identity and Asian Bias

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A_i	A_i	A_i	A_i	A_i	A_i	A_i	A_i
Bias	−0.04*** (0.01)	−0.14*** (0.04)	−0.02*** (0.01)	−0.02 (0.03)	−0.03*** (0.01)	−0.07** (0.03)	−0.10*** (0.03)	−0.04 (0.03)
Female	−0.01** (0.00)	−0.01** (0.00)	−0.01** (0.00)	−0.01* (0.00)	−0.01** (0.00)	−0.01* (0.00)	−0.01* (0.00)	−0.01* (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*** (0.03)	0.63*** (0.03)	0.62*** (0.03)	0.62*** (0.03)	0.63*** (0.03)	0.63*** (0.03)	0.63*** (0.03)	0.62*** (0.03)
First Gen	0.01 (0.01)	0.02 (0.01)	0.02* (0.01)	0.02** (0.01)	0.02* (0.01)	0.02** (0.01)	0.02* (0.01)	0.02** (0.01)
Second Gen	0.02 (0.01)	0.02 (0.01)	0.01 (0.01)	0.02 (0.02)	0.02 (0.02)	0.02 (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.2: 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*** (0.03)	-0.05 (0.04)	-0.08** (0.03)	-0.08** (0.03)
Female	-0.01* (0.00)	-0.01 (0.01)	0.00 (0.00)	-0.01 (0.01)
College Graduate: Mother	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)	0.03 (0.02)
College Graduate: Father	0.01** (0.01)	0.02** (0.01)	0.00 (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 \times 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 \times 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.3: Relationship Between Bias and Self-Reported Asian identity Among Second-Generation Asian Immigrants: By Parental Type

Parents Type	Both Parents		Father	Mother
	All	from Asian Country	from Asian Country	from Asian Country
		(AA)	(AW)	(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.4: Logistic Regression Analysis of Bias and Interracial Marriages

		Asian Men	Asian Women
	(1)	(2)	(3)
	Interethnic	Interethnic	Interethnic
Bias	0.38*** (0.11)	−0.19 (0.16)	0.33** (0.14)
College Graduate: Wife	0.35*** (0.04)	0.44*** (0.06)	0.56*** (0.05)
College Graduate: Husband	−0.06 (0.04)	−0.03 (0.06)	−0.15*** (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 (5) as a logistic regression. The coefficients are exponentiated, thus should be interpreted as odds ratios.

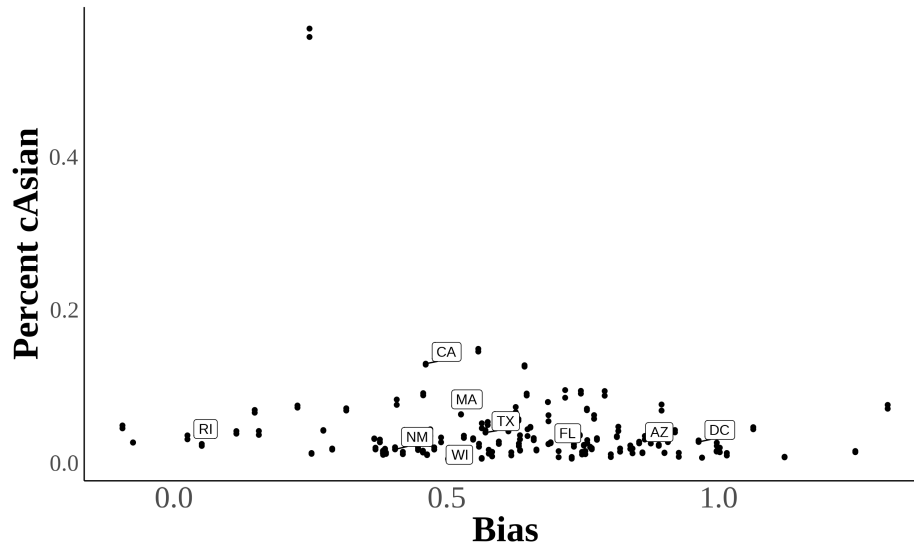
² I include controls for partners' sex, age, education, and years since immigrating to the United States. Standard errors are clustered on the household level.

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

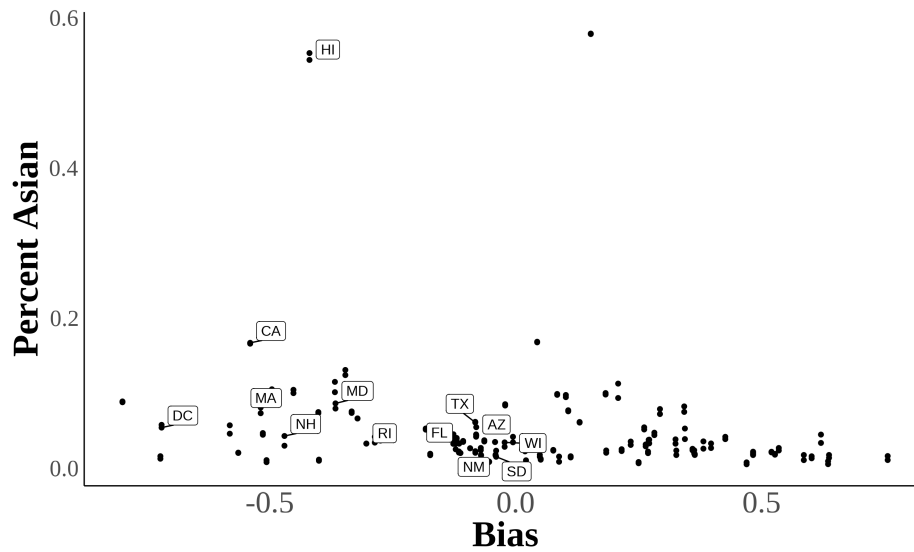
C Figures

Figure A.2: Scatter Plot of Proportion Subjectively Asian on Bias

(a) Year < 2015



(b) Year \geq 2015



Here are two scatter plots showing the relationship between bias and subjective Asian population in a state. Each dot represents a state in a certain year. Percent subjectively Asian = $\frac{\#Asian}{Population}$

Source. 2004-2021 Current Population Survey.

C.1 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-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:

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

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 :

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

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

References for Online Appendix

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>.