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

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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

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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.

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.

[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.

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 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

[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).

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).

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, 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 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 examine 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.

The rest of this paper proceeds as follows. First, I discuss the theoretical framework in section (2). Second, I describe the data sources in section (3). Third, I present the empirical approach and results in sections (4) and (5). Fourth, I discuss robustness checks and alternative explanations in section (6). Finally, I conclude in section (7).

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 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:

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

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 $\frac{dI_i}{da_i} \neq 0$ and $\frac{\partial U_i}{\partial I_i} \neq 0$. This framework suggests empirical analysis

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

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 genera-

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

tions. 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, 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.[5] 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.[6] 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 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

[5] I restrict first-generation cases to those whose parents were born in Asian countries to exclude US citizens born abroad to American parents.

[6] 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.

Asian Americans, I document significant attrition among third-generation Asian Americans.[7] Table (2) displays these patterns: most first- and 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.[8] 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 Black Americans. ANES, conducted since 1948, enjoys widespread political science usage. The survey examines attitudes to-

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

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

ward 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.[9]

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.[10] 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).

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:

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

Where A^g_{ist} 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 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.[11] Additionally, γ_{rt} represents region-time fixed effects controlling for region $\times$

[9] 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."

[10] Additional methodological details appear in the Data Online Appendix, Section C.1.

[11] 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.

year specific shocks.[12] Region × 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 × 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 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

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

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:

$$\mathtt{interracial}^2_{ist} = \beta^2_1 \mathtt{AntiAsianBias}_{st} + X^2_{ist}\pi + \gamma_{rt} + \varepsilon_{ist} \tag{5}$$

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 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 husband 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:

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

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

Where $\mathtt{BirthPlaceMigration}^2_{ist}$ indicates whether person i in state s at interview t lives in states different from birth states. $\mathtt{BirthPlaceMigration}^2_{ilb}$ 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 $\mathtt{BirthPlaceMigration}^2_{ist}$. Second specification from equation (7) estimates relationships between average bias in birth state l at birth year b and $\mathtt{BirthPlaceMigration}^2_{ilb}$.

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

$$Y_{ist} = \beta_0 + \beta^2_1 \mathtt{Asian}_{ist} + X^2_{ist}\pi + \varepsilon_{ist} \tag{8}$$

Where $Y_{ist} \equiv \mathtt{AntiAsianBias}_{ist} - \mathtt{AntiAsianBias}_{ilb}$, $\mathtt{AntiAsianBias}_{ist}$ represents i's anti-Asian bias in state s at interview time t, and $\mathtt{AntiAsianBias}_{ilb}$ 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.[13]

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

[13] 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.

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.

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.

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.

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, Dolly Chugh, and Sendhil Mullainathan. 2005. "Implicit Discrimination." *American Economic Review* 95, no. 2 (May): 94–98. https://doi.org/10.1257/000282805774670365.

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.

Carlana, Michela. 2019. "Implicit Stereotypes: Evidence from Teachers' Gender Bias." *Quarterly Journal of Economics* 134, no. 3 (August): 1163–1224. https://doi.org/10.1093/qje/qjz008.

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.

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.

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.

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: Asian Self-identification by Generation

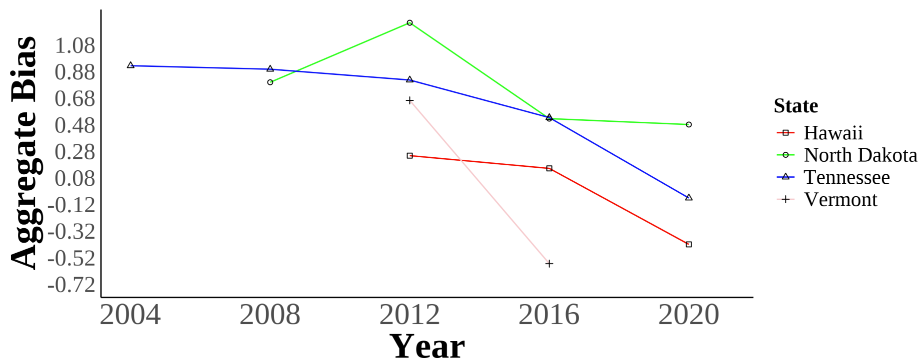
	Self-identify as Asian	Self-identify as non-Asian	% Self-identify as Asian	% Self-identify as non-Asian
1st Gen.	14,811	688	0.96	0.04
2nd Gen.	58,756	21,381	0.73	0.27
Asian on:				
Both Sides	49,118	1,717	0.97	0.03
One Side	9,638	19,664	0.33	0.67
3rd Gen.	10,394	23,048	0.31	0.69
Asian on:				
Both Sides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

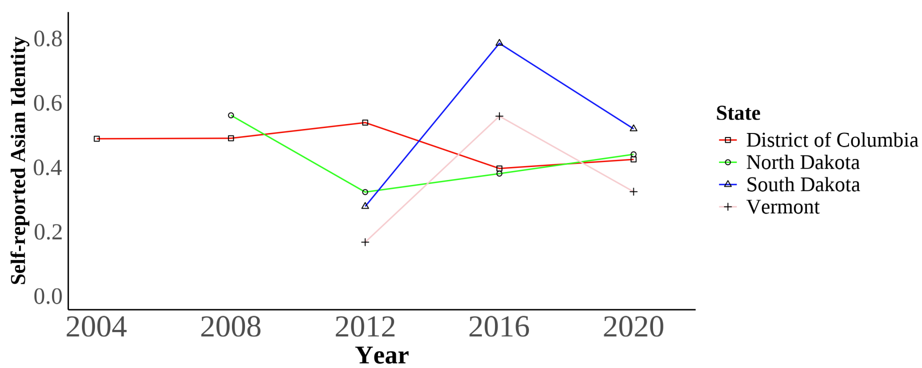
[2] Data source is the 2004-2021 Current Population Survey.

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 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 2: Diagram of the Three Different Generations of Asian Immigrants.

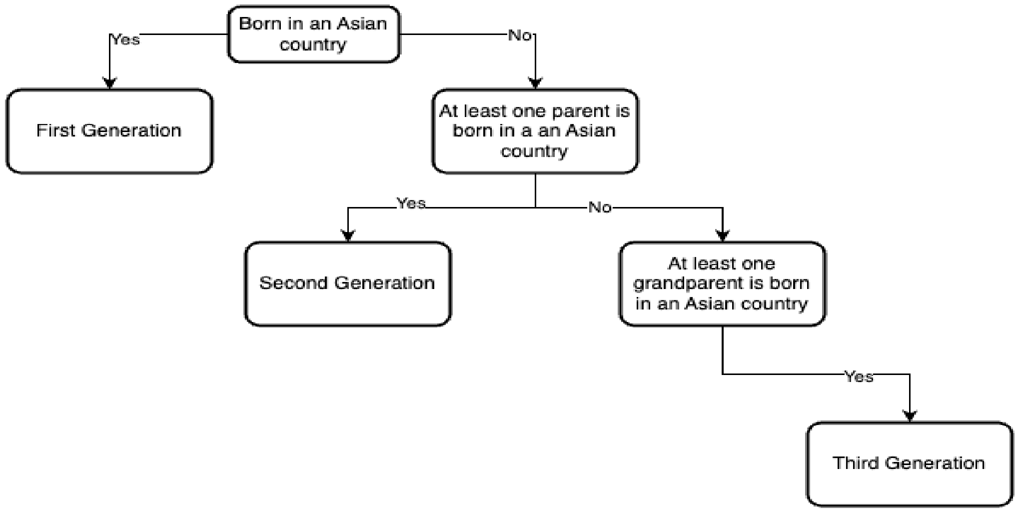
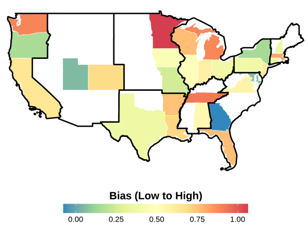
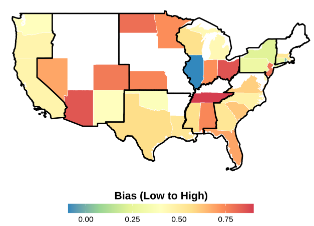


Figure 3: Maps of State-level Association Test Bias Over Time Measure with Census Division Regional Boundaries

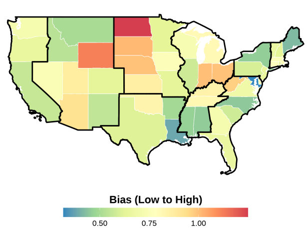
(a) State-level Bias in 2004



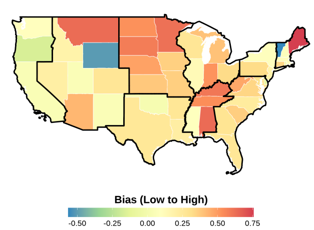
(b) State-level Bias in 2008



(c) State-level Bias in 2012

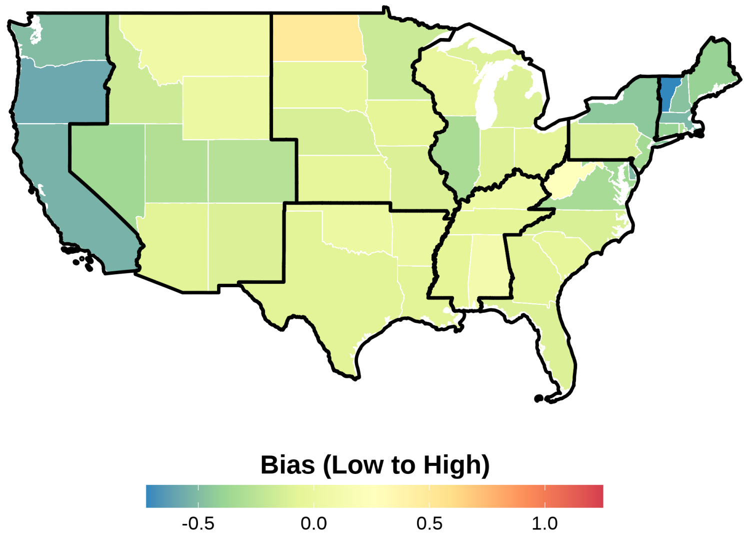


(d) State-level Bias in 2016



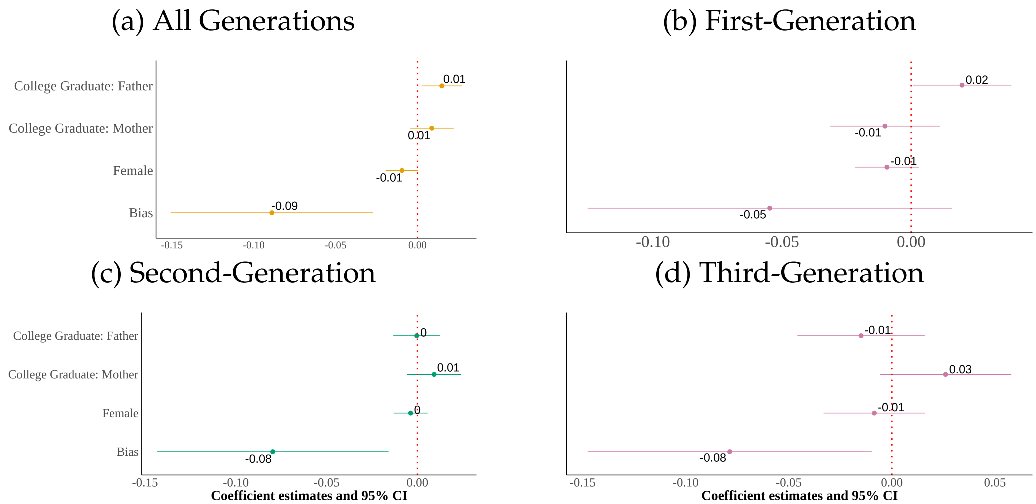
This figure shows the state-level bias index in different years in the sample. The bias units are in standard deviations and ranges from low to high bias. Bias index is constructed following Lubotsky and Wittenberg (2006). The data is from the 2004-2021 Harvard's Project Implicit Association Test scores,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

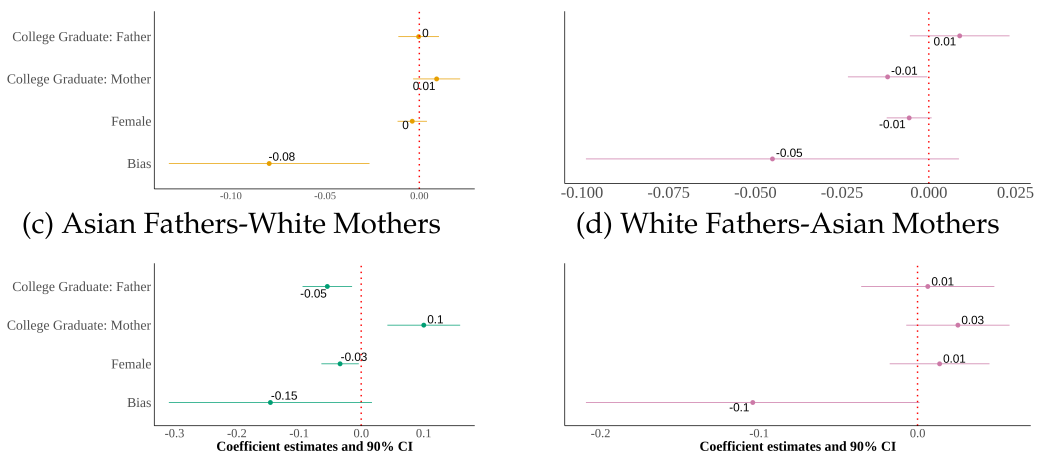


I show four panels of estimating equation (4). I include region × year fixed effects with controls for sex, quartic age, and parental education. The dependent variable is self-reported Asian identity and the independent variable is state-level bias. Each panel is the results from the same regression 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

(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 × 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) 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 4: 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 (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) $\mathtt{Bias}_{\mathtt{ist}} - \mathtt{Bias}_{\mathtt{ilb}}$
$\mathtt{Bias}_{\mathtt{st}}$	0.13*		
	(0.07)		
$\mathtt{Bias}_{\mathtt{lb}}$		-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 × Region FE	X		
Birthyear × 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 × 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.

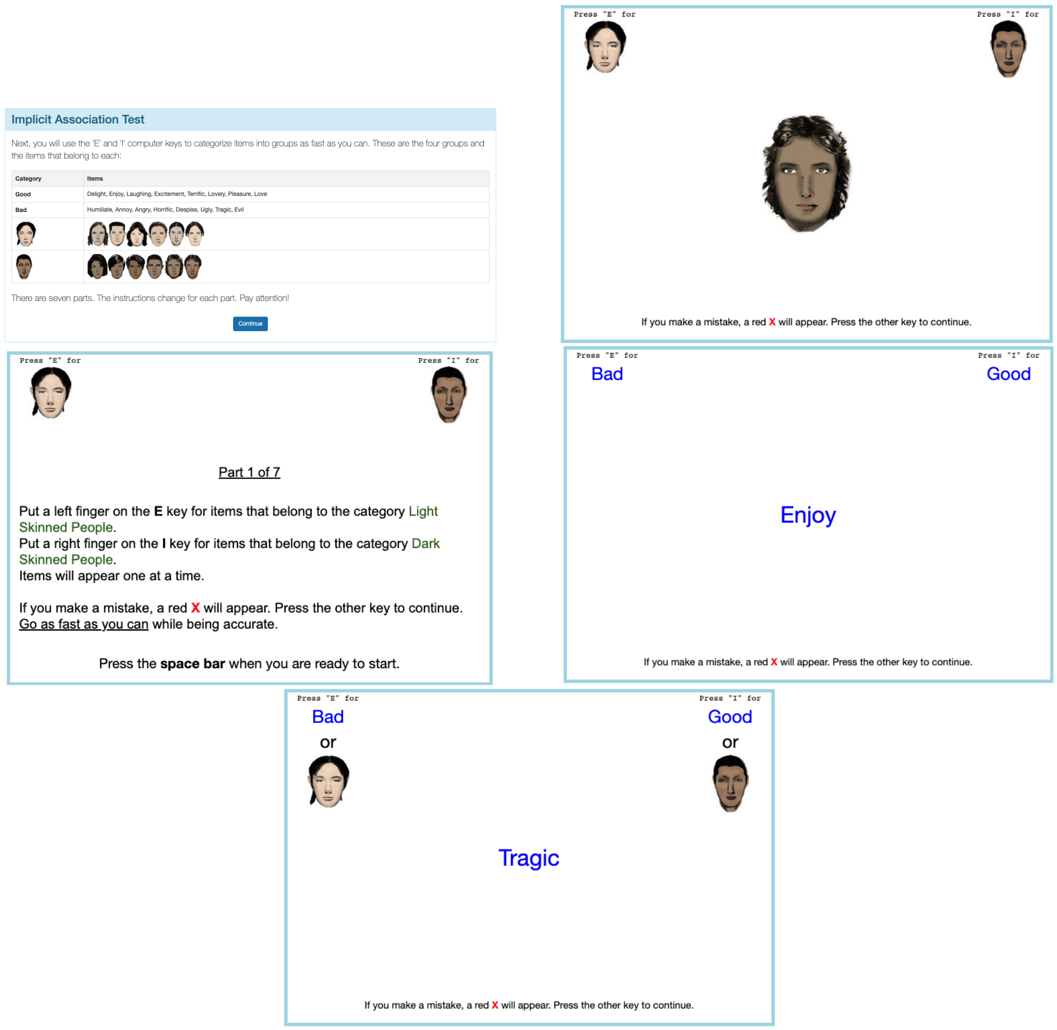
ONLINE APPENDIX

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

Hussain Hadah

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) 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.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***	-0.05	-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.3: 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) A^2	(2) A^2	(3) A^2	(4) 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) 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 (5) as a logistic regression. The coefficients are exponentiated, thus should be interpreted as odds ratios.

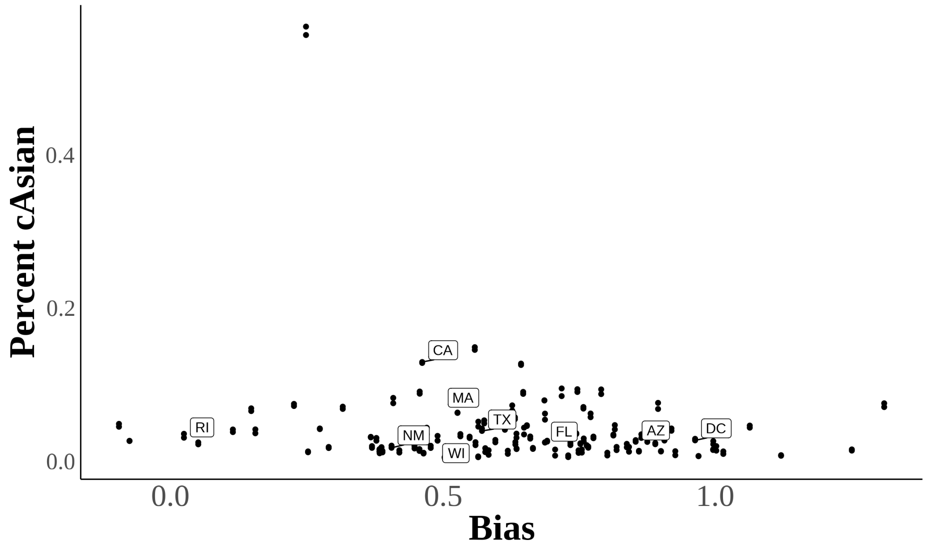
[2] I include controls for partners' sex, age, education, and years since immigrating to the United States. Standard errors are clustered on the household level.

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

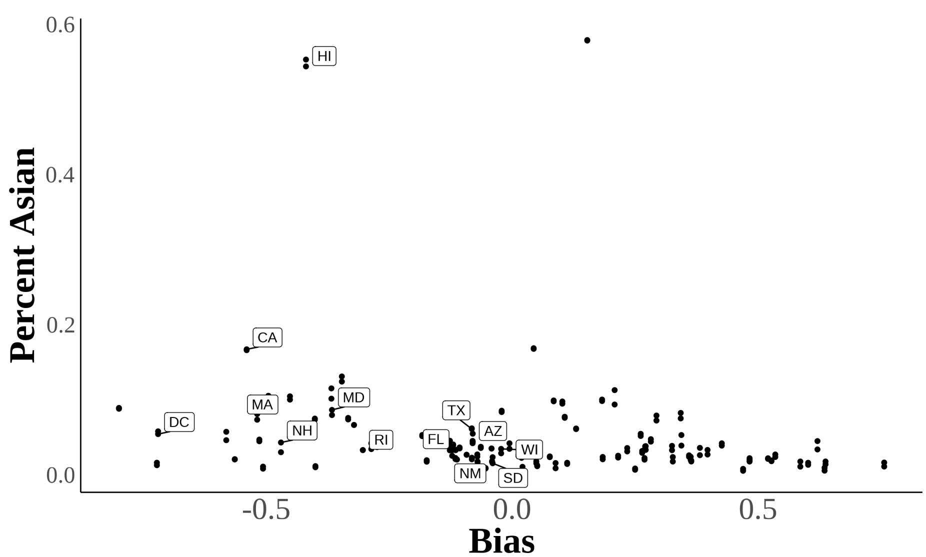
C Figures

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

(a) Year < 2015



(b) Year $\geqslant$ 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 = $\frac{\#\text{Asian}}{\text{Population}}$
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:

$$\begin{aligned} y &= \alpha + \beta x^* + \epsilon \\ x_1 &= x^* + \mu_1 \\ x_2 &= x^* + \mu_2 \end{aligned}$$

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.