White Flight from Asian Immigration: Evidence from California Public Schools*

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Abstract

Studies of white flight from racial minorities rarely distinguish Asians as a unique minority group, despite their heterogeneous economic and educational outcomes, which may imply that whites react differently to the arrival of Asian vs. other minority immigrants. This paper develops a spatial model of white school-district residence decisions to generate empirically testable predictions about whites' response to the arrival of Asian students in their district. Using California public schools as a case study, our empirical analysis reveals that the arrival of one Asian student leads to 2.6 white departures. We further find suggestive evidence that this flight is mainly due to whites' aversion to school with stereotypically higher-achieving Asian peers rather than to the positive preferences they may have for improved school quality.

1 Introduction

Asian Americans have been the fastest-growing racial group in the United States over the past couple of decades: their population increased by 72% between 2000 and 2015, that is, 12 percentage points higher than Hispanic Americans, the second fastest-growing racial group (Pew Research Center, 2017, 2019).

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At the same time, Americans' long-lasting distaste for racial diversity has led to persistent racial segregation across U.S. neighborhoods, labor markets and schools[1].[2] This racial segregation can partly be explained by "white flight," i.e., the departure of whites from areas increasingly populated by non-white minorities. A large body of economic literature has focused on identifying the existence, magnitude, and mechanisms of white flight in response to in-migration of Blacks and Hispanics.[3] However, we do not know much about flight in response to inflows of Asians.

This paper investigates the extent to which the arrival of Asian students in a school district cause white students to leave the public school system in that district. We present a theoretical model of white spatial location decisions in response to Asian enrollment inflows, and empirically test these predictions to distinguish between three potential channels: (i) racially-agnostic white departures due to bid-up housing prices, (ii) pure racial distaste for Asians, and (iii) aversion to educational competition with stereotypically higher-achieving Asian peers.

Our empirical analysis uses Californian public school districts over the 2001-2016 period as a case study to explore whether or not white flight exists, and to what degree and the direction, as well as the mechanisms behind flight. California constitutes a very interesting and relevant case for our purpose because it has the largest Asian American population in the U.S., with more than six million people – that is, slightly more than 15% of the total population of the state (U.S. Census Bureau, 2019); it is in fact the home to one-third of the total Asian population in the U.S. (Pew Research Center, 2017). We focus on its public school districts because, in addition to its publicly available data, there exists substantial variation in Asian population shares across that state (ranging from Asian "ethnoburbs" in the San Francisco Bay and Los Angeles Areas (Li, 2009; Lin and Robinson, 2005) to rural areas with minimal Asian residents), and there is anecdotal evidence of educational competition-drive white flight in its public school system (see Section 2 for more details).

To identify a causal relationship between the enrollment of new Asian students and the departure of white students, we use a predicted-flow shift-share instrument (also known as "Bartik instrument"), which was pioneered by Card (2001) and is now common in the im-

[1]Despite the fact that racial segregation in U.S. public schools has been illegal since the Supreme Court's 1954 *Brown vs. Board of Education* decision, today "more than half of the nation's schoolchildren are in racially concentrated districts, where over 75% of students are either white or nonwhite" (New York Times, 2019).

[2]See for example Cutler, Glaeser, and Vigdor (1999), Card, Mas, and Rothstein (2008) and Zhang (2011) for neighborhoods, Higgs (1977), Carrington and Troske (1998) and Hellerstein, McInerney, and Neumark (2011) for labor markets, and Caetano and Maheshri (2017) for schools.

[3]See, for example, (Boustan, 2010) for white flight from inflows of Blacks and (Cascio and Lewis, 2012) for white flight from inflows of Hispanics; both papers are briefly discussed later in this section.

migration literature (see Jaeger, Ruist, and Stuhler (2018) for a recent review). Without this instrumental-variable method, the causality would be less clear because district migration is a function of not just white but also Asian location decisions. The idea behind our instrument is to use the historical migration patterns from Asian countries as a supply-push ("shift") component of inflows to a particular school district, and to exploit the variation in the initial settlement of Asians in California as a demand-pull ("share") component. More specifically, this instrument uses tract- and county-level population counts and national new immigrant inflows to assign predicted flows of Asian immigrants according to established settlement patterns in California. The key assumption underlying the instrument is that new immigrants are attracted to districts where existing Asian communities already exist. Thus, given an initial exogenous settlement of Asians throughout California, future Asian settlement patterns can be decomposed into an endogenous portion (based on future economic, public utility, schooling, or other factors) and an exogenous portion (based on the tendency of immigrants to settle in immigrant enclaves).

To conduct our analysis, we combine school-enrollment data from the California Department of Education (DOE) with population data from the U.S. Census Bureau and the Homeland Security Yearbook of Immigration Statistics. We use the California DOE data to obtain enrollment counts by ethnic group in all of the state public schools for each academic year between 1981 and 2017, for grades K-12. The population data enable us to construct our shift-share instrument. From the U.S. Census Bureau, we get data on school district boundaries as well as decennial Census tract data on population by racial category. In addition, we use the Homeland Security Yearbook of Immigration Statistics data to obtain yearly inflows of immigrants by country of origin up to 2016 and national population levels of Asians by country of origin.

Our main empirical finding indicates that there exists white flight in Californian public schools over the 2001-2016 period. Our causal estimates suggest, however, that the white displacement occurs only in suburban areas. In particular, on average, each newly enrolled Asian student causes the departure of approximately 2.6 white students in these areas.

Further analyses indicate that it is richer white students who tend to flee, in spite of the fact that the arrival of Asian students improves school quality in their district. These results suggest that beyond pure white racial distaste for Asians, whites' aversion to educational competition with their typically higher-achieving Asian peers is stronger that the preference they may have for improved school quality. This proposed explanation is also confirmed by anecdotal evidence from newspapers and online reviews (see Section 2 for more detail).

We conclude our analysis by providing suggestive evidence that this observed white flight is not due to an increase in housing prices caused by the arrival of new Asian families. The fact that we find that the presence of white displacement only in school districts that have on average grown over time (in terms of their student population sizes) suggests that bid-up housing prices is not the main cause behind the observed flight. Indeed, housing supply is likely inelastic only in the short run, so as the population grows, it should adjust to housing demand so that housing prices do not increase that much.

Our study makes three main contributions to the literature. First, we add to the economic literature on white flight from non-white minorities, by studying flight from Asians, a racial group that has so far either been ignored or been treated as a homogeneous group alongside Blacks and Hispanics, despite their heterogeneous economic and educational outcomes. Second, our paper contributes to the general body of academic work on Asian Americans, of which very little dedicated economic knowledge exists. Studying the dynamics between Asians and whites in the U.S., especially in the context of Asians' unique immigration history and trajectory of income and education growth, is imperative to understand a growing and increasingly significant – both in numbers and in economic, social, and cultural impact – subset of the American population. Third, this paper also adds to knowledge of the Card (2001) shift-share instrument. Though widely used to predict aggregate new immigrant inflows to the U.S. from past immigrant settlement, often from 1970 or earlier, we find that new Asian settlement cannot be predicted from initial settlements even as late as 1990 in California. This result suggests that the underlying logic that later cohorts are drawn to settle in existing immigrant enclaves may often fail for Asians if initial base years are too early – and that existing papers which construct the shift-share instrument for aggregate U.S. immigration likely fail to get any "bite" from migrants from Asian countries of origin.

Our work relates to several past studies on white/native flight.[4] Most papers that study that phenomenon measure the direct displacement of white residents by minority entrants (Card, 2001; Boustan, 2010; Cascio and Lewis, 2012) or estimate tipping points, at which majority-white neighborhoods "tip" beyond a certain tolerated minority share to become majority-minority (Card, Mas, and Rothstein, 2008; Zheng, 2013; Blair, 2016). Our paper is most closely related to the former strand of the literature. We here only refer to papers that have in common with our study the use of a shift-share instrument as part of their identification strategy. Card (2001) uses the 1985 geographic distribution of immigrants who entered the U.S. between 1975-1984 to predict inflows between 1985-1990 from 17 source countries. Boustan (2010) studies the Black migration from the rural South to industrial cities in the North and West of the U.S. during the postwar suburbanization. She finds that on average, the arrival of a Black resident caused 2.7 whites to leave the city. Cascio and Lewis

[4] See Jaeger, Ruist, and Stuhler (2018) for a comprehensive review on the use of shift-share instruments in the migration literature.

(2012) examine the native flight from low-skilled Hispanic immigration in California between 1970-2000. In isolating native flight due to reduction in public school demand and not to other immigrant-related factors, they estimate that the average California school district lost 1.4 non-Hispanic households for every additional household enrolling low-English Hispanic schoolchildren. Other studies also use a shift-share instrument but to analyze *native* flight. In the context of the United Kingdom, Sá (2015) investigates the effect of immigration on housing prices and finds that immigrants negatively affect housing prices. She explains this negative effect by the fact that richer natives move to other areas, which decreases housing demand and thus housing prices too. Murray (2016) and Farre, Ortega, and Tanaka (2018) examine the native flight from public schools to privates ones in response to the rising enrollments of foreign-born students in the U.S. and in Spain, respectively. In the U.S., Murray (2016) finds that there exists native flight to private schools, but that flight among white native students occurs in smaller school districts located in states that did not traditionally received immigrants whereas flight among native minorities and Hispanics occurs instead in school districts located in states that traditionally received immigrants. In Spain, Farre, Ortega, and Tanaka (2018) find that tuition-free, public schools with a higher concentration of immigrants tend to generate native flight towards private ones.

2 Trends in Asian Immigration in the U.S.

Large-scale Asian immigration to the United States is still a fairly nascent phenomenon, having only begun to reach substantive levels within the last century. While the first waves of Asian immigrants were low-income and low-educated, the recent waves came from more diverse socio-economic backgrounds (see Appendix A for more detail about the history of Asian migration waves to the U.S.).

The patterns of Asian immigrant settlement have changed over time (Li, Skop, and Yu, 2007). Asian migrants used to settle in central city enclaves, such as "Chinatown," "Little Tokyo," or "Manilatown." Today these traditional enclaves no longer absorb the majority of Asian newcomers. Perhaps surprisingly, Asian Americans, unlike other racial minority groups, exhibit an intriguing pattern of rapid rate of suburbanization in the United States. Indeed, a lot of Asian immigrants no longer consider the often run-down and crowded neighborhoods in central cities as their ideal places to live. Instead, Asian newcomers, especially those who belong to the middle and upper classes, tend to avoid central city enclaves because they can afford to settle directly in suburbs, which typically offer superior living conditions and public amenities, decent housing, and high-performing schools.

This change in Asian immigrant settlement patterns is particularly true in California, where one-third of the total Asian population in the U.S. live today. Using Asian student enrollment in Californian public schools as a proxy for Asian settlement in California, Appendix Figure B.1 shows that California has a higher share of Asians than the rest of the U.S.. However, both in California and the U.S., the Asian enrollment has grown in suburban areas. Focusing on California, Figure 1 shows that the share of Asian students in suburban areas has been steadily growing over time, from approximately 6.5% to almost 14% between 1981 and 2017. By contrast, the share of Asian students in rural areas remained low (below 3%) whereas the share of Asian students in urban areas increased starting in the 1980s, then stagnated before steadily falling from the mid-1990s onwards.

In some school districts, the shares of Asian students have grown rapidly over time, sometimes reaching more than 60% of the student body in a given school district, as displayed in Figure 2. That figure also shows that the shares of white students decrease at more or less the same rate as the Asian shares increase, if not more rapidly.

One can therefore wonder how white families would react to the arrival of Asian students in their school district. On the one hand, white flight could occur "mechanically," simply because of market forces in the housing market – i.e., the arrival of new Asian families leads to an increase in the demand for housing, which in turn raises housing prices because housing supply is inelastic at least in the short run and may make housing less affordable for white families. On the other hand, the literature on white flight from Black and Hispanic neighborhoods suggests that beyond just pure racial animus, whites associate inflows of these minorities with lower income and lower quality of public education; thus white families move away to higher-achieving, higher-income neighborhoods. However, if so, given that Asian American educational attainment and median income are significantly higher than the overall U.S. population's,[5] would not there be white *attraction* to Asian neighborhoods? The answer seems to be that too much of a good thing is no longer a good thing.

According to news articles that document white flight in schools across the country from California to New Jersey, flight may be driven by *too much* academic achievement. For example, as early as 2005, a *Wall Street Journal* column attributed the rapid drop in white enrollments (by almost half over the 1995-2005 period) in Cupertino and San Jose, California to the rise of the high-tech industry in Silicon Valley, which transformed previously more rural, whiter communities into suburbs teeming with Chinese and South Asian immigrant engineers and their families (Wall Street Journal, 2005). That column also documents that "many White parents say they're leaving because the schools are too academically driven

[5] In 2015 slightly more than half of Asian Americans aged 25 or older have at least a Bachelor's degree, compared to roughly a third of the U.S. population; and, Asian American median household income was approximately $73,000 in 2015, compared to $53,6000 for the overall U.S. population (Pew Research Center, 2019).

and too narrowly invested in subjects such as math and science at the expense of liberal arts and extracurriculars like sports and other personal interests [...]. The two schools, put another way that parents rarely articulate so bluntly, are too Asian." Interestingly, it adds: "Top schools in nearby, whiter Palo Alto, which also have very high test scores, also feature heavy course loads, long hours of homework and overly stressed students [...]. But whites don't seem to be avoiding those institutions, or making the same negative generalizations [...], suggesting that it's not academic competition that makes white parents uncomfortable but academic competition with Asian-Americans." In the same vein, a recent *Los Angeles Times* column reports about Irvine, California: "For white residents of Irvine, the boom has brought much to like – rising home values, stellar test scores and an explosion of ethnic restaurants, cultural celebrations and retail spaces that have brought international sophistication to a place once known as cookie-cutter suburbia." (Los Angeles Times, 2017). Similar reports from Rockville, Maryland (Wall Street Journal, 2005), Tenafly, New York (Wall Street Journal, 2005), Johns Creek, Georgia (Pacific Standard, 2017),[6] and Princeton, New Jersey (New York Times, 2015) echo these sentiments and show that white flight from academically high-achieving Asian "ethnoburbs" (a term first coined by Li (2009)) is not limited to California.

Online reviews of high schools on Yelp confirms non-Asian parents' aversion to sending their kids to schools with a high share of Asian students because of the stereotype that they are excessively competitive and single-minded. One review about a high school in San Jose, California reads: "White kids with good grades get looked at like they have "passing" grades, while Asian kids with "passing" grades seem to be looked at as invalids. The school was 75% Asian in 2005 so... you can draw your own conclusions as to how this will factor into your or your child's experience here." (Yelp, 2011) Another review about a high school in Saratoga, California reports: "The pressure seemed to make [Saratoga High School] one of the top schools in the state but now it's just about band kids and generic asians. Everyone has a 4.0, and anything below is considered a failure. The tradition the school once had has been lost. [...] The school completely lacks spirit, homecoming week used to be the biggest week of the year and the entire school would show up to decorate, now people stay home to study for SATs or just don't care at all." (Yelp, 2008).

Thus far, we have presented qualitative and anecdotal evidence that white flight exists in multiple Asian ethnoburbs and seems to be primarily driven by academic competition from

[6] The column from the *Pacific Standard* reports concerns of a parent who lives in Johns Creek, Georgia: "Nora's good at math. There are too many kids here good at math. They're affecting her self-esteem. Asian parents take their kids for extra tutoring. It's not fair for the "regular" kids. The high school is too competitive. My kids won't get into a good college because of all of the Asians. I want my children to grow up in the real world. This is not the real world." (Pacific Standard, 2017).

rising Asian enrollment. We next lay out a spatial model to rationalize this phenomenon.

3 Spatial Model to Explain White Flight

In this section, we present a theoretical model of white spatial location decisions in response to an Asian inflow, in order to generate testable empirical predictions (which we summarize in Appendix Section C). The following simple theoretical model follows from similar exercises by Boustan (2010) and Cascio and Lewis (2012).

Suppose white households are exogenously assigned to different regions (e.g., by job opportunities) and within each region, choose a school district to reside in. The utility associated with a school district for a white household is:

$$U(p, k, z) = \bar{u} \tag{1}$$

where p denotes the price of housing, k denotes the Asian share of district enrollment, and z denotes the quality of public schools. Let total district enrollment be $L = W + A + O$, where W, A, and O are the district's enrollments of white, Asian, and other ethnic groups, respectively. U is decreasing in housing price p. The price of housing is a function of the number of households in the district, which can be proxied by total district enrollment L, and is determined specifically by the price elasticity of housing supply. We assume that U is (weakly) decreasing in the Asian share of district enrollment, $k = A/L$, and (weakly) increasing in public school quality z. Further, we also model z as a function of k; that is, we assume that the quality of a public school depends on its Asian enrollment.

In equilibrium, no household can increase its utility by moving to another district; that is, $\bar{u} = u$ for the next highest utility u which the marginal household would experience if it chose to move to a different school district in its pool of choice. The model implies that a district with high school quality (which increases household utility) must also have a compensating characteristic, such as higher housing costs (which decreases household utility). Note that the same basic model in (1) drives Asian residential choices. We address this identification problem with the instrumental-variable approach described below in subsection 4.1. Given this decomposition of Asian settlement into exogenous and endogenous demand, in spatial equilibrium, all white households prefer their district of residence to all others in their pool of choice (within a given geographic region). In each district there exists an equilibrium housing price p^*, equilibrium Asian share of enrollment k^*, and equilibrium level of public school quality z^*.

Now suppose a district receives an inflow of Asian students. What does this model imply for the number of whites that will leave (or enter) the district? First, assume that white utility neither directly responds to Asian enrollment ($\partial U/\partial k = 0$), nor indirectly responds via school quality ($(\partial U/\partial z)(\partial z/\partial k) = 0$, either because white utility is indifferent to school quality, or because Asian enrollment does not affect school quality, or both). If housing supply is not perfectly elastic, the population growth from the inflow will lower white demand by raising housing costs ($(\partial U/\partial p)(\partial p/\partial k) < 0$). The spatial equilibrium is only restored to p^* (assumed to be a function of total district population) after an Asian inflow if there is exactly a one-to-one displacement of white students in response to Asian students (Boustan, 2010). Hence, if whites' district demand is only affected by the population inflow through the housing price channel, regardless of the race of the new immigrants, the model predicts one white departure when one new Asian resident arrives. Now, assume that whites exhibit distaste for Asian students in schools ($\partial U/\partial k < 0$) and are still unaffected by school quality ($\partial U/\partial z = 0$). Then white demand will decrease even further, and we expect more than one white departure for every Asian departure in this situation, as compared to the first.

We now add the final assumption that white utility is increasing in school quality ($\partial U/\partial z > 0$). If Asians do not affect the quality of public schools ($\partial z/\partial k = 0$), then the prediction is unchanged from the prior one (as $(\partial U/\partial z)(\partial z/\partial k) = 0$). If Asians decrease the quality of public schools (if $\partial z/\partial k < 0$, such that $(\partial U/\partial z)(\partial z/\partial k) < 0$), then even more whites will depart in response to an Asian inflow. However, if Asians improve the quality of public schools (if $(\partial z/\partial k) > 0$, such that $(\partial U/\partial z)(\partial z/\partial k) > 0$), then white demand may actually *increase*, depending on how much whites care about school quality and how much quality changes in response to Asian enrollment. Whereas most literature assumes that inflows of other non-white minorities negatively impact school quality amenities, evidence that Asian Americans attain higher levels of education and at higher rates than whites in the United States (Pew Research Center, 2019) supports the assumption that Asians may raise the quality of public education, given that students experience academic peer effects (Hoxby, 2000; Sacerdote, 2001; Abdulkadiroglu, Pathak, Schellenberg, and Walters, 2019).[7] This potentially countervailing response means that even the direction of white migration in response to an Asian inflow is uncertain. In this theoretical setup, we tentatively assume that Asians improve the quality of public schools ($\partial z/\partial k > 0$); we empirically test this assumption later in Section 6.

While the economic literature suggests that household utility is increasing in school qual-

[7]Claiming that all Asians are more highly-educated obscures well-documented heterogeneity between East and South Asian immigrants (e.g., Chinese, Japanese, Korean, Asian Indian, Singaporean) and Southeast Asian immigrants (e.g., Filipino, Vietnamese, Laotian) (Pew Research Center, 2019). However, as our enrollment dataset's definition of Asian primarily encompasses the former group, we assume that $\partial z/\partial k > 0$ holds true for our sample of interest.

ity (Black, 1999; Deming, Hastings, Kane, and Staiger, 2014; Abdulkadiroglu, Pathak, Schellenberg, and Walters, 2019), the qualitative evidence we present in Section 2 indicate that some white parents dislike the new educational achievement and competition that Asian students bring into the classroom. We reconcile this response by arguing that this observed preference is not a preference against higher public school quality, but just one potential component of distaste for Asian students. The relationship $\partial U/\partial k < 0$ thus encompasses a distaste for Asian-specific educational values, cultural practices, or simply racial prejudice.

Our model is unique in the literature in that it incorporates the opposing forces of whites' negative preference for Asian diversity and positive preference for academic quality, and that even the direction of white flight is ambiguous without empirical evidence of each force's effect on whites' utility. Note that we model the decision to migrate as a household decision, but we measure the displacement of individuals. We also study the entrances and exits of students, not residents. Nevertheless, these predictions serve as a useful starting point for how to think about the magnitude and direction of results in the following sections.

4 Shift-Share Instrument to Identify the Causal Effect of Asian Student Arrivals on White Student Departures

4.1 Identification Strategy

To examine the migration response of white students to the arrival of Asian students,[8] we begin by estimating a linear relationship between the number of Asian public school students ($Asian_{d,t}$) and the number of white public school students ($White_{d,t}$) in school district d and year t, loosely based off of the specification in Boustan (2010):

$$White_{d,t} = \alpha_0 + \alpha_1 \cdot Asian_{d,t} + \alpha_2 \cdot Total_{d,t-1} + \pi_t + \delta_d + \epsilon_{d,t} \tag{2}$$

We control for initial trends by including year and district fixed effects (π_t and δ_d, respectively). We also control for the total enrollment of a school district in the previous year ($Total_{d,t-1}$), as growing regions will likely attract large flows of both white and Asian mi-

[8]Throughout the analysis conducted in this paper, unless otherwise mentioned, we will exclude from our definition of "Asian students" individuals who self-identified as Filipino and Pacific Islander. There exists indeed some evidence these populations are not as successful in school as, say, students with Eastern and Southeastern Asian origins (Paik, Kula, Saito, Rahman, and Witenstein, 2014; Lung-Amam, 2017; Oakley, 2019; Pew Research Center, 2019).

grants.[9] We explain in Appendix Section D why we choose to estimate the relationship in levels rather than between first differences, as is more common in the immigration displacement literature.

Nonetheless, the ordinary least-square (OLS) specification only provides an associative relationship between White and Asian enrollment; it does not claim the causality needed to establish directional white flight from Asian arrivals. For instance, if Asians prefer to locate in districts with low White populations, then any negative associations found would not be driven by white flight but instead by Asian demand, implying reverse causality. Also, Asian families might sort into ethnic enclaves because of, say, the network they have there, which might help them get job opportunities. By not accounting for sorting patterns and potential reverse causality, our estimated effect may be biased towards zero.

To establish causality in the direction of White flight in response to Asian arrivals, we employ an instrumental-variable (IV) strategy, which uses a shift-share instrument. The logic behind our predicted flows shift-share instrument, first introduced by Card (2001) and now classic in the immigration literature, is to instrument for the endogenous settlements with the supply-push component of migrant flows, which is arguably exogenous to the demand-pull component. The exogeneity argument follows from the assumption that new immigrants are drawn to settle in enclaves established by earlier immigrants from the same source countries. This settlement pattern occurs due to information networks between immigrants and their source countries, which aid the job search and assimilation processes (Munshi, 2003). Picking an early enough year to base the predicted flows off of ensures that the instrument estimates the number of immigrants who would have settled in a district based on historical settlement, absent any current local demand forces.

To our knowledge, our paper is the first to construct and assess the validity of the predicted flows instrument using only Asian countries of origin over this time period. The existing literature finds the predicted flows instrument to be strongly relevant to actual flows, mostly in predicting long-term (decade-long or greater) changes in immigrant populations in the latter half of the 20th century. Previous papers primarily either look at aggregate flows from all Census countries of origin or at Hispanic population flows from Mexico into the U.S. (see, for example, Card (2001); Saiz (2007); Boustan (2010); Cortes (2008); Peri and Sparber (2009); Lewis (2011); Cascio and Lewis (2012); Ottaviano, Peri, and Wright (2013); Foged and Peri (2016)).[10]

[9]We include lagged total enrollment rather than total enrollment in the same year, as doing the latter will lead to an estimate of a mechanical effect of Asian arrivals on white population rather than true displacement (i.e., given a fixed total number of students in a school district, an increase in the size of one group must lead to a decrease in the size of another).

[10]This shift-share instrument is widely used not just in the literature on immigration impacts on native outcomes, but also in studying innovation, education, crime, and productivity. For an exhaustive list, see

To construct our shift-share instrument, we first compute the predicted inflow of Asian schoolchildren into district d in year t, $\Delta \widehat{AsianEnr}_{d,t}$ as follows. Let $Share_{j,d,\tau}$ be the initial base-year (τ)[11] share of residents in ethnic group $j \in$ {Asian Indian, Chinese, Japanese, Korean, Vietnamese} in school district d, and let $Flow_{j,t}$ denote the national inflow of ethnic group j in year t. $AsianEnr_{d,\tau}$ is the enrollment of Asian students in school district d in the base year τ, and $AsianPop_{d,\tau}$ is the total population of Asian residents in school district d in the base year τ. The predicted inflow of Asian schoolchildren into district d in year t, using initial base year τ, is:

$$\Delta \widehat{AsianEnr}_{d,t} = \frac{AsianEnr_{d,\tau}}{AsianPop_{d,\tau}} \sum_j (Share_{j,d,\tau} \times Flow_{j,t}) \tag{3}$$

We then generate a predicted enrollment inflow for each district by first computing the initial Asian ethnic group population as a share of the total national Asian ethnic group population in the base year. We then multiply this share by the national inflow in year t for each ethnic group, and aggregate these district-level inflows across ethnic groups, resulting in a predicted Asian ethnic group inflow for the district in a given year. In order to scale this inflow down to the subset of public school students, we multiply this sum by the fraction of total Asian public school enrollment over total Asian population for the district in the base year.[12]

We finally arrive at the instrument, the predicted level enrollment of Asian schoolchildren in district d in year t ($\widehat{AsianPred}_{d,t}$), by advancing the initial base-year enrollment ($AsianEnr_{d,\tau}$) forward by these predicted inflows:[13]

$$\widehat{AsianPred}_{d,t} = AsianEnr_{d,\tau} + \sum_{i=\tau}^{t} \Delta \widehat{AsianEnr}_{d,i} \tag{4}$$

the Appendix Table compiled in Jaeger, Ruist, and Stuhler (2018), which lists about 60 publications using this instrument.

[11] We try 1990 and 2000 as base years because according to the sociology literature, these follow the start of the third wave of Asian immigration to the U.S. in the mid-1980s (Paik, Kula, Saito, Rahman, and Witenstein, 2014). We show in Section 5 that 2000 is the most relevant base year.

[12] If enrollment data by Asian ethnic group were available, it would be preferable to perform this scaling from total population to students at the ethnic group level, as different ethnic groups may have different age compositions.

[13] This procedure is complicated slightly in cases where spatial and enrollment district boundaries do not align (e.g., elementary districts that feed to neighboring secondary or unified districts for secondary grade levels). We discuss the construction process for these cases in more detail in Appendix Section E. As school boundary data is not available for us to map tract/county populations to, we are only able to construct this predicted flows instrument and use an IV identification strategy at the district level.

We can now take our instrument to estimate a two-stage least-square (2SLS) linear regression. The first stage (equation (5) below) regresses actual Asian enrollment for district d in year t on the shift-share predicted Asian enrollment instrument. The second stage (equation (6) below) regresses white enrollment on the fitted values from this first stage. As before, we include $Total_{d,t-1}$, lagged total enrollment in district d, and year and district fixed effects (π_t and δ_d):

$$Asian_{d,t} = \beta_0 + \beta_1 \cdot \widehat{AsianPred}_{d,t} + \beta_2 \cdot Total_{d,t-1} + \pi_t + \delta_d + \eta_{d,t} \tag{5}$$

$$White_{d,t} = \gamma_0 + \gamma_1 \cdot \widehat{Asian}_{d,t} + \gamma_2 \cdot Total_{d,t-1} + \pi_t + \delta_d + \varepsilon_{d,t} \tag{6}$$

For our empirical strategy to be valid, it must be that the only channel through which the distribution of Asian immigrants in the base year and national annual inflows of Asian immigrants affect white public school enrollment is in their effects on the actual distribution of Asian public schoolchildren across school districts. Satisfying this requirement would guarantee that our instrument is valid for causal identification – i.e., that it is relevant and exogenous. The relevance condition requires that new Asian immigrants do actually settle where their historical brethren settled. That is, predicted Asian schoolchildren enrollment is strongly and positively correlated with actual Asian schoolchildren enrollment in each school district. The exogeneity assumption requires that the national flow of Asian immigrants in a given year is exogenous to differential shocks to school districts. In other words, it requires that unobserved factors determining the initial distribution of Asian immigrants among California school districts in the base year are uncorrelated with local economic conditions and all other determinants of white location choice in subsequent years.

4.2 Data

We use two types of data for our analysis – namely, education data and population data.

The education data come from the California Department of Education. The dataset contains annual school-level enrollment data for every public school in each academic year over the 1981-2017 period. It reports enrollment counts by gender and by ethnic group[14] for each grade level (K-12). Although the dataset includes other types of districts (i.e., State Special Schools, Statewide Benefit Charter School), we restrict the sample to just unified, elementary, and secondary school districts. The state is fully divisible into these three types of districts. The majority of California school districts are unified districts (i.e., encompassing grades K-12), but some areas are only covered by elementary school districts (encompassing

[14] Ethnic designations are coded as: American Indian or Alaska Native; Asian; Pacific Islander; Filipino; Hispanic or Latino; African American, not Hispanic; White, not Hispanic.

grades K-8). Students in these elementary districts later attend high school in a neighboring unified or secondary school district. In general, most urban/metropolitan areas are served by unified school districts, while the elementary/secondary district split is more common in rural areas of California. Appendix Figure B.3 visually delineates the boundaries of California school districts. We also combine the California DOE enrollment data with IPUMS data on metropolitan areas to construct variables that determine if a school district is in a rural, suburban or urban area (see Appendix Section F for more detail on the construction of those variables).

The population data is required for the construction of our shift-share instrument, as it uses tract- and county-level population counts and national new immigrant inflows to assign predicted flows of Asian immigrants according to established settlement patterns in California. For the shift component, we use national immigration data from the annual Homeland Security Yearbook of Immigration Statistics, which reports yearly inflows of immigrants by country of origin. As the data only report inflows up to 2016, our analysis sample excludes the 2017 enrollment data. For the share component, we use the same yearbook data to obtain national population levels of Asians by country of origin in our candidate base years, 1990 and 2000. For district Asian populations, we use decennial Census tract data on population by racial category. Tracts, which generally encompass areas of between 2,500 to 8,000 people, are necessary instead of more granular units such as Public Use Microdata Areas (PUMAs) because the tract race variable breaks down "Asian" as a broad racial category into Japanese, Chinese, Filipino, Korean, Asian Indian, and Vietnamese. This allows us to map national flows/stocks from these respective countries of origin to the tract-level stocks.[15] California is fully tracted in every census year from 1990 onward. We use the 2017 TIGER/Line GIS files from the U.S. Census Bureau to get school district boundaries. We assume that school district boundaries have not changed significantly since 1990.[16] We then map the tract/county boundaries to the school district boundaries by tabulating the spatial intersections between tracts/counties and districts in ArcGIS into smaller "fragments" which can be uniquely identified. We assume an even distribution of headcount over geographic area to calculate the settlement of Asians in each school fragment.[17] By summing up Asian populations from the unique fragments within each school district boundary, we arrive at a

[15]We map the following countries of migrant origin to the Census and California DOE ethnic categories: Bangladesh, India, Pakistan → Asian Indian; China, Taiwan, Hong Kong → Chinese; Japan → Japanese; Korea, Democratic People's Republic of Korea → Korean; Vietnam → Vietnamese.

[16]Source: California Department of Education.

[17]For instance, if 1/3 of the area of a tract lies geographically in fragment A and the other 2/3 lies in fragment B, we assign 1/3 of the tract population to A and 2/3 to B.

remapping of tract/county populations into district populations.[18]

5 Main Result: White Flight from Asian Students in Suburban Areas

We start our analysis by estimating our OLS, first-stage and second-stage specifications (i.e., equations (2), (5) and (6), respectively) using our full sample. Appendix Table B.2 reports the results. Although the OLS coefficient suggests there is some flight, it is marginally statistically significant and small in magnitude (column (1)). Moreover, the 2SLS results suggest no effect: the first stage is very weak (F-stat of less than one) and the second stage yields an insignificant coefficient. These results are not surprising given that we observe most of the Asian inflows in suburban areas (Figure 1). We thus turn to our main analysis, which presents results by urban status subsample.

Table 1 presents the regression output from estimating equations (2), (5) and (6), separately for rural/suburban/urban areas.[19] As seen in columns (2) and (8), the first-stage estimates in rural and urban areas, respectively, are in the "wrong direction." Indeed, for our instrument to be valid, we require that our predicted shift-share instrument would positively affect the actual number of enrolled Asian students. For rural and urban areas, we find the opposite effect. Therefore, in our remaining analyses, we will focus solely on our suburban-area subsample. In column (5), we find a positive first-stage estimate in suburban areas, which supports the validity of our shift-share instrument. Our IV estimate in column (6) indicates that there is white flight from public schools – the enrollment of one new Asian student causes approximately 2.6 white students to leave. We note, however, that our first-stage F-statistic is lower than the rule-of-thumb of 10 which would comfort us regarding the relevance of our instrument. We also report in Appendix Table B.3 the results with Huber-White robust standard errors instead of standard errors clustered at the school district level (which allows for serial correlations within districts but not across them), and we find a much higher first-stage F-statistic (greater than 30) there.

We also perform the same analyses as in Appendix Table B.2 and Table 1 but using 1990 instead of 2000 as the base year for our shift-share instrument; the results are reported

[18]The mapping between our shift-share instrument and our enrollment data is complicated by the fact that there is no standardized common identifier for school districts between the Census data and the California DOE data. In order to match school-district data, we string match districts on name and county and utilize the fuzzy string matching packages in Python (e.g., `fuzzywuzzy`). We am able to match approximately 70% of the districts in the DOE enrollment data to ones in the Census data. A robustness check ensures that the unmatched districts do not differ significantly from the matched ones, so the sample should be unbiased.

[19]We detail in Appendix Section F how we construct the variable to define these areas.

in Appendix Tables B.4 and B.5. Here as well, the first-stage estimate is negative, which suggests our instrument is not valid in this specification (column (2) in Appendix Table B.4). Turning to our analysis by subsample (Appendix Table B.5), here again, the first-stage estimate has the expected sign only in the suburban subsample. However, the F-statistic is even lower than before and the IV estimate is anyways statistically insignificant.

The contradictory results from the 1990 instrument most likely reflect that the 1990 areas that Asians settled in were fundamentally different from those they settled in a decade later – likely another result of a general trend toward suburbs rather than urban areas. The implication for our analysis from these results is that only the 2000 instrument has sufficient relevance for our identification strategy to hold. The results from the 1990 instruments suggest that 21st-century Asian settlement in California followed an entirely different trajectory from earlier settlement.

One plausible explanation for this result is the rise of the "dot-com bubble," a period of rapid adoption of Internet usage and thus extreme growth and speculation in Internet-based companies from around 1995 to 2000. California's Silicon Valley was considered the epicenter of the dot-com boom. By 2000, demand for skilled technical professions was so high that the high-tech industry lobbied for greater visa quotas (often for high-skilled Asian workers) to fill open positions. During the NASDAQ stock market dot-com crash, which lasted from March 2000 to October 2002, more people moved out of the Silicon Valley area than into it for the first time since the start of the bubble (Lowenstein, 2004). The dramatic change in settlement patterns resulting from the dot-com boom may explain the failure of earlier base years to predict 21st century settlement, especially given that Asians made up such a large demographic share of dot-com industry workers (Nakaso, 2012).

A resulting concern from this explanation is that the distribution of Asian settlement across districts in 2000 may not be plausibly exogenous to economic and educational demand-pull factors in subsequent years. For instance, if Asians moving away from the dot-com bubble in 2000 decided to settle in up-and-coming areas that continued to grow and appear economically attractive to subsequent cohorts of Asian immigrants, the initial 2000 settlement would be correlated with demand-pull factors in later years. The yearly national inflows may also face exogeneity concerns. Qualitative evidence suggests that residence in certain highly competitive California school districts was so coveted overseas that real estate agents posted listings on Taiwanese and mainland Chinese news sites to attract Asian parents thinking of moving to the United States (Lung-Amam, 2017) – while perhaps less likely that overseas attraction to these particular districts influenced the total national flow of Asian immigrants to a significant enough magnitude to be concerning, the possibility exists. These concerns are not empirically testable, but represent possible threats to exogeneity that we refer back to in our discussion of results in the next section.

The broader implication of this exercise is that the key assumption of the Card (2001) instrument, that new immigrants tend to settle in existing communities, and thus that an initial distribution of the immigrant population predicts new immigrant settlement patterns, may not hold across time, and/or may not hold for specific subgroups. The papers discussed in Section 1 as examples of this predicted-flow identification strategy primarily use base years of 1970 and 1980, but our results show that even the 1990 base year distribution of Asians failed to predict later Asian settlement. Papers that construct this instrument for immigrants in aggregate may see strong overall first stage results, but likely get no "bite" from Asian immigrants, who make up a substantial share of national inflows. This result may caution future researchers to decompose immigrant flows by country of origin and ensure that the past settlement logic is valid for all immigrant groups.

In our case, we think of 2000 as a new starting point in time for the formation of ethnic enclaves that differed substantially from any earlier ones. The formation of these ethnoburbs is also backed up by the literature in sociology (Li, 2005; Lin and Robinson, 2005; Li, 2009; Pew Research Center, 2012; Kye, 2018). In the remainder of this paper, we will therefore only use 2000 as the base year for our shift-share instrument.

6 Discussion: Who Flee and Why?

In this section, we seek to understand (i) who are the white students who flee the public school system upon the arrival of Asian students and (ii) the mechanisms underlying the observed white flight (i.e., is it due to pure racial prejudice, aversion to school competition, and/or bid-up housing prices?).

Table 2 presents the OLS and IV results for our suburban subsample, split by thirds of the 2000 school district socio-economic status (SES) index. That index is constructed as the average of two standardized variables (i.e., each demeaned and divided by its standard deviation), both measured in 2000: the percent of students eligible to free or reduced-price meals (FRPM) and school quality as proxied by the Academic Performance Index (API).[20] The OLS results suggest that there exists white flight everywhere (columns (2)-(3)), except for the subsample of the bottom third of the 2000 school-district SES index (column (4)). However, the IV results show that there is white flight only in school districts that are in the top third of the 2000 school district SES index, as indicated by the strong first-stage (F-stat of nearly 20) and the only statistically significantly, negative coefficient (column (6)). This result suggests that it is richer white students who are more responsive to the arrival of

[20] Appendix Tables B.6 and B.7 present the results using each of these two variables separately.

Asian students in their school district. We also note that for school districts that are in the bottom third of the 2000 school district SES index, if anything, there is attraction to Asian students (column (8)).

Is this flight due to pure racial prejudice, or is there a school quality mechanism also at work? Recall from our model in Section 3 that the sign of $\partial z/\partial k$ enables us to disentangle these two channels. If, following the literature on other non-white minorities, public school quality is assumed to be decreasing in the share of Asian enrollment, some of this flight may be due to negative preference for decreased school quality, and some to pure (non-school quality-related) racial distaste. If, as we initially assume in our theoretical setup, public school quality is increasing in the share of Asian enrollment, this implies that observed flight is *net of* a positive school quality effect, and that net departures (minus one)[21] are in fact a lower bound on the magnitude of racial distaste. Unlike the partial derivatives of white utility, $\partial z/\partial k$ is a quantity that is estimable from data; we thus next estimate the relationship between school quality and Asian enrollment. Confirming the sign of $\partial z/\partial k$ will clarify the interpretation of the net flight finding as a result of pure racial distaste versus school quality.

Table 3 presents the OLS and IV results from regressing a proxy for school quality (API score) on the share of Asian students enrolled in the school district. When split by thirds of the distribution of the 2000 API score, we do not find any statistically significant effects, except for the subsample of the top third API. Specifically, even though the statistical significant is only at the 10% level, increasing the share of Asian students by one percentage point leads to a 189-point increase in the API score, which corresponds to a 20-percent increase from a base API score of 837 (column (6)).

Taken together, the results from Tables 2 and 3 suggest that wealthier white students flee school districts where the school quality improves with the proportion of Asian students. On net, it seems that white students are unhappy about educational competition with Asian students. However, the flight could also partly also be explained by an increase in housing prices following the arrival of new Asian families in the district. We next try to rule out that potential channel.

Table 4 presents the OLS and IV results for the full sample (columns (1) and (4)) and for districts that are on average growing (columns (2) and (5)) and for those that are on average shrinking (columns (3) and (6)).[22] Both the OLS and IV results suggest that the main result of white flight are driven by growing districts. Focusing on the IV results, the greater than one-to-one displacement of white students by Asian students in growing districts

[21]Recall that the housing price effect in isolation should lead to one-to-one displacement.

[22]Growing (shrinking) districts are those with a non-negative (negative) average annual growth rate over the 1981-2016 period.

is still indicative of white flight induced by racial distaste, and of distaste outweighing school quality improvements (column 5). The direction of this result is consistent with our main result, though the magnitude is slightly smaller, at 2.3 white departures. Interestingly, in shrinking districts, if anything, the arrival of new Asian students attracts white students into the public school system of the school district. However, we note that these results should be taken with some caution given the weak first-stage results, as indicated by the F-statistics that are below 10 for both types of school districts.[23] Nonetheless, the results here suggest that since we observe white flight only in growing areas, we should not expect to find any housing price effects that would be consistent with the observed white flight. Indeed, areas that have experienced population growth presumably had more time to adjust their housing supply over time, which should counteract the housing price increase due to a housing supply shortage in the short run.

7 Concluding Remarks

Over the past couple of decades, Californian suburban areas have experienced a rapid and regular increase in the share of Asian students that are enrolled in its public school system. How did the arrival of new Asian students in a given school district affect white students? Did white students respond by leaving their schools? If so, what are the mechanisms behind the observed white flight?

This paper shows that there exists white flight from Asian students in Californian public schools – on average, the arrival of one Asian students leads to the departure of 2.6 white students from the school district. It seems that the effect is driven by white students who live in richer school districts. The degree of flight implies both that white racial distaste for Asians exists and that the magnitude of negative racial distaste outweighs the positive preference whites have for improved school quality, which Asian enrollment also increases. Moreover, given that the white flight is observed mainly in growing school districts, we are more confident in ruling out the increased housing prices as a possible explanation. Our results instead support the hypothesis of some aversion that white families may have to educational competition with Asian students, stereotyped as being very competitive and single-minded. This channel is also backed up by qualitative evidence.

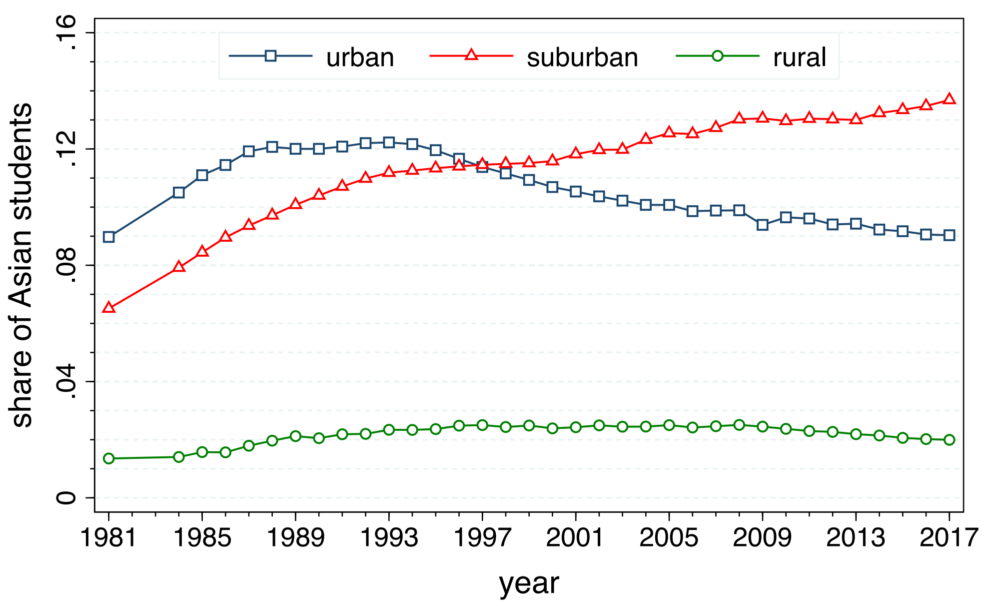
To supplement the analyses we have conducted so far, there are various things we could try to do in the future. First, given that our current shift-share instrument may no longer

[23] Although here as well, the Huber-White standard errors yield much higher F-statistics, as displayed in Appendix Table B.8. We prefer the standard errors clustered at the school district level to be more conservative, as we allow for serial correlation within districts but not across them.

be state-of-the-art due to recent methodological advances (Goldsmith-Pinkham, Sorkin, and Swift, 2019), we may want to use the Asian financial crisis and/or the changes in the H-1B visa cap as natural experiments to see if Asian migrations respond to these arguably exogenous shocks. Second, we could also get population data by age at the tract level, to check the age distribution of the Asian population who migrate to/within California. Third, it may also be interesting to extend the paper by investigating where white students flee to – do they move out of the school district or do they stay in the same school district but go to a private school? Fourth, as a robustness check, it would be nice to get housing price data to comfortably rule out the housing market as a potential channel for the observed white flight. Finally, it may be worth redoing the analysis with a Census-based income measure (as a robustness check for the analysis using the 2000 school district SES index).

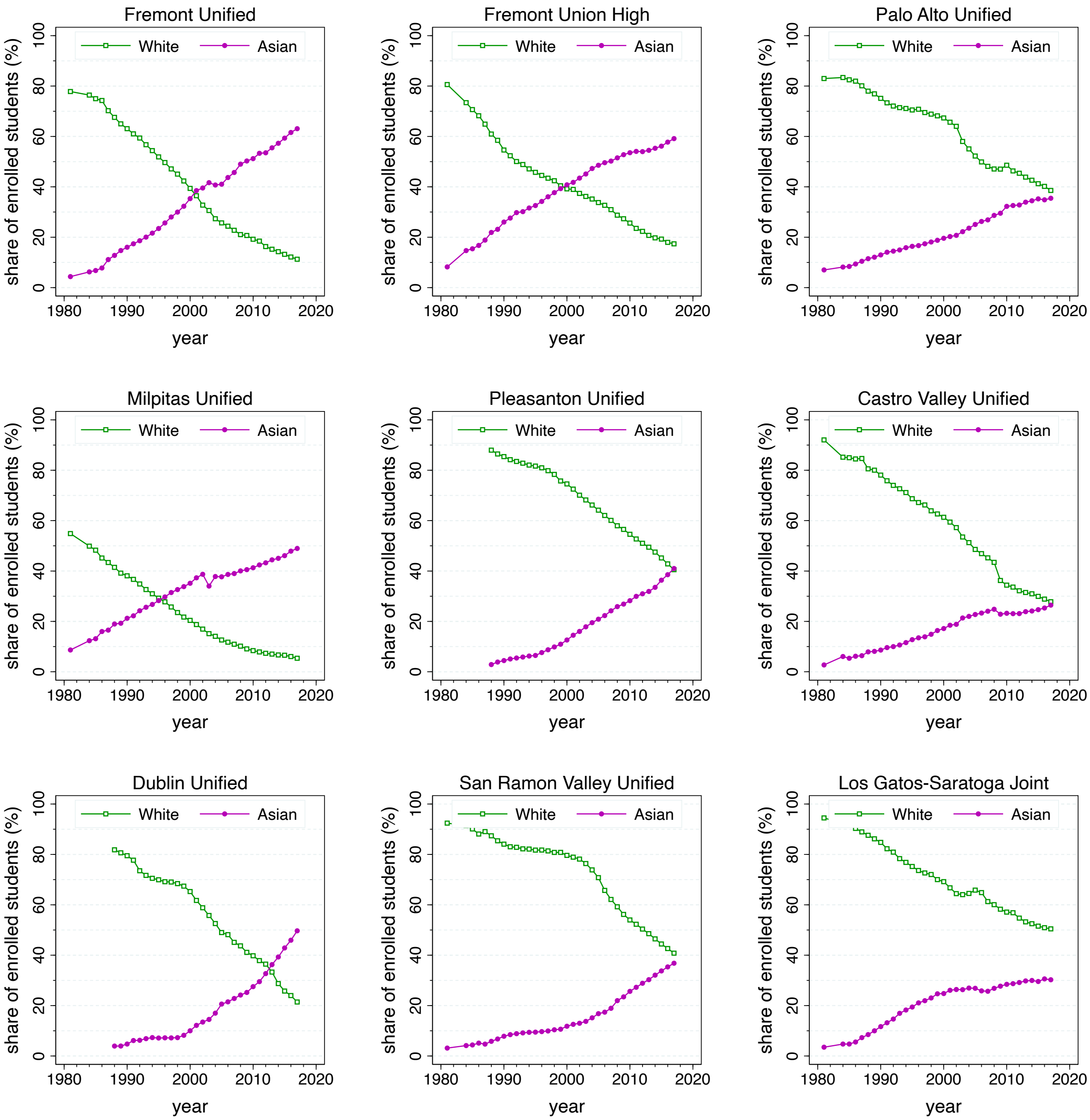
Main Figures and Tables

Figure 1: Growing share of Asian students enrolled in Californian public schools over time



Notes: This figure displays the evolution of the share of Asian students enrolled in Californian public schools between 1981 and 2017, by urban area. The share of Asian students for each urban area is computed as follows: for each year of interest, we sum up the number of Asian students and the total number of students in the school districts located in a(n) urban/suburban/rural area, and we then divide the sum of Asian students by the total number of students in that given area. The data come from the California Department of Education.

Figure 2: Rapidly increasing shares of Asian students in select Bay area school districts



Notes: This figure displays the evolution over time of the share of White vs. Asian students in select Bay area public school districts between 1981 and 2017. The data come from the California Department of Education.

Table 1: White flight from Asian students only in suburban areas

Sample:	Rural			Suburban			Urban		
Specification:	OLS	1st stage	IV	OLS	1st stage	IV	OLS	1st stage	IV
Dependent variable:	White	Asian	White	White	Asian	White	White	Asian	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asian	0.536		11.94	-0.451***		-2.568**	0.544		0.136
	(0.792)		(14.63)	(0.114)		(1.247)	(0.352)		(0.713)
$\widehat{\text{AsianPred}}$		-0.309			0.448**			-0.772***	
		(0.322)			(0.219)			(0.170)	
Total_{t-1}	0.563***	0.00564	0.459***	0.152***	0.152***	0.461**	0.0339	0.0561***	0.0955
	(0.0693)	(0.00424)	(0.115)	(0.0399)	(0.0267)	(0.185)	(0.100)	(0.0195)	(0.0987)
Observations	1,999	1,999	1,999	9,538	9,538	9,538	432	432	432
First-stage F-stat	–	–	0.92	–	–	4.17	–	–	20.58

Notes: This table displays the OLS and IV (and its first-stage) regressions of the number of White students ("White") on the number of Asian students ("Asian"), controlling for the total number of students in the previous year ("Total_{t-1}"), for each urban status sample. All specifications include year fixed effects and district fixed effects. The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table 2: Richer white students are more responsive

Dependent variable:	White							
Specification:	OLS				IV			
Sample:	Non-missing 2000 school district SES index	Top third 2000 school district SES index	Middle third 2000 school district SES index	Bottom third 2000 school district SES index	Non-missing 2000 school district SES index	Top third 2000 school district SES index	Middle third 2000 school district SES index	Bottom third 2000 school district SES index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	-0.451***	-0.670***	-0.845**	0.711***	-2.568**	-1.378***	-15.86	6.154
	(0.114)	(0.122)	(0.416)	(0.187)	(1.247)	(0.437)	(64.04)	(5.640)
Total_{t-1}	0.152***	0.285**	0.243***	0.00784	0.461**	0.467***	2.554	-0.369
	(0.0399)	(0.118)	(0.0729)	(0.0462)	(0.185)	(0.171)	(9.928)	(0.349)
Observations	9,538	3,375	3,158	3,005	9,538	3,375	3,158	3,005
First-stage F-stat	–	–	–	–	4.17	19.70	0.06	0.96
Dep. var. mean	2,176	2,907	2,394	1,124	2,176	2,907	2,394	1,124

Notes: The 2000 school district index encompasses school quality and the percent of students eligible to free or reduced-price meals as of 2000. All specifications include year fixed effects and district fixed effects. The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table 3: Having more Asians improves school quality at the top

Dependent variable:	API score (school quality)							
Specification:	OLS				IV			
Sample:	Non-missing 2000 API score	Top third 2000 API	Middle third 2000 API	Bottom third 2000 API	Non-missing 2000 API score	Top third 2000 API	Middle third 2000 API	Bottom third 2000 API
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian share	-116.0***	50.83	-12.71	175.1	-191.4	188.7*	317.7	5360.4
	(37.64)	(37.90)	(28.09)	(135.5)	(147.4)	(99.26)	(675.7)	(9917.5)
Total_{t-1} ($\div$ 1000)	0.210	0.821	1.334	-0.294	0.388	0.104	0.610	-4.534
	(0.656)	(1.034)	(0.883)	(0.797)	(0.745)	(1.208)	(1.551)	(8.291)
Observations	7,081	2,461	2,368	2,252	7,081	2,461	2,368	2,252
First-stage F-stat	–	–	–	–	12.43	46.53	1.07	0.31
Dep. var. mean	755.4	837.0	747.5	674.7	755.4	837.0	747.5	674.7

Notes: API is measured in 2000 stands for Academic Performance Index and ranges from 200 to 1000; it serves as a proxy for initial school quality. All specifications include year fixed effects and district fixed effects. The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Sample restricted to suburban areas. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table 4: Stronger effects in growing school districts

Dependent variable:	White					
Specification:	OLS			IV		
Sample:	Non-missing average growth	Average growing	Average shrinking	Non-missing average growth	Average growing	Average shrinking
	(1)	(2)	(3)	(4)	(5)	(6)
Asian	-0.451***	-0.481***	0.158	-2.568**	-2.305**	0.774*
	(0.114)	(0.115)	(0.183)	(1.247)	(0.995)	(0.461)
Total_{t-1}	0.152***	0.173***	0.0750	0.461**	0.453***	0.0317
	(0.0399)	(0.0447)	(0.0538)	(0.185)	(0.161)	(0.0577)
Observations	9,538	8,028	1,510	9,538	8,028	1,510
First-stage F-stat	–	–	–	4.17	5.38	7.46
Dep. var. mean	2,176	2,394	1,015	2,176	2,394	1,015

Notes: Growing (shrinking) districts are those with a non-negative (negative) average annual growth rate over the 1981-2016 period. All specifications include year fixed effects and district fixed effects. The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

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Appendix

A Asian Migrations to the United States

For over a century between 1850 and 1960, the United States struggled to reconcile its identity as an equal-rights nation of European immigrants with its rejection of a different set of racially-distinct Asian immigrants. The first waves of Chinese, Japanese, Korean, and Filipino immigrants to the US, who initially settled on the West Coast as contract workers on Hawaiian plantations or as Transcontinental Railroad workers on the continent, were racialized as the "Yellow Peril" invasion. Most of these immigrants had to borrow money for the cost of their passage to the United States and worked for a fixed number of years at contract wages to pay it back, but this practice attached a stigma of unfree "coolie" labor to Asians. The racialization of the "coolie" label ascribed free will, independence, and citizenship to White men and none of the above to Asian men. Unlike African Americans and Mexican Americans, Asians' status as a wholly distinct immigrant group who lacked a minority presence in the United States before countryhood also contributed to the idea that Asians were unassimilable and excludable (Hsu, 2016).

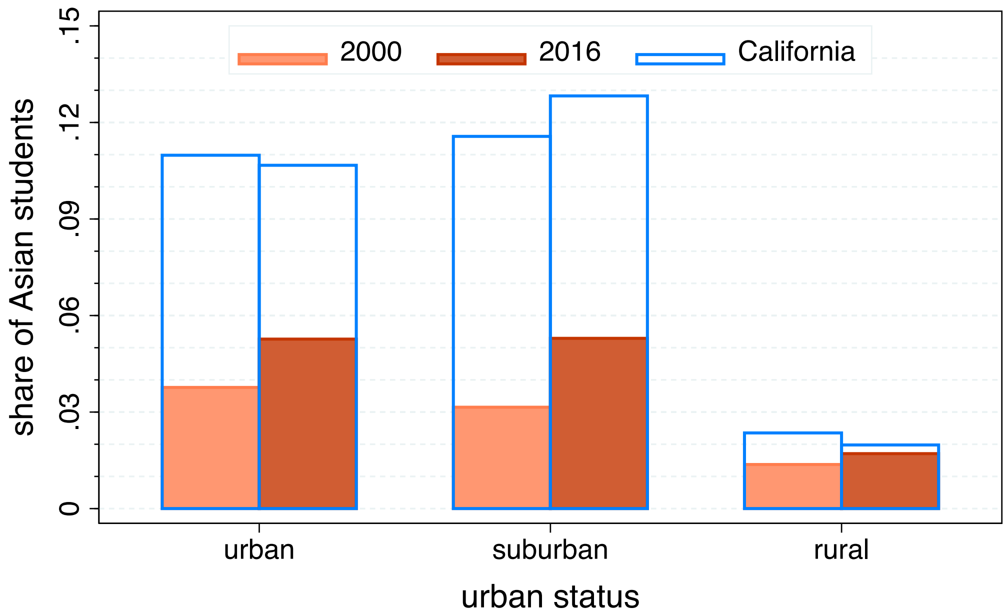
These early racial beliefs drove much of the United States' 19th and 20th century immigration policy, beginning with the 1790 Nationality Act, which limited the right of citizenship by naturalization to "free White persons." Through the 1870s, Congress passed a series of bills aimed at limiting Chinese entry (for instance, by restricting prostitute entry, as most Chinese women were thought to be prostitutes, and by limiting the number of Chinese passengers per ship), culminating in the 1882 Chinese Restriction Act; Chinese exclusion was not repealed until 1943. A 1907 Congress-appointed commission on eugenics and immigrations advised that the United States impose immigration quotas in order to reach its ideal racial composition, giving preference to the most "readily assimilated" races (Hsu, 2016). The resulting 1924 Johnson-Reed Immigration Act barred all immigration from Asia. Anti-Asian sentiment reached peak tension in this era during World War II, against not just Japanese Americans but anyone who resembled the "enemy race" (Takaki, 1998).

The turning tide toward Asian acceptance began in 1940, first with a reconsideration of the status of the Chinese (as the United States' main World War II ally against Japan), then followed by admittance of Indians and Filipinos, and finally of Japanese. Up until this point, Asian exclusion had clearly worked – during the 1930s, fewer than 10,000 total Chinese, Japanese, Korean, Filipino, and Indian immigrants entered the United States. Only after the passing of the 1965 Immigration and Nationalization Act, which overturned the national-origins quota system, did the Asian American population begin growing rapidly as immigrants previously barred in the Asian-Pacific Triangle qualified for education and employment visas (Hsu, 2016).

The immigrants who came after 1965 were positively selected on the basis of education, skill, and employability (Pew Research Center, 2012). Today's "model minority" Asian stereotype is based in large part on the perception of these highly-educated, self-selected migrants, whose immigration growth disproportionately surpassed other Asian groups (Hsu, 2016). This stereotype claims that Asians "avoid the negative outcomes associated with other minority groups because they possess an inherent cultural orientation and work ethic that other non-Whites supposedly lack" (Jiménez and Horowitz, 2013). Though another substantive flow came in the form of Vietnamese refugees fleeing the Vietnam War in the 1970s, and today's overall population of Asian Americans vary greatly in origin country, socioeconomic background, and generation in America (Takaki, 1998), this mythos has widely persisted and has become attached to some of the educational competition-based White distaste discussed in this paper.

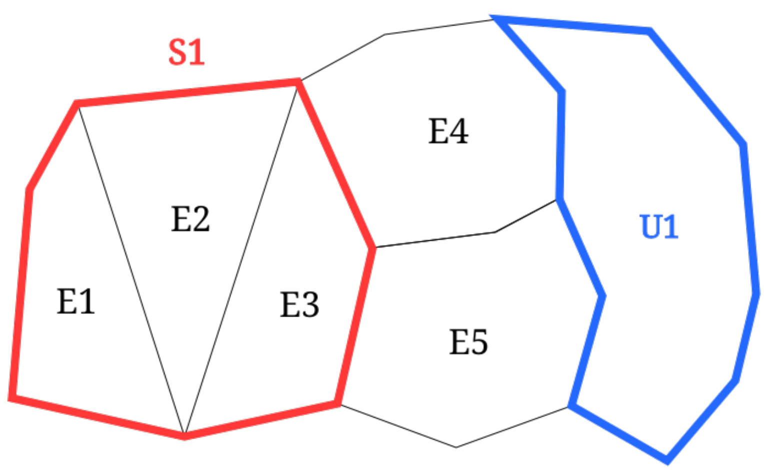
B Appendix Figures and Tables

Appendix Figure B.1: Asian student enrollment in the United States and California, by urban area: 2000 vs. 2016



Notes: This figure displays the evolution over time of the share of Asian students enrolled in public schools in the US (excluding California) and in California in 2000 and 2016, by urban area. The share of Asian students for each urban area is computed as follows: for each year of interest, we sum up the number of Asian students and the total number of students in the schools located in a(n) urban/suburban/rural area, and we then divide the sum of Asian students by the total number of students in that given area. The data come from the National Center for Education and Statistics (NCES).

Appendix Figure B.2: District boundaries example

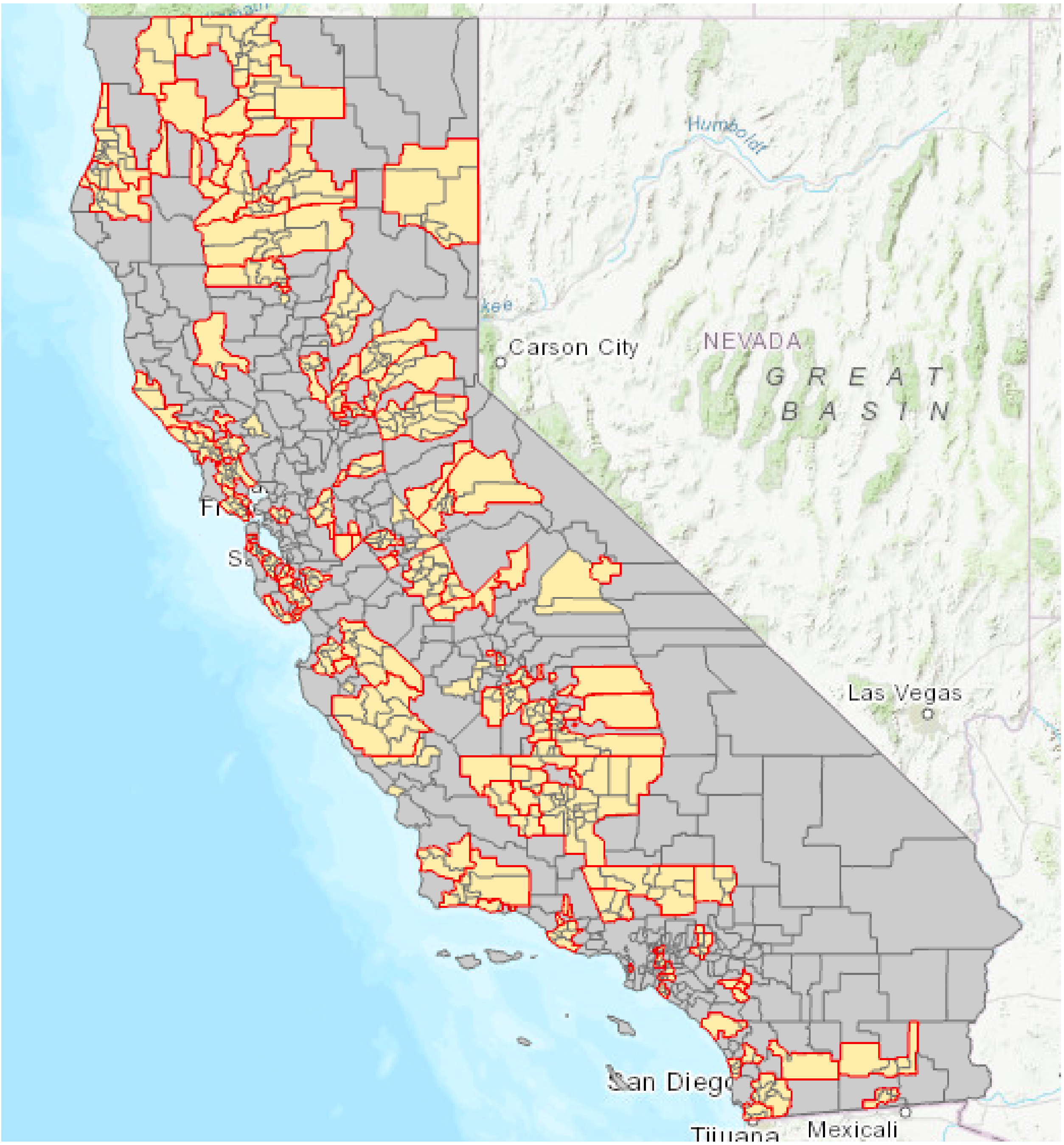


Appendix Table B.1: "Orphan districts" mapping

Elementary District	Secondary or Unified District
Mission Union Elementary	Soledad Unified
Cayucos Elementary	Central Union High
San Miguel Joint Union Elementary	Paso Robles Joint Union High
Pleasant Valley Joint Union Elementary	Paso Robles Joint Union High
Westside Union Elementary	Riverdale Joint Union High
Burrel Union Elementary	Riverdale Joint Union High
Raisin City Elementary	Caruthers Union High
Alvina Elementary	Caruthers Union High
Monroe Elementary	Caruthers Union High
Pine Ridge Elementary	Sierra Joint Union High
Big Creek Elementary	Sierra Joint Union High
Gratton Elementary	Hughson Union High
Hickman Community Charter	Hughson Union High
Roberts Ferry Union Elementary	Waterford Unified
Knights Ferry Elementary	Oakdale Joint Union High
Valley Home Joint Elementary	Oakdale Joint Union High
Howell Mountain Elementary	Saint Helena Unified
Pope Valley Union Elementary	Saint Helena Unified
Manzanita Elementary	Gridley Union High
Camptonville Elementary	Nevada Joint Union High
Plaza Elementary	Orland Joint Union High
Lake Elementary	Orland Joint Union High
Kneeland Elementary	Eureka City High
Garfield Elementary	San Leandro Unified
Freshwater Elementary	Eureka City High
Cutten Elementary	Eureka City High
South Bay Union Elementary	Sweetwater Union High
Hermosa Beach City Elementary	Manhattan Beach Unified

Notes: Mappings obtained in some cases by browsing school district websites; in most cases, by calling each school district and asking administrators. Elementary districts feed to multiple districts for secondary school, but for simplicity, we map to the district which administrators say most students end up attending.

Appendix Figure B.3: California school district boundaries (2017)



Notes: Unified school districts in gray, elementary school districts in yellow, and secondary school districts in red borders.

Appendix Table B.2: Asian vs. white enrollment
Full sample

Specification:	OLS	1st stage	IV
Dependent variable:	White	Asian	White
	(1)	(2)	(3)
Asian	-0.297*		-5.164
	(0.160)		(5.498)
$\widehat{\text{AsianPred}}$		0.209	
		(0.224)	
Total_{t-1}	0.138***	0.152***	0.853
	(0.0386)	(0.0263)	(0.811)
Observations	11,969	11,969	11,969
First-stage F-stat	–	–	0.87

Notes: This table displays the OLS and IV (and its first-stage) regressions of the number of White students ("White") on the number of Asian students ("Asian"), controlling for the total number of students in the previous year ("Total_{t-1}"), for the full sample. All specifications include year fixed effects and district fixed effects, and control for the total number of students in the previous year ("Total_{t-1}"). The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendix Table B.3: White flight from Asian students only in suburban areas

Sample:	Rural			Suburban			Urban		
Specification:	OLS	1st stage	IV	OLS	1st stage	IV	OLS	1st stage	IV
Dependent variable:	White	Asian	White	White	Asian	White	White	Asian	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asian	0.536		11.94**	-0.451***		-2.568***	0.544***		0.136
	(0.396)		(5.505)	(0.0472)		(0.446)	(0.143)		(0.258)
$\widehat{\text{AsianPred}}$		-0.309**			0.448***			-0.772***	
		(0.122)			(0.0785)			(0.0665)	
Total_{t-1}	0.563***	0.00564***	0.459***	0.152***	0.152***	0.461***	0.0339	0.0561***	0.0955*
	(0.0386)	(0.00193)	(0.0522)	(0.0171)	(0.0115)	(0.0705)	(0.0503)	(0.0105)	(0.0535)
Observations	1,999	1,999	1,999	9,538	9,538	9,538	432	432	432
First-stage F-stat	–	–	6.38	–	–	32.55	–	–	134.72

Notes: This table displays the OLS and IV (and its first-stage) regressions of the number of White students ("White") on the number of Asian students ("Asian"), controlling for the total number of students in the previous year ("Total_{t-1}"), for each urban status sample. All specifications include year fixed effects and district fixed effects. The unit of observation is a school district $\times$ year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Robust standard errors reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendix Table B.4: Asian vs. white enrollment
1990 as base year, full sample

Specification:	OLS	1st stage	IV
Dependent variable:	White	Asian	White
	(1)	(2)	(3)
Asian	-0.304**		74.54
	(0.148)		(971.5)
$\widehat{\text{AsianPred}}$		-0.0104	
		(0.134)	
Total_{t-1}	0.149***	0.151***	-11.19
	(0.0405)	(0.0289)	(147.4)
Observations	10,999	10,999	10,999
First-stage F-stat	–	–	0.01

Notes: All specifications include year fixed effects and district fixed effects, and control for the total number of students in the previous year ("Total_{t-1}"). The unit of observation is a school district $\times$ year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 1990 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendix Table B.5: Asian vs. white enrollment
1990 as base year, by urban status

Sample:	Rural			Suburban			Urban		
Specification:	OLS	1st stage	IV	OLS	1st stage	IV	OLS	1st stage	IV
Dependent variable:	White	Asian	White	White	Asian	White	White	Asian	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Asian	1.285		2.600	-0.442***		-4.106	0.504*		0.397
	(0.866)		(1.945)	(0.105)		(2.835)	(0.295)		(0.493)
$\widehat{\text{AsianPred}}$		-0.420***			0.239			-0.402***	
		(0.0858)			(0.182)			(0.103)	
Total_{t-1}	0.515***	0.00998***	0.500***	0.147***	0.164***	0.706*	0.118	0.0206	0.133
	(0.0746)	(0.00315)	(0.0781)	(0.0408)	(0.0304)	(0.422)	(0.0989)	(0.0255)	(0.0860)
Observations	1,725	1,725	1,725	8,794	8,794	8,794	480	480	480
First-stage F-stat	–	–	24.04	–	–	1.72	–	–	15.13

Notes: All specifications include year fixed effects and district fixed effects, and control for the total number of students in the previous year ("Total_{t-1}"). The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 1990 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendix Table B.6: Asian vs. white enrollment
Heterogeneity by initial (i.e., 2000) school quality (API)

Dependent variable:	White							
Specification:	OLS				IV			
Sample:	Non-missing 2000 API	Top third 2000 API	Middle third 2000 API	Bottom third 2000 API	Non-missing 2000 API	Top third 2000 API	Middle third 2000 API	Bottom third 2000 API
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	-0.450***	-0.627***	-0.952**	0.711***	-2.563**	-1.300***	-15.47	6.157
	(0.114)	(0.116)	(0.424)	(0.187)	(1.244)	(0.404)	(57.99)	(5.644)
Total_{t-1}	0.152***	0.249**	0.281***	0.00788	0.460**	0.425**	2.466	-0.369
	(0.0399)	(0.113)	(0.0791)	(0.0462)	(0.185)	(0.166)	(8.794)	(0.349)
Observations	9,482	3,295	3,182	3,005	9,482	3,295	3,182	3,005
First-stage F-stat	–	–	–	–	4.17	19.25	0.07	0.96
Dep. var. mean	2,188	2,816	2,543	1,124	2,188	2,816	2,543	1,124

Notes: All specifications include year fixed effects and district fixed effects. The unit of observation is a school district $\times$ year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendix Table B.7: Asian vs. white enrollment
Heterogeneity by initial (i.e., 2000) % eligible to FRPM

Dependent variable:	White							
Specification:	OLS				IV			
Sample:	Non-missing 2000 perc. elig. FRPM	Top third 2000 perc. elig. FRPM	Middle third 2000 perc. elig. FRPM	Bottom third 2000 perc. elig. FRPM	Non-missing 2000 perc. elig. FRPM	Top third 2000 perc. elig. FRPM	Middle third 2000 perc. elig. FRPM	Bottom third 2000 perc. elig. FRPM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Asian	-0.451***	0.451	-0.805**	-0.650***	-2.568**	3.661	-5.401	-1.342***
	(0.114)	(0.291)	(0.337)	(0.111)	(1.247)	(4.688)	(4.198)	(0.409)
Total_{t-1}	0.152***	0.0752	0.158**	0.296***	0.461**	-0.170	0.776	0.470***
	(0.0399)	(0.0530)	(0.0749)	(0.110)	(0.185)	(0.316)	(0.519)	(0.161)
Observations	9,538	2,940	3,247	3,351	9,538	2,940	3,247	3,351
First-stage F-stat	–	–	–	–	4.17	0.63	1.30	16.96
Dep. var. mean	2,176	894	2,625	2,865	2,176	894	2,625	2,865

Notes: All specifications include year fixed effects and district fixed effects. The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Standard errors clustered at the district level reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Appendix Table B.8: Asian vs. white enrollment
Heterogeneity by below-median vs above-median average district enrollment growth
Robust standard errors

Dependent variable:	White					
Specification:	OLS			IV		
Sample:	Non-missing average growth	Average growing	Average shrinking	Non-missing average growth	Average growing	Average shrinking
	(1)	(2)	(3)	(4)	(5)	(6)
Asian	-0.451***	-0.481***	0.158**	-2.568***	-2.305***	0.774***
	(0.0472)	(0.0490)	(0.0729)	(0.446)	(0.357)	(0.154)
Total_{t-1}	0.152***	0.173***	0.0750***	0.461***	0.453***	0.0317*
	(0.0171)	(0.0198)	(0.0177)	(0.0705)	(0.0632)	(0.0191)
Observations	9,538	8,028	1,510	9,538	8,028	1,510
First-stage F-stat	–	–	–	32.55	41.51	59.75
Dep. var. mean	2,176	2,394	1,015	2,176	2,394	1,015

Notes: All specifications include year fixed effects and district fixed effects. The unit of observation is a school district × year. District IV sample used (only the districts for which the instrument is available; Los Angeles Unified and San Francisco Unified Districts dropped) for the 2001-2016 period. The instrument ($\widehat{AsianPred}$) uses 2000 as base year. Robust standard errors reported in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

C Summary of the Model's Predictions

The predictions of the model laid out in Section 3 can be summarized as follows:

1. If we observe exactly one white departure for every Asian entrant, then only the housing price mechanism is at work, and white location decisions are racially agnostic.

   - If we further assume that $\partial z/\partial k > 0$, this implies $|\partial U/\partial k| = |(\partial U/\partial z)(\partial z/\partial k)|$. In this case, we can only conclude that the two effects cancel each other out, but cannot distinguish whether they are zero or nonzero (i.e., unable to conclude whether whites exhibit racial distaste or not).

2. If we observe more than one white departure for every Asian entrant, then this implies whites do exhibit racial distaste for Asians.

   - If we further assume that $\partial z/\partial k > 0$, this implies $|\partial U/\partial k| > |(\partial U/\partial z)(\partial z/\partial k)|$; that is, the magnitude of whites' negative racial distaste outweighs the positive preference for the increase in school quality also conferred by the Asian inflow.

3. If we observe less than one white departure for every Asian entrant, then this implies whites actually exhibit racial attraction for Asians.

   - If we further assume that $\partial z/\partial k > 0$, this implies $|\partial U/\partial k| < |(\partial U/\partial z)(\partial z/\partial k)|$; that is, the magnitude of whites' positive preference for the increase in school quality outweighs their racial distaste (if any exists; we cannot conclude that $\partial U/\partial k$ is nonzero in this case).

D Why Estimate in Levels Rather Than in Differences

The most common alternate specifications in the immigration displacement literature involve estimating the relationship between first differences ($Race_{t-(t-1)}$) rather than levels, and including total population as a divisor of the race terms rather than as a regressor.[24]

We choose to use specification (2) rather than these alternatives for two reasons. First, we can interpret regressing $White$ on $Asian$ as identifying the white student response to an increase in the total enrollment stock of Asians, while regressing $White_{t-(t-1)}$ on $Asian_{t-(t-1)}$ identifies the white student response to an increase in the yearly *inflow* of Asians. The former is a more meaningful question for this paper, as we hypothesize that white students respond more to the total number of Asian peers around them in a given school year, rather than the

[24] See Peri and Sparber (2011) for an example of a specification using both.

change in Asians from the previous year. For example, in rural districts, going from a yearly inflow of one Asian to ten Asian students (a relatively large change) may not matter to white students if the total number of Asian peers is negligible, while in Los Angeles, yearly Asian inflow might not increase, but high levels of historical Asian enrollment may incentivize white students to leave. The greater ease of interpretation of the levels specification is an additional advantage.

Second, although dividing by lagged population and including it as a regressor are both techniques to control for district size, the former can introduce "division bias" when there is measurement error in the population control. If there is bias in total enrollment, an overstated $White/Total$ share would be associated with an overstated $Asian/Total$ share and an understated $White/Total$ share would be associated with an understated $Asian/Total$, leading to a spurious positive correlation.

This claim of division bias seems to be supported when we run specification (2) but with $Total_{d,t-1}$ as a divisor of $White_{d,t}$ and $Asian_{d,t}$. Estimates of α_1 are higher and more positive than when the lagged population control is included as a separate term. However, we hesitate to draw a conclusive statement from this result as there is no way to determine the "ground truth" for an underlying structural relationship between White and Asian enrollment.

E "Orphan" Districts

As discussed earlier, elementary (K-8) and unified (K-12) school district boundaries uniquely and fully divide up the state of California. The secondary districts (9-12) spatially cover some but not all of the elementary districts in a many-to-one elementary-to-secondary district mapping. The elementary districts which are not spatially contained within the boundaries of a secondary district feed into neighboring secondary or unified districts (we refer to these as "orphan" districts).

There are 27 "orphan" districts in our dataset. Information on which secondary or unified school districts these elementary districts feed into is not readily available online, so we called each district office to inquire. In most cases students are given an option to attend different districts for secondary school, but there is one primary district that most students choose to attend. For simplicity, we map each "orphan" district to just this primary unified or secondary school district. This manual map is included in Appendix Table B.1.

The idea behind our IV approach is to instrument for actual district attendance with predicted attendance. However, in the case of the "orphan" districts, spatial and enrollment district boundaries no longer match up, as students who reside in one district and attend elementary school there then attend high school in another district. This means that the instrument will underestimate actual attendance for the unified and secondary school districts which these "orphan" districts feed into, as these districts actually also receive an influx of non-resident students for grades 9-12, in addition to their resident attendees.

In order to address this issue, we re-compute $\Delta\widehat{Asian}_{d,t}$ for each school district using enrollment for that district but population from the districts which feed into it. We concretize this point with the following example. Say, elementary school districts E1, E2, and E3 are contained within the boundaries of secondary school district S1 and their students feed into S1 for grades 9-12. Orphan school district E4 enrolls students from grades K-8 but also feeds into secondary school district S1 for grades 9-12. Orphan school district E5 enrolls students from grades K-8 but then feeds into unified school district U1 for grades 9-12. U1 also enrolls its resident attendees from grades K-12. Appendix Figure B.2 illustrates these boundaries. For simplicity of notation, let $\sum_j Share_{j,d,\tau} \times Flow_{j,t}$ be called $\Delta\widehat{AsianPop}_{d,t}$, which represents the total predicted number of Asian residents in a district in year t. Below, we compute $\Delta\widehat{AsianEnr}_{d,t}$ for several districts to illustrate and discuss. (For further simplicity of notation and without loss of generality, we drop the time index on terms which denote quantities in the base year T.)

$$\Delta\widehat{AsianEnr}_{E1,t} = \frac{AsianEnr_{E1}}{AsianPop_{E1}} \times \Delta\widehat{AsianPop}_{E1,t} \tag{7}$$

$$\Delta\widehat{AsianEnr}_{S1,t} = \frac{AsianEnr_{S1}}{AsianPop_{S1} + AsianPop_{E4}} \times (\Delta\widehat{AsianPop}_{S1,t} + \Delta\widehat{AsianPop}_{E4,t}) \tag{8}$$

$$\begin{aligned} \Delta\widehat{AsianEnr}_{U1,t} = {} & \frac{AsianEnr_{U1}[\text{K-8}]}{AsianPop_{U1}} \times \Delta\widehat{AsianPop}_{U1,t} \\ & + \frac{AsianEnr_{U1}[\text{9-12}]}{AsianPop_{U1} + AsianPop_{E5}} \times (\Delta\widehat{AsianPop}_{U1,t} + \Delta\widehat{AsianPop}_{E5,t}) \end{aligned} \tag{9}$$

Equation (2) is the simplest case of computing total district enrollment for any elementary school district, or for a secondary or unified school district which does not take in orphan feeder districts. In Equation (3), because $AsianEnr_{S1}$ encompasses 9-12 attendees from both the residents of $S1$ and $E4$, we add $AsianPop_{E4}$ and $\Delta AsianPop_{E4,t}$ to the respective $S1$ terms. In Equation (4), we divide the unified enrollment of $U1$ into a K-8 component, which only comprises the residents of $U1$, and a 9-12 component, which comprises the residents of $U1$ and of $E5$. One important note is that although the district data tabulates enrollment by grade level and also by ethnic group, it does not tabulate by grade level $\times$ ethnic group. Therefore, while we do not have the exact number $AsianEnr_{U1}[\text{K-8}]$, we can estimate this by taking $AsianEnr_{U1} \times (TotalEnr[\text{K-8}]/TotalEnr[\text{K-12}])$. The end result of this procedure is a dataset of school district predicted inflows which accurately reflect the underlying residence/attendance patterns and still allow the full sample of elementary, secondary, and unified school districts to be used in our analysis.

F Defining Rural/Suburban/Urban Areas

To construct the variables that we will use to define if a school district is in a rural, suburban or urban area, we combine data on public-school enrollment from the California DOE and data on the county composition of U.S. metropolitan areas from IPUMS USA.

We first map each county of California to its corresponding metropolitan area, using the 2000-2011 definition from IPUMS USA (2019). This enables us to build a crosswalk dataset of counties and metropolitan areas in California.

We then combine this crosswalk dataset with the public-school enrollment data from the California DOE, and define our urban status variable as follows:

1. We restrict the sample to the state of California (the IPUMS USA data covers the whole U.S.).
2. Any counties that is in California but not in one of the counties that appear in the IPUMS data is assigned to belong to rural areas.
3. We sort the dataset by county and school district size (based on total enrollment).
4. The largest school district (based on its public-school student population) is assigned to belong to urban areas.
5. The remaining school districts are assigned to belong to suburban areas.